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AN INFORMATION ADAPTIVE SYSTEM STUDY REPORT AND DEVELOPMENT PLAN

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TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

TABLE OF CONTENTS (Continued)

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

LIST OF FIGURES (Continued)

LIST OF TABLES

1.0 INTRODUCTION

An information adaptive system, under the NEEDS program, has been studied and a development plan which identifies areas of further needed research has been established. The purpose of the information adaptive system (IAS) study is to determine how some selected earth resource applications may be processed onboard a spacecraft and to provide a detailed preliminary IAS design for these applications. Detailed investigations of a number of applications were studied with regard to IAS and three were selected for further analysis. This additional analysis allowed us to determine just how far we can go today in the performance of onboard algorithms and what areas of research are needed in order to permit applications to be processed onboard in the future. The IAS development plan shows future research needs for the onboard processing of these applications. The ultimate goal of the IAS study was to establish an IAS development plan. This development plan details the areas of future research and development that are required to make an IAS system feasible. This plan entails:

- Algorithmic specifications
- System design specifications
- IAS recommended time lines

The study was functionally dissected into five tasks:

- Pre-study
- Attributes/selection
- Sub-systems design and specification
- The design of an on-board classifier
- IAS development plan

1.1 Study Elements

During the pre-study task, five meetings were held with NASA personnel in order to obtain information and direct the progress of the study. Appendix A contains the minutes of these meetings.

In the attributes/selection task, 155 different earth resource applications were examined and disected into scenarios of processing algorithms. Algorithmic attributes were established as they relate to IAS implementation and system design desires. A trade-off study associated with measures for these attributes permitted the selection of three most favorable applications for IAS.

- Sea Ice Mapping.
- Snow Melt Runoff Forecasting.
- Land Use Classification/Inventory.

In addition, information adaptive techniques were studied with regard to methods of reducing the volume of data which would be required for these onboard applications. Six techniques were identified and proposed:

- Onboard information extraction
- Selective data capture and region encoding
- Partial data processing (information conserving compression/representation)
- Adaptive control functions
- User defined processing scenarios
- Evolutionary growth.

These concepts were studied in relationship to each application in order to establish concepts for onboard implementation.

In the sub-systems design and specification task, requirements for the end-to-end implementation of the three selected applications were established. Both near-term information adaptive system requirements and long-term development requirements for IAS were established. These requirements were then used to provide a preliminary end-to-end system design specifications for the three applications. Also, all IAS sub-systems in the algorithmic functional and system areas were examined in order to identify problems that may be expected to arise in each of these areas. It is the list of these potential problem areas that constitutes the essential results of this study.

In the on-board classifier design task, the on-board implementation of an autonomous feature extracor/adaptive classifier was discussed. System specifications and recommendations were given. In addition, available technologies and hardware architecture for the implementation of such an on-board unit were examined. These results were used to demonstrate through a scenario of operations of how an on-board classifier might be performed and to point out some of the logistical and technical problems. It is this design task that shows the integration of the IAS techniques into an on-board system.

In the IAS development plan task, potential cost benefits that would result from an information adaptive system were assessed and the inter-relationships of the IAS NEED elements with other NEED elements were examined. In addition, present technological growth parameters were examined so as to ascertain subsystem viability as a function of time. These studies were integrated then into an IAS development plan.

1.2 Summary of the Report

Section 2.0 contains our executive summary. Therein contained is a description of IAS in relationship to other NEEDS elements. The objectives of the study and the study approach are described along with the essential results and a list of recommendations are to be found.

Section 3.0 consists of details of each of the different phases of the study. Section 3.1 gives the results of our pre-study and provides the rationale for application selection; Section 3.2 gives our subsystems design/specification study in which requirements for the three selected applications are presented. It also provides specifications in the algorithmic, functional and interface areas and includes problems which have been identified in these areas; Section 3.3 provides a detailed design of an on-board classifier which is applicable to the three selected applications.

Section 4.0 gives our conclusions and recommendations which fall into the categories of general conclusions, identification of problem areas, recommended approaches to problem solving and recommended time lines for IAS development.

2.0 EXECUTIVE SUMMARY

This section describes the essential results of the study. It contains the objectives, rationale, study approaches, results, and recommendations.

2.1 IAS Rationale

At the present time, the NASA data system is loaded to its capacity and has significant operational limitations. The mission model will be significantly altered in order to meet the 1980 through 1990 mission requirements. The number and kind of spaceborne sensors will significantly change; and the data rates and number of space data users will increase by an order of magnitude. This implies that expansion of the data system and changes in the support system are needed. The NASA end-to-end data system (NEEDS) program is an attempt to meet these future challenges. One of the important elements of the NEEDS program is the Information Adaptive Systems (IAS).

The NEEDS program attempts to significantly increase the effectiveness and efficiency of information systems that provide application information to users through the processing of data taken from onboard sensors. Six major concepts have evolved from the NEEDS program. These concepts are:

- Data and information autonomy
- Platform and instrument autonomy
- Reduction of data to information as soon as possible
- Use of standardized interfaces and protocols
- Build to integrated/test/fly
- Design to a modular fail soft redundancy philosophy.

The diversity of information and the volume and bit rate to be produced by the spaceborn sensors planned for the 1980-up time frame will require a more reliable, responsive, and expandable data/information (DI) system at a far more reasonable price than would be projected by the use of current technology. Figure 2.1-1 illustrates the trend in communications

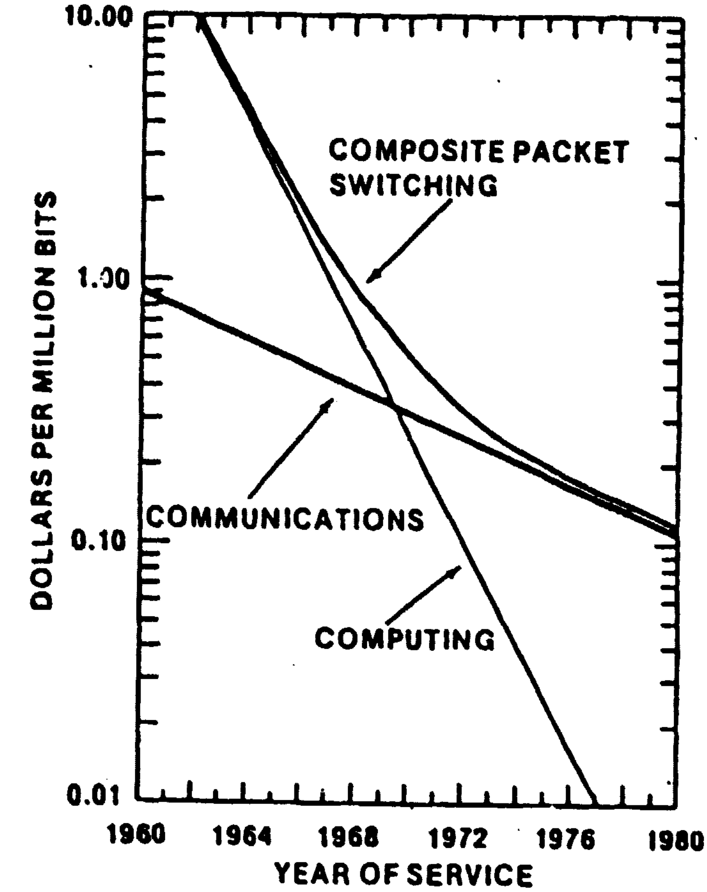


Figure 2.1-1 Cost/Performance of Computing and Communications

PROGRAM ELEMENT	SYSTEMS ANALYSIS AND INTEGRATION	MODULAR DATA SYSTEM	INFORMATION ADAPTIVE SYSTEM	DATA BASE MANAGEMENT	DISTRIBUTED CONTROL CONCEPT	SOFTWARE V&V	PARALLEL PROCESSORS	ARCHIVAL MASS MEMORY
ESSENTIAL CONCEPT								
(1) DATA AND INFORMATION AUTONOMY	X	X		X			X	X
(2) SPACECRAFT AND INSTRUMENT AUTONOMY	X	X	X		X		X	
(3) REDUCE DATA TO INFORMATION AS SOON AS POSSIBLE	X		X				X	
(4) INTERFACE DEFINITIONS AND PROTOCOLS	X	X	X	X	X	X		X
(5) BUILD TO INTEGRATE/TEST/FLY	X	X	X		X	X	X	
(6) FAIL SOFT MODULAR REDUNDANCY	X	X	X		X	X	X	X

Table 2.1-1 Relationship of Essential NEEDS Concepts to Program Elements

costs vs computing cost. The NEEDS program goal is to increase the efficiency and effectiveness of the end-to-end data-to-information transformation by two orders of magnitude. Through-put, system access time, and support costs are being attacked. The long range goals of the NEEDS program are (1) to increase the data/information through-put by a factor of one thousand, (2) to reduce the system access time for space acquired data by a factor of one hundred, and (3) to reduce the support costs by a factor of ten.

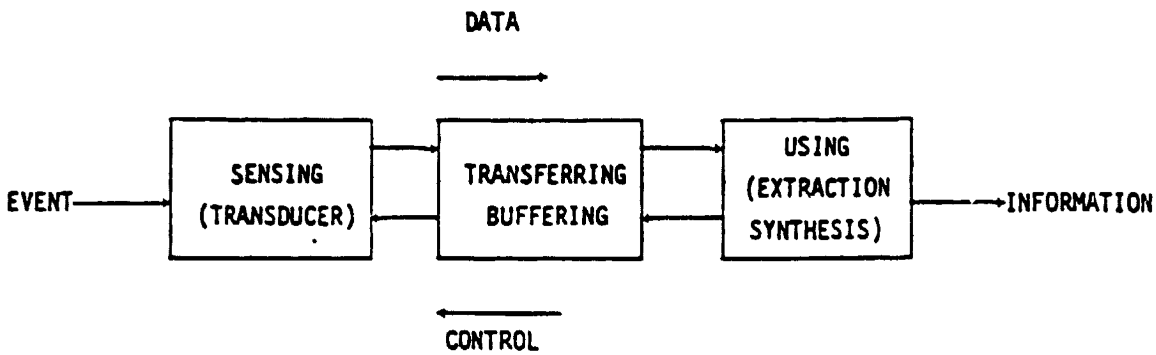
The primary approaches to be used in accomplishing the goals of the NEEDS program are:

(1) Establishing more effective ways to deliver information to the users, and
(2) feeding back control information to the "smart" sensor from:
- the user
- other sensors
- spacecraft attitude and orbit state.

This feedback information will be used in an adaptive manner to condition the IAS system to respond only to specific events. In this way, the user will be provided only that data/information which he actually desires.

The principal functions to be performed by a data/information (DI) system are: sensing an event, transferring data, extracting information, learning, planning, feeding back user information, and sensor conditioning. The flow of data and control for event detection and subsequent transformation to information within the DI system is shown in Figure 2.1-2. The essential ingredient of this NASA end-to-end data/information system is the control function which opens the gateway to the effective use of "smart" sensors.

There are eight functional elements of the NEEDS Phase II program that must be integrated in order to accomplish the program goals. They are:



From the detection of an event to the output of information, including the planning and feedback of conditioning for event detection.

Figure 2.1-2 The NASA End-to-End Data/Information System

- System analysis
- Information adaptive system
- Modular data systems
- Data base management
- Parallel processors
- Archival mass memory
- Distributed control concepts
- Software verification and validation.

It is the intent of the NEEDS program to use these specific program elements as a test bed upon which to evaluate, in a quantitative way, the six concepts that have been previously defined. The relationship between the NEEDS concepts and its functional elements is shown in Table 2.1-1. In particular, Table 2.1-1 shows the interdependency between the Information Adaptive System (IAS) element to six of the essential concepts. The key to understanding the requirements of IAS is embodied on concept 3, i.e., the reduction of data to information as soon as possible. The adaptive control aspect of the IAS is embodied in concept 2, i.e., spacecraft and instrument autonomy. In designing the IAS system for specific applications, care must be taken to ensure the proper interface to all modular aspects of the data system design element. The concept of fail soft modular redundancy will be a key driver in the adaptive control design of the "smart" sensor. Table 2.1-2 summarizes the rationale for an IAS system.

ESSENTIAL CONCEPT \ PROGRAM ELEMENT	SYSTEMS ANALYSIS AND INTEGRATION	MODULAR DATA SYSTEM	INFORMATION ADAPTIVE SYSTEM	DATA BASE MANAGEMENT	DISTRIBUTED CONTROL CONCEPT	SOFTWARE V&V	PARALLEL PROCESSORS	ARCHIVAL MASS MEMORY
(1) DATA AND INFORMATION AUTONOMY	X	X		X			X	X
(2) SPACECRAFT AND INSTRUMENT AUTONOMY	X	X	X		X		X	
(3) REDUCE DATA TO INFORMATION AS SOON AS POSSIBLE	X		X				X	
(4) INTERFACE DEFINITIONS AND PROTOCOLS	X	X	X	X	X	X		X
(5) BUILD TO INTEGRATE/TEST/FLY	X	X	X		X	X	X	
(6) FAIL SOFT MODULAR REDUNDANCY	X	X	X		X	X	X	X

Table 2.1-1 Relationship of Essential NEEDS Concepts to Program Elements

• Multi-craft
• System maintenance cost savings for ground stations
• Real time packet switching to users
• Archival savings
• Improved reliability
• Product repeatability
• Cost of wide band data transmission
• Increased responsiveness
• Selection of only useful data
• Increased standardization
• User driven system
• Reduction of data
• More timely data to product reduction

Table 2.1-2 IAS Rational Concepts

2.2 Study Objectives

Prestudy

The prestudy task entails three activities (subtasks):

- Algorithmic feasibility
- Ensemble of application
- Hardware and system feasibility.

It had, as its objective, the review of algorithms that are feasible for IAS implementation and the collection of an ensemble of applications which are *a priori* candidates for an onboard information adaptive system. A further objective of the study is to conceptualize a system containing hardware and software from which to guide the selection of favorable applications. The results of the prestudy tasks is a listing of applications which is divided into two categories: an infeasible list which is no longer considered, and the remaining feasible set of applications which was further studied.

The objectives of the attributes/selection task was to select two or three applications which are most favorable to IAS.

Criteria for selection include:

- Feasibility measures
- Desirability measures
- Maturity measures
- NASA benefits
- User benefits.

Attributes/Selection

The attributes/selection task consists of five steps and has as its objective the selection of favorable applications for IAS. These steps are:

- Algorithmic attributes
- Desired attributes of system
- Trade-off study
- Other attributes
- Select most favorable applications.

In the first phase of the study algorithmic attributes were defined and an algorithmic feasibility cost was generated for each algorithm. The 155 applications were groupd into 18 representative application classes to which algorithmic costs were computed. Based on algorithmic feasibility, the applications were ordered. This ordered list was divided into feasible and infeasible applications.

The selection criteria considered feasibility, desirability, maturity, NASA benefits, and user benefit measures. Pairwise costing procedures were developed in selecting two most favorable applications:

- Sea ice
- Land use.

A third application (snow melt) was added in response to NASA requests.

The investigation into IAS techniques had led to a tree structure control approach and the use of decision tree classifiers for onboard processing.

Sub-System Design

The design task consists of three objectives:

- Feasible design of onboard algorithms
- End-to-end functional requirements
- Preliminary end-to-end system design specifications

Onboard algorithms for each of the selected applications were studied for IAS. Some of these algorithms involved the use of information adaptive techniques such as geographic data selection. These too were included in our design. Later, the need for control algorithms and for methods of determining spacecraft position and attitude to accuracies beyond which the spacecraft is controlled appear to be desired in the context of this study. These too are added to our IAS design. Also included are tree structure control algorithms and decision tree classifiers for a multi-spectral classification. An end-to-end functional requirements document for IAS was written and included a preliminary end-to-end system design from which the remainder of the study could be conducted.

Sub-system Specifications

The sub-system specification task consisted of three objectives:

- Sub-system algorithm specifications and problems identification
- Sub-system interface specifications and problems identification
- Sub-system functional specifications and problems identification

In this task the preliminary system design was broken into sub-systems in the algorithmic, functional and interface areas. These areas were studied with the particular desire to identify problems that are likely to occur in these three areas. Sections 3.2 and 3.3 present a list of problem areas that need to be solved before a viable IAS system can evolve. It can be seen from this task that the major areas of concern are onboard hardware and feasibility demonstrations.

Onboard Classifier Design

The onboard classifier design task is a conceptual design of a viable IAS unit for the autonomous feature extraction and classification of remotely sensed data. The final goal of this task is to generate system specifications, to specify methodologies, to propose hardware architecture, and to give recommendations for the development and implementation of such units. The objectives are listed below:

- To develop algorithms for feature extraction
- To design optimum decision tree classifiers
- To develop table look-up procedures for classification
- To examine adaptive procedures for onboard real-time classification
- To specify onboard computing hardware required for such unit
- To demonstrate the process through a scenario of operations
- To provide recommendations and point out problems.

IAS Development Plan and Recommendations

The IAS development plan consists of three subtasks:

- IAS benefit assessment
- Inter-relationship with other NEEDS elements
- IAS development plan.

In this task benefits to NASA for having an information adaptive onboard processing system are assessed. In addition, the relationship of IAS with other NEEDS elements, especially the data packet concepts are studied and areas of communication with these elements are identified. The problem areas of the previous task are analyzed in relationship to

- Potential solutions
- Research requirements
- Demonstration requirements
- Evolving technologies
- Viable hardware architectures

and an IAS development plan is evolved showing timelines needed in the solution of problem areas in order to evolve onboard information extraction capability in a realistic time frame.

2.3 Study Approach

The approach used to accomplish the IAS tasks are embodied in Figure 2.3-1. Here the functional work flow is presented. For each of the five tasks, a set of subtasks are shown which feed into other subtasks, finally resulting in an IAS development plan. In the pre-study task, an a priori ensemble of applications was extended to include 155 applications. This task was done by an extensive review of the current literature and by reading a large volume of reports on the types of applications being done today. A review of these applications permitted us to

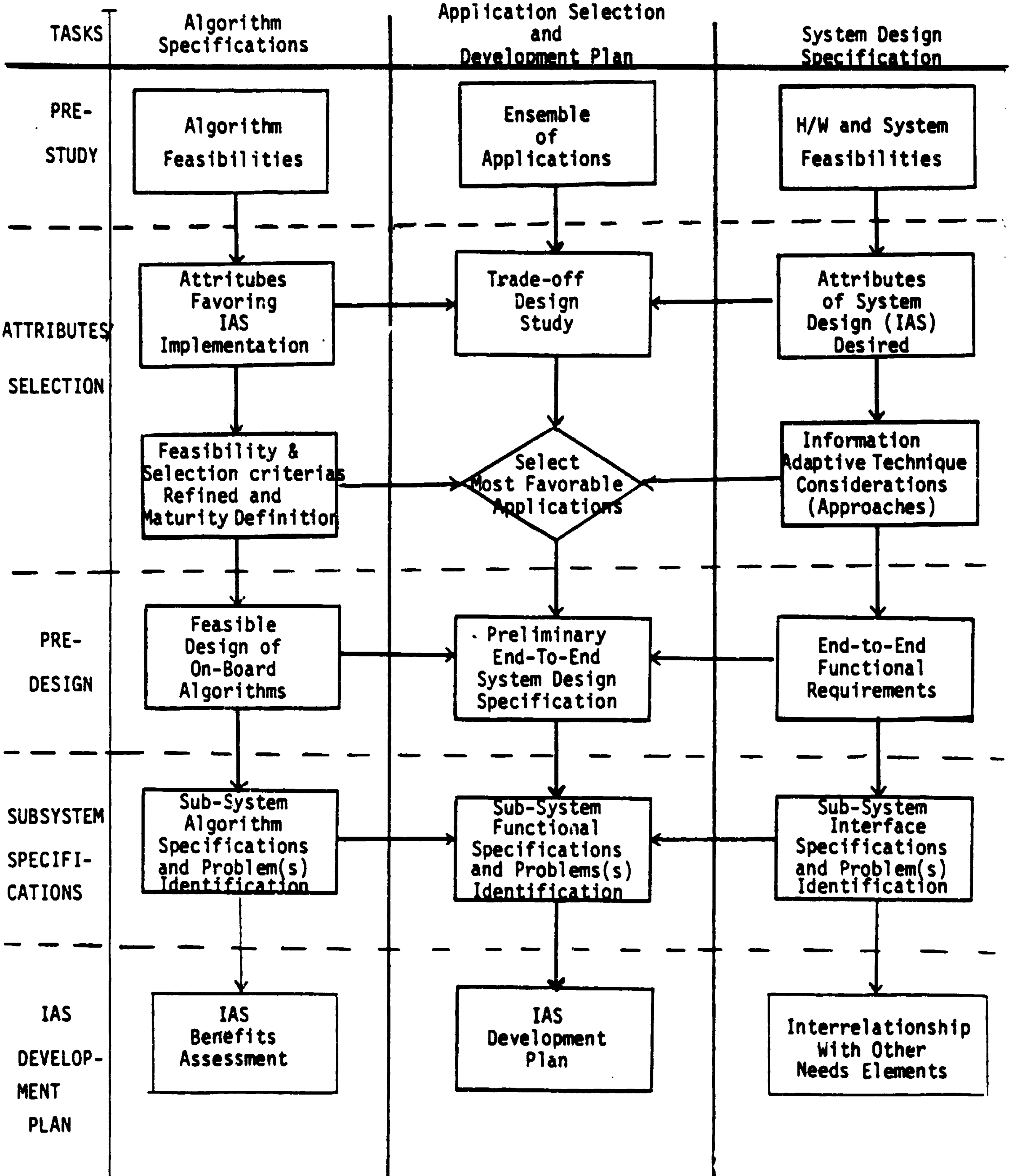


Figure 2.3-1 Functional Work Flow

assess the initial user benefits associated with each application and to further investigate the set of algorithms, procedures and techniques that are required to implement each application. This set of algorithms, etc., initially numbered approximately 60 but were reduced to 35. The 25 infeasible procedures were judged so because most required very extensive spatial processing or required extensive storage, and were thus determined to be not suitable for onboard processing. Each of the remaining 35 algorithms were considered potentially feasible for IAS. In addition, hardware and system feasibilities were considered which resulted in a prototype functional block diagram for IAS shown in Figure 2.3-2.

2.4 Results

2.4.1 Results of the Pre-study and Attributes/Selection Study

- IAS Library: During the pre-sduty literature search a library of IAS references has been established to assist in future research efforts.

- Ensenble of Applications: A comprehensive list of 155 remote sensing applications was generated during the literature search. This list was used to generate potential IAS applications.

- Ensemble of Algorithms: A list was generated which represented image processing algorithms and procedures used to implement the applications.

- Application Scenarios: Algorithmic processing scenarios were specified for each of the 155 application areas.

- Relative Merit Costing Technique: A comparison procedure which allows the combination of dissimilar attributes of an IAS favorability measure, such as feasibility, desirability and maturity was developed. It utilizes the concept of equivalent costs between attributes.

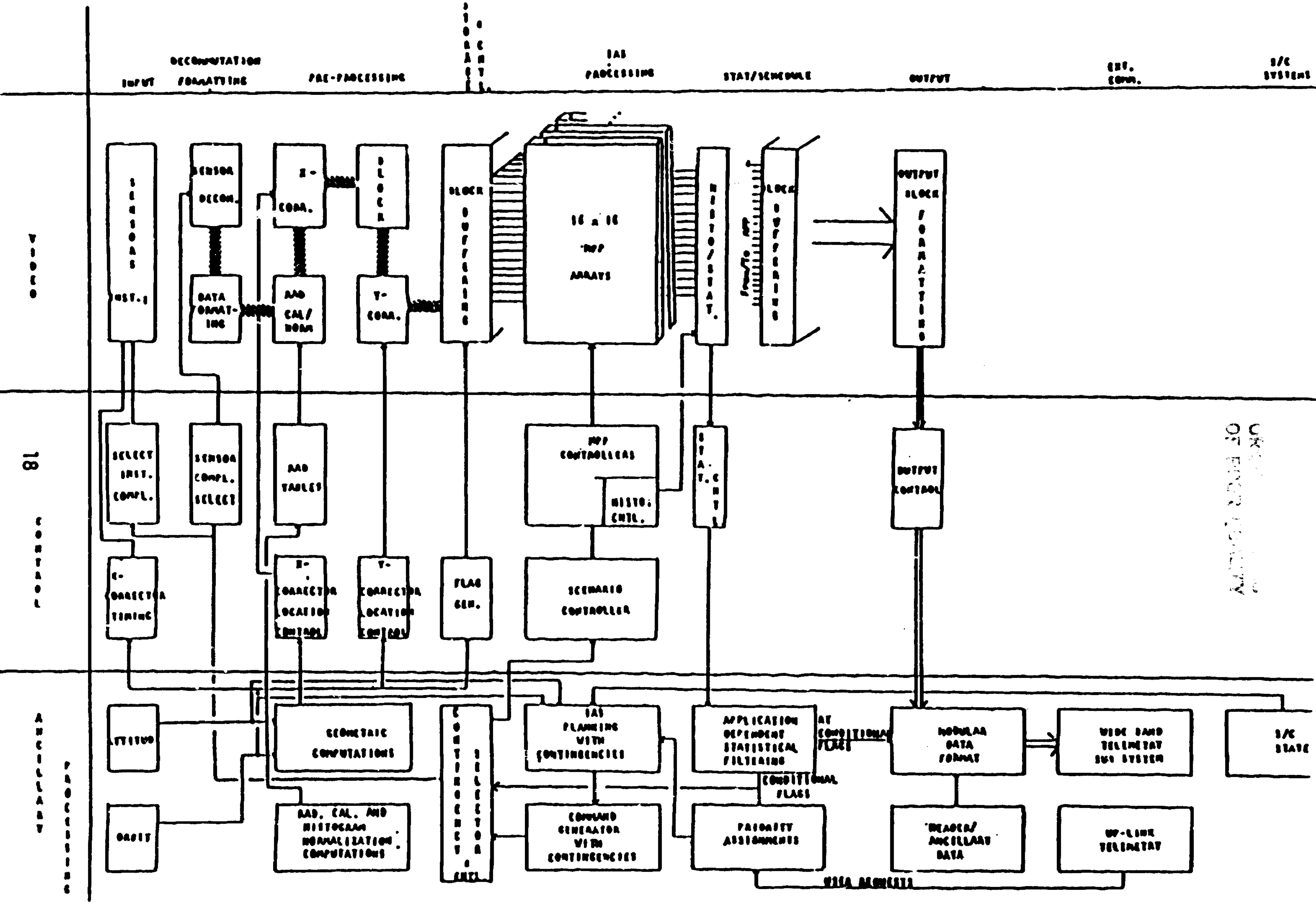


Figure 2.3-2 IAS Prototype Functional System Block Diagram

- Algorithmic Attributes: A set of 8 attributes was specified in order to assess the feasibility "cost" of an algorithm

- Algorithmic Feasibility Costs: The "cost" of the algorithms within an IAS context were determined by measuring each algorithm attributes and applying the costing procedure.

- Application Classes: Similar processing scenarios were defined and the 155 applications were grouped into 18 representative classes.

- Application Feasibility Measures: Using the algorithmic scenarios for each application class the algorithmic costs were applied and a feasibility cost for each application class was calculated.

- Feasible vs. Infeasible Applications: Using the application feasibility measures and considering certain special factors the 18 classes wee grouped into 8 feasibile applications and 10 infeasible applications.

- Desirability Attributes: Described are the desirability attributes and the components that make them up. These attributes are defined from an IAS control desirability viewpoint.

- Maturity Attributes: BTS defines the attributes that are associated with the success that has been achieved in specific applications for creating image products for the end user.

- Pairwise Costing Procedure: Recognizing NASA's desire to choose two dissimilar applications BTS developed a technique for doing pairwise comparison of applications.

- IAS Techniques: BTS has defined and described 6 techniques that we feel represent techniques for IAS implementation.

- Tree Structure Control: BTS describes the control structure it will use for scheduling, prioritization and classification. We also describe decision tree classifiers and how they interface in the control structure.

Later studies showed many of the elements of this prototype functional system block diagram to be impractical. For example, the initial concept considered a 16 by 16 massively parallel processor or groups of processors as the methodology by which image processing would be performed. This turned out to be impractical for two reasons:

- The massively parallel processor is insufficiently flexible enough to handle all algorithmic requirements for IAS.

- This processor is too hardware intensive for onboard applications.

The resulting three applications selected from the trade-off study are:

(1) Sea ice mapping,

(2) Land use classification/inventory, and

(3) Snow melt runoff prediction.

2.4.2 Results of the Sub-Systems Configuration Study

Studies were performed on preliminary system configurations for an IAS system. The results provide both a near term implementation of a basic IAS, as well as for long term development. These results were established in the context of three applications -- sea ice mapping, land use classification/inventory, and snow melt runoff forecasting. The results also provide IAS system concepts, techniques, and technology which could increase the system responsiveness, reduce the relative cost of information extraction, and increase the degree of standardization.

The concluding remarks of this system configuration study are as follows:

- The near-term IAS is within our technical capabilities at the present time.
- The long-term IAS -- the Ultimate Information Adaptive System -- can be realized by a reasonable research effort. With the present technology, years of effort will be required to achieve the capabilities of such systems.
- To benefit users of the IAS, the following features are required:
  (1) Geographic selection of data
  (2) Detection and disposal of obscured data
  (3) Data compression to user relevant units
  (4) Autonomous message packets
  (5) Modular, standardized communications from end-to-end
  (6) Autonomous operation from user request to information delivery.

2.4.3 Results of the On-board Classifier Design Task

An on-board classifier is viable. There are both possible gains and hazards associated with it. Also, there are significant problems which must be overcome before this proposed classifier could become reality. The following lists a few of the problems, benefits, and solutions.

(a) Data will be available to the ground user in minutes rather than months.

(b) Data storage on ground will be reduced tremendously due to the availability of classified results.

(c) On-board classification provides a reasonable direct user interaction with the satellite which benefits users for specifying their needs.

(d) The one factor which some users may consider hazardous in such proposed systems is the fact that the raw data is no longer available to the users. In some cases, a user may wish to do post-classification processing to improve accuracy. Since the raw data is no longer available and the only available data sets are the training data and the classified data, post-classification processing might seem impossible.

(e) A significant amount of pre-processing, for example, correction for geometric distortion, must be done prior to classification. It imposes some constraints in operating speed and additional on-board hardware.

(f) Continued technological improvement is necessary to produce faster, more compact and lower power system components for on-board implementation.

(g) Future research is necessary to provide more applicable adaptive processing theories for the tracking and updating of classifier parameters. Research topics include filtering theories, mathematical modeling of scene variations, and implementation of adaptive processors.

(h) The recent development of the "smart sensor" also shows considerable promise. It performs detection and processing directly at the focal plane of a sensor and achieves full-frame processing in real-time.

2.5 IAS Recommendations

The concept of performing significant processing on-board is unfamiliar to most users. In addition, the user community generally feels that any irreversible manipulation of the data produces a contamination of that data such that the accuracy of the information extracted may be impaired. The users thus wish that no processing be performed outside of their direct supervision. Such a philosophical stance is in direct opposition of the long-term goals of both NEEDS and IAS.

The early experiments involving on-board processing must be structured in such a way as to minimize the user communities opposition to the on-board processing. Just as users had to be conditioned to accept remotely sensed data, the users will have to be conditioned to accept remotely processed data. To accomplish this, the early IAS missions must be structured with two capabilities.

The first capability must be to permit the acquisition of data with little, if any, actual data processing. This would indicate the ability to select data from user-specified geographic regions, and perhaps to delete data which is overly obscured by clouds. This capability would significantly reduce the data volume delivered to any user and would clearly illustrate the benefits to be gained by providing some intelligence on-board.

The second capability which should be provided is that of selectively conducting IAS experiments. By this we mean that certain users could direct the spacecraft to perform certain preliminary processing functions on-board. These processing functions involve such things as radiometric correction, dimensionality reduction through transformations, the suppression of unnecessary data, or the reduction of resolution through pixel averaging or subsampling. Each of these processing techniques has a substantial benefit to users employing them if these techniques are performed on-board. This would clearly indicate the value of distributing the processing responsibility. A key factor, however, is that the user must feel as though he is still in control of the system.

It may well be necessary to provide the user community with positive incentives for conducting IAS experiments. The incentives could involve the reduction of delivery costs, based on the volume of data delivered, the improvement of data delivery timeliness, or the greatly reduced cost for processing in the users own shop.

After the user community has had the opportunity to make use of these limited IAS capabilities for a period of several years, they would generally be more ameanable to taking the next step. This next step would involve the performance of sophisticated on-board processing. Of necessity, this will impose a significant development burden on NASA because of the substantial amount of on-board hardware required. However, the dramatic reduction in ground-based processing facilities and the timeliness with which data could be delivered to the user community would provide a substantial incentive. The major prerequisite for the on-board processing functions is that the accuracy of the data not be impaired as a result of limited facilities. This demands a considerable study effort be undertaken to evolve new techniques and to improve hardware.

3.0 STUDY PHASES

The IAS study is presented in three sections:

- Pre-study and application selection (Section 3.1)
- Sub-systems design and specification (Section 3.2)
- The design of an on-board classifier (Section 3.3).

3.1 Pre-study and Application Selection

In this study phase, the following activities were pursued:

- Delineation of a list of study assumptions
- Literature survey
- Extensive list of applications and algorithms
- Algorithmic feasibility costing technique
- Feasibility measurements and selection criteria
- Hardware and system feasibility
- Proposed IAS techniques
- Proposed tree structure control.

3.1.1 Study Assumptions

In the work which was performed in the pre-study and application selection phase for IAS, an attempt was made to delineate all of the assumptions used in the study. The list of study assumptions are listed below:

(1) The use of modular data structures, e.g., 16x16 array ≡ 256 pixels.

(2) Modular algorithmic structure.

(3) Free flyer earth mission.

(4) Modular code for algorithms.

(5) Only simplistic algorithms can be used.

(6) Use of MDTS communication measures.

(7) System must be capable of generating a spectrum of alternative products.

(8) The user is the determining factor in the level of data required.

(9) No on-board data compression prior to information extraction.

(10) A unit cost of human interaction is equivalent to a unit cost of a primitive.

(11) Rough Order of Magnitude is sufficient for relative ordering of applications.

3.1.2 Literature Survey

An extensive literature survey has been conducted during the pre-study phase in order to determine what applications are currently being done and what procedures are being used in order to implement these applications. Extensive reading of the current literature available today was done. References which have been used during the initial literature survey are listed below. During this time, the ongoing IAS study library was begun.

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3.1.3 Ensemble of Applications and Algorithms

During the literature survey, extensive documentation was done delineating the various applications that are currently being done today. In total, a list of 155 applications was created. This list has been established as a result of the reading during the literature survey. Table 3.1.3-1 shows the list of applications broken down into application areas. Table 3.1.3-1 also illustrates the application numbering scheme that was created to keep track of the various applications that we investigated. Also, in this table, is a ·.y for the initial user benefit as determined

Key: Measure of Global Benefit

VB - Very Beneficial
MB - Moderately Beneficial
B - Beneficial
LB - Little Benefit
NB - No Benefit

Application Numbering Scheme

A## - Agricultural
F## - Forestry
R## - Range Resources
L## - Land Use/Geography/Mineral Resources
W## - Water Resources/Hydrology
E## - Environmental Studies
C## - Coastal Zone Studies/Marine Resources
G## - Geological Structures
M## - Meterology
O## - Global Oceanology

Agricultural

A01 Agricultural Crop Inventory (VB)
A02 Multi-Data Agricultural Crop Inventory (VB)
A03 Monitoring World Wide Food Productivity (VB)
A04 Plant Species Identification (VB)
A05 Plant Disease Detection (MB)
A06 Rice Inventory/Disease (LB)
A07 Plant Stress (due to insects, drought, moisture) (MB)
A08 Estimation of Winter Wheat Yield (MB)
A09 Soil Conservation Practices (B)

Table 3.1.3-1 Ensemble of Applications

A10 Soil Diagnosis (B)
A11 Soil Surveying (B)
A12 Acreage Measurement (LB)
A13 Agricultural Mensuration (B)
A14 Large Area Crop Inventory (VB)
A15 Location of Citrus Tress (NB)
A16 Estimating Wheat Acreage (MB)
A17 Detection and Classification of Infestations of Crop Insect Pests and Diseases (NB)
A18 Mapping Soil (B)

Forestry (F)

F01 Forestry Classification and Timber Inventory (VB)
F02 Forest Typing (VB)
F03 Forest-Non-Forest Defoliation (LB)
F04 Detection of Forest Fires (MB)
F05 SO_2 Damage to Forests (NB)
F06 Forest Density (MB)
F07 Gypsy Moth Defoliation (LB)
F08 Estimating Timber Volumes (MB)
F09 Plant Stress Detection (MB)

Range Resources

R01 Range Resource Identification (VB)
R02 Vegetation Density (B)
R03 Estimating Vegatative Biomass for Range Management (LB)
R04 Plant Development and Range Conditions (B)
R05 Vegetation Conditions for Range Management (B)
R06 Classification of Vegetation (MB)
R07 Natural Resource Inventory (VB)
R08 Natural Resource Management (VB)

Table 3.1.3-1 Ensemble of Applications (Continued)

Land Use/Geography/Mineral Resources

L01 Land Use Classification (MB)
L02 Site Planning (MB)
L03 Large Area Mosaics (B)
L04 Monitor Reclamation of Land (LB)
L05 Urban Growth (B)
L06 Area Measurements (B)
L07 Power Plant Siting (LB)
L08 Revise Geographic and Road Maps (MB)
L09 Inventory of Ponds (LB)
L10 Petroleum Exploration (VB)
L11 Mineral Exploration (VB)
L12 Monitoring Surface Mines (LB)
L13 Land Use Change (B)
L14 Delineation of Urban/Rural Areas (LB)
L15 Detailed Urban Structure (B)
L16 Traditional Map Preparation (VB)
L17 Changes in U.S. Metropolitan Regions (B)
L18 Regional Planning and Urban Development (B)
L19 Strip Mine Location (LB)
L20 Mapping Acid Mine Drainage (NB)
L21 Inventory of Surface Mined Areas (NB)
L22 Delineating Land Water Cover in Coal Mining Regions (NB)
L23 Classification of Inland Lakes (LB)
L24 Tropic Status of Inland Lakes (LB)
L25 Identification of Potential Recreation Areas (B)
L26 Mineral Exploration (VB)
L27 Base Metal Deposits (VB)
L28 Road Alignment (LB)
L29 Mapping of Wildland Fuel Characteristics (VB)
L30 Regional Mapping (MB)
L31 Change Detection (B)
L32 Interpretation of Rivers and Roads (B)

Table 3.1.3-1 Ensemble of Applications (Continued)

Water Resources/Hydrology

W01 Watershed Management (MB)
W02 Measure Snow Areas (B)
W03 Turbidity Pattern Identification (MB)
W04 Delineation of Land Water Boundaries (VB)
W05 Delineation of Hydrologically-Related Terrain Hectares (B)
W06 Hydrodynamics, Including Floods, Reservoirs, Estuaries (VB)
W07 Water Quality Evaluation (MB)
W08 Snow Cover and Evaluation (B)
W01 Dynamics of Playa Lakes (NB)
W10 Water Management (VB)
W11 Measuring Watershed Runoff (B)
W12 Flood Hazards (MB)
W13 Watershed Wide Evapotranspiration (LB)
W14 Flood Plain Mapping (MB)
W15 Snow Mapping (B)
W16 Mapping of Hydrothermal Alternation Zones (LB) 1213

Environmental Studies

E01 Environmental Surveys (VB)
E02 Wildlife Habitat Evaluation (MB)
E03 Thermal Pollution (VB)
E04 Air Pollution Studies (VB)
E05 Measure Atmospheric Aerosol Content (B)
E06 Strip Mine and Reclamation Maps (LB)
E07 Environmental Impact of Freeways (LB)
E08 Grizzly Bear Habitat Analysis (NB)
E09 Breeding Habitat of Migratory Waterfowl (NB)
E10 Wildlife Management (VB)
E11 Screwworm eradication (NB)
E12 Defining Salt Marsh Mosquito Breeding Areas (LB)

Table 3.1.3-1 Ensemble of Applications (Continued)

E13 Inventory and Analysis of Environmental Problems (MB)
E14 Human Impact on Tropical Vegetation (B)
E15 Locust Breeding (B)

Marine Resources/Coastal Zone Studies

C01 Marine Resources (VB)
C02 Location of Schools of Fish (LB)
C03 Monitor Off-Shore Oil Production (VB)
C04 Algae Concentration Determination (B)
C05 Coastal Zone Resources (VB)
C06 Coastal Zone Management (VB)
C07 Mapping of Shorelines (VB)
C08 Mapping of Shoals (MB)
C09 Wetlands Inventory (B)
C10 Bathymetry Determination (B)
C11 Bottom Topography Studies (B)
C12 Mean High/Low Water Line Determination (LB)
C13 Pollution Detection (MB)
C14 Coastal Wetland Detection (MB)
C15 Wetland Characterization (MB)
C16 Availability and Distribution of Living Marine Resources (VB)
C17 Coastal and Navigational Charts (VB)
C18 Monitoring Coastal Water Properties and Current Circulation (VB)
C19 Eastuarine and Coastal Oceanography (VB)
C20 Mapping of Sediment Concentration in Tidal Estuaries (LB)
C21 Mapping of Coastal Wetlands (VB)

Geological Structures

G01 Terrain Feature Analysis (VB)
G02 Structural Geology (Faults, Folds, Lineaments) (MB)
G03 Geomophlogy (Landform Classification) (MB)
G04 Lithological Mapping (B)
G05 Geological Hazards (MB)

Table 3.1.3-1 Ensemble of Applications (Continued)

G06 Landslides (NB)
G07 Volcano Studies (LB)
G08 Vehicular Scars (NB)
G09 Surface Lithologies (MB)
G10 Stratigraphic Subdivision of the Transvaal Dolomite (NB)
G11 Major Sand Seas in Desert Areas (LB)
G12 Monitoring Global Volcanic Activity (B)
G13 Spectral Geological Mapping (MB)
G14 Earthquakes and Tetonic Evolution (B)
G15 Roof Falls in Underground Coal Mines (NB)
G16 Geological Significance of Temporal Changes (B)
G17 Significance of Selected Lineaments (B)
G18 Geomorphical Evaluation of Lake Basins (LB)
G19 Boundaries of a Buried Pre-Glacial Valley (NB)

Meteorology

M01 Determination of Wind Fields (VB)
M02 Cloud Classification (VB)
M03 Temperature Profiles (VB)
M04 Surface Temperatures (MB)
M05 Cloud Cover Survey (MB)
M06 Prediction and Assessment of Natural Disasters (VB)
M07 Freeze Prediction Based on Surface Temperatures (B)
M08 Mapping Soil Moisture (B)
M09 Mapping Rainfall (VB)

Global Oceanology

OØ1 Determination of Sea State (VB)
OØ2 Chart Unknown Reefs (VB)
OØ3 Assist Navigation (VB)
OØ4 Location of Ice Masses (VB)
OØ5 Study of Biological Processes (MB)
OØ6 Study of Current Patterns (VB)
OØ7 Ocean Interval Waves (B)
OØ8 Sea Ice Surveillance (VB)

Table 3.1.3-1 Ensemble of Applications (Continued)

from our reading. This user benefit, noted as a measure of global benefit, varied from no benefit to very beneficial. Having created this list, each of the applications was studied in order to determine the scenario of image processing algorithms and procedures that are required to extract information for each application. Note here that many applications can be done using different scenarios since there are often many ways to attack a particular application problem. The effort here was to choose a scenario which was most representative of the way the user community was solving these application problems. Note also that some of these, in fact, many of these application areas required non-algorithmic processing such as user interaction so that the list of application algorithms was extended to account for these various other techniques. Table 3.1.3-2 delineates this extended list of algorithms which was generated during the literature survey. Those algorithms delineated by a star imply a large degree of difficulty for IAS and have not been considered viable for the preliminary IAS and have not been considered viable for the preliminary system. This was done because one of our study assumptions was that only simple type algorithms would be feasible for an IAS type application, that is, an on-board type application.

As stated above, a typical scenario of processing for each application has been developed. Appendix B shows the list of applications versus the list of algorithms and, where appropriate, a sequence of numbers in this cross matrix represents the detailed scenario required to extract information useful to the application. Numbers that appear in parenthesis are considered to be optional in the processing of the application. Items such as human interaction are flagged with a check mark when that application requires it.

Ground Processing*
Human Interaction/Interpretation*
Temporal Data*
Regression
Threshold Limits
Number (Theme)
Theme Mean
Theme Variance
Ground Truth Sampling
Ratios (Spectral)
Mean
Variances
Spectral Weighted Signature
Histogram Normalization (Haze Cor.)
Theme Generation
Allignment (Spatial)*
Contour Mapping*
Moment Description*
Chain Encoding*
Region Growing*
Point Detection
Line Detection
Edge Detection
Corner Detection
Karhunen-Loeve Transformation
Averaging
Relaxation Methods*

*Large degree of difficulty for IAS.

Table 3.1.3-2 Ensemble of Algorithms

Curvature Principle Axes*
Edge Preserving Smoothing
Huckle Edge-Line Model*
Mixed Pixel Classification
Linear Noise Suppression*
Linear Filtering - Smoothing
Linear Filtering - Derivatives
Line Enhancement
FFT - Correlation*
FFT - Power Spectral*
Statistical Noise Suppression
Curve Length Measurements*
Straight Length Measurements
Hierarchical Classifiers
Syntactic Approaches*
Perceptron
Nearest Neighbor Clustering
N-Dimensional Classifier
2-Dimensional Classifier
Bayesian Techniques
Maximum Likelihood
Texture Recognition
Table Look Up 4D
Table Look Up 2D
Supervised Training
Non-Supervised Clustering
Non-Parametric Clustering
Parametric Clustering
N Dimensional Histograms
1 Dimensional Histograms

Table 3.1.3-2 Ensemble of Algorithms (Continued)

3.1.4 Algorithmic Feasibility Costing Technique

The objectives of the algorithmic prestudy were two-fold:

(1) To assemble a list of comprehensive algorithms which have, or could have application in the extraction of information from image data. This was a task which we found better suited and completed during the literature survey, and

(2) To establish a technique for measuring the feasibility of algorithms within the context of IAS.

It is clear that if we are to compare algorithms, it is required to develop a "costing technique" which will allow us to compare the relative merits of these algorithms. It became our purpose to use the procedures that we developed here, that is the costing technique, to determine the various favorability measures which make up our final selection criteria. These measures initially consisted of application feasibility, application desirability, and application maturity. Later in the study, we added two other favorability measures to the selection criteria, they being user benefits and NASA benefits. Therefore, there are five IAS favorability measures which will be used and combined in the process of selecting the two most favorable applications for IAS. To perform the evaluation, a technique for comparing relative merits had to be developed. Most of the above favorability measures consist of dissimilar components which do not lend themselves to easy combination and evaluation. This need to combine dissimilar components has led to the development of an "Equivalence Concept Approach to Linear Superposition". A description of the procedure is in order.

Assume there is some favorability measure Z which is made up of four components $X_1 \ldots X_4$ and we wish to find the cost of Z for a particular application. To do this we must measure and combine the four components $X_1 \cdots X_4$. Now let us assume, for simplicity and clarity, that X_1 is measured in apples, X_2 pears, X_3 bananas and X_4 oranges. Clearly, we cannot simply add the components together to get a total cost. There is a need to establish the equivalent cost between X_1, X_2, X_3, and X_4 so that one can state that the cost is

$$\text{Cost} = \sum_{i=1}^{4} \alpha_i X_i$$

where X_i is the measured value and α_i is the equivalence cost coefficient. Using this equation, one can now determine how different applications relate to each other in terms of the cost of Z by measuring the values of $X_1 \cdots X_4$ for each application and evaluating the expression.

This technique will also be used in determining the measures in our final selection criteria. It has proved invaluable in allowing us to complete a task where we were required to compare dissimilar items and generate a list of relative merits.

3.1.5 Feasibility Measurements and Selection Criteria

(a) Algorithmic Feasibility Measures

The first step in evaluating algorithmic feasibility is to determine the various attributes of our costing technique. Having done this, one must then examine these attributes to determine the various equivalence coefficients so that we can combine these values to determine a total algorithmic cost per each algorithm. (See Section 3.1.4.)

Table 3.1.5-1 delineates a list of attributes which make up the feasibility measure. These attributes were determined by communications with NASA. Note that Table 3.1.5-1 clearly shows the fact that we are combining very dissimilar measurements, for instance, X_1 , the degree of human interaction and, X_5 , computational requirements. Clearly, some special technique, as the costing technique, is required to evaluate the cost of an algorithm in an IAS context. The feasibility measures that are generated using these attributes have been utilized to determine the

X_1 = Degree of Human Interaction
$\doteq$ Number of Human Provided Parameters
X_2 = Algorithmic Complexity
$\doteq$ Number of Distinct Primitives
X_3 = Adaptivity
$\doteq$ Average Number of Iterations
X_4 = Data Storage
$\doteq$ Number of Bytes
X_5 = Computational Requirements
$\doteq$ Number of Micro Operations for One Iteration
X_6 = *A priori* Knowledge
$\doteq$ Number of Bytes
X_7 = Control Requirements
$\doteq$ Number of Flag Tests Required
X_8 = Data Structuring
$\doteq$ Maximum Packet Dimension Required

Table 3.1.5-1 Algorithmic Feasibility Attributes

viability of each algorithm for IAS processing. These measures are then combined and used as a means of prefiltering the list of applications into a set of feasible and infeasible applications. The feasible applications will be studied in more detail. The following discusses the algorithmic feasibility measurements.

Degree of Human Interaction

A distinction must be made between the degree of human interaction which is required for information extraction and from the use of knowledge in the extraction of information. By human interaction, we mean that decisions must be made on the basis of information extracted from the data in a way which requires the human to be in the loop. If an algorithm requires human interaction, it is clear that real time communications with the data stream is necessary. A measure of the degree of human interaction is the number of input parameters that must be established by the human in real time.

Algorithm Complexity

An algorithm is conceived of being a list or scenario of primitives. Each primitive is considered to be of approximately equal complexity so that an algorithmic process may be measured in complexity by specifying the number of distinct primitives required for its execution. Now this measure is intended to be independent of the computational requirements of the algorithm or the degree of adaptivity that the algorithm must have in establishing output data. Hence, it is only the number of distinct primitives that are used in a measure without regard to the number of times this primitive might be used within the scenario. See Appendix E for a list of preliminary MPP type primitives.

Adaptivity

Certain algorithms require adaptivity as a result of an iteration process. A measure of adaptivity is the expected number of iterations required of the scenario or a piece of the scenario in order to establish convergence.

Data Storage

The concept of data storage is intended to be independent of data complexity or structure. It is merely the amount of storage required to execute the algorithm and is measured in terms of number of bytes of storage required.

Computational Requirements

The computational requirements of an algorithm is merely an estimate of the number of micro operations required to execute the algorithm.

A Priori Knowledge

As distinguished from the degree of human interaction, a priori knowledge consists of coefficients that are required for processing which are either fixed, established by the data over a long time period, or data that may change seasonally but for which there is no urgency in transmission of such data to the spacecraft. The degree of a priori knowledge required of an algorithm will be specified in terms of the number of bytes of data needed.

Control Requirements

The degree of control required of an algorithm will be delineated as the number of decision making operations required of the algorithm. These decisions are made by testing flag bytes and the measure for control requirements will be the number of flag tests needed.

Data Structuring

It is the intent of data structuring measures to penalyze an algorithm that requires information that may be remote in storage from other data requirements. Typically, the required data is packaged as a multi-dimensional structure or packet (image array). The maximum image array dimension for data organization required of an algorithm will be the measure of data structuring.

Note that all of these components are negative attributes for IAS implementation. Further note that each of the attributes is linear in the sense that their impact on IAS doubles if their measure doubles. Hence, a total measure of algorithmic feasibility will be a weighted sum of the individual attribute values.

Appendix C explains the rationale behind these algorithmic feasibility attributes in detail.

The first step in determining a measure of algorithmic feasibility was the calculation of the equivalence cost coefficients. To do this, we need to find equivalent costs between attributes. At this point, it is important to re-examine our final purpose in this exercise, it being the relative ordering of applications based on feasibility. The coefficients and the attribute measurements were generated to produce an ordered list of applications relative to each other. That is, it is the relative ordering that is important and not the actual total cost measurement itself. We generated a list whereby we could claim that application A is more feasible than application B.

The next step was the trade-off study. It reduced the number of applications that will be considered for further study and to define our approach to prioritization, that is the feasibility measures, desirability measures, maturity measures, NASA benefits and user benefits. If one examines Appendix B in more detail, a striking yet expected factor is observed. One will note that there are a great number of applications which have very similar or even identical algorithmic scenarios. Due to this fact, the trade-off study was first to define various application classes which represent typical algorithmic scenarios. Doing this, we were able to reduce the IAS applications to 18 representative application classes. Table 3.1.5-2 lists these 18 application classes. They are not

Application Classes
• Snow Mapping
• Location of Ice Masses
• Cartographic Applications
• Terrain Feature Analysis/Mineral Exploration
• Cloud Classification and Mapping
• Wildlife Management
• Location of Living Marine Resources
• Rangeland Classification/Inventory
• Natural Resource Classification/Inventory
• Agricultural Crop Classification/Inventory
• Land Use Classification/Inventory
• Water Quality Studies
• Soil Mapping
• Forest Classification/Inventory
• Watershed Management
• Air Quality Studies
• Coastal Marine Studies
• Sensing of Ocean Surface and Sea State

Table 3.1.5-2 Applications Classes

listed in any special order. The next step was to take these 18 application classes and apply the algorithmic feasibility measures to their algorithm scenarios. In this way, the application feasibility measure for each application can be determined. Once these measures have been determined, an ordered list was generated such that the most feasible application is at the top and the least feasible at the bottom.

Tables 3.1.5-3 and 3.1.5-4 list the feasible and infeasible applications. A few special notes in regard to Table 3.1.5-4 and the infeasible applications should be made at this time.

During the study, it became obvious that there were some special additional factors that entered into application feasibility yet did not impact on the applications algorithmically. For example, referring to Table 3.1.5-4 we consider Cartographic Applications to be placed in the infeasible category. Closer examination of the application reveals that the application itself is more of a special partial processing application, that is, an enhanced image for traditional image processing techniques where the amount of data is reduced very little. Further, and more important, is the fact that to produce any large benefit, much higher resolution than is available through remote sensing techniques is required. For these reasons, it has been placed in the infeasible category. This is an area that may, in the future, be a viable and valuable IAS application.

This type of situation has resulted in the special factors column of Table 3.1.5-4. It is recognized that this goes beyond the pure concept of application algorithmic feasibility however since it is the purpose of the Trade-off Study to reduce the number of applications for further study BTS feels that these special factors must be considered and be considered at this point.

Some additional comments on these special applications are in order. Natural resource classification and inventory has been classified as infeasible because although it is very similar in processing scenario to rangeland classification and inventory, to garner any real benefits a

APPLICATIONS	
Snow Mapping	↑ FEASIBILITY
Location Of Ice Masses	
Cloud Classification And Mapping	
Rangeland Classification/Inventory	
Agricultural Crop Classification/Inventory	
Forest Classification/Inventory	
Land Use Classification/Inventory	
Water Quality Studies	

Table 3.1.5-3 Algorithmic Feasible Applications

APPLICATION	SPECIAL FACTORS
• Cartographic Applications	Image Enhancement application requiring much higher resolution
• Terrain Feature Analysis/Mineral Exploration	Image Enhancement application requiring heavy human interpretation
• Wildlife Management	Image Enhancement application requiring heavy human interpretation
• Location Of Living Marine Resources	Human Interpretive, very subtle signature and requires large amounts of data from other sources
• Natural Resource Classification/Inventory	Human interpretive requiring data from other sources
• Soil Mapping	Too complex
• Watershed Management	Human interpretive requiring other data sources. Very complex
• Coastal Marine Studies	Human interpretive requiring other data sources. Very complex
• Air Quality Studies	Human interpretive requiring other data sources. Very complex and subtle
• Sensing of Ocean And Sea State	Human interpretive requiring other data scurce. Very complex and subtle. Feasible areas covered in Water Quality Studies

INFEASIBILITY

Table 3.1.5-4 Infeasible Applications

large degree of human interpretation is required. Note here the distinction between human inter--tion with the algorithms and human interpretation of the data. A good deal of work that is currently done in the natural resource area is done through traditional visual interpretation techniques. Terrain Feature analysis/mineral exploration is very similar to cartographic work in that it also is a partial processing image enhancement application requiring large amounts of traditional visual interpretation techniques and human interpretation. Once again there is little data reduction. Wildlife management and location of living marine resources are two applications that require very large amounts of human interpretation and a great deal of data from other special sources. Also in the case of living marine resources the signatures themselves are much too subtle for an IAS system to handle at this time.

Four applications, watershed management, coastal marine studies, ensing of ocean surface and sea state, and air quality studies required such a large degree of human interacion, human interpretation, and data from additional sources other than the remote sensing data itself, that these were deemed a priori to be infeasible applications and, as such, were not chosen for further study.

BTS wishes to emphasize the point that these applications, although they are classified as infeasible may, some day, be feasible for IAS applications. The purpose here was to limit the number of applications that will be studied further and have the other favorability measures applied to them on the way to the final selection of the two most favorable applications for IAS implementation.

(b) Other Attribute Measures

It is the purpose of this task to consider the significant refinement of the methodology to be used in the selection process of viable IAS applications. Initially, there were three favorability measures that would be combined to generate the final selection, those measures being, application feasibility, desirability and maturity. In the process of refinement, we have added two new measures, user benefits and NASA benefits. We have also established a technique whereby the final selection shall occur as a result of a pairwise costing process. It has been anticipated that a listing of application areas or classes on the basis of a single prioritization measure would be inadequate for the selection of two IAS applications for further study. The rationale for this statement comes from the notion that the two highest priority applications will probably be rather similar in nature and would, therefore, not demonstrate a rich variety of processing alternatives. Hence, the eight application classes that we will be examining further will be grouped into twenty-eight pairs and the costing procedure will be applied to these twenty-eight pairs instead of the individual applications. A technique for measuring these attributes in relationship to pairs of applications has been established and the five classes of pairwise measures will be combined to a single prioritization measure for a pair. In this way, the single maximum score would define the best pair of applications to be used for IAS. It would then take into consideration the additional benefits, especially to NASA, for having distinctly different kinds of applications as the two choices.

Once we have generated twenty-eight pairwise cost measures of application feasibility, desirability, maturity, NASA benefits and user benefits, it will become necessary to thus combine these measures with a similar costing procedure, to generate a single ordered list of application favorability. From this list we will then pick the two most favorable applications.

Appendix D gives the rationale for desirability attribute measures and maturity attribute measures. The proposed IAS favorability scale (Appendix D) was used to generate these attribute measures. Tables 3.1.5-5, 3.1.5-6, and 3.1.5-7 list the results of the favorability measures. These measurements were then combined using the costing proceudre to generate an ordered list. Two most favorable applications were picked. A third application

application feasibility, desirability and maturity. In the process of refinement, we have added two new measures, user benefits and NASA benefits. We have also established a technique whereby the final selection shall occur as a result of a pairwise costing process. It has been anticipated that a listing of application areas or classes on the basis of a single prioritization measure would be inadequate for the selection of two IAS applications for further study. The rationale for this statement comes from the notion that the two highest priority applications will probably be rather similar in nature and would, therefore, not demonstrate a rich variety of processing alternatives. Hence, the eight application classes that we will be examining further will be grouped into twenty-eight pairs and the costing procedure will be applied to these twenty-eight pairs instead of the individual applications. A technique for measuring these attributes in relationship to pairs of applications has been established and the five classes of pairwise measures will be combined to a single prioritization measure for a pair. In this way, the single maximum score would define the best pair of applications to be used for IAS. It would then take into consideration the additional benefits, especially to NASA, for having distinctly different kinds of applications as the two choices.

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APPLICATIONS	X_1: User Benefit for Timely End-To-End Information Extraction and Distribution	X_2: Cost Reduction to User for Pre-Processing	X_3: Cost Reduction to User for Partial Processing	X_4: Cost Reduction to User for Complete Product Processing	X_5: Utility of Reduced Data Volume	X_6: Utility of Increased Standardization
Snow Mapping	1	-2	2	2	0	-1
Location of Ice Masses	3	-2	2	2	0	1
Cloud Classification and Mapping	3	0	2	1	0	2
Rangeland Classification/Inventory	-2	2	-1	2	1	0
Agricultural Crop Classification/Inventory	-1	3	-1	3	1	2
Forest Classification/Inventory	-3	1	-1	3	2	1
Land Use Classification/Inventory	-2	2	0	2	3	1
Water Quality Studies	0	1	1	2	-1	-2

DESIRABILITY ATTRIBUTES (X_i)

Table 3.1.5-5 Desirability Attributes vs. Applications

MATURITY ATTRIBUTES (X_i)

X_1: Years of Experience for Application
X_2: Years of Development Required for On Board System
X_3: Time To/From Pre-Operational System/Autonomous Lab Demo
X_4: Relative Ease (Measured on IAS Favorability Scale, Appendix D)
X_5: Available Funding (Measured on IAS Favorability Scale, Appendix D)
X_6: Number of Distinct Technologies
X_7: Application Visibility (Size of User Base Measured on IAS Favorability Scale Appendix D)

APPLICATIONS	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Snow Mapping	6	2	3	1	1	2	-1
Location of Ice Masses	4	1	2	3	2	1	1
Cloud Classification and Mapping	17	2	3	2	3	2	3
Rangeland Classification/Inventory	7	3	4	-2	0	1	0
Agricultural Crop Classification/Inventory	7	5	6	-3	3	2	3
Forest Classification/Inventory	6	4	5	-2	1	3	1
Land Use Classification/Inventory	7	3	4	0	2	2	2
Water Quality Studies	5	4	5	-2	0	1	-3

Table 3.1.5-6 Maturity Attributes vs. Applications

APPLICATIONS	X_1: Savings of Dollars	X_2: Speed Processing Time	X_3: Reduced Data Volume
	NASA BENEFIT ATTRIBUTES (X_i)		
Snow Mapping	0	1	-1
Location of Ice Masses	2	3	1
Cloud Classification and Mapping	-2	2	3
Rangeland Classification/Inventory	1	2	0
Agricultural Crop Classification/Inventory	3	1	0
Forest Classification/Inventory	1	1	1
Land Use Classification/Inventory	2	0	2
Water Quality Studies	1	1	-1

Table 3.1.5-7 NASA Benefit Attributes vs. Applications

was added later in response to NASA requests. They are:

(1) Sea ice mapping

(2) Land use classification/inventory

(3) Snow melt run off forecasting.

3.1.6 Hardware and System Feasibilities

The IAS system must be fabricated/designed in such a way that information extraction special purpose hardware, such as a massively parallel processor or a programmable pipeline processor, is the heart of the system and other functions subservient to it. In the choice of such a processor, low power operations are a requirement and it is anticipated that data organization and algorithmic organizations will play a very important role. Of course, in the study of algorithms, it is necessary that the information be extracted autonomously with man out of the loop. In order to simplify the information extraction process, it may be assumed that onboard image corrections will be a vital part. As such, it may be required to modify sensor design so as to simplify the image correction system. The adaptive aspects of the system permit data to be rejected on the basis of cloud cover, geographic location, priority or other system requirements. It is envisioned that IAS may have output products that range from raw data, on the one hand. to relatively simple flag setting on the other.

It is anticipated that users will be uncomfortable with any product which is produced autonomously and that IAS evolution will be required as part of an educational process for the users. Table 3.1.6-1 lists a set of potential output products of IAS. Because of the adaptive aspects of IAS, it will also be necessary to establish contingency plans in the event that the highest priority product becomes infeasible.

The current state of the art in information extraction from remotely sensed data involves a highly user interactive system which has dictated, Extraction Of Information

- Multi Spectral Images
- Three Channel Color Image
- Multi-Class Thematic Display
- Single Class Thematic Display
- Spatially Smoothed Thematic Image
- Chain Encoded Regions Boundaries
- Semantic Description of Thematic Regions
- Density Maps of Identified Features
- Statistics Files
- Inferred Information (Using Ground Truth)
- Warning Flags (For Disasters)
- Internal (S/C) Control Information Extraction

Table 3.1.6-1 Classes of Output Products and placed emphasis upon, certain classes of processing algorithms. In the absence of this user interaction, it is anticipated that some new image processing algorithms will have to be borne in order to get man out of the loop. The new and old algorithms that are developed for IAS must operate upon standard data structures and be envisioned as sequences of primitives. This data structure and scenario of primitives for viable image processing algorithms will be used in the design of IAS. Table 3.1.6-2 contains a list of IAS hardware and system concepts. These concepts involve standardizing and classifying output products with appropriate interfaces to the modular data transport system formats. The intermediate data structures are expected to be image arrays of possibly 16x16 multi-channel data which could then be selected for processing. The process to be performed would be based upon user requests and it may be necessary to have several massively parallel processors in order to meet the throughput requirements. It is further anticipated that there shall be several sensors which will be selected based upon user requests for information and that these input sensor data should be required to be packetized into image arrays in a system standard manner. The primitives which have been established for image processing functions would be firmware on the various MPP processors and scenarios of such modular primitives would be performed as required of the algorithms. The primitives are related to several data processing functions:

- Input processing
- Data decomutation and formatting
- Pre-processing
- Storage and control
- IAS image processing
- Statistical/schedule processing
- Output processing
- External communications
- Spacecraft system processing.

Included within this system are contingency command generation which permits the system to adapt autonomously to varying conditions such as cloud, haze,

- Classes of Output Product with Standard MDTS Formats
- Data Packet Processing
- Data Packet Selection
- Several MPP Packet Processors
- Sensor Input Packet Standards
- Modular MPP Primitives
- Scenario Management
- Limited Number of Processing Data Types
- Contingency Command Generation System
- Merge Pre-Processing and Product Processing Concepts
- Multi-Spectral Multi-Line Scanner(s)

Table 3.1.6-2 IAS Hardware and System Concepts geographic location, pri -ity and time. Also within this system we have explicitly delineated the pre-processing functions from the IAS image processing. Such a separation was performed because of the initial IAS desires to separate out product processing studies from pre-processing studies. However, in our studies it became eminently evident that most of the pre-processing functions of radiometric and geometric corrections could be performed as packet processes on an MPP.

In summary, the basic system consists of several multi-line scanners having selectable spectral channels, the data of which is decomutated and formatted specifically for pre-processing and image processing functions. The preprocessing functions, although shown separated from the image processing functions, in fact, could be performed on an MPP module. Also shown on the hardware chart is a histogram/statistics interface box to the application dependent statistical filtering algorithms in the main control computer. This is an existing interface function within the MPP design. Depending upon the data type, the results of image processing will be locked out for output. An output controller will packetize the data in the modular data format and present it to the modular data transport system. It must be emphasized that this system, as presented, is preliminary and is being used primarily as a vehicle for assessing alternative applications for IAS and assessing the feasibility of IAS onboard processing. A more refined and delineated system for IAS will be established further on in the study.

IAS in communication with relay satellites will make use of the NEEDS MDTS concepts. Packet switching is a technology which has proved to be very reliable and flexible. The existence and performance of the ARPANET and similar networks certainly illustrate this. BTS feels that the MDTS concepts will be of great benefit to IAS. The major reason being that the biggest problem with remote sensing data is very often its timeliness of delivery to the end user. MDTS should vastly improve these distribution problems and combined with IAS, will deliver timely finished products for the end user.

3.1.7 Proposed IAS Techniques

The proposed IAS technique subtask has, as its objective, the identification of approaches to be used in establishing a methodology within the system for incorporating the information adaptive techniques or concepts. At the present time, six techniques have been identified:

- Onboard information extraction
- Selective data capture
- Partial data processing (information conserving compression/ representation)
- Adaptive control functions
- User defined processing scenario
- Evolutionary growth.

Onboard Information Extraction

The onboard information extraction technique provides for the identification of products which could be extracted from raw sensor data prior to its packetization and transmission to the user. A particular advantage of this technique is that it essentially eliminates all delays between the sensing of an event and the delivery of an output product. The technique also provides for an enormous reduction in data which must be transmitted. There are a number of assumptions which are made in the IAS study which makes this technique viable. In the following we shall discuss the rational for onboard information extraction.

One might ask why one would ever want to extract information onboard a spacecraft rather than at the ground station which receives wide band width data. One of the minor reasons for doing this is that any ground station must allocate its resources to many activities and the activity of product processing may be expected to take a back seat to other activities that may have a direct impact upon spacecraft operations. Hence, we may lose reliability in the area of timeliness of product delivery. Another disadvantage for ground processing is that equipment which is cost effective for ground processors require significant maintenance and usually may require operational personnel, so that although the initial cost for the ground station computers for information extraction may be lower, there shall nonetheless, be significant recuring costs involving man operations. But these reasons or rationale are quite secondary to the overall concept of an earth resource satellite system which is being projected in the future. In the future, we envision scores of spacecraft in various polar orbits which are sensing activity on the surface of the earth. On the other hand, the number of relay satellites and their associated ground stations and ground station maintenance personnel are envisioned to be few in number due to their impending cost. Hence, with many high band-width sensors onboard a multitude of spacecraft, all desiring to share in the communication band-width capability of a relay satellite, we quickly realize that service to all spacecraft simultaneously becomes impossible if we desire to transfer every bit of information which is acquired onboard. There is a real need to avoid transmission of data/information which is not going to be useful to mankind. All of the IAS techniques that we are talking about provide a means by which only useful information need be communicated via relay satellites to the ground. The more we can extract information and reduce channel capacity per orbiting spacecraft and sensor, the more spacecraft and spacecraft sensors we can fly given the limited resources of several relay satellites.

Of course, extraction of information from raw data onboard a spacecraft in realtime is not an easy task. The difficulties for performing this onboard processing are among the major concerns in considering this approach. In particular, our IAS feasibility study is directly related to the difficulty of extracting the desired information for various application areas and, indeed, many application areas are just simply infeasible or too complex at this time, for onboard information extraction.

Selective Data Capture

The selective data capture technique implies methodologies by which a large reduction in the volume of data that must be transmitted is reduced simply by identifying that data which will not be useful for further information extraction. Several concepts are important in establishing approaches to the selective data capture technique. These concepts involve:

- Identification of cloud covered areas
- Water covered area identification
- Land covered area identification
- Geographic boundary specification for information
- Geometry/ground resolution requirement for the specific application
- Data quality
- Solar condition requirements
- User directed requests for information
- Event sensing
- Dimensionality reduction in the number of spectral channels required
- Resolution reduction
- Reduction of radiance resolution.

Partial Data Processing

Another technique which is viable for IAS is that of partial data processing. This phase of partial data processing should not be confused with the technique of onboard information extraction which might be inferred as complete data processing. The partial data processing technique is intended to convey the notion that alternative representations of the data may contain the information which is desired in specific applications and that the improved representation will reduce transmission requirements but that complete onboard information extraction is not appropriate because of significant requirements for human a priori knowledge. Hence this technique could be considered as one of information conserving compression/representation techniques. In particular, many options are open for consideration. Examples are given in the following list:

- Reduction of pixel description to a semantic regional description of data.
- Statistical representation of identified classes with associated signatures and covariances.
- Description of isolated bodies through boundary detection and body descriptions.
- Spatial and spectral rectification and reduction of multi-channels into three color channels.
- Feature detections
- Event detection.

Adaptive Control Functions

One of the most promising techniques for data reduction is that of the adaptive control functions or techniques required for IAS. Here we are talking about the ability of IAS to control such functions as:

- Instrument selection
- Channel selection
- Sensor pointing
- Algorithm selection
- Prioritization control
- Target selection
- Conflict resolution
- Data transmission control
- Contingency planning
- Response to human decision making

User Defined Processing Scenarios

The user defined processing scenarios is a new technique which BTS has identified as viable for IAS. This technique stems from the realization that users will have a learning curve with respect to IAS because they shall be reluctant to have the data tampered with prior to their specific interpretations. In keeping with the assumptions of IAS, a limited band width is very likely to be allocated to each user. The user should be free to use this allocated band width in any manner he sees fit. If he desires raw data from all of the sensors, he may get a limited amount of such data which he then must process within his own facilities. As you can imagine, if the user can perform a certain degree of onboard processing for the reduction of data to information, he may very well receive a data stream containing more information than he would otherwise had he received just the raw data and, in addition, the amount of processing that would be required of him would be significantly lowered. BTS envisions a system in which the user may establish his own processing requirements by defining the sequence of operations that he desires for his application. In this way, IAS avoids the very cumbersome political issue associated with someone else "contaminating" his data.

Evolutionary Growth

Another technique which BTS has identified for IAS is the technique noted by evolutionary growth. The approach is one of a modular system view for IAS which takes into consideration the ever changing environment for onboard information extraction and data packetization which will occur as users learn how better to use an IAS ensemble of remote sensing spacecraft. The evolutionary growth technique provides for:

- Increased flexibility
- Increased onboard computational capabilities
- Wide range of potential output products
- Philosophical control over IAS operations

- An IAS library for the definition of information extraction processing scenarios.
- Expansion in the number of basic information extraction primitives which can be placed onboard.

3.1.8 Tree Structure Control

One of the most important facets of the IAS study is the development of a system which will allow growth in the future as research develops new techniques and procedures. It is anticipated that as research in the remote processing area continues, new ways of classification and extraction of information will be developed. It is the purpose of BTS to develop a system which will allow us to imbed these new ideas and new research developments into the IAS system. With this in mind, BTS envisions a tree structure control system. This tree structure appraoch will provide many capabilities such as:

- Great flexibility
- Scheduling capabilities
- Prioritization
- Classification flexibility
- Instrument control
- Processing scenario control
- Interface to ground related functions.

Figure 3.1.8-1 illustrates a conceptual tree structured design of a control system. If we examine this figure in a little more detail, we see that at each node there is some control information, that is we make certain decisions at each node. Those decisions may be as simple as whether to transmit the data to the ground or to continue processing of that data. At each node we can control the path the data takes, that is the scenario of processing, thus giving us great control over the products that are produced. At each node we can also have scheduling imbedded. Basically a tree structure provides a great deal of power in

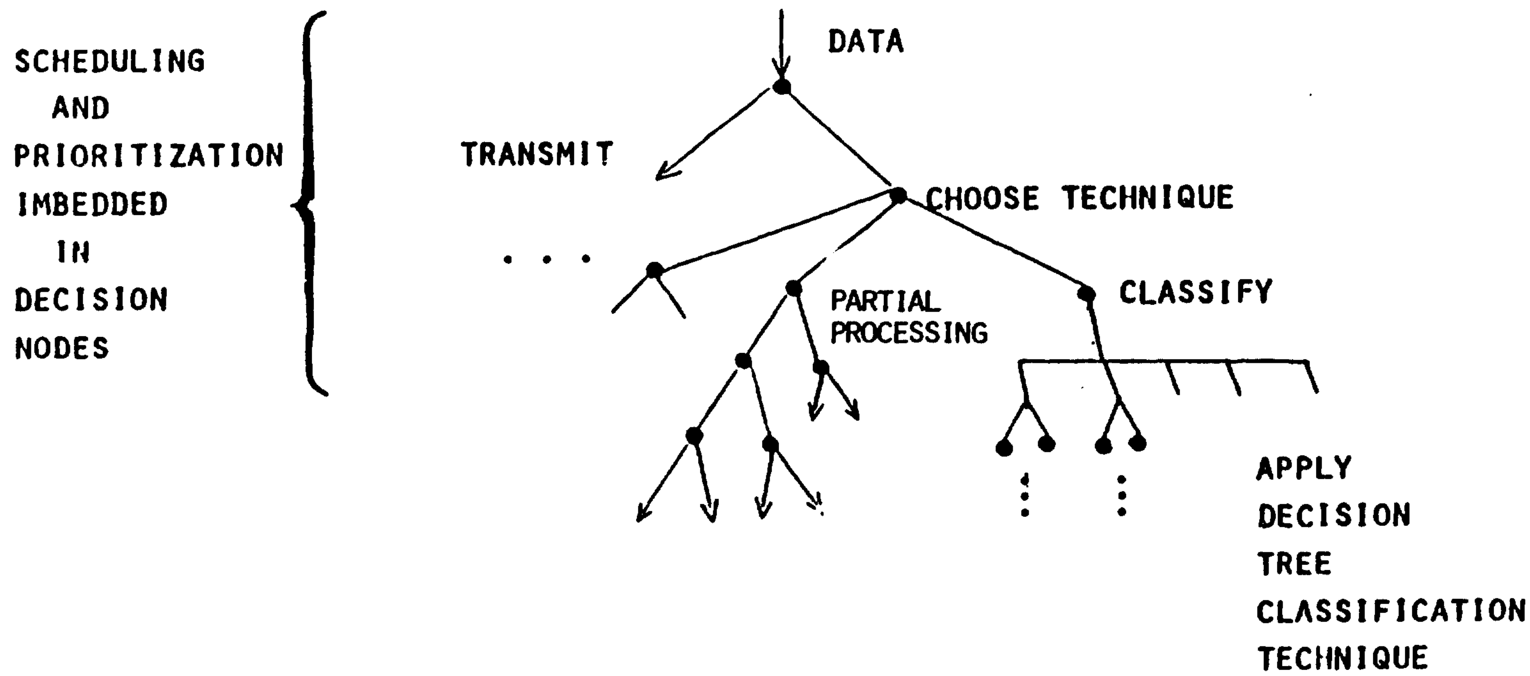


Figure 3.1.8-1 Conceptual Tree Structure Control Design

the scheduling and prioritization areas. Note also that tree structure control interfaces very well with the concept of a decision tree classifier. All of the information adaptive system techniques can be imbedded in a tree approach to IAS decision making. The same techniques can be utilized, at the level of information extraction, as a decision tree classifier which, in fact, will be more efficient and provide much greater flexibility than conventional one-stage procedures.

Overall this concept of tree structure control provides a more global view of the problem. It allows us to take a top-down structured approach to the extraction of information. It allows for a multi-purpose philosophy thus producing a multi-application approach when utilizing proper modular design structure of the algorithms. As research continues, we will be able to add new capabilities to the system without major restructuring of the algorithmic techniques. This flexibility will provide the kind of growth that we desire. This flexibility will provide the ability to users to control the scenarios of processing they desire. These ideas, combined with the concept of primitives, whereby algorithms are executed as a series of primitive functions, will provide the flexibility and power to give us the kind of IAS system that will provide benefits now and in the future.

3.2 Sub-systems Design and Specifications

This section describes the three applications for the near-term implementation of IAS. The sub-systems are described in terms of overall objectives and the requirements for each sub-system are stated. The near-term IAS as described is within our technical capabilities at this time. This does not mean that further developments are not required -- only that the required technology can be in place within the next five to seven years. To achieve this will require that a reasonable effort begin shortly.

3.2.1 Application Description

The three applications selected for detailed study share a common set of characteristics which will exploit the capabilities of an Information Adaptive System. These characteristics are:

(1) Geographic data set selection
(2) Spatial signature data set solution
(3) Spectral signature data set selection
(4) Cloud detection
(5) Signature tracking
(6) Event detection and reporting
(7) Event tracking
(8) Data compression through on-board processing
(9) Real time response
(10) Evolutionary development of system capabilities

The role each of these characteristics plays in the applications will be described below.

3.2.1.1 Sea Ice Mapping

The IAS application of sea ice mapping to Arctic waters, the Great Lakes, and the Gulf of St. Lawrance have the potential of satisfying numerous real time, near term, and long term information requirements of the shipping industry, oil industry, and the scientific community (Miller, 1977; Sabins, 1978). Real time information includes the identification of navigable waters, the identification of potentially clearable shipping channels and the location of navigational hazards such as iceburgs and ice flows. Near term information includes the scheduling of shipping activities based on the accurate prediction of the time and location of spring thaw and winter freeze, the location of opening and closing leads, and the tracking of iceburg and large ice masses. The long term information includes the collection of synoptic data on sea ice, such as concentration, age, thickness, extent, opening and closing of leads, motion of ice flows, motion of pack ice and topography of ice sheets. The long term information will contribute to the scientific communities understanding of the characteristics and dynamics of the arctic environment, from which global heat budget models and ocean and atmospheric circulation models can be developed.

The generalized real time sea ice mapping scenario goes as follows:

(1) Locate and map ice masses, sea water, and land
(2) Classify ice masses (suitable classification is given in Table 3.2.1.1-2)
(3) Display navigable waters and navigational hazards.

The near term information will result from repeating the above as often as necessary or as often as possible to monitor change. Mobile navigational hazards can be tracked and compared against likely path as predicted by ocean current models. The long term information will result from collecting the above information over several seasons or years.

Four conditions and/or requirements must be considered when performing Arctic sea ice mapping via remote sensing (Sabins, 1978) they are:

(1) Darkness or twilight persist for several months of each year (late October to late March)
(2) Clouds and fog persist for much of the year
(3) Broad regional coverage is needed
(4) Repeated coverage is needed to analyze ice movement during the spring breakup.

Table 3.2.1.1-1 lists commonly used sea ice terminology. Figure 3.2.1.1-1 illustrates several of these terms. Table 3.2.1.1-2 lists possible sea ice classification that is applicable in this application.

TABLE 2.1.1-1
Sea Ice Terminology
(From World Meterological Organization Publication No. 259. (TP145))

Feature	Description
Fast ice	Ice which forms and remains attached to the shore. May extend seaward for a few meters to several hundred kilometers from the coast.
Floe	Any relatively flat piece of sea ice 20 m or more across. Floes are classified according to size.
Pack ice	General term for any area of sea ice, other than fast ice, regardless of form or occurrence. Pack ice is classified by concentration of the floes.
Lead	Any fracture or passageway through sea ice that is navigable by surface vessels. Leads may be open or refrozen. A flaw lead separates fast ice from pack ice.
First-year ice	Sea ice of not more than one winter's growth. Thickness ranges from 30 cm to 2 m.
Second-year ice	Old ice that has survived only one summer's melt. Because it is thicker and less dense than first year ice, it stands higher out of the water.
Multi-year ice	Old ice 3 m or more thick that has survived at least two summers' melt.
Pressure ridge	Wall of broken ice forced up by pressure
Brash ice	Accumulations of floating ice made up of fragments not more than 2 m across; the wreckage of other forms of ice
Iceberg	A massive piece of ice extending more than 5 m above sea level that has broken away from a glacier. Icebergs are classified according to shape.

Table 3.2.1.1-1 Sea Ice Terminology

(From World Meteorological Organization Publication No. 259 (TP145))

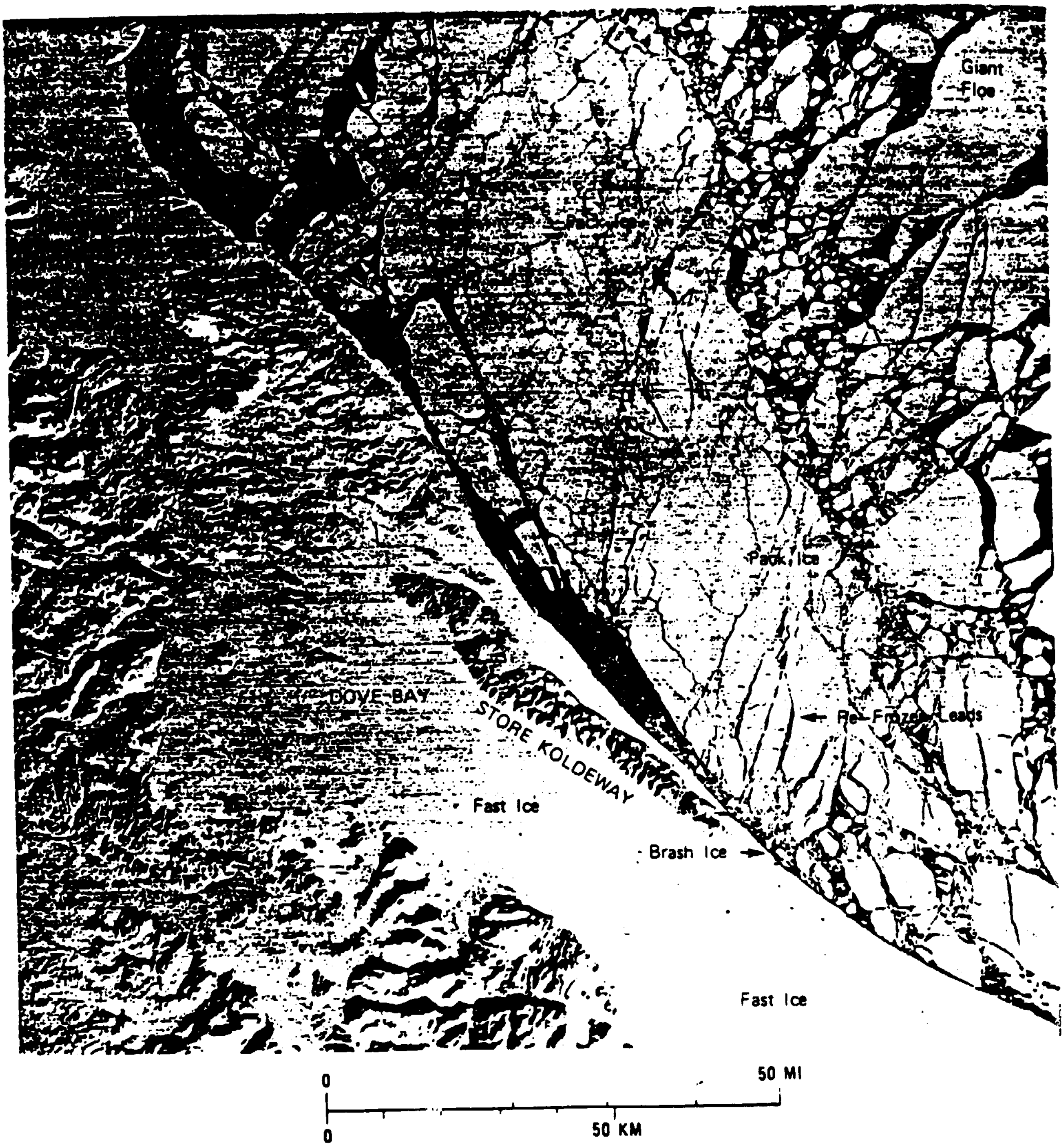


Figure 3.2.1.1-1 LANDSAT image of sea ice features in vicinity of Dove Bay on east coast of Greenland. LANDSAT 1245-13423, band 7, acquired March 25, 1973 (from Sabins, 1978)

	LEVEL I General Classification	LEVEL II Specific Classification
INCREASING MOBILITY	LAND	
	SEA ICE	FAST ICE PACK ICE BRASH ICE SEA ICE HAZZARDS
	NAVIGABLE WATERS (including LEADS)	

Table 3.2.1.1-2 Suggested Classification System for Sea Ice Mapping

In order to satisfy the requirements of IAS sea ice mapping, both on board processing and ground base processing are required. The on-board capabilities will be utilized to identify sea ice within the candidate geographic regions. If any sea ice is detected, its location, classification and size will be transmitted to the ground station via MTDS.

Assuming that the sensor platform is a free flyer spacecraft, there will be only one view per pass of any sea ice mass detected. The monitoring of sea ice motion requires a collection of several consecutive scenes over a period of time. The high latitude loction of Arctic sea ice can be used to an advantage. Landsat orbit's coverage near the poles provide three to four consecutive days of coverage due to overlap, for each 18 day cycle (Sabins, 1978) if daily viewing is required. Still, not one but five to six separate spacecraft are required to give daily coverage. Such complete coverage is important mostly during the spring thaw when many icebergs and giant floes are spawned. Free floating sea ice moves with a velocity of about one half of a kilometer a day (Barns and Bowley, 1974).

Actual tracking will require ground based processing. Given the location and size of the sea ice mass, and the a priori knowledge of the directional velocity of ocean currents, it is possible to project the location of the ice masses on subsequent days. Subsequent views of the sea ice mass will provide projection updates and current model refinements.

The major limiting factor in all of this is the fact that multispectral scanners and thematic mappers require visual contact with the ocean surface in order to observe surface phenomenum such as ice. The result is that the cloud cover which is normally present in these geographic regions will make it relatively difficult to obtain continuous readings of the sea surface. To overcome this problem totally, a scanner system capable of penetrating the cloud layers is required. For example, a synthetic apperature radar could be used. However, if we are willing to accept the limitations of visible scanners, in any case, it is still possible to produce a very workable system. The major drawback will be the number of spacecraft needed to obtain a sufficiently high frequency of observation of the regions of interest.

The sea ice mapping task satisfies the concept of IAS from at least two standpoints. The first is that the transmission of data to the ground will be based not only on whether or not a particular geographic region is being observed, but whether or not there is cloud cover or whether or not a target of interest (sea ice) is being observed. Secondly, the reporting of information to the various users will be based on the occurrence of events of interest. In this case, if the project motion of a sea ice mass will take it into a navigation lane, the event will be reported to the users. Hence, data flow in this application will be held to an absolute minimum and users will be given information which is meaningful to their particular interests.

3.2.1.2 LAND USE Classification and Inventory

The purpose of the IAS application of LAND USE classification and inventory is to monitor the impact of man's activities in the use of land for habitation, agriculture and resource extraction. There are many facets to this subject, and, in fact, this application encompasses a large number of other specialities. Our definition of LAND USE will be based on the classification system devised by Anderson et al (1976) shown in Table 3.2.1.2-1. Level III and IV classifications exist but require algorithmic developments beyond the envision IAS capabilities at this time.

The information time frame is not as strict as for sea ice mapping. Classifications are generally required on a seasonal basis at most, or on a yearly basis. Acquisition of consecutive LAND USE classification will produce a long term product in terms of change detection mapping.

This application lends itself to on-board processing with techniques currently well developed. The concept of decision tree classification is particularly relevant in this context from the standpoint that additional algorithmic refinement can be introduced simply by extending the decision tree. Hence, as the future unfolds, we may be able to penetrate the LAND USE category to an ever increasing extent simply by adding nodes and leaves

Level I	Level II
Urban or built-up land	Residential Commercial and services Industrial Extractive Transportation, communications, and utilities Industrial and commercial complexes Mixed urban or built-up land Other urban or built-up land
Agricultural land	Cropland and pasture Orchards, groves, vineyards, nurseries, and ornamental horticultural areas Confined feeding operations Other agricultural land
Rangeland	Herbaceous rangeland Shrub and brush rangeland Mixed rangeland
Forest land	Deciduous forest land Evergreen forest land Mixed forest land
Water	Streams and canals Lakes Reservoirs Bays and estuaries
Wetland	Forested wetland Nonforested wetland
Barren land	Dry salt flats Beaches Sandy areas other than beaches Bare exposed rock Strip mines, quarries, and gravel pits Transitional areas Mixed barren land
Tundra	Shrub and brush tundra Herbaceous tundra Bare-ground tundra Wet tundra Mixed tundra
Perennial snow or ice	Perennial snowfields

Table 3.2.1.2-1 Classification System of Land Use and Land Cover for Use with Remote-Sensor Data (Source: From Anderson and others (1976))

to the decision tree. With the proper structure to the hardware, and software, such changes could be implemented even after the spacecraft has been launched.

The generalized processing scheme is to (1) locate specified region of interest; (2) delete or mask out cloud from scene; (3) perform a Level 1 classification; and (4) perform a Level II classification.

While some of these items are very easily performed on-board, it appears, as with the Sea Ice application, that certain aspects of the LAND USE application will have to be performed by a cooperative effort of flight and ground hardware. For example, it is relatively easy to separate an image into water and land regions on-board the spacecraft. Such a separation is particularly effective in reducing the data transmission bandwidth because the entire image could be conveyed on a basis of one bit per pixel (or even less). However, comparing the map of water over a given region with a reference map to locate flood areas is best performed on the ground because of the need for the relatively extensive historic data set.

3.2.1.3 Snowmelt-runoff Forecasting

Snowmelt-runoff forecasting is an IAS application that is particularly relevant to land use and water-management problems in geographic areas that depend primarily on snowpack for their water supply and/or hydroelectric power. Successful land use and water-management requires that the snowmelt runoff forecasting results be provided on a seasonal as well as on a short term basis. On a seasonal basis, where the time scale is on the order of a few months or longer, forecast results can be used in agricultural planning, irrigation scheduling, and long term reservoir level management. On a short term basis, where the time scale is on the order of a few days (24 to 72 hours), forecast results can be used in flood prediction and reservoir management for power production.

Present remotely sensed snow mapping techniques are still in the system verification stage or in laboratory study stage. See Rango 1975, 1977, and 1978. System verification centers around regression analysis of percent snow cover versus annual runoff, on a basin by basin basis. Results have been positive and are most successful in basins with the longest snow cover records, or whose snow cover history include more than usual or less than usual snow. Percent snow cover, along with precipitation and temperature data are input parameters for watersned basin hydrologic models, also developed and tuned on a basin by basin fashion. These models can be used to forecast daily stream flow. Investigation of active and passive microwave measurement techniques are underway in hopes of adding other parameters to the watershed models. These additional parameters are snow depth, snow wetness and snow water content (Linlor et al, 1975; and Hall et al, 1978).

Three requirements and/or conditions should be considered when performing snowmelt-runoff forecasting:

(1) Sensor/processing system must discriminate between snow and clouds, since both features tend to saturate current sensor systems in the visible wavelength bands.

(2) Sensor/processing system must be able to perform area accumulation and watershed masking.

(3) Repeat coverage is required for monitoring changes in snowpack parameters.

The general processing scheme for the seasonal forecasting is to (1) locate geographic area of interest; (2) mask out areas outside watershed area; (3) detect or mask clouds from scene, and (4) calculate percent snow cover in scene. The general processing scheme for short term forecasting is the same with the possible addition of the measurement of additional snowpack parameters, as the watershed hydrological model require, or as technology allows.

The relationship between the long term and short term forecasting observation requirements is shown in Figure 3.2.1.3-1 for a hypothetical watershed basin. The regression analysis approach for forecasting seasonal runoff does not require continuous monitoring. The goal is to obtain cloud free scenes of the watershed during peak accumulation (coverage). For the hypothetical watershed basin, January is the start of significant snow cover. Snow cover accumulation could extend into May, as indicated by the dashed lines. Acquisition of scenes is not critical except for during a period when peak accumulation historically occurs for the basin. For the hypothetical watershed, the date is on or about April 1. Observat , should be scheduled for a period that brackets April 1. Continuous monitoring on a daily basis begins when the snowpack starts to deplete. Present hydrological models use snowcover extent, precipitation and temperatures as input parameters to predict daily streamflow. Passive and active microwave techniques have the potential of providing additional input parameters such as snow tempera-

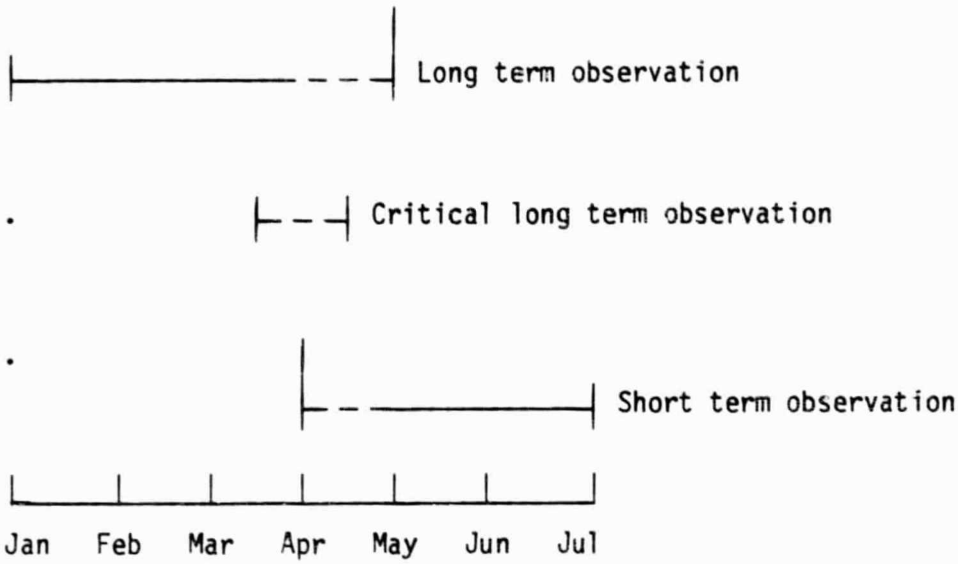


Figure 3.2.1.3-1 Observation Time Frame for Short and Long Term Forecasting for a Hypothetical Watershed Basin

ture, snow depth, snow water content or other properties germane to run-off prediction.

Snowmelt-runoff forecasting is an application well suited for IAS. Present studies suggest that both the regression analysis and the hydrological model approach require only key parameters that are dependent on the whole scene. In the case of the long term forecasting, only the percent snow cover is required. A snow cover map with the non-watershed areas masked out could be produced but is not necessary in making the forecast. Actual forecasting will be done on the ground but area calculation can be done on board. For the short term forecasting, only snow-pack parameters germane to a particular hydrologic model, gathered on a whole scene basis, are required. The forecast equation is in the following form (Rango et al, 1977):

$$Y = a_1X_1+a_2X_2+a_3X_3+\cdots\cdot a_nX_n+K$$

where Y is the runoff volumn, the a's are the parameter coefficients, the X's are the unit less parameter indices obtained from the scene, and K is the basin constant. The parameter indices are calculated on board and transmitted to the user who does the actual forecasting calculations.

As with the Sea Ice Mapping task, the major limiting factor is the availability of a scanner system or algorithm that will discriminate between cloud and snow. Near infrared frequencies (Bartolucci et al, 1975) or microwave techniques have the potential of accomplishing this goal. Another drawback is the number of spacecraft needed to provide frequent observations.

3.2.2 End-to-End System Configuration

While these applications share certain characteristics, there are significant differences to warrant exploring the system characteristics separately. An attempt will be made to satisfy these applications with a single system since the processing loads imposed by the three applications are nearly separate time-wise. In establishing the overall system configuration, the capabilities (MIPS, bandwidth, storage, etc.) at each point in the system will be specified to handle the more stringent of the three applications. Such details will be provided in the system specifications.

3.2.2.1 Sea Ice Mapping System Configuration

Figure 3.2.2.1-1 depicts a conceptual view of the flight segment of the IAS subsystem for the Sea Ice Mapping System. The flight segment of the IAS subsystem consists of five modules; geographic region selector, cloud detector, sea ice classifier, geographic region descriptor, and message formatter. The observed scene data is delivered to the IAS subsystem by the spacecraft sensor system. The nature and configuration of the sensor system are not yet defined but is a NEEDS element. The scene, as received by the IAS, subsystem, is radiometrically and geometrically correct.

The input to geographic region selection module is the observed scene, spacecraft ephemeris and IAS geographic region descriptor. This module will extract from the observed scene only those scene elements which pertain to predefined geographic regions. A method to select geographical regions is presented in Appendix F. It illustrates how the problem can be solved. This technique can be shared by all three applications in specifying their onboard geographic region selection modules.

These predefined geographic regions will be received via the MDTS uplink by the geographic region descriptor module. This module will store the geographic region descriptions prepared on the ground and, at the appropriate time, transform the descriptions into control data which will be used by the region selection module.

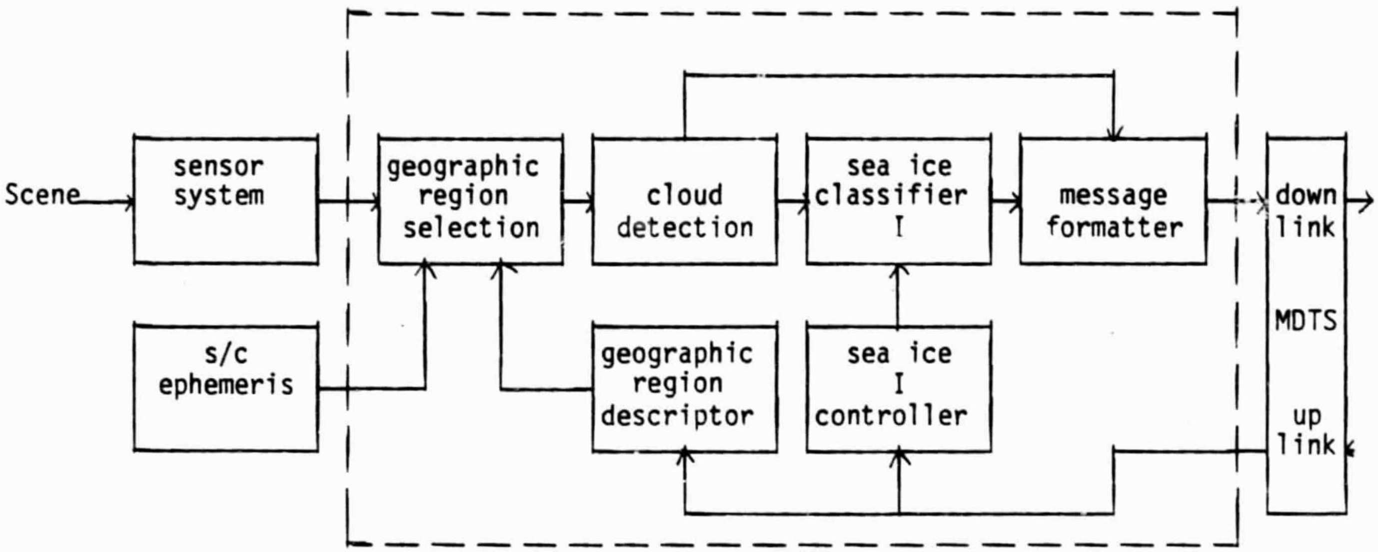


Figure 3.2.2.1-1 Flight Segment of Sea Ice Mapping I

The cloud detection module will detect and separate out those portions of the scene that are obscured by cloud cover. Only those portions of the scene that survive this module will undergo further processing. Should the sensor system be chosen such that it is not affected by cloud cover, this module will be eliminated from the system. However, it is assumed an MSS-like sensor platform will be used and will therefore nee the cloud detection module.

Data which survives the geographic region selector and the cloud detection modules will be passed to the sea ice classification module. This module will examine the scene and separate out land, sea ice and navigable waters. At this point, depending on user define requirements, several data product choices can be produced. A binary bit map can be used in place of multispectral data to divide the scene into regions of navigable waters versus non-navigable waters, or regions of sea ice versus non-sea ice. A pixel element defined by two bits can produce a general classification map of the land (for geographic fix in traveling) sea ice and navigable waters. Multispectral data will be used when there is a requirement to separate sea ice into several classes. The number of bits required will be a function of product choice.

The message formatter will also provide feedback to the ground support segment. If the cloud detection module indicates a whole region is deleted because of excessive cloud cover, or if the sea ice classifier detects no sea ice, this information will be transformed into status report by the message formatter and down-linked to the ground. The ground segment will, therefore, be able to monitor the operation of the spacecraft and track the flow of data.

The message formatter module will receive the resultant classification maps, product code, latitude and longitude data, and structure the message to be transmitted to the ground through the MDTS down-link. Each such message will contain sufficient emphemeris data to identify accurately the location of the ice map on the surface of the earth.

The sea ice mapping ground system is depicted in Figure 3.2.2.1-2 Shown on the left is the MDTS interface to the spacecraft. All communications to and from the spacecraft will pass through this MDTS interface.

Messages received from the spacecraft will be initially processed by the down-link interface. The sea ice maps will be stored in the DBMS for processing by other modules, and the status reports indicating which regions have been mapped and which have not will be transferred to the ground segment control module.

The ground segment control module is the focal point for all control activities over ground operations. It will control the user interface as well as the interfaces to the spacecraft and other modules within the ground segment. Upon receipt of a status report, the ground segment control module will initiate whatever additional activities as required by the user or the system. For example, if a ship in Arctic waters used a map of present and projected sea ice hazards, such information will be transmitted to the user as it becomes available.

The DBMS is used to store and retrieve the sea ice maps and other related information such as their location, date, time, etc. Since the data received from the spacecraft has been highly compressed due to the significant processing which has taken place on board the spacecraft, the DBMS itself need not be extremely large.

The sea ice classification II module will further classify sea ice into the Level II classification (Table 3.2.1.2-1). Of major concern is the sea ice hazards. Sea ice hazards consist of icebergs and large ice floes in navigable water and may be considered under one classification. However, sea ice hazards may be divided in actual and potential sea ice hazards. Icebergs are most readily identified by their shadows while in fast ice, and therefore, can be flagged as potential sea ice hazards. Large floes can be identified while locked up in pack ice and likewise can be flagged as potential sea ice hazards. Along with the sea ice tracking model, these sea ice hazards can be tracked long before they break away and enter into navigab' ers.

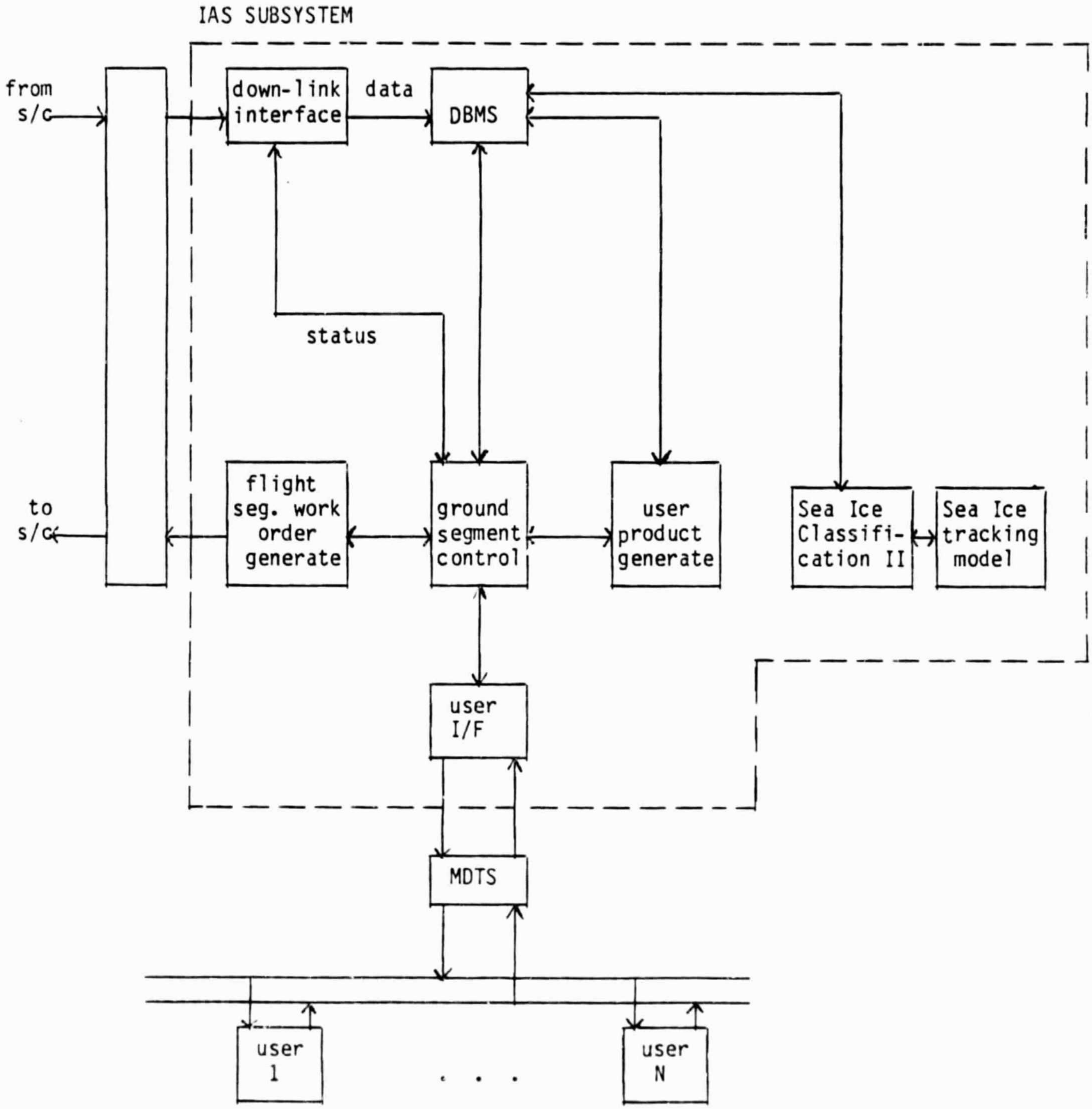
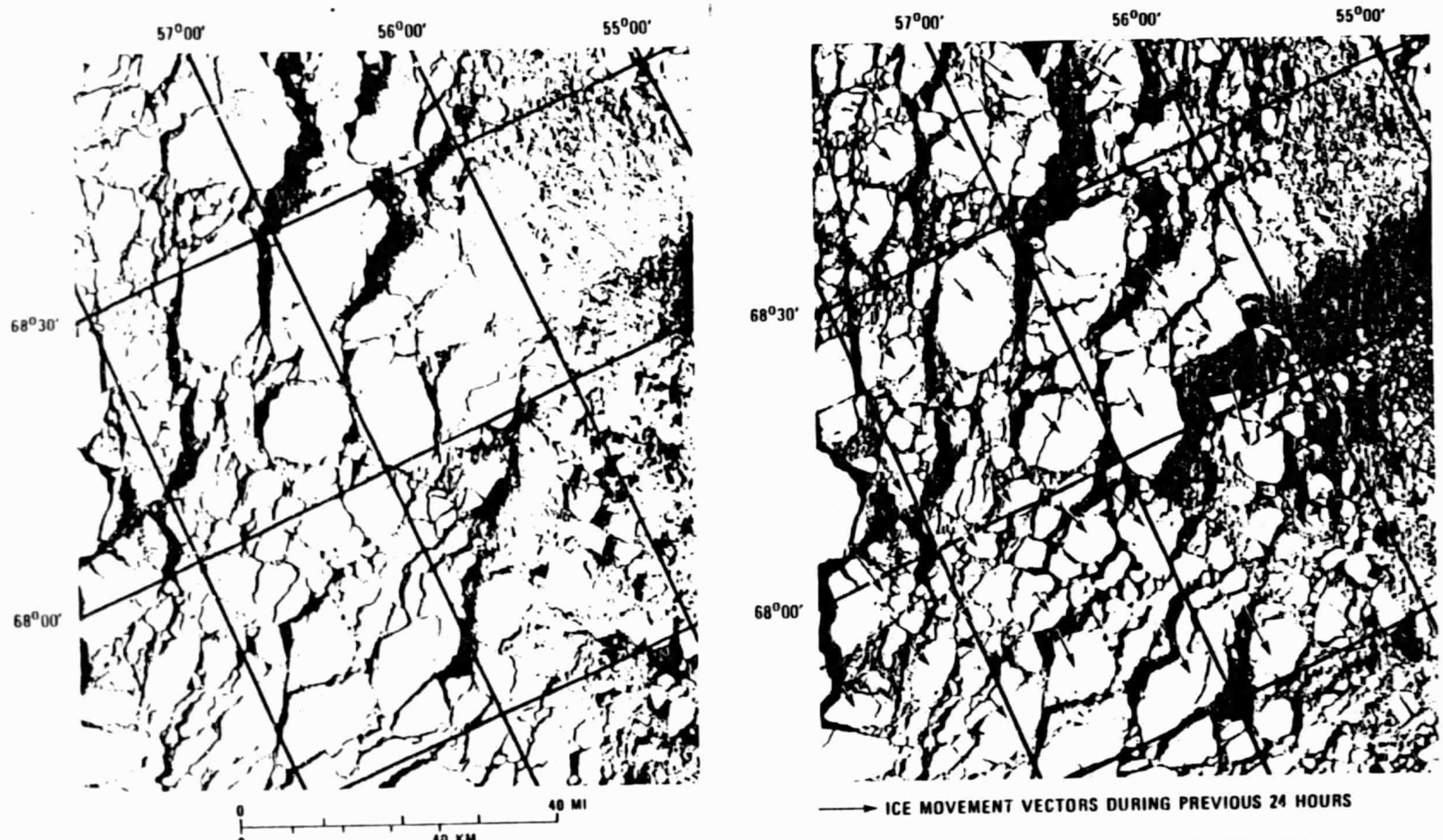


Figure 3.2.2.1-2 Ground Segment of Sea Ice Mapping II

Sea ice movement can be tracked by viewing consecutive scenes as illustrated in Figure 3.2.2.1-3. Alternatively, the sea ice tracking model can make use of a priori knowledge of ocean currents in the regions of interest. It is possible that the movement of a sea ice hazard over a reasonable period of time could be predicted by knowing this information. Additional study will be required to determine whether or not additional information such as sea level wind velocities, and individual iceberg's size and shape are factors which must be considered.

The user product generate module references the DBMS via the ground segment controller to develop the desired user products. For example, the DBMS will maintain not only the current location sea ice hazards, but sufficient information to extrapolate the position of ice. Thus, the user product generation function is decoupled from the spacecraft in that it will normally only reference items which are stored in the DBMS. As icebergs drift toward the Equator and melt, they will ultimately vanish and be disgarded from the DBMS. As a rough indication of the storage requirement there is on the average, approximately fifteen thousand icebergs which occur annually (Newmann and Pierson, 1966). Since these icebergs occur over a fairly long period of time measured in months, the target tracking system does not have to perform in any particularly speedy fashion.

The user interface is used to pass all information between the user community and the ground spacecraft systems. Through this interface, users present their requests for information and receive that desired information. To the greatest extent possible, the user interface will be configured to allow users to specify the delivery of products in a format which best serves their interests. The user interface should be provided with a library of functional capabilities to be used in constructing individual user products. A user could, therefore, specify his geographic region of interest and declare those processing functions which he wished applied to his data, and receive data in a format which is most likely to be of immediate value to him.



A. MARCH 20, 1973 AT 11:00 A.M. LANDSAT 1240-15000.

B. MARCH 21, 1973 AT 11:05 A.M. LANDSAT 1241-15055.

Figure 3.2.2.1-3 Movement of Sea Ice Measured on Band 7 LANDSAT Images Acquired on Successive Days. Davis Strait, West of Greenland. (From Sabins, 1978.)

For reasons of standardization, the user community will interact with the ground segment via the MDTS system. In this way, users co-located with the ground segment, as well as remote users, will be able to interact with the system in a standardized, economical fashion. MDTS will have to be configured in such a way that message blocks which are transferred are highly adaptable to serving a variety of needs. This implies such things as variable block sizes, to accommodate the different length messages which users will request, and it implies error control algorithms to maximize the probability that accurate information is delivered to the user.

The MDTS system must support data rates adequate transfer to the user products in a timely but economical manner. At this time, the required data rates are not known, however, allowing for the fairly massive compression of data to information, it is very likely that data rates of no more than 1 or 2 megabits per second would suffice for virtually all users. In fact, it is quite conceivable that the typical user could be adequately supported by the data rates now achievable on voice grade telephone lines.

The flight segment work order generate module performs all functions related to spacecraft command control and status monitoring. The work orders generated are both related to the functioning of the spacecraft, as well as work orders related to the sea ice mapping function. They would include all information needed for the total operation of the spacecraft.

In addition, this module will oversee the health and well being of the spacecraft via an analysis of the status reports, and provide any necessary interaction with operations personnel. Such interactions could take place through customized interfaces to the module as is traditionally done in spacecraft operations control centers, or these interactions could take place using the provisions of the user interface and MDTS. There are significant economies to be gained by using the MDTS interface in that the control centers could be considerably more modular than they now are. Such modularity could also provide backup capabilities through the interconnection of control centers using MDTS. Thus, it would be possible to provide effective backup for a number of control centers by providing far less than the same number of redundant control centers.

3.2.2.2 LAND USE Classification and Inventory Configuration

Figure 3.2.2.2-1 depicts a conceptual view of the IAS portions of the spacecraft for LAND USE classification and inventory. The sensor system is a multispectral scanner or thematic mapper-like sensor platform. This configuration introduces four modules not used in the sea ice mapping application. Again, it is assumed that geometrically and radiometrically correct data are received by the IAS portion of the spacecraft. Previously discussed IAS subsystem modules will not be discussed again.

Data which survives the cloud deletion module will be forwarded to the Level I classifier module. This module will sort the data in up to nine different ways to correspond to the definition of Level I classification. In addition, depending upon the nature of the user request, some of these categories may be directly forwarded to the ground by the function of the message formatter. They may be combined, and they may be disgarded. A last option is that certain of the Level I classes may be passed to the Level II classifier for further processing.

The Level I control module receives work orders up-linked via MDTS and translates these work orders into a scenario of activities to be performed by the Level I classifier. Such work orders would consist of the nature of the classification to be performed on any specific geographic region and the ultimate fate of the classified data whether that data be disregarded, processed by the Level II classifier or forwarded directly via the message formatter.

The Level I classifier is also able to perform rather substantial editing and processing of the data. For example, while it is necessary to have multispectral data available to do the classification function, the user may well only need an indication of the class to which the area has been assigned. Hence, it may be possible to transform multispectral pixels into 4 bit integers from 1 to 9 to indicate the class assignment. This would, in addition, have the benefit of dramatically reducing the down-link data rate. If the sensor system were a multispectral scanner (MSS), this operation alone would result in a 6 to 1 reduction in data rate.

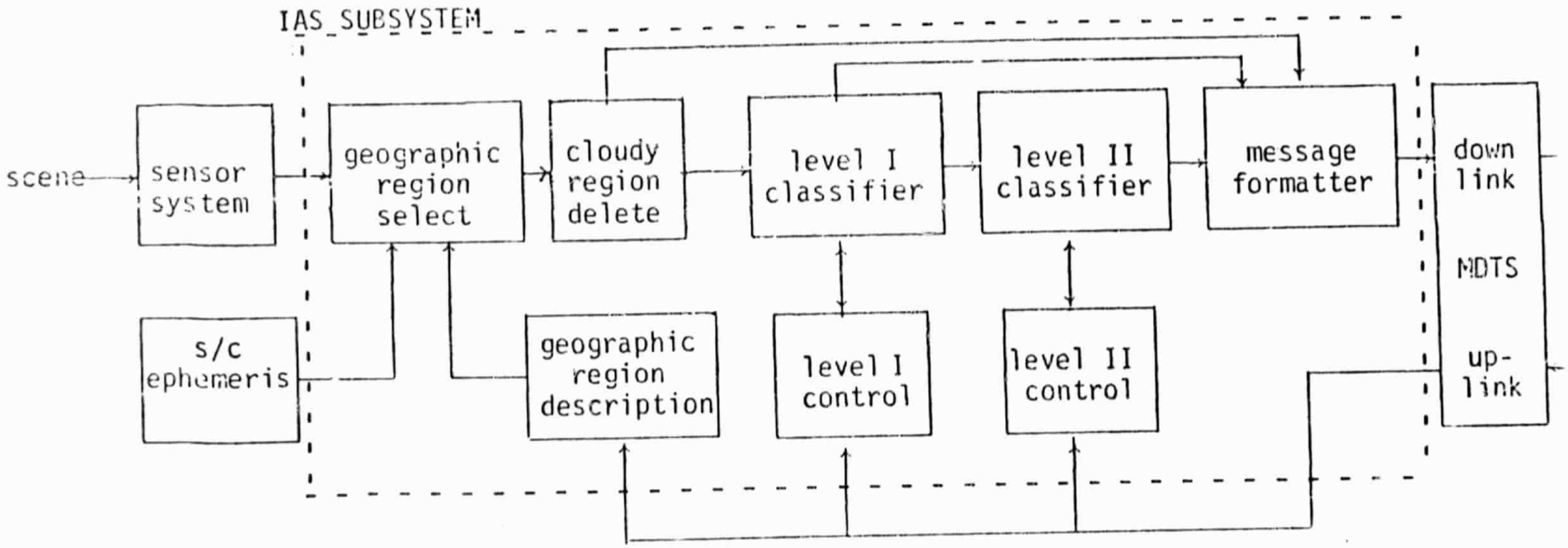


Figure 3.2.2.2-1 Flight Segment of LAND USE Classification/Inventory

C-2

The Level II classifier provides a more detailed use analysis of the classes generated by the Level I classifier. Again, this module performs in response to specific user requests. This module can be used to sub-classify data and then discard or significantly abbreviate the data which it has processed.

The Level II control module also receives work orders via the MDTS up-link. It transforms these work orders into instructions to the Level II classifier. These instructions are related to geographic regions of interest and to secific output products from the Level I classifier.

While the algorithms for complete Level II classification are not totally known or accepted at this time, it is felt that substantial progress has been made in recent years and that, with a reasonable effort, such classification could be performed autonomously in the near term future, and could be available for a spacecraft mission in the 1985 time frame.

Figure 3.2.2.2-2 entitled "Ground Segment" depicts, at a high level, the structure of the ground segment. On the left we see the MDTS interface to the flight segment. Messages received from the spacecraft are handled by the down-link interface. Data blocks are transferred to the DBMS for storage while status messages are transferred to the ground segment control module for examination. In addition, the down-link interface reports the arrival of data blocks to the control module so that related processing steps can be initiated.

The DBMS is used to store for both long and short periods of time the data which has been received. It provides the working store for all data acquired by the system. Data blocks are autonomous since each contains all relevant identifying information within them. The DBMS catalog is updated at the same time the data is stored within the DBMS.

The ground segment control module supervises all of the activities within the ground segment. It receives from the user interface, work

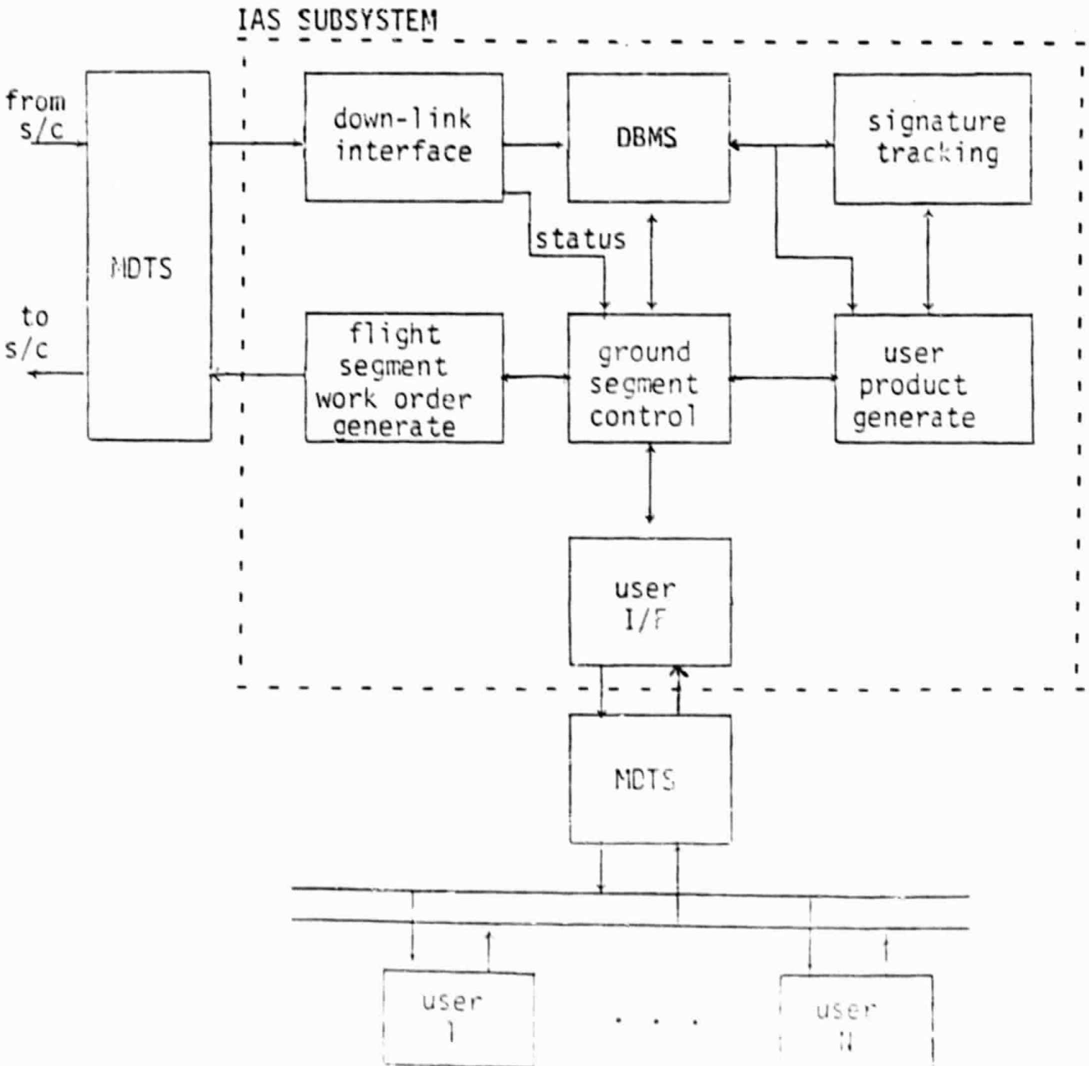


Figure 3.2.2.2-2 Ground Segment of LAND USE Classification/Inventory

orders which indicate tasks desired by the users, and distributes these work orders to the user product generate module and the flight segment work order generate module. In addition, it responds to the user requests with information which indicates the viability of the requests. Should a user require new data be taken by a spacecraft, the ground segment control module will indicate that data to the flight segment control as well as store work orders for future execution by the user product generate module.

The flight segment work order generate module is responsible for all ground based activities involving the spacecraft. The control center will interface to the spacecraft through this module all commands and status reports involving the spacecraft will be processed by this module, and all flight activities will be scheduled here as well.

User requests for data acquisition will be transformed into work orders and be transmitted to the spacecraft with any related parameters or data required by the spacecraft at the time the data is actually being acquired. For example, it is possible for a user to request that data be gathered from a specific county. In such a case, the flight segment control would generate a work order and data message which described the geography of that county so that the spacecraft could select data from that geographic region. In addition, the nature of the data to be acquired would also be indicated.

The user product generate module will perform any ground based processing required to satisfy the user request. In doing so, it will draw upon any needed data from the DBMS. All user requests will ultimately be processed by this module when the data has been delivered to the DBMS. User requests will probably result in a work order whose execution was deferred until the data had been received from the spacecraft.

The functions requested by the users will be structured in such a way that a relatively limited number of processing algorithms will be available. The processing concept is that the user will pass his data through a sequence of subroutine calls, each of which will produce a well defined transform of the data into an information product. The sequence of such transforms will be specified by the user. The result of this will be the basic information product which he is seeking. In the event that he requires processing scenarios which cannot be completely achieved by the system, it will be necessary for him to either perform the balance of the processing in his own system or to add to the user product generate module the processing algorithms he requires.

The signature tracking module is present because it is anticipated that tracking of signatures throughout the year will be necessary in order to provide the Levels I and II classification. There is further work to be done along these lines in order to achieve autonomous classification of data. It is anticipated that having once classified the data within a geographic region, that the system should be able to repeat that classification process by using the knowledge it gained the first time through. For example, the signature of some agricultural regions changes from season to season because of numerous factors. However, should such a region be classified at any time as an agricultural region, the system should be able to make use of that knowledge to aid in future classification attempts.

The signature tracking module is intended to provide the long term observation of known regions, to provide change detection capabilities, and to maintain an updated model of the signatures to be expected for land use of various classifications. There will be required substantial further study in order to explore, develop, and demonstrate the algorithms necessary to perform this function.

The user interface provides for the exchange of work order requests, work order products, and work order status information between the individual users and the IAS system. All communications with the user community should take place using the facilities of MDTS. In this way, maximum standardization and significant economy can be achieved. Considerable effort will be required to develop a user interface which lends itself to the wide variety of tasks to be expected of this system. Key objectives are to achieve a high degree of standardization, to achieve a user friendly interface, and to achieve a means whereby the system can possess considerable flexibility.

There are available today a number of algorithms as well as software packages which allow for the implementation of a user interface with the desired properties. In addition to offering flexibility to the user, such an interface should also protect against inter-user interactions. This will serve to minimize or eliminate the system downtime due to human error.

The user community will interface to the system using the facilities of MDTS. This will allow for considerable standardization in both the hardware and software required to bring a given user on line. The MDTS system should have adequate flexibility within the data formats to handle different length messages. In addition, MDTS should employ error prevention or error recovery methods to minimize the likelihood of data errors. Because of the data compression performed by this system through the intensive use of processing at a number of points between the sensor system and the users, the consequences of data errors are more severe since the data redundancy is not as great as with current systems.

3.2.2.3 Snowmelt-runoff Forecasting Configuration

Figure 3.2.2.3-1 depicts a conceptual view of the flight segment of the IAS subsystem of the spacecraft for the Snowmelt-runoff Forecasting System. This configuration introduces two modules not used in the previous two applications. It is assumed that geometrically and radiometrically correct data are received by the IAS portion of the spacecraft. Previously discussed IAS subsystem modules will not be discussed again.

Data which survives the cloud detection module will be forwarded to the Snow Mapper. This module classifies the scene, with the non-watershed area masked out, into snow and non-snow. The snow pixels are counted and their percent coverage are calculated. At the user's option, a binary bit

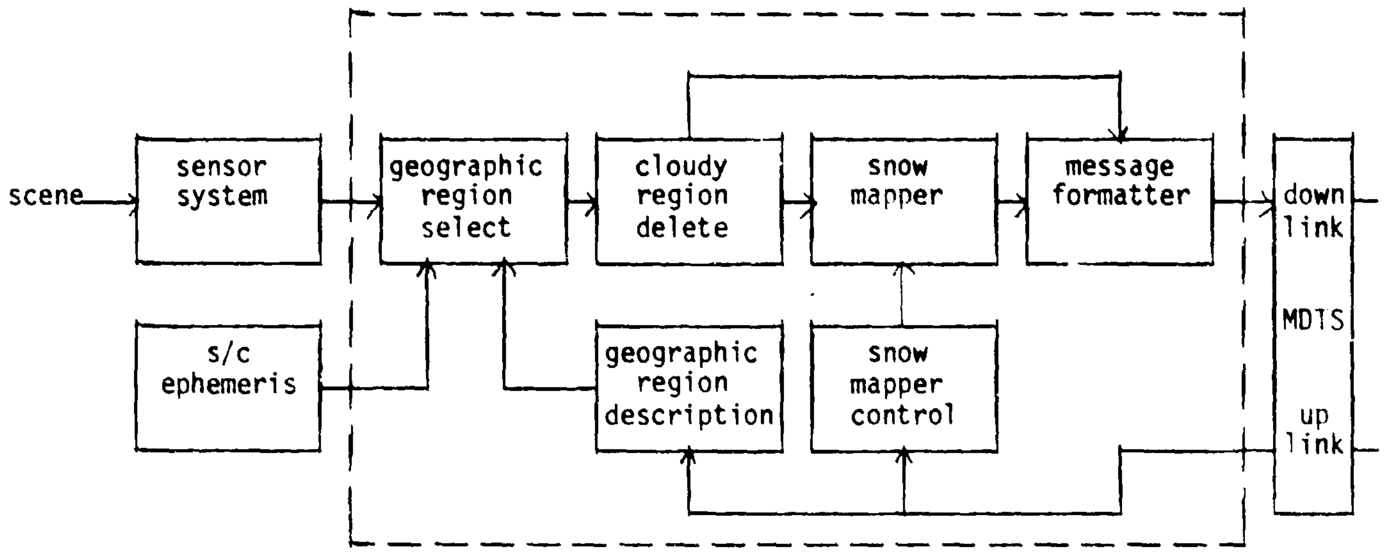


Figure 3.2.2.3-1 Flight Segment of Snowmelt Runoff Forecasting

map of the watershed can be produced, depicting areas with or without snow. A pixel element defined by one bit will suffice to display snow and non-snow (including non-watershed).

For short term forecasting which requires other snowpack parameters in addition to percent snow cover, the scene will be processed further. Assuming that a microwave radiometer is defined as the sensor, calibrated mircowave brightness temperature of snow can be used to infer snow depth, snow wetness, or snow water content. Under the control of the user, the appropriate parameter is measured, and the parameter, in the form of a model index, is calculated on a whole scene basis. At the user's option, a digital map of the parameter is measured for the watershed and can be produced. For example, if the index is mean snow depth, the scene, consisting of microwave brightness temperatures, can be converted to snow depth contour map using a calibration curve. Each pixel will represent a finite contour interval rather than absolute values, thereby reducing the amount of bits transmitted.

For both the long term and short term forecast, the actual prediction calculation is performed by the user. Each user watershed will have a unique regression equation and a unique set of coefficients and constants for their hydrologic model. IAS supplies only the measured parameters or indices, thereby relieving IAS from storing each basin's individual regression equation or hydrologic model.

The Snow Mapper Control module translates work orders, up-linked via MDTS, into a processing scenario to be performed by the Snow Mapper module. The work order determines the type of forecasting to be performed, the kinds of data products, and the particular parameters to be measured. Work orders also contain basin model constants required to calculate model indices.

Figure 3.2.2.3-2 depicts the conceptual view of the ground segment of the IAS subsystem. No new ground modules are introduced in this application.

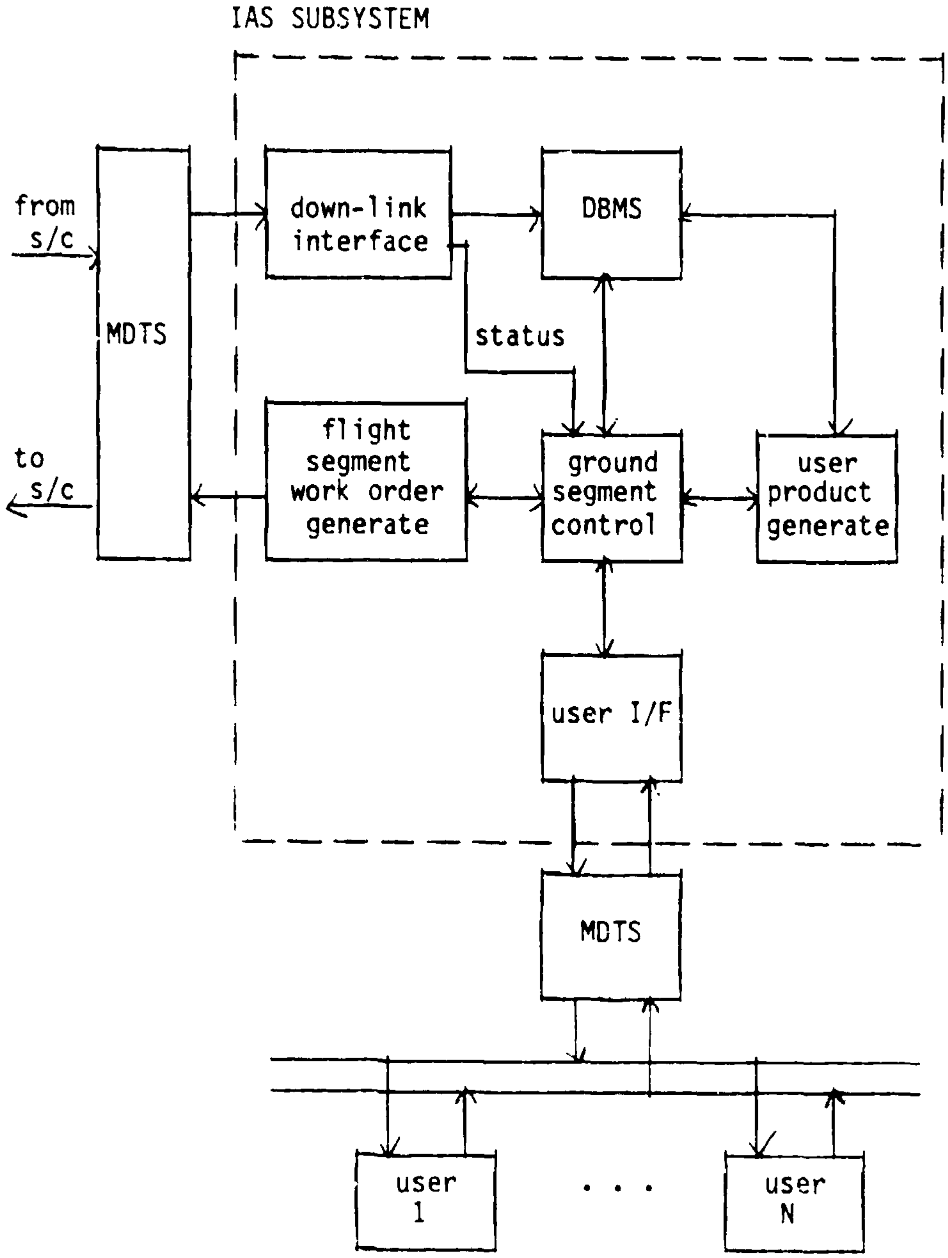


Figure 3.2.2.3-2 Ground Segment of Snowmelt-Runoff Forecasting

The basic ground base activity is to up-line user request, and to channel forecast parameters or indices to the requesting user.

3.2.3 System Requirements

The system configuration described in the preceding paragraphs have been examined and a high degree of commonality has been found to exist for the two applications. In addition, the timeliness for a system processing both applications are highly separable. For these reasons, it is reasonable to assume that a single system could perform both applications. This will prove to be of considerable benefit in that with one such system the aspects of real time response, as well as non-time critical response, can both be investigated.

Table 3.2.3-1 is a tabulation of the eleven system requirements which have been extracted from the study.

The first requirement specifies that the sensor system provide radiometrically and geometrically correct data. This is necessary to avoid the lengthy and time consuming correction process now performed on the ground. Presently, emphemeris data and image data reside in two autonomous data bases. While functionally, the same correction process must be performed, significant economies will be achieved if done in real time on-board, since the image and emphemeris data are both readily available. The result will be autonomous data packets. Any collection of data generated by the spacecraft will contain all ancillary information required to identify the source and location of that data.

The second requirement specifies that the spacecraft maintain its own emphemeris computations on board. While the mechanism for achieving this is not well defined at this time, it is felt that the capabilities of either Tracking and Data Relay Satellite System (TDRSS) or Global Positioning System (GPS), when augmented by a more refined attitude control and determination system, will allow this to be achieved.

(1)	Radiometrically and geometrically correct data to be generated by the sensor system.
(2)	On-board emphemeris determination and maintenance is to be achieved.
(3)	The facilities of MDTS are to be utilized where ever possible.
(4)	Data sets are to be selected through geographic region specification.
(5)	Autonomous algorithmic image processing is to be utilized to the greatest extent permitted by the state-of-the-art.
(6)	There is to be a flexible user friendly interface to the system via MDTS.
(7)	There is to be on-board cloud detection and data deletion.
(8)	There is to be on-board pixel classification at Levels I and II.
(9)	The system will perform the signature tracking necessary to permit autonomous classification to take place.
(10)	The system will provide for target identification and tracking between periods of observation.
(11)	The system will provide an on-line long and short term data base.

Table 3.2.3-1 System Requirements

The third requirement specifies that all communications both within the system and to the user community should take place using the facilities of MDTS. Such a requirement will offer considerable economy in that the data formats which appear throughout the system will be standardized. To the user community such standardization will permit the relatively low cost means for connecting to the system. In addition, a modular communications system will enhance the project by allowing for more rapid test and integration of the various components.

The fourth requirement specifies that data be geographically selected based on requests submitted by users. This is a significant departure from the traditional way in which remote sensing systems have performed. The traditional way placed an excessive burden on the communications networks by virtue of continuous high data rate. In addition, the costs of acquiring, storing, and processing the enormous quantities of data collected in the historical fashion are becoming excessive. As a result, data must be gathered in a way which reflects the interests of the user community.

The fifth requirement specifies that all image processing be performed within the system throughout the use of autonomous algorithmic functions. The objective of minimizing the data transmission rates throughout the system are such that data processing functions should be performed at the earliest possible point within the data stream. In order to do this, real time processing is needed.

The sixth requirement specifies that there be a flexible user friendly interface between the user community and the system. This interface should allow individual users to submit work orders to specify geographic regions of interest in a convenient way and to build algorithmic processing scenarios which will subsequently be applied to their data. The processing scenarios themselves should consist of a sequence of basic processing functions which are callable from a library as subroutines. While the users should be permitted to provide parameters to these processing functions, the actual performance of these functions should take place autonomously with the resultant output products delivered to the users in the most expeditious manner.

The seventh requirement specifies that the spacecraft must include a cloud detection function. This function should delete data regions which are obscured by cloud cover. This will significantly reduce the required band width of the communications channels and will have a beneficial effect on the processing rates and the size of the DBMS.

The eighth requirement specifies that there be on-board pixel classification at Levels I and II. For such applications it is rarely necessary that full multispectral signatures be delivered to the requesting user. In general, the typical user is only interested in perhaps 4 bits of data per pixel. As a result, this classification process can dramatically reduce the data rate. In order to provide for the needs of signature tracking, it will occasionally be necessary to transfer full resolution multispectral data. However, such data could be selected based on the on-board classification itself. For example, if it is desired to track agricultural signatures, it would only be necessary to first classify a region as to whether or not it was in agricultural use and, if so, then and only then transmit the multispectral signature. It is conceivable that such transfers for signature tracking purposes could be significantly reduced in resolution by on-board processing. Thus, only means and covariances would have to be transmitted instead of relatively large arrays of multispectral data.

The ninth requirement specifies that the system include autonomous signature tracking. The nature of multispectral signatures is such that they vary substantially from season to season. However, with the ability to do geographic selection of data, it is possible that the signatures of key representative geographic areas could be maintained and tracked continuously to provide a basis of information to assist in the autonomous classification process. It is felt that a reasonable amount of effort will be required to reduce this to practice.

The tenth major system requirement specifies that there be autonomous target identification and tracking. This requirement is needed by the sea ice mapping application to allow for the monitoring of sea ice hazards as they drift toward the Equator. This requirement is not felt to be particularly difficult to achieve since the concepts of target recognition and tracking have been extensively explored for radar applications. It is quite possible that similar or related techniques would be applicable here. However, this must be demonstrated.

The last major system requirement specifies that there be a long and short term online DBMS. The objective of this to dramatically minimize the handling of data by providing for its direct transfer to the DBMS at the time it is initially received on the ground. This becomes significantly easier to achieve in light of the fact that our data blocks themselves are structured with all relevant ancillary information needed to identify the data. Hence, the DBMS catalog could be created in real time as the data was acquired.

3.2.4 System Concepts

IAS has two major objectives which guide the development of the overall system concepts. The first is to achieve minimum data transmission volumes throughout the system; the second is to deliver user products in as close to final form as is reasonable.

Previous and currently planned missions utilize sensor platforms and processing systems which make little use of known data. That is, on each pass over a region, data is gathered, transmitted to the ground, processed, and added to the DBMS with little regard for user interest or the amount of new "information" conveyed. This leads to a data base which grows monotonically at an enormous rate, and an "information" base which grows at a slow rate.

A key concept which will alleviate this problem is the "region of interest" concept. When coupled with the "target of interest" concept, a massive reduction in data flow will result.

The remaining paragraphs of this section will provide some concepts which may be of value in the implementation of a system designed for sea ice mapping, land use classification/inventory, and snowmelt-runoff forecasting.

3.2.4.1 Sea Ice Mapping

This application can benefit significantly from the concept of "target of interest". There are two areas of interest, as well as a seasonal factor involved.

Pack ice of various types is found along certain coast lines. The extent of the pack ice "grows" in a well known way as winter progresses. Thus, this form of ice can be monitored easily by describing the coast lines geometrically with the spacecraft performing its sensing tasks within the regions described. While it may be possible to classify the pack ice, further effort may be required.

A second goal for this application is the location and tracking of icebergs. In this case, the targets of interest will be moving. On the assumption that the pack ice regions can be sampled at a high enough frequency to see all icebergs which are calved, a good model will allow these icebergs to be tracked as they proceed toward the Equator. In this case, the geographic region of interest could be just large enough to include the iceberg after making allowances for any errors in the tracking model. Far less area than the entire North Atlantic would have to be scanned.

With this application, multispectral pixels are almost totally without value. Hence, the spacecraft could discard such imagery and transmit only enough information to locate the ice and describe its shape or other characteristics. Using ground-based target tracking and position description, the user would receive maps which indicated the present and predicted locations of only those icebergs likely to be in his neighborhood during a voyage.

3.2.4.2 LAND USE Classification and Inventory

This application can also benefit significantly from the concepts of regions and targets of information. However, another concept of value is that of signature tracking to aid in classification.

Current practice relies upon human interaction with ground truth and raw multispectral imagery to perform classification, particularly at the lower levels. This is due to a number of factors:

- Seasonal variations
- Recent climatic influences.

To achieve the greatest benefit from IAS, it will be necessary to get man out of the loop so that the classification process can proceed autonomously on-board.

Three concepts should be investigated to determine the extent to which man can be eliminated:

- Signature tracking
- Mixed pixel detection
- Up-link of a priori information.

Signature tracking involves the construction of a model by which signatures can be predicted through seasonal and climatic variations. It is felt that autonomous classification could be aided by providing the on-board classifier with "approximate initial values" for the expected signatures. Then, the classifier could track the signatures through the geographic region of interest and maintain a high accuracy.

The concept of mixed pixel detection implies the determination (on-board) that a given pixel does not represent only one item. Such pixels should not be used in determining class statistics since, by definition, they do not represent "a class". Pixels which lie on or near boundaries can be considered mixed. After the "pure" pixels have been classified, the "mixed" pixels can be assigned in a systematic way.

The last concept apparent at this time is the up-link of a priori data. The on-board classifier will benefit by having access to a small amount of "ground truth" data. This will aid in the determination of class signatures and improve the system accuracy.

These ideas should be explored in a logical way. It is felt that one or more of these ideas will be of benefit in achieving a successful system.

3.2.4.3 Snowmelt-runoff Forecasting

This application benefits the most from the concept of "region of interest". In order to do forecasting only specific whole scene (watershed) parameters are measured. For long term forecasting, only percent snow cover is required. For short term forecasting, percent snow cover and other snowpack parameters, measured on a whole scene basis, are required. Multispectral information is not required, and the spacecraft transmits only a few selected snowpack parameters per watershed encountered.

While this application is a prime example of an IAS task, its success depends on the successful verification of experimental forecasting techniques. Once this is accomplished, each watershed basin that participates in IAS will have to develop their own set of basin and model constants.

3.2.5 Subsystem Specification

The purpose of this section is to present the system specifications for each of the applications. Two of the applications, Snowmelt-runoff Forecasting and Sea Ice Monitoring, were broken up into two or more subsystems to facilitate the discussion of essentially different algorithms and functions. As a result, the three applications broke down into six subsystems.

Snowmelt-runoff forecasting developed into two subsystems. The first subsystem, designated Snowmelt I, is considered operational in the near term. The second subsystem, designated Snowmelt II, is a research item. The objective of Snowmelt I is to provide seasonal runoff estimates using percent snow coverage. The objective of Snowmelt II is to extract snowpack parameters such as snow wetness and snow depth.

Sea Ice Monitoring developed into three subsystems. Sea Ice I and II are considered to be operational in the near term. Sea Ice III is considered a research item. The objective of Sea Ice I is point-to-point navigation. The objective of Sea Ice II is iceberg tracking. The objective of Sea Ice III is sea ice parameter extraction.

3.2.5.1 Snowmelt I

The sensor selected is a Thematic Mapper type sensor, from which one visible and one or two middle IR bands are utilized. The suggested visible band is between .6 and .7 μm and the middle IR bands are between 1.5 and 2.35 μm. The input data will be eight bit spectral data which will be classified into snow, clouds and others. The spatial resolution is one kilometer. The frequency of coverage is once daily for a period, starting one week before the traditional peak snow accummulation date, and ending when actual peak accummulation is determined.

The sensor selected is the same as that used for the Land Use application. However, only one visible band is utilized and there is a specific stipulation that at least one or more middle IR bands (in the range specified) are included. The spatial resolution is courser than that specified for Land Use application but is sufficiently accurate for this application. The advantage is a reduction in computational load.

Algorithm and Input/Output Specifications

Input for the onboard Snowmelt Classifier is listed as follows:

A. Two or three bands of spectral data (received from Geographic Region Selector).

B. Watershed size, and watershed snowmelt yield linear regression equation (received from Snowmelt Controller).

The Snowmelt Classifier contains the following processing elements and steps:

A. Table lookup classifier I: snow candidate versus others.

B. Table lookup classifier II: snow candidates subdivided to snow versus clouds.

C. Histogram of snow, clouds and others (expressed in terms of percentage of watershed).

D. Threshold percent cloud cover; stop processing if $\geq$50 percent (nominal value).

E. Snow cover yield calculations using the linear regression equation for a watershed.

The output is as follows (as passed to message formatter):

A. Processing status flag (go/no go).

B. Seasonal watershed yield in cubic meters (condition flag is go).

The processing scheme relies on two factors: (1) in the visible bands, the two classes of snow and clouds will saturate the sensors; all pixels that are not saturated will be considered into a class called others, and (2) in the middle IR band, snow, which has a much lower reflectivity than clouds, will appear several levels darker than clouds. The processing scheme is simply that of classification whereby we extract three classes. The classes are snow, clouds, and others. If the percentage of clouds exceeds a certain threshold (say 50 percent), processing will stop and the scene will be repeated on the next pass. If the threshold is not exceeded, snow will be then expressed in terms of percent snow cover for a water basin. This value will then be entered into the linear regression equation to extract the seasonal yield for the watershed. (Note, the percent snowcover, adjusted for clouds, from table lookup I should be used since it generally gives a larger percentage).

The linear regression equation must be developed on a basin by basin level, and this must be done prior to the launching of the platform. As a general rule, at least six years of data must be collected. The regression equation is percent snowcover versus watershed yield. The linear regression equation will be updated once the platform is operational on a yearly basis.

Hardware and Algorithm Problems

No hardware problems are envisioned for this application.

The only algorithm problem is the development of the class statistics for the table lookup classifiers. An onboad table lookup classifier implies that snow, clouds and others are universally discernible in the visible and middle IR bands. In other applications, involving other classes, this is not the case. Current implications are that, if we restrict ourselves to the three classes, the three classes are universally separable and the table lookup classifier approach can be used.

3.2.5.2 Snowmelt II

Functional Specifications

The sensor for Snowmelt II is a multispectral microwave radiometer. The bands are some combination of C, X, and K bands. The data type are sixteen bit antenna brightness temperatures from which will be extracted snow wetness and snow depth. The spatial resolution is one kilometer (this is a research item). Frequency of coverage is daily from the period of peak accumulation to depletion of snowpack (April to June, typically).

Microwave radiometer provides a unique means to obtain data on surface temperatures and emissive characteristics. They can operate day or night and almost independently of weather conditions. The passive microwave sensor can obtain information on materials which, although they may have the same actual temperatures, are quite different. In addition, passive microwave detectors provide a means of obtaining data on subsurface phenomena such as snow depth.

Emissivity of snow decreases with increasing snow wetness (i.e., water content). Runoff begins when a critical snow wetness is reached. The reason for multifrequencies and longer wave lengths (at the expense of lower resolution) is that different wave lengths give different snow depth penetration. The longer wave lengths have the most penetration. Daily coverage is needed for detection of the onset of snow melt (i.e., when snowpack reaches a critical wetness). This information is critical for flood forecasting.

Algorithm and Input/Output Specifications

As mentioned above, Snowmelt II is a research item and does not appear to be operational in the near term. Present technique relies on multiple/regression analysis approach that is computationally intensive, and therefore not suitable for onboard processing.

Hardware and Algorithm Problems

The main hardware problem is resolution. Resolution is limited by several factors. Broad area coverage requires fast scanning. The number of samples picked along a scan is limited by the integration time. With the present technology, the integration time is quite long, therefore reducing the number of samples along scan and reducing the resolution. The requirement for longer wave lengths will also reduce resolution. Longer wave lengths require longer integration time. NIMBUS-7 microwave radiometer resolution is 30 kilometers. Resolution for the microwave radiometer on the NOSS platform is estimated to be eight kilometers. The goal of application is 1 kilometer resolution.

Algorithmically, operational snowpack analysis of Snowmelt II is not eminent because of complexities involved in data analysis. Some of the problems are as follows:

A. Antenna Pattern Correction

Antenna pattern correction techniques are presently computationally intensive. The correction is needed in order to gain radiometric correctness. A much more effective technique is required if the processing is to be done onboard or in real time.

B. RF Interference

C bands have characteristic wave lengths that are useful for snow-mapping. However, this information may be confused with communications links that operate in C band regions. Techniques must be developed in order to reduce this interference.

C. Snow pack parameters are still in the research mode. Presently the work is being done in the labs or in situ. Algorithm complexity and processing load is expected to be similar to that presently done for NIMBUS-7 SMMR data, but at a higher rate. SMMR processing is done on the ground in a non-real time mode. Approximately 24,000 lines of code are required, and the processing time is approximately two hours per orbit.

3.2.5.3 Sea Ice I

Functional Specification

The sensor selected for Sea Ice I is a multispectral microwave radiometer utilizing a combination of X, C, and K bands. The data type is 16 bit antenna brightness temperatures from which surface brightness temperatures are extracted. The proposed spatial resolution goal is 250 meters. The frequency of coverage is daily.

The rationale for selecting this sensor is the same as for Snowmelt I with a few additional considerations. Ice in the water possesses different emissivity and can readily be separated even when the temperatures are similar. The emissivity of ice is approximately twice that of water. If ice and water are equal in temperature, ice will radiate twice as much energy as water. Therefore, water will appear "colder" than ice. Ice itself shows differential brightness temperatures according to surface roughness and composition. Ice of different age and types therefore may be classified. This may be accomplished either day or night during polar nights winter in spite of inclement weather. The purpose of multispectral scanning microwave radiometer is obtaining more information about the surface of the earth through the use of various sensing parameters. The parameters are derived from the received signal strength as a function of wavelength and polarization. Microwave radar wavelengths which are of the order of the microscopic roughness of the earth's surface interact with the roughness of a reflectant surface in such a matter as to control reflectivity and diffusivity. Differential images of a surface produced with different wavelengths provide a measure of the scale of roughness of the surface. The roughness scale of a surface can be indicated by the relative reflectance of the two or more wavelengths. The comparison of the reflection of the two or more wavelengths therefore indicate the roughness of the reflectance surface which, in turn, helps to identify and discriminate the surface.

Algorithm and Input/Output Specifications

The Sea Ice I classifier contains the following processing elements and steps:

A. Data base containing surface types (received from Sea Ice I Controller).

The surface types are:

1. Ocean, no ice possible
2. Ocean, sea ice possible
3. Others.

B. Multispectral microwave data as received from the sensor (after being processed by the Geographic Region Selector).

The Sea Ice I classifier contains the following processing elements and steps:

A. Test pixel against data base for possibility of sea ice.

B. Those pixels that could possibly contain sea ice, are then classified using the Table lookup classifier.

C. Produce classification map with the classes ocean, sea ice and others.

D. Perform minimum path, point-to-point navigation course calculations.

The output is a classification map displaying ocean, ice and others, overlaid with the navigation course.

Each pixel after it has been earth located will be checked against the data base. If the pixel falls into class 2 of the data base (i.e., ocean with ice possible), this pixel will then be classified according to the table lookup. Table lookup classification relies on the fact that ice and open water are radiometrically different. The multi-frequencies are used to insure that sea surface due to wind do not affect the classification of the higher frequencies. After all pixels are classified, a minimum path point-to-point navigational course is calculated.

Hardware and Algorithm Problems

The hardware problem is the same as those expressed for Snowmelt II.

In the algorithm area, the same antenna pattern correction and RF interference problem exists as for Snowmelt II. However, since we are dealing with the classification of sea ice versus ocean versus others, the actual algorithm/processing requirements are a lot less complicated than for extracting snowpack parameters in Snowmelt II. The question that remains is the universatility of the table lookup classifier as discussed under Snowmelt I.

3.2.5.4 Sea Ice II

Functional Specification

The sensor selected for Sea Ice II is the same as for Sea Ice I. It is a microwave radiometer utilizing some combination of the X, C, and K bands. The data type are 16 bit antenna brightness temperatures from which sea surface brightness temperatures are extracted. The spatial resolution goal is the same at 250 meters.

The microwave radiometer was chosen for its all-weather capabilities. In the area of the Grand Banks in the western Atlantic ocean, the maximum occurrence of icebergs coincided with the maximum occurrence of fog in that area. Additional reasons for selecting the microwave radiometer are the same as those expressed for Sea Ice I. One additional rationale is that icebergs that are calved from glaciers consist totally of pure water as opposed to brine. The lower the brine content, the brighter the pixel. In the lower latitudes the icebergs contrast dramatically with the ocean.

Algorithm and Input/Output Specifications

The Sea Ice II classifier contains the following elements and steps:

A. The previous orbits' classification summary indicating the presence or non-presence of icerbergs, and how many there were, if any (received from Sea Ice I controller).

B. Multispectral microwave data (received from Geographic Region Selector)

C. Region data base containing ocean current vector information (i.e., mean ocean current velocity and direction). Also included in the data base are surface types (land or ocean).

The main objective of Sea Ice II is to detect free floating icebergs that may come into conflict with ships in designated shipping lanes. As such, the region of interest is further south than for Sea Ice I and is not in conflict in terms of processing.

Sea Ice II classifier will first determine if processing is necessary by examining the previous orbits' summary. If there were icebergs, processing continues. The sensor data for area of interest is then checked against the data base to determine land or ocean. If the surface type is ocean, the pixel is classified using table lookup. After the region is classified, the number of icebergs are counted and compared to previous orbits' count. Each iceberg is then relocated by knowing the mean regional ocean current velocity and direction.

The output are a classification summary (yes/no iceberg flag, and iceberg count), and two classification maps (present location and future location).

Hardware and Algorithm Problems

The basic hardware problems are frequency of coverage and resolution. Repeat observations of the same spot may become more difficult, as the icebergs drift further south. At lower latitudes the orbits diverge. The resolution problem is that the location of any iceberg should be known to 1 kilometer and the smallest iceberg detected to 2 meters by 2 meters in dimension. The 2 meter feature resolution seems somewhat unreasonable at first glance but becomes less so when the fact that about nine-tenth's of the iceberg is submerged is taken into consideration. The smallest iceberg may be 2 meters by 2 meters by 1 meter above water, but is 2 meters by 2 meters by 18 meters below the sea surface.

Algorithmically, the same problems exist as discussed before for the other microwave radiometer applications. A specific problem in this application is the confusion of icebergs with ships. If the iceberg count goes up, there is definitely a ship in the count. If the count goes down, there is still a question of which are ships and which are icebergs. Change detection by means of differencing before and after images might be the solution, but this will be done at the expense of additional onboard memory and processing.

3.2.5.5 Sea Ice III

Functional Specification

The sensors selected for Sea Ice III are the same as that for Sea Ice I and II. This is a multispectral radiometer utilizing some combination of C, X, and K bands. Data types are 16 bit antenna brightness temperatures from which sea ice parameters such as age, thickness, and type are extracted. The proposed spatial resolution is one kilometer, but this is to be considered a research item. The frequency of coverage is considered to be daily (also a research item). The rationale for selecting a microwave radiometer is the same as expressed for the other applications. The radiometer is an all-weather instrument that has a capability of extracting ice surface temperatures, ice age, ice salinity and ice thickness.

Algorithm and Input/Output Specifications

Operational sea ice monitoring III is not eminent because of the complexities involved in daily analysis.

Hardware and Algorithm Problems

The problems of hardware and algorithms are the same as those discussed under Snowmelt II.

3.2.5.6 Land Use and Inventory

Functional Specification

The sensor proposed for this application is the thematic mapper type sensor with the addition of one thermal IR band. The data type is eight bit spectral data from which land use information is extracted. The frequency of coverage is one cloud free scene each season or as needed by user. The goal of a cloud free scene means that several attempts at obtaining a scene must be made for each season, or that an acceptable amount of cloud coverage must be tolerated.

The thematic mapper offers higher spatial resolution (30 m) and improved spectral sensitivity (lower signal to noise ratio and increased quantization levels). The multiple frequencies facilitates the discrimination of different features that no one single frequency can (i.e., covariance between frequencies).

Algorithm and Input/Output Specifications

Before proceeding with the discussion, the objective of Land Use and Inventory should be restated. The objective of Land Use and Inventory is to classify the land areas of the earth into land use classes. There are two levels of land use classes. At Level I, there are nine classes that range from tundra to urban buildup. In Level II, each of the nine classes are subdivided into several subclasses (37 total). Inventory classification implies specific features other than the 37 land use classes. A broad spectrum of users with different information requirements are envisioned (as opposed to other applications which have one user group). As a general rule, the timeliness of Land Use and Inventory is seasonal. The scenes themselves have a temporal nature to them.

Onboard classification for Land Use and Inventory for the purposes of data comparison, appears impractical with present and near term technology. In particular, the more classes that are introduced, the less accurate the classification. Supervised classification accuracy increases with thoughtful training site selection and sampling for each class, but this implies very large onboard memory requirements. Training on a scene is no longer possible since there are no longer scenes. Universal class statistics are not likely, and if they are, they must allow for temporal changes. Unsupervised classification (cluster analysis) requires large memory (i.e., preserving a whole scene) and computational power.

In light of the large and complex hardware requirements needed for onboard classification for this application, it is suggested that the classification be performed on the ground. In order to reduce the amount

The thematic mapper offers higher spatial resolution (30 m) and improved spectral sensitivity (lower signal to noise ratio and increased quantization levels). The multiple frequencies facilitates the discrimination of different features that no one single frequency can (i.e., covariance between frequencies).

Algorithm and Input/Output Specifications

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3.3 The Design of an Onboard Classifier

3.3.1 Needs for Autonomous Data Extraction and Classification

Satellite borne remote sensing instruments of the future will be characterized by a substantially increased (1) data volume, (2) data rate, (3) number of spectral bands, and (4) spacial resolutions.

At the present time the NASA data system is incapable of coping with such increases in data volume and rates because it is loaded to its capacity and has significant operational limitations. The mission model must be significantly altered in order to meet the 1980-1990 mission requirements. The NASA end-to-end data system (NEEDS) program is an attempt to meet this future challenge. As part of the NEEDS program an information adaptive system is being conceived in which much of the data processing and operational burden will be transferred to on-board requirements. The desire to reduce data to information as soon as possible implies the need for developing more efficient and/or autonomous classification techniques. Hence, non-interactive and interdisciplinary feature extraction and classification procedures are required. In addition, the resulting algorithms and scenario of operations should be designed for maximum efficiency by taking advantage of new computing hardware technologies such as parallel processors and new memory devices.

3.3.2 Study Objectives

It is the intent of this study to provide a means of identifying problems in areas that might hinder future developments for onboard implementation of an adaptive and autonomous feature extraction/classifier for remotely sensed data. The end item or goal of this study is to generate system specifications and to give recommendations for the development of autonomous feature extraction and classification techniques. Our approach to the development of this plan is embodied in the following functional tasks:

(a) To develop and specify algorithms for the autonomous extraction of linear features in one and two dimensions from multi-spectral data which utilizes the notion of maximizing the probabilities of correct classification.

(b) To investigate the use of decision tree classification techniques and to ascertain a methodology of determining optimum tree structures which maximize the global classification accuracy under the assumption of optimum linear extracted features at each node.

(c) To examine the accuracy and efficiency of table look-up procedures for an on-board classifier in the two-dimensional feature space.

(d) To study algorithms which will adaptively modify the parameters that are required in the on-board decision tree classifier.

(e) To provide recommendations and specifications for on-board computing hardware architecture required for autonomous feature extraction and classification.

(f) To demonstrate through a scenario of how an on-board classification might be performed and to point out the logistical and technical problems which must be overcome before benefits of on-board classification could become reality.

Figure 3.3-1 shows a block diagram of a simplified classification system. The device which extracts the feature measurements from the high dimensional data is called a feature extractor. The device which performs the mapping of these features to appropriate classes is called a classifier.

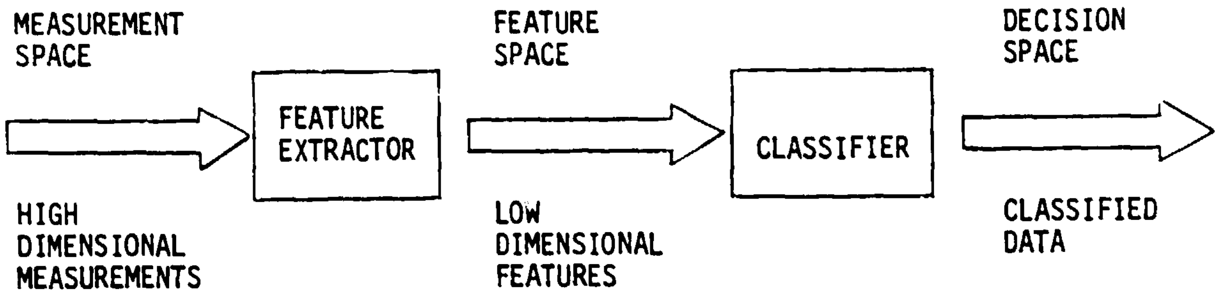


Figure 3.3-1 A Simplified Classification System

For the study objectives outlined above to be a feasible approach to on-board classification design, two basic requirements must be satisfied:

(a) A decision rule must be available which affords a satisfactory compromise between accuracy and computational efficiency.

(b) The hardware implemenation of such a decision rule must be feasible.

Condition (a) can be met with a two-dimensional linear feature extraction matched with Bayesian table look-up design rule. The table look-up approach requires two dimensional transformation of the MSS data and is described in the following section. Condition (b) will be discussed in Section 3.3.6.

3.3.3 Feature Extraction

The tendency in remote sensing technology is toward the merging of remote sensing information with collateral data to form high dimensional data sets. The classification of such data to produce conventional thematic maps creates problems of two kinds. First, the computational expense associated with classification increases steeply with dimension. Second, there is the familiar fact [1], [2], and [3] that for a fixed number of training samples, classification accuracy can actually decline with an increase in dimension. A conventional solution to these problems is to reduce dimensionality by means of a feature extraction transformation, the coefficients of which are chosen so as to optimize a class separability measure [4], [5], and [6].

The purpose of feature space transformation is to transform the original measurement space into lower dimensional feature space for class discrimination. Dimensionality reduction investigated in this study is to (1) choose an optimal two-dimensional feature in which to perform classification, and (2) improve the computational efficiency.

In all that follows the transformation used for dimensionality reduction are linear; that is, the variables in the feature space are always linear combinations of the original measurements.

Linear feature selection documentation was studied which included work performed on one-dimensional feature selection which maximizes the probability of successful classification based upon Bayesian statistics [7]. It was recognized that the computation of means and covariances for any linear combination of spectral classes could be accomplished given the mean and covariance of the original higher dimensional spectral features. Hence, it became obvious that the use of Gaussian or related statistics will simplify much of the computations required to compute the probability of successful classification for any specific classification strategy.

3.3.3.1 The Linear Feature Transformation

The dimensionality reduction from N-dimension to M-dimension involves the transformation matrix $\vec{V}$ and displacement $\vec{Y}_0$ according to the equation

$$\vec{Y} = \vec{V}^T \vec{X} - \vec{Y}_0$$

where $\vec{V}^T$ is a M x N matrix, and $\vec{Y}_o$ is a M x 1 vector.

Also, $\vec{X} = (X_1, X_2, \cdots X_N)^T$ denote a vector of measurements (e.g., MSS data) taken from an arbitrary element of $\bigcup_{i=1}^{K} \theta i$, where θ_i is a distinct class with known *a priori* probability and known class statistics such as means, $\vec{m}_i$, and covariances, $\vec{\sigma}_i$. Then, the required transformed means and covariances are defined as:

$$\vec{\mu} = \vec{\vartheta}^T \vec{m} - \vec{Y}_0$$

$$\vec{\Sigma} = \vec{\vartheta}^T \vec{\sigma} \vec{\vartheta}$$

For example, to reduce the dimensionality from N-dimension to two dimension, one merely projects the N-dimensional data onto a plane. Of course, even if the samples formed well-separated, compact clusters in N-space, projection on an arbitrary plane will usually produce a confused mixture of samples from all of the classes. However, by moving the plane around, one might be able to find an orientation for which the projected samples are well separated. This is exactly the goal of a canonical analysis approach known as Fisher Linear Discriminant analysis [8], [9], [10].

The idea of projecting samples from a higher dimensional space to a lower dimensional space with well separated features can be shown by a simple example. We can reduce the dimensionality from N-dimensions to one dimension if we merely project the N-dimensional data onto a line. Suppose that we have a set of n two-dimensional samples $\vec{X}_i$, $i=1,\cdots n$ where $\vec{X}_i = (X_1, X_2)^T$, and there are n_1 samples labelled 0 and n_2 samples labelled *. If we form a linear combination of the components of $\vec{X}$, we obtain the scalar $\vec{Y} = \vec{\vartheta}^T\vec{X}$ and a corresponding set of n samples $Y_1, Y_2, \cdots Y_n$. If we imagine that the samples labelled 0 fall more or less in one cluster in the two-dimensional space while those labelled * fall in another, we want the projections falliing on the line to be well separated. Figure 3.3-2 illustrates the effect of choosing two different values for $\vec{\vartheta}$ for a two-dimensional example.

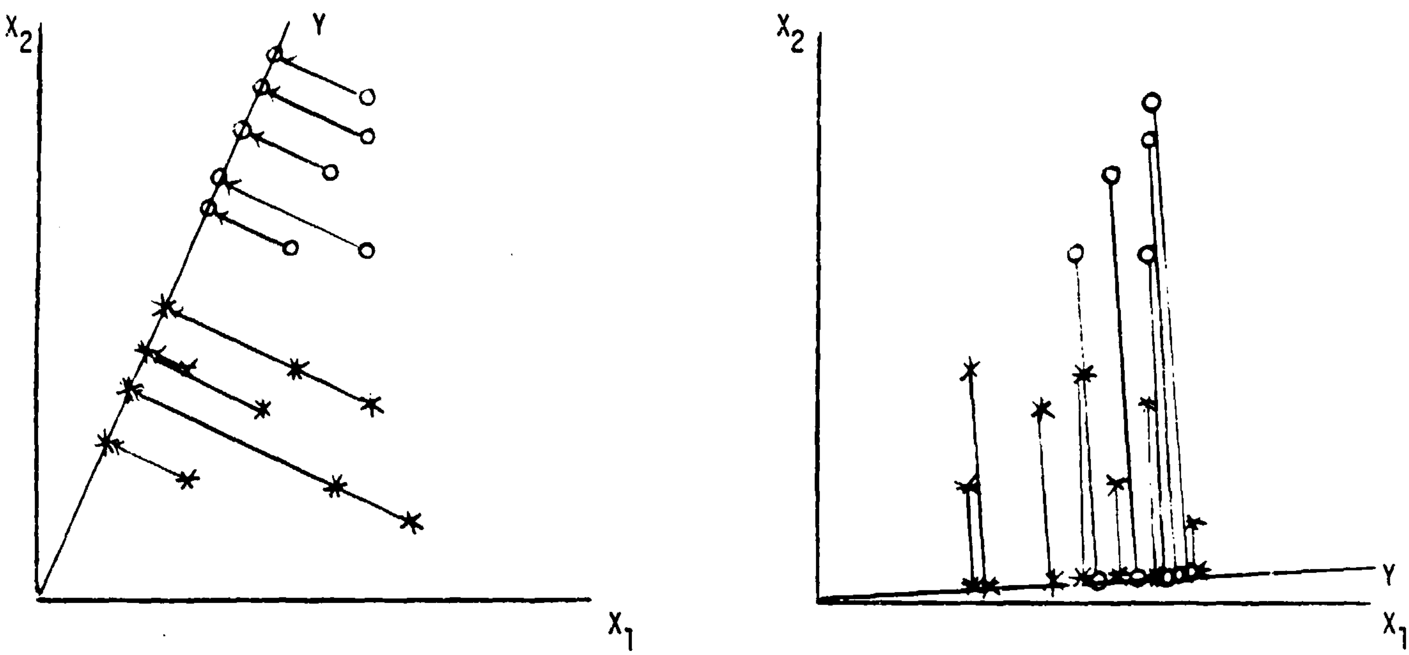


Figure 3.3-2 Projection of Two-Dimensional Samples Onto a Line

3.3.3.2 The Transformation Coefficients

The feature extraction could be performed by means of a canonical analysis approach as suggested by Merembeck and Turner [8]. That is, if N is the dimension of the sample set, we first seek an N dimensional column vector $\vec{V}_1$ which maximizes the F-ratio, or so-called Fisher linear discriminant function

$$F_V = \frac{\vec{V}^T \vec{B} \vec{V}}{\vec{V}^T \vec{W} \vec{V}}$$

where $\vec{B}$ is the between class covariance matrix as defined from class mean vectors and $\vec{W}$ is the pooled within class covariance matrix. The required $\vec{V}_1$ is the eigenvector associated with the largest eigenvalue of $\vec{W}^{-1}\vec{B}$. Having determined $\vec{V}_1$ we seek a column vector $\vec{V}_2$ in the orthogonal compliment of $\vec{V}_1$ which maximizes the F-ratio defined by the above equation. It, in turn, is the eigenvector associated with the second largest eigenvalue of $\vec{W}^{-1}\vec{B}$. Our required two-dimensional transformation matrix has $\vec{V}_1$ as the first column and $\vec{V}_2$ as the second column. This described procedure has been implemented, tested, and proven to be applicable to the dimensionality reduction of remote sensing data problem by Argentiero, Chin, and Beaudet [11].

Finally, a few observations about this procedure are in order. First, we have obtained Fisher's linear discriminant, the linear function with the maximum ratio of between-class matrix to with-class matrix. The problem has been converted from a N-dimensional problem to a hopefully more manageable two-dimensional problem suitable for table look-up philosophy. The mapping in theory cannot possibly reduce the error rate. In general, one is willing to sacrifice some of the theoretically attainable performance for the advantages of working in a lower dimension. Next, we observe that in general the solution for $\vec{V}$ is not unique. The allowable transformations include rotating and scaling the axes in various ways. It primarily provides a reasonable way of reducing the dimensionality of the problem. Parametric or nonparametric techniques that might not have been feasible in the original space may work well in the two-dimensional space. Finally, we know the fact that in general, the transformation causes some unnecessary overlapping of the data and increases the theoretically achievable error rate, and the problem of classifying the data still remains.

3.3.4 Decision Tree Classifier

Most work on pattern recognition deals with single stage classifiers and different types of discriminant function. The conventional approach to multivariate and multiclass classification would be to perform tests on unknown pattern against <u>all</u> classes using a particular feature subset and then assign the unknown to one of these classes. From the tree structure viewpoint, this conventional classifier can be expressed as a single-stage classifier which uses a particular multispectral data set to perform complex computations associated with each class. See Figure 3.3-3.

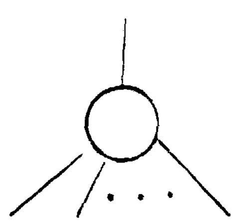


Figure 3.3-3 A Single-Node Classifier

In some practical applications, the number of spacial bands and the number of classes K are both very large. In such cases the usual computations are prohibitive; it would be advantageous to perform classification in lower dimension. That is, a decision rule is applied to assign the reduced dimensional samples to the available classes. But the feature extraction represents a compromise since the separability measure to be optimized must take into account the overlap of each class with each other class. Hence, classification accuracy is not always satisfactory.

This study presents an alternative approach to dimensionality reduction and classification which involves a procedure for the automated design of a decision tree classifer [12]. This approach to classification will be described in more detail in the following section, but basically it is characterized by the fact that samples are subjected to a sequence of decision rules before they are assigned to a unique class. Each decision rule can leave ambiguity with regard to the precise class assignment of a sample. If the ambiguity is unacceptable for a particular application it can be removed by subsequently applied decision rules. When the structure is diagrammed to show the heirarchy among the decision rules it exhibits a characteristic tree-like aspect--thus the rubric "decision tree classifier."

The overall performance of a decision-tree classifier had been shown in a lot of cases to be better than that of the conventional single stage classifier [13], [14]. There are numerous advantages to decision tree classification. Most importantly, the decision rules can be designed to be both inexpensive and effective since each rule is required to take into account only a small subset of the original classes and it is not required to remove all ambiguities. Also there is considerable generality and flexibility associated with this type of classification. For instance, collateral data of a categorical nature such as soil type or political boundaries can be readily incorporated within the framework of a decision tree classifier. Also, it is easy to avoid situations in which computer time is spent in removing ambiguities which are irrelevant to a particular application such as distinguishing among confuser crops in an agricultural scene. Of course, for these benefits to be realized it is important for decision trees to be well designed.

3.3.4.1 Decision Tree Design

The study performed for this report presents an automated technique for designing effective decision tree classifiers predicted only on *a priori* statistics. The procedure relies on a set of two-dimensional feature extractions and Bayes look-up decision rules. Associated error matrices are computed and utilized to provide an optimal design of the decision tree at each so-called "node".

A complete decision tree can be designed in a natural fashion by first defining a structure for the parent node, the first node of the tree. Next, for every output branches associated with the parent node it is necessary to define another node which performs a further decomposition into nodes with smaller class subsets. The designing process continues until terminal nodes are achieved and no further decomposition is possible. A terminal node is defined as a node without offspring. Also, three other conditions have to be satisfied for a complete definition of a decision tree.

(a) There is just one parent node.
(b) Every node which is not a parent node has a single parent.
(c) The number of terminal nodes is equal to the number of classes handled by the decision tree.

A mathematical description of decision tree classification can be found in [11].

At each step of the design process we are confronted with the problem of decomposing a certain class set into a set of subsets or branches, and developing a computationally efficient generalized decision rule which maps sample features into the branches in a way that provides adequate classification accuracy. A solution to this problem had been studied and reported [15]. It is an automated technique for effective decision tree design which relies only on *a priori* class statistics. The result is satisfactory and is applicable to the on-board data reduction problem. We now describe the solution briefly.

Let f be a decision rule which unambiguously assigns sample features $\tilde{X}$ to branches. Associated with f is an error matrix E_f, or so-called the confusion matrix defined as:

$E_f(i,j)$: conditional probability that a sample from a class indexed by j is classified by decision rule f to the class indexed by i.

Given error matrix E_f one can readily compute the probability of correct classification at each node of the tree. Also, it represents a very simple and efficient algorithm for computing classification accuracy. Hence, even for relatively large class sets, it is possible to investigate every generalized decision tree (that is, every possible tree structures) and to choose the one associated with maximum classification accuracy. In this fashion, it is possible to generate a decision rule with high classification accuracy.

3.3.4.2 Table Look-Up Classifier

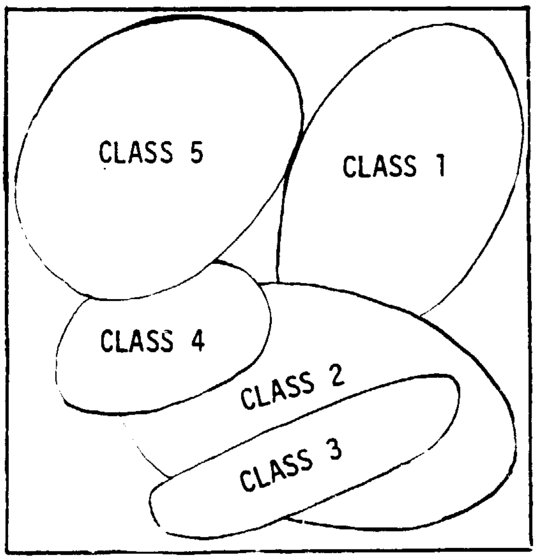
For the procedure outlined above to be a feasible approach to on-board decision tree design, two requirements must be satisfied:

(a) a decision rule must be available to offer accurate on-line classification
(b) the error matrix E_f must be computable.

The first requirement can be met with an associated table look-up classifier. After the two-dimensional linear feature transformation, the process in designing the table look-up classifier is to specify a location and dimensions of a rectangle in the transformed two-dimensional feature space such that the rectangle contains at least 99% of the probability associated with each class density function under the usual normality asssumption. Next the rectangle is divided into 256 equal area grid elements. Each element is associated with a class index according to the maximum likelihood classification of its midpoint. The resulting decision rule simply assigns to each transformed sample the class index of the grid element in which it is contained. Samples which fall outside of the rectangle are assigned to the nearest grid element. Figure 3.3-4 shows the idea graphically.

It remains to define how the error matrix E_f of the above described table look-up decision rule is computed. A given element $E(i,j)$ of E_f can be obtained by summing the integrals of the transformed normal density function associated with the j^{th} class over each grid element indexed by i. We have found that good approximation can be obtained if the density functions are first represented in each grid by a two-dimensional second order Taylor series expanded about the grid midpoint. The Taylor series representations rather than the density functions are then integrated over the appropriate grid elements.

Of particular interest is the possibility of encoding each dimension with four bits thereby leading to an eight bit (256 grid elements) table look-up classifier. This idea is incorporated into the hardware implementation of such clasisifer for onboard classification.



A Decision Plain Containing
Five Classes

5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	1
5	5	5	5	5	5	1	1	1	1	1	1	1	1	1	1
5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1
5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1
5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1
5	5	5	5	5	5	5	5	1	1	1	1	1	1	1	1
5	5	5	5	5	5	5	1	1	1	1	1	1	1	1	1
5	5	5	5	5	5	4	1	1	1	1	1	1	1	1	1
5	5	5	4	4	4	4	4	1	1	1	1	1	1	1	1
4	4	4	4	4	4	4	4	1	1	1	1	1	1	1	1
4	4	4	4	4	4	4	4	1	1	1	1	1	1	1	1
4	4	4	4	4	4	4	2	3	3	3	3	3	3	3	3
4	2	2	2	2	3	3	3	3	3	3	3	3	3	3	2
2	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2
3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2
3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2

A 16 x 16 Table Look-Up
Decision Plain

Figure 3.3-4 Two-Dimensional Table Look-Up Classifier for Five Classes

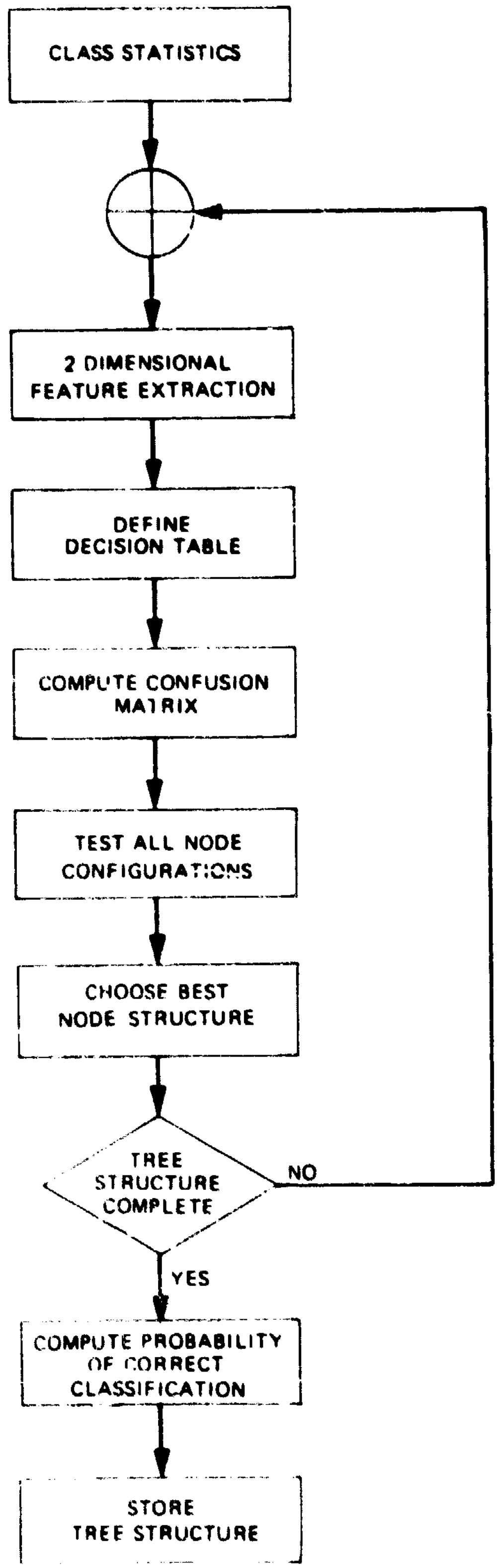


Figure 3.3-5 Flow Chart for Design of Table Look-Up Decision Tree Classifier

3.3.4.3 An Example

The procedure outlined in Sections 3.3.4.1 and 3.3.4.2 for automated design of autonomous data extraction and decision tree classification had been implemented and tested [11], [15]. The input to the design process is a set of class mean vectors and covariance matrices. The output is a structural description of each node of a decision tree. Each node description consists of a decomposition of a set of classes into branches, the coefficients of the two-dimensional linear feature extraction, a decision table for the table look-up classifier and its associated error matrix. As described in Section 3.3.4.1, the procedure designs the decision tree from the top down starting from the parent node. The design terminates when each of the original classes appears as a terminal node. A simple flow chart for the design procedure is included in Figure 3.3-5.

An example of the application of the design procedure is provided here to illustrate the automated design philosophy. Class statistics were obtained from a LANDSAT 2 scene taken over Finney County, Kansas during May of 1975 [16]. The five classes consisted to two types of winter wheat and three confuser crops. The class statistics were obtained from well known sites in Finney County. The four channels are those of the Multi-spectral Scanner on-board the LANDSAT 2. The sizes of the training sample sets range from about one hundred to about three hundred. The information was used as input to the design procedure and the resulting decision tree and all the associated decision tables are shown in Figure 3.3-6.

3.3.5 Adaptive Classification

The proposed classification scheme in forms of decision trees is generated by using the above described procedure in which *a priori* knowledge of scene statistics for the classes of interest is used. This information normally takes the form of training sets extracted over a typical scene containing predetermined samples of signals from each class. These training sets are used to estimate the parameters of a Gaussian distribution for each class.

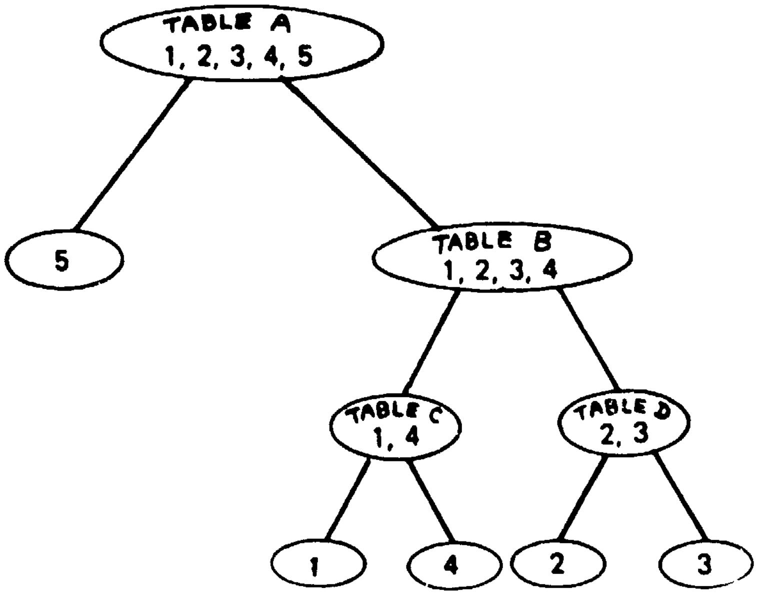


Table A	Table B	Table C	Table D
5511111111111111	1111111111111111	1111111111111111	2222222222223333
5511111111111111	1111111111111111	1111111111111111	2222222222223333
5551111111111111	1111111111111111	1111111111111111	2222222222223333
5555111111111111	1111111111111111	1111444444444444	2222222222233333
5555511111111111	1111111111111111	1111444444444444	2222222222233333
5555511111111111	1111111111111111	1111111444444444	2222222222333333
5555551111111111	1111111111111111	1111111111111111	2222222223333322
5555555111111111	1111111111111111	1111111111111111	2222222233333222
5555555111111111	1111111111111111	1111111111111111	2222222333322222
5555544111111111	1111444441111111	1111111111111111	2222233333322222
2244444111111111	1114444444444411	1111111111111111	2223333333222222
2222223333322222	1333333222222222	1111111111111111	2333333332222222
3333332222222222	2222222222333333	1111111111111111	3333333332222222
3333222222222222	2222222222233333	1111111111111111	3333333332222222
1112222222222222	1111222221111111	1111111111111111	3333333322222222
1111222222222222	1111111111111111	1111111111111111	3333333322222222

Figure 3.3-6
Design of Decision Tree Classifier Associated with Statistics Obtained from [16], and Table Look-Up Classifiers Associated with the Four Nodes of the Tree.

Sources of difficulty and error in this multispectral data classification procedure stem mainly from natural variabilities normally found in scene composition as well as atmosphere. Variability in the scene is the main cause of error, and arises from many sources. First, the classes to be mapped are not uniform - for example, wheat in a given area may be in various stages of maturity or some may have been damaged by weather. This will result in variations of class statistics from scene to scene and even from sub-scene to sub-scene. Second, changing meteorological conditions can also bring changes in observed radiances. Such variations make it impossible to classify classes successfully by using fixed class statistics. Also, a fixed signature may not adequately describe a class because of many reasons such as, (a) there may be an insufficient number of data points in the training set; (b) the class may be composed of subclasses with different reflectances and the signature could describe only one subclass; and (c) the illumination and viewing geometry could differ for training and non-training data.

3.3.5.1 Adaptive Algorithms

Adaptive processing to permit changes in signature parameters would appear to offer hope for improving classification accuracy. It also provides a feasible solution for on-board implementation of such classifier where scene is changing continuously. Errors resulting from drifts of many kinds and from changing scene conditions can be adaptively corrected by "tracking" the scene statistics as objects are classified. But no extant theory appears directly applicable to this specific problem. So existing theories have to be examined to guide the choice of adaptive procedures for our particular application

The task of compensating for variations in the signatures can be achieved through one of the these approaches [28], [33].

(a) The first approach is based on in-scene references, where changes that occur in selected fields are assumed to reflect changes in all of the data. Such changes could be detected by suitable averaging or preprocessing techniques. This approach can best handle systematic variations common to all scene materials; they do not, however, permit the signatures for each scene material to be independently updated. [34]

(b) A second approach uses functions of the data, such as ratios of channels, for classification. Generally, functions cannot be found that are completely independent of atmospheric or ground cover changes [35], [36].

(c) The third approach uses radiance and reflectance models to estimate and account for the changes that are occuring. [37]

(d) The fourth approach allows independent updating to be performed without the necessity of additional *a priori* information (ground truth). This approach is more suitable for on-board classification. This class of adaptive classifiers is being developed at the Environmental Research Institute of Michigan [28], [29], [32], [33]. It is a decision-directed approach based on Kalman filter theory [31]. In this approach the mean vectors are slowly updated based on the decisions which the classifier makes and on the actual values of the individual data vectors which are classified.

3.3.5.2 An Adaptive Procedure

The decision-directed adaptive approach to permit changes in signature parameters would appear to offer hope for tracking the individual primitive class statistics continuously for on-board classification. The approach is based on the following idea. Suppose a sequence of observation $(X_i, X_{i+1}, \cdots)$ were all classified as class A by the on-board classifier, but that these observations tended to cluster to one side of the current estimate of the mean, μ_A , of class A. This would provide us with some evidence that the mean of class A had shifted. The decision-directed procedure is to adjust μ_A so as to bring it closer to the current observations which were classified as class A. In the simpliest case, the adaptive process bases upon the observation and classification of one multispectral data. This simple procedure is discussed below to illustrate the idea of adaptive classification.

A multispectral signal X is classified as class A if

$$f_A(X) \geq f_i(X) \text{ for all } i$$

where $f_i(X)$ is the Gaussian density of the distribution associated with the i^{th} class. Then, the present mean of class A, μ_A , is updated to a new mean by the following relation,

$$\Delta_A = (X_A - \mu_A)/W$$
$$\mu_A^{new} = \mu_A + \Delta_A$$

where X_A is the signal classified as A, and
W is the weighting constant.

The above procedure can be written as

$$\mu_A^k = \mu_A^{k-1} + (X_A^k - \mu_A^{k-1})/W$$

where μ_A^k is the mean of class A at the K^{th} recognition. Different weighting constants had been tested empirically [28]. They are the (a) exponentially weighted running estimates, and (b) posterior probability weighted estimates. Some theoretical justification for the above procedure may be found in reference 30 where the problem of tracking a slowly varying mean of a Gaussian distribution is considered. Figure 3.3-7 shows the functional blocks of a conceptual adaptive classifier.

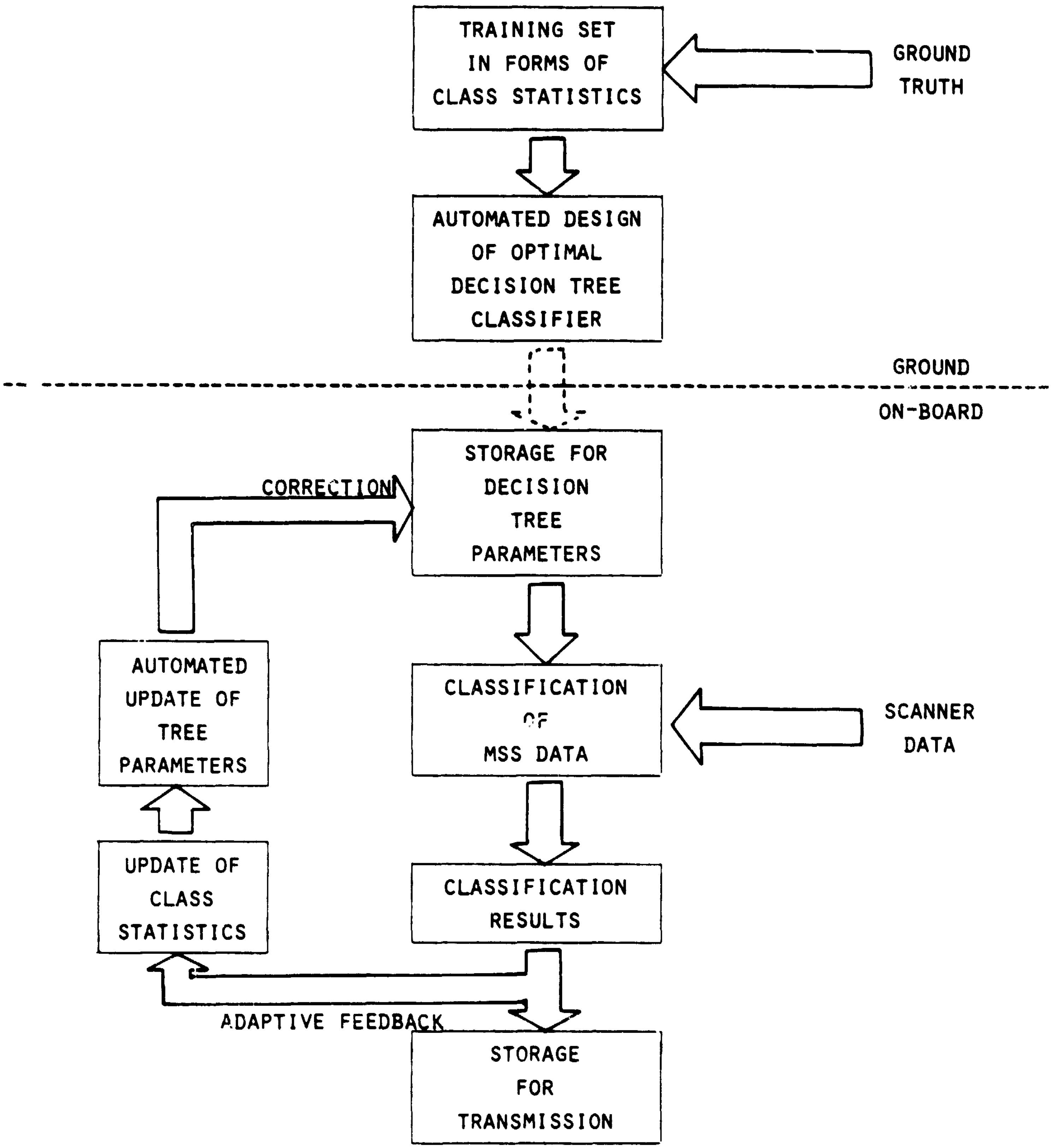


Figure 3.3-7 Conceptual System of an Adaptive Classifier

3.3.5.3 Kalman Filter

In practice there are additional considerations concerning the decision-directed adaptive classifier. They are (a) the amount by which the signature is modified in a updating cycle, (b) the ability to adapt all signatures based upon the observations and classifications of one or a few data, and (c) the ability to avoid using bad observations such as signal elements overlapping two or more different crop types. Kalman filter theory provides a framework within which these considerations and others can be combined into one systematic approach. The Kalman filter is an iterative filter ideally suited for use with digital computations, and of providing a general formulation that combines many techniques for improving recognition. It produces an estimate of a time sequence of state vectors from a corresponding time sequence of measurement vectors. Detailed discussions on applying the Kalman filter to remote sensing data can be found in references 32 and 33. These published results confirm an improvement in performance in a classifier for recognition of objects in a scene as observed by a multispectral scanner.

3.3.6 Recommendations on Implementation of an Onboard Classifier

It is the intent of this section to provide recommendations and conceptual specifications for computing hardware architecture required for the autonomous feature extraction and classification algorithms which were described in the previous sections. An assumption associated with this task is that the proposed feature extraction and classification could be implemented for on-board classification.

Of particular interest to NASA are technologies which may lead to flyable on-board processors, units on the satellite which can classify as MSS image in real-time or near real-time and transmit to the ground only the classified image. A system must meet several requirements before it can be used in such an application.

(a) It must be fast enough to process data in real-time.

(b) It must be fully automatic because human interaction is not recommended.

(c) Since the resulting image is the only information transmitted to the ground, the system must have acceptable accuracy.

(d) It must be capable of dealing with the analog data directly as it comes from the sensors.

(e) It must consume little power, be light in weight, and be highly reliable.

(f) The system must be programmable from the ground and capable of adapting itself or deriving its own classification parameters.

3.3.6.1 Available Technologies

High speed is the primary requirement for the system used for on-board classification. The fact that present general purpose processing techniques are too slow and too expensive to reduce the LANDSAT data to classified images, future studies are necessary to contribute to the solution of this data processing bottleneck. One area of research needed to improve the high-speed requirement is the design of processors that manipulate and process data in parallel or simultaneously instead of single pixel-point processes. The availability of array processors and array computers such as the Massively Parallel Processor [17] and many others [18], [19], [20], [21] that offer high computational speed allows the implementation of dimensionality reduction and classification tasks in real-time.

The use of semiconductor technologies in the construction of hardware-based pattern classifiers is another potential solution to the on-board classification problem. In some studies, the uses of charge transfer devices such as CCD were explored in the implementation of classification systems [22], [23], [24]. When used as analog signal processors, charge transfer devices may be used to obtain complex functions of the input signal. The functions may include linear combination, correlation, convolution, filtering and a number of other operations. By performing the processing of functions directly in the charge domain at the plane of metal-oxide-semiconductor, the device can achieve full-frame processing in real-time.

The storage requirements of an on-board classifier are easy to meet. A lot of desirable mass storage devices -- such as bubble memory, CCD, and other solid state devices -- are becoming more available. Some of these memory devices should offer a satisfactory solution to the on-board hardware problem. Another technological advance that should improve the performance of on-board classifier systems is the development of firmware operating systems in read-only-memories (ROMs). The firmware allows the control of data paths and the flow of imagery data in a relatively high speed. It also allows the pre-programming of classifier parameters (such as transformation coefficients, tables, and decision tree structures) and the storage of image-processing algorithms for fast pre-processing.

One area of technology in which continuous efforts are being done is in system design concepts. This includes system design techniques, hardware architecture, and software preparation. The old approach of recognition system design concepts is to design human interactive equipment. New design approaches emphasize the design of autonomous classification systems through special-purpose subsystems, programming flexibility, and adaptability.

Extensive image proc[illegible] techniques have been developed for interpreting LANDSAT images. Techniques include image transformation, image enhancement, image restoration, and image understanding. Image transforms can be used to compress data, remove redundancy, select features, and perform spatial filtering. With image enhancement, improved viewing conditions and better interpretations of imagery can be achieved.

In image restoration, degraded images caused by sensor noise, defocusing, and nonlinear response of the sensor can be eliminated by developing appropriate restoration filters. Pre-processing using image analysis techniques is very useful in the classification application and is expected to play an important role in the implementation of on-board units. More progress in such areas is necessary. The task of building a machine to understand and classify images in real-time on-board is relatively difficult, if not impossible. But extensive research is being done to provide insights into this task.

3.3.6.2 Hardware Architecture

The two basic functions associated with each node of the decision tree classifier described in previous sections are:

(a) linear combinations, and
(b) table look-up.

3.3.6.2.1 Table Look-Up Hardware

The key to the viability of an onboard implementation of these algorithms resides in data structures. Here the notion of table look-up plays an eminent role. It is anticipated that complex special-purpose hardware is not required for onboard classification, since the proposed classification algorithm requires only simple linear transformation and table look-up. These functions can be implemented easily as onboard hardware. It is based on pre-storing in fast, random-access, storage memory the desired answer (example: crop-type) for all combinations of two-dimensional transformed features. Specifically, each set of multispectral scanner outputs from selected channels from a given point on the ground is transformed into features and then interpreted as that address in storage memory (table) where the answer can be retrieved. Substituting the simple retrieval operation for the lengthy computations required by the conventional approach offers two advantages:

(a) The processing time is greatly reduced.

(b) The multispectral scanner data can be processed by processors having minimal sophistication and complexity.

These two advantages may make it more possible to use an on-board computer to perform the classification function in flight. A table look-up unit is illustrated in Figure 3.3-8 in the architectural and data structure domains. It shows the simplicity of the hardware implementation. Still another advantage is the fact that the table look-up approach does not involve multiplication nor floating-point operations. For this reason, classification can be done in very high speed with minimal sophistication, cost, and hardware complexity.

3.3.6.2.2 Feature Extraction Hardware

The proposed feature extraction algorithm is a simple linear combination function. It reduces the multispectral data into a two-dimensional feature space. It has the form of $\sum V_i X_i$ where X_i's are samples of the input and the V_i's are weighting coefficients, or elements of the transformation matrix.

One approach for implementing "linear combination" devices is illustrated in Figure 3.3-9. The corresponding storage elements of two storage arrays can be connected to multipliers and the multiplier outputs then summed. The resulting output is $\sum V_i X_i$. X_i's are stored in the first storage array and the weighting coefficients are determend by the data stored in the second array and both data may be changed simply by clocking in new data.

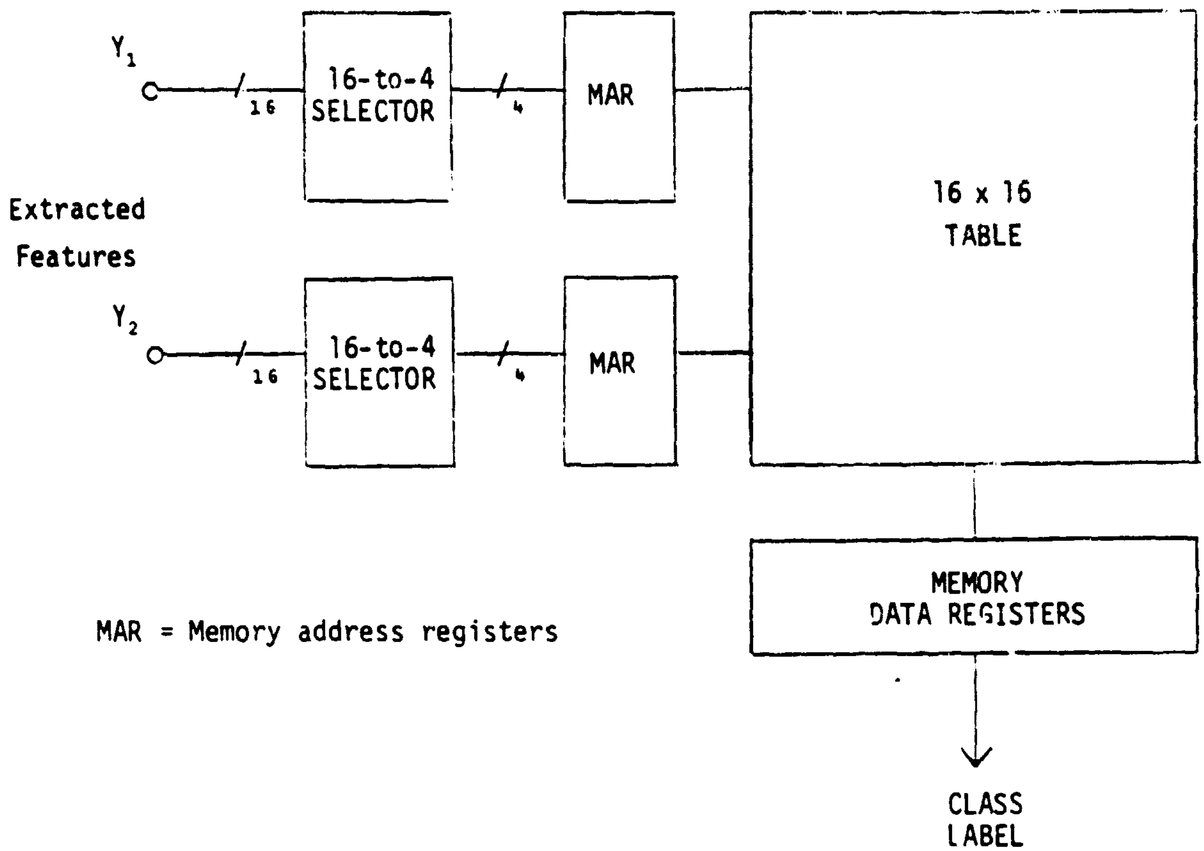


Figure 3.3-8 A Table Look-Up Unit for a Node in a Decision Tree Classifier

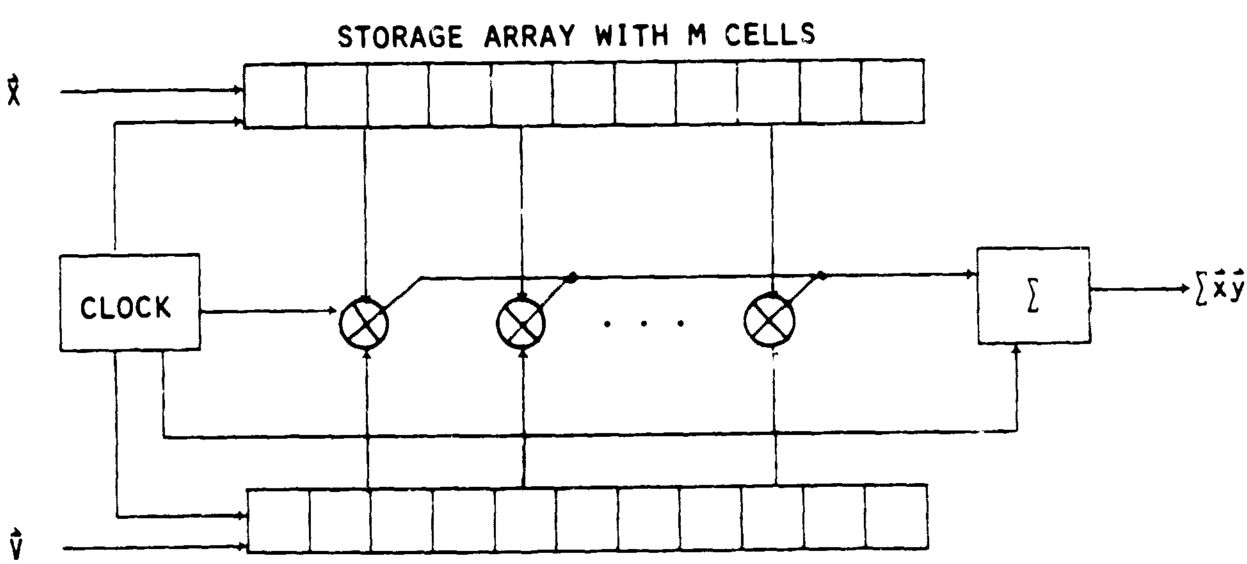


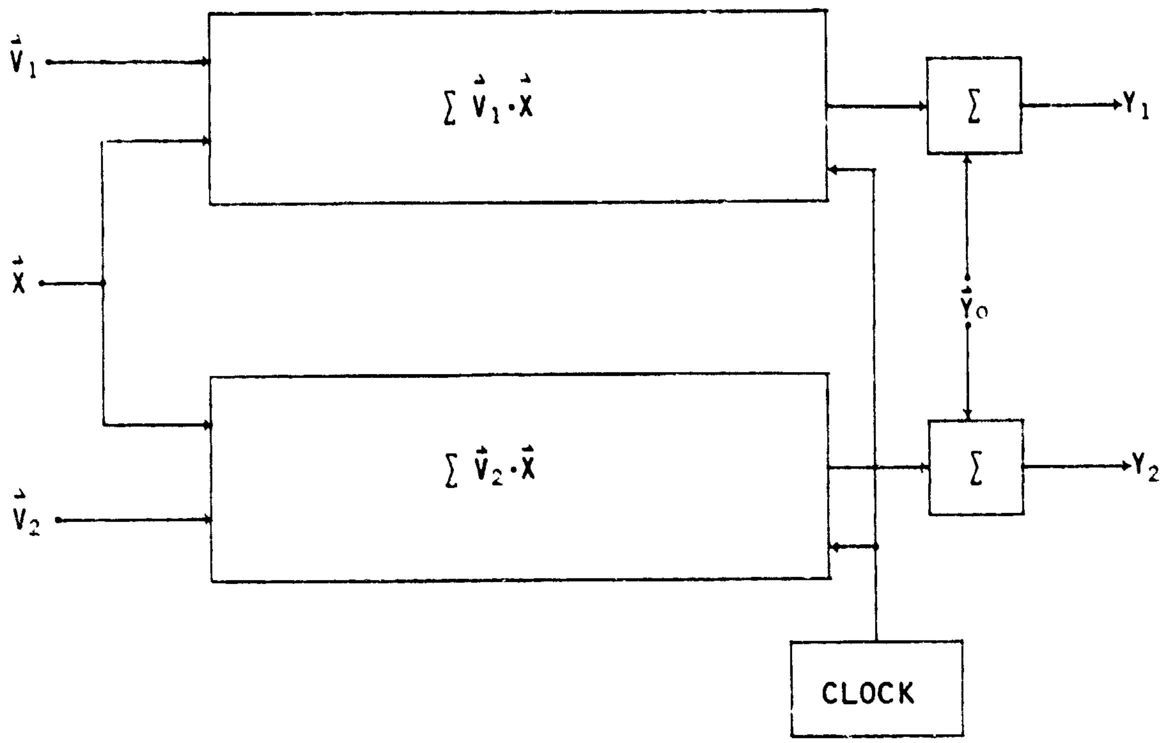
Figure 3.3-9 A Linear Combination (or Sum of Products) Device

Charge Coupled Devices (CCD) may be used to implement this device. It moves charge linearly in synchronism with a clock. If the charge is quantized as binary digits, CCD may be used as shift register memories. CCD is a special variant of a metal oxide semiconductor device and was initially designed as shift register of block-oriented random access memories. The basic device is an analog shift register in which an applied electrical field induces potential minima for signal charge packets at storage sites at the surface of the semiconductor material. Varying the applied electric field shifts the potential minima to adjacent storage sites by transferring the signal charge in a controlled manner within the substrate from storage site to adjacent storage site in serial fashion. Thus, electrical signal charges, representing information can be read in, shifted, and read out. See references 25, 26, and 27.

When used as analog signal processors, CCD may be employed in the construction of special purpose devices such as the "linear combination" device [23]. In this potential application, the corresponding cells of two CCD delay lines is connected to multipliers and data stored in each delay line may be changed by shifting. More important to this application is the fact that CCD operates on discrete data samples, hence variable linear combination devices may be put together to generate the vector dot product:

$$\vec{V} \cdot \vec{X} = \sum_{i=1}^{n} V_i \; X_i$$

where n is the dimension of the vector and may be as large as the number of cells in the CCD. The result is obtained by loading one vector into one side of the CCD and the second vector into the other. In other words, the output is the result of one row by column operation of a matrix multiplication. In our proposed M-dimension to 2-dimension feature extraction, two linear combination devices will be used. Figure 3.3-10 shows the implementation approach.



$$\vec{Y} = \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \vec{V}^t \vec{X} - \vec{Y}_o$$

$$\vec{Y} = \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} \vec{V}_1 \\ \vec{V}_2 \end{pmatrix} \vec{X} - \vec{Y}_o = \begin{pmatrix} V_{11} V_{21} \cdots V_{m1} \\ V_{12} V_{22} \cdots V_{m2} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_m \end{pmatrix} - \begin{pmatrix} Y_{o1} \\ Y_{o2} \end{pmatrix}$$

$\sum$: adder/subtractor

$\sum \vec{V} \cdot \vec{X}$: linear combination device

Figure 3.3-10

M to 2 Dimensionality Reduction Using Two Linear Combination Devices.

3.3.6.2.3 Adaptive Classification Hardware

The proposed classification scheme in forms of decision trees (see Section 3.3.3 and Section 3.3.4) is generated using *a priori* class statistics. The decision tree parameters include:

(a) a well defined tree structure,

(b) a set of transformation coefficients for each node, and

(c) a table look-up classifier associated with each node.

All pixels belonging to a given class may be described typically by a multivariate normal distribution. Therefore, the statistics consist of means and covariance matrices only. Variations from scene to scene cause difficulties in classification. Adaptive processing to permit changes in these statistical parameters would appear to offer hope for improving classification accuracy. Section 3.3.5 discusses appropriate adaptive algorithms for this purpose.

The task of on-board classification also requires the implementation of adaptive processors. In this case, the transformation coefficients and the table classifiers will be updated continuously. This updating process will allow independent signature corrections to be performed without the necessity of additional *a priori* information. In this approach the class statistics are updated based on the decision results, and the decision tree parameters (transformation coefficients and table classifiers) are updated based on the updated class statistics.

It has been shown in Section 3.3.3.2 and Reference 9 that for the purpose of feature extraction, a canonical analysis approach may be used. That is, the procedure involves the solving of the eigensystem:

$$\vec{B}\,\vec{V} = \lambda\,\vec{W}\,\vec{V}$$

where

$$\vec{B} = \sum_i N_i(\vec{M}_i - \vec{M}_T)\,(\vec{M}_i - \vec{M}_T)^T$$

$$\vec{W} = \sum_i N_i\,\vec{\sigma}_i$$

and

$\vec{N}_i =$ the number of pixels in class i

$\vec{M}_i =$ the mean vector of class i

$\vec{\sigma}_i =$ the covariance matrix of i

$\vec{M}_T =$ the average mean vector, i.e.:

$$\vec{M}_T = \frac{1}{\text{total pixels}} \sum_i N_i\,\vec{M}_i \quad .$$

The proposed hardware implementation of the feature extraction procedure is shown in Figure 3.3-11. Again, the linear combination devices (or sum of product devices) are the primarily components used. The inputs to the subsystem are the undated class statistics and the outputs are the two-dimensional transformation matrix and the offsets. A microprocessor is used to control the data flow and solve the linear system of equations.

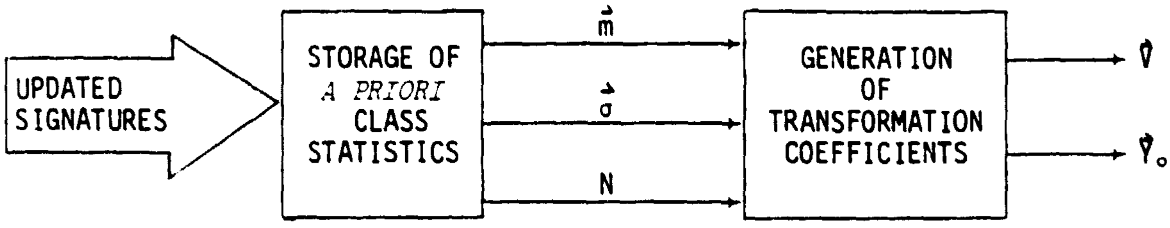
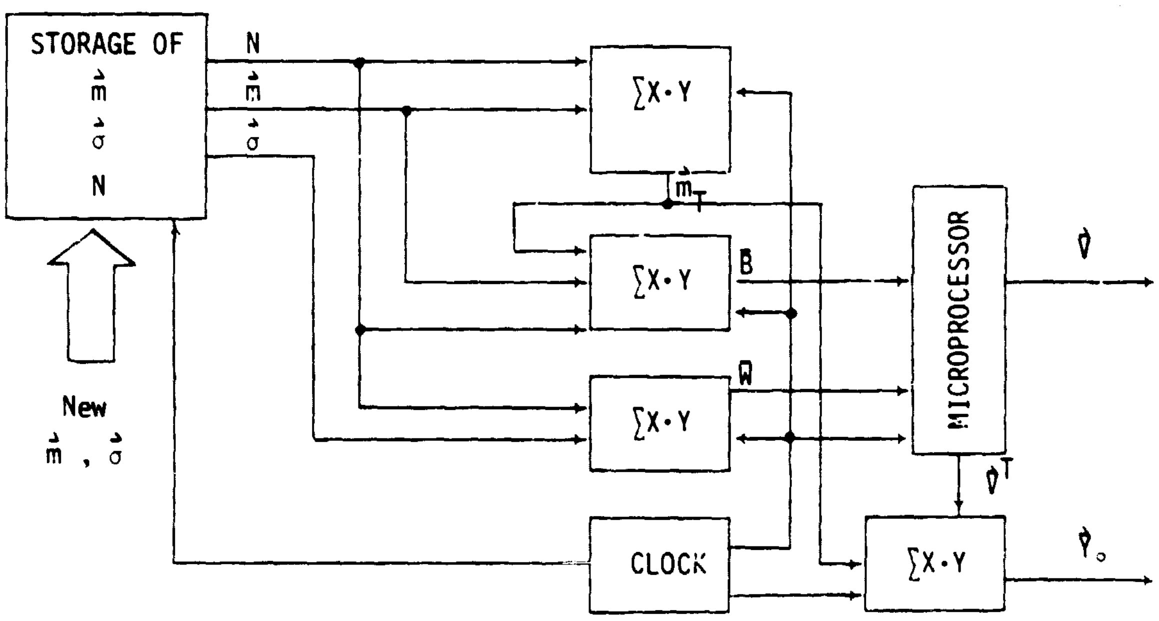


Figure 3.3-11(a)
Generation of Feature Extraction Coefficients
Hardware Organization



$\sum X \cdot Y$ linear combination device
$\vec{v}_o = \vec{v}^T \cdot \vec{m}_T$

Figure 3.3-11(b)
Block Diagram for Generating Two-Dimensional Feature Extraction Coefficients

To update the table look-up classifiers, the likelihood of each grid element will be computed at the midpoint for all classes and an updated class index will be assigned according to the maximum likelihood. Maximum likelihood classification at each grid then consists of determining which of several distributions has the highest probability and assigning the class index to the grids having the highest probability. With this procedure, the probability that a two dimensional vector $\vec{Y}$, a point within the table, belongs to a class i is:

$$P_i = \frac{1}{2\pi|\sum_i|^{\frac{1}{2}}} \exp\{-\tfrac{1}{2}(\vec{Y} - \vec{\mu})^T \textstyle\sum_i^{-1} (\vec{Y} - \vec{\mu}_i)\}$$

where $\sum_i$ and $\vec{\mu}_i$ are the 2x2 covariance matrix and 2x1 mean vector respectively. The usual definition of the maximum likelihood classification includes a term representing the *a priori* probability. For the purpose of simplification, the *a priori* probabilities can be treated as equal, hence for the purposes of classification, the *a priori* probabilities may be neglected. The table look-up classification rule becomes:

> "A class index i is assigned to a grid inside the defined table with midpoint $\vec{Y}$, if $P_i(\vec{Y}) \geq P_j(\vec{Y})$ for all j."

The probability function is simplified as follows. Exponential function is time consuming and difficlt to implement, therefore, by taking the logarithm of P_i the function becomes $d_i(\vec{Y}) = \ln P_i(\vec{Y})$, a discriminant function:

$$d_i(\vec{Y}) = -\tfrac{1}{2}(\vec{Y} - \vec{\mu}_i)^T \textstyle\sum_i^{-1} (\vec{Y} - \vec{u}_i) + \ln|\sum_i|^{-\frac{1}{2}} + \ln(2\pi)$$

Since the $\ln$ function is monotonic, the class having the largest $d_i(\vec{Y})$ for a given $\vec{Y}$ will also be the class having the largest probability $P_i(\vec{Y})$. The third term of the right hand side of the above equation is a constant for all classes and therefore can be omitted. $\ln|\sum_i|^{-\frac{1}{2}}$ needs to be computed only once for each class and therefore does not contribute to the computational inefficiency problem.

$(\vec{Y} - \vec{\mu}_i)^T \Sigma_i^{-1} (\vec{Y} - \vec{\mu}_i)$ must be computed for 256 x K times for each node, where 256 is the number of boxes within the defined table and K is the number of classes. By observing the fact that Σ_i is a symmetrical matrix, the equation $(\vec{Y} - \vec{\mu}_i)^T \Sigma_i^{-1} (\vec{Y} - \vec{\mu}_i)$ may be further simplified. Let $\vec{X} = (\vec{Y} - \vec{\mu}_i)$ and $\vec{Z}$ be the upper triangular matrix of Σ_i^{-1}, then the equation can be written as

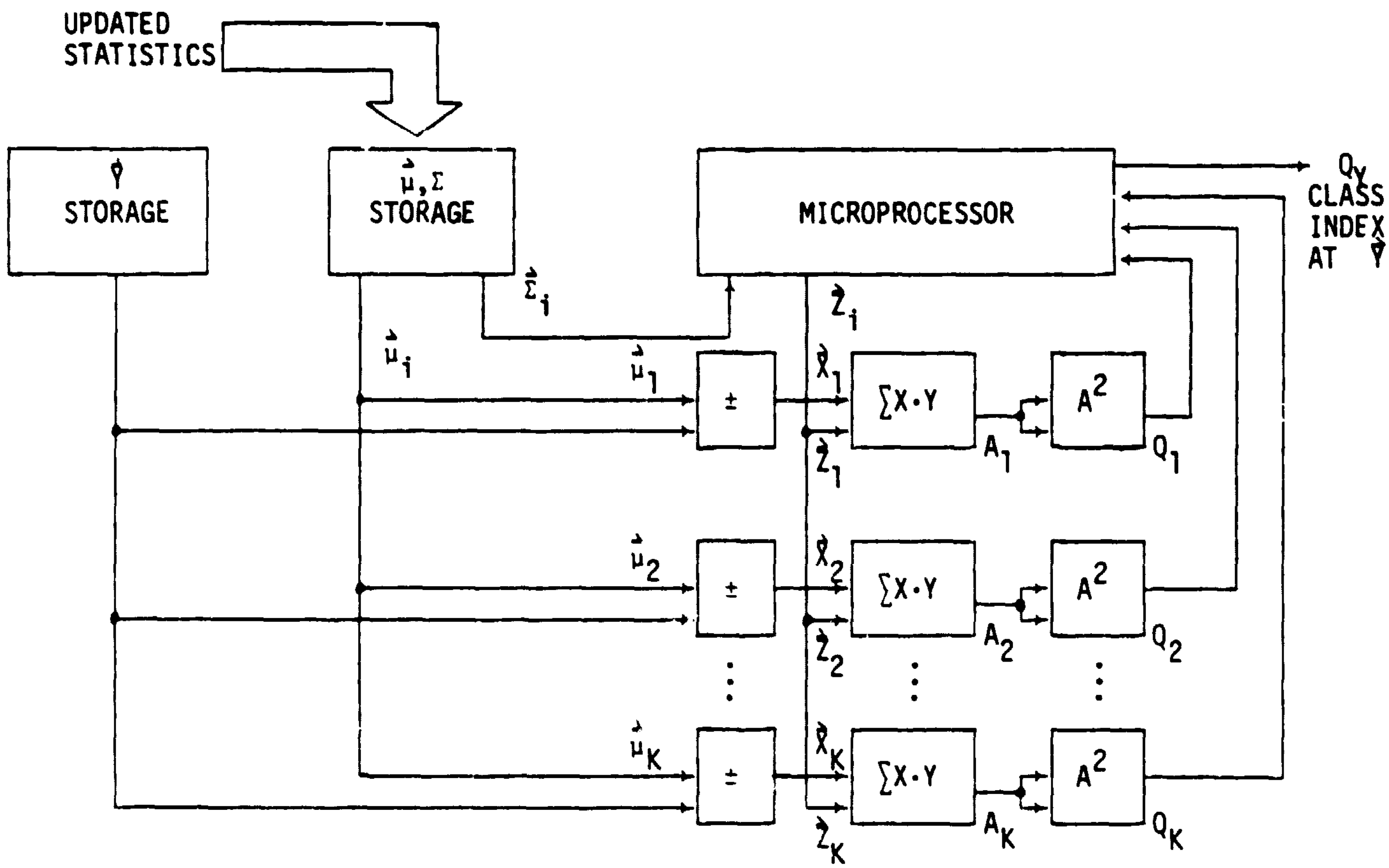
$$\vec{X}^T \vec{Z}^T \vec{Z} \vec{X}$$

$$= [\vec{X}^T \vec{Z}^T][\vec{Z} \vec{X}]$$

$$= [\vec{A}^T][\vec{A}]$$

$$= \vec{A}^2 .$$

It involves matrix multiplications and square operations. In other words, the discriminant function may be implemented by linear combination devices where each of the row-column dot product operations is performed in a CCD device. Figure 3.3-12 shows the hardware organization.



± : adder/subtractor

$\sum X \cdot Y$: matrix multiplier

A^2: square operator

Q_Y is the class label (out of K classes) assigned to the grid with center $\vec{Y}$.

Figure 3.3-12
An Organization for Generating the Table
Look-Up Classifier

The above proposed subsystem is one method of implementing dedicated hardware for pattern classification. At the conclusion of the training phase, the controlling processor fetches and loads the class statistics, tables, and tree structure parameters into the hardware subsystems. At this point, the hardware controller takes over and performs the two-dimensional feature extraction (Figure 3.3-10) and table look-up classification (Figure 3.3-8). The results of each classification are passed through the adaptive processing subsystems to update the mean vectors and covariance matrices associated with all classes. The updated class statistics are then fed into the (a) Feature Extraction Coefficients Generator (Figure 3.3-11) to update the transformation coefficients, and (b) Table Look-Up Classifier Generator (Figure 3.3-12) to correct the table classifiers. In this manner the classification can be done onboard where the scene is changing continuously. Recent technology developments have made such proposed classifiers feasible.

3.3.7 A Scenario

An on-board classifier offers significant potential gains in performance of the satellite system. In this section, we demonstrate through a scenario how an onboard classification might be performed and to point out some of the logistical and technical problems.

A typical on-board classification might be performed by the following procedures:

(1) An agricultural agent specifies and designs a decision tree classifier by the automated designing approach as proposed in Section 3.3.4. The decision rule is designed with ground truths for some known areas by some automatic designing tools at the ground station.

(2) He then reserves the satellite for its next pass over by specifying the starting coordinates of the known areas (geographic regions selection).

(3) The decision rule parameters and the coordinates are transmitted to the satellite. The classifier is initialized by loading the statistics and tables into its storage.

(4) As the satellite passes over the specified areas, image data is acquired. The on-board classifier performs dimensional reduction (feature extraction) and table look-up operation, and the data is then classified into one of the class indexes.

(5) The results of the classification are fed back to the adaptive processing hardware units to update the class statistics and change the decision rule parameters. This enables the classification to be performed from scene to scene without further human intervention. The results of the classification are then encoded and transmitted to the ground.

(6) The ground station receives a coded map of the areas with the classification results.

In an alternative proposed procedure [22], the training phase is done on-board by performing a cluster analysis on the training sets and deriving a Gaussian fit for each cluster. This approach requires additional hardware units on-board and is unable to have an optimal decision rule to work with.

There are both possible gains and hazards associated with on-board classification. Also, there are significant problems which must be overcome before this proposed system could become reality. The following lists a few of the problems, benefits, and solutions.

(a) Data will be available to the ground user in minutes rather than months.

(b) Data storage on ground will be reduced tremendously due to the availability of classified results.

(c) On-board classification provides a reasonable direct user interaction with the satellite which benefits users for specifying their needs.

(d) The one factor which some users may consider hazardous in such proposed systems is the fact that the raw data is no longer available to the users. In some cases, a user may wish to do post-classification processing to improve accuracy. Since the raw data is no longer available and the only available data sets are the training data and the classified data, post-classification processing might seem impossible.

(e) A significant amount of pre-processing, for example, correction for geometric distortion, must be done prior to classification. It imposes some constraints in operating speed and additional onboard hardware.

(f) Continued technological improvement is necessary to produce faster, more compact and lower power system components for on-board implementation.

(g) Future research is necessary to provide more applicable adaptive processing theories for the tracking and updating of classifier parameters. Research topics include filtering theories, mathematical modeling of scene variations, and implementation of adaptive processors.

(h) The recent development of the "smart sensor" also shows considerable promise. It performs detection and processing directly at the focal plane of a sensor and achieves full-frame processing in real-time.

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4.0 LONG TERM DEVELOPMENT AND RECOMMENDATION OF IAS

The incorporation of IAS concepts into actual remote sensing missions will be a long term evolutionary effort. Capabilities which exist today will be exploited on early missions and as experience is gained and new technology becomes available, the scope of IAS will be expanded. The purpose of this section is to indicate the general direction which this evolution might take. To do this, we will describe what we consider to be an "ultimate IAS". Our ultimate Information Adaptive System incorporates as many features as can be conceived of at this time.

4.1 The Ultimate System

The conceptual view of the ultimate IAS is depicted in Figure 4.1-1 Shown here are the various elements required to transform an observed scene requested by the user.

All of the communications links which connect the various elements of the system are implemented using the techniques of the Modular Data Transmission System. The system, therefore, can be optimized from the standpoint of flexibility. The various elements can be developed individually and interconnected in an orderly fashion with minimal additional development time. Furthermore, certain resources can be shared, thereby minimizing cost. The data available in one data base is available for use by all systems and can be incorporated in whatever information extraction process is taking place.

The user processor may be located at a great distance from the ground based hardware. MDTS makes the location of the user in relation to the ground irrelevant. The user need only submit his requests to the IAS ground based control system through an MDTS link.

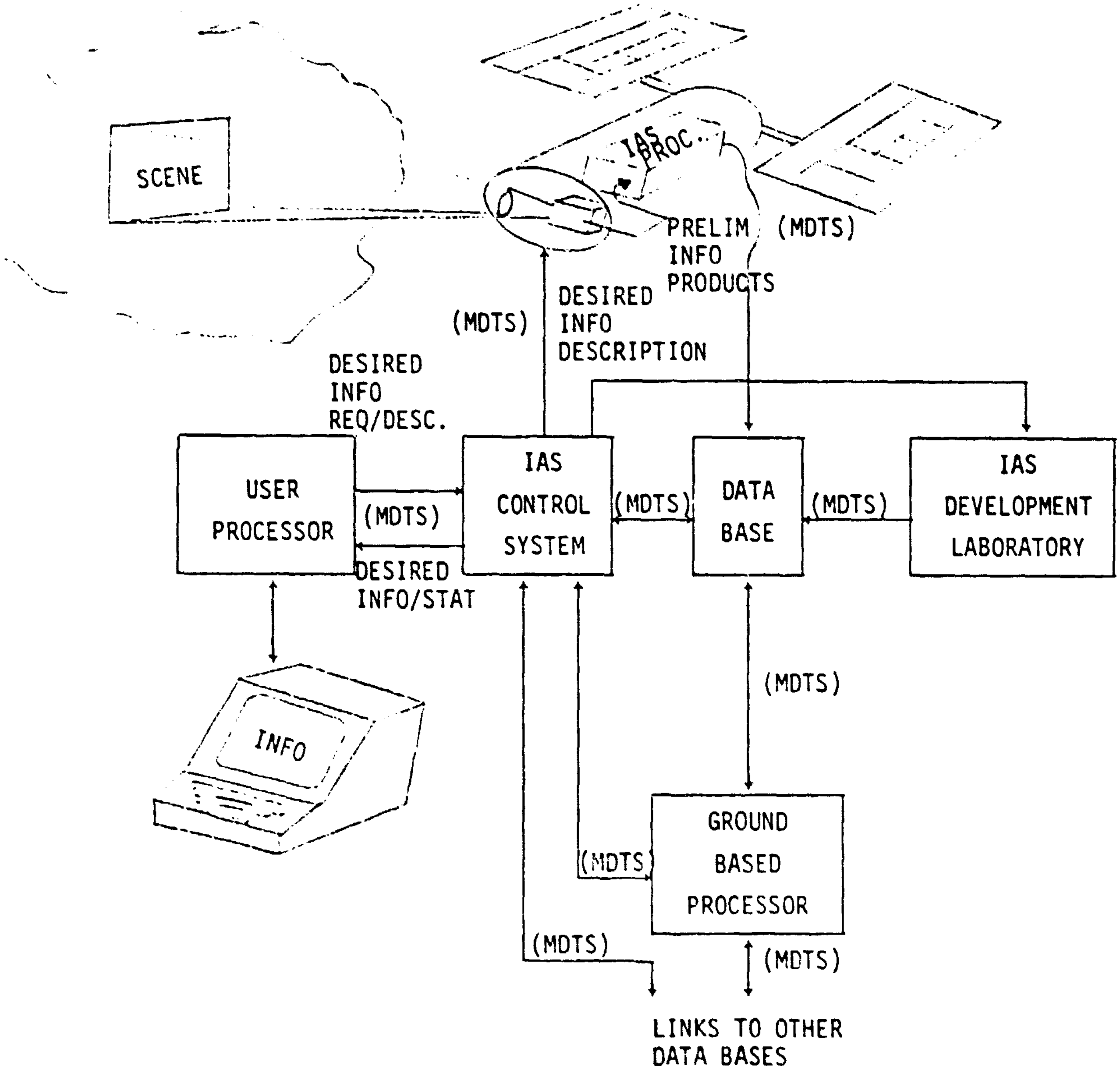

Figure 4.1-1 Conceptual View of Ultimate IAS

The control system will decompose the request into a series of work orders, some of which will be performed on-board the spacecraft if new data must be acquired; others will be delivered to the ground based processor. Further, the control system will provide the user with status messages indicating the current phase of execution of his request as well as estimates of the time required before the request is fulfilled.

On-board the spacecraft, the sensor system will observe the desired scene and transfer radiometrically and geometrically correct data to the on-board IAS processor. The processor will perform whatever information extraction processes can be performed in space, and relay the preliminary information products to the data base.

The data base will serve as a focal point for the acquisition of all data. When the data base is updated, the ground processor will perform the balance of the processing tasks to be handled by the IAS system. These tasks might include such things as tracking algorithms, correlations with previously acquired data, the assembly of information messages with data from a variety of sources, etc. These completed information products will be forwarded over MDTS links to the user processor. At the same time, the control system will record the fact that the work order has been completed. Once the information has been delivered to the user and his processor, it is available for whatever subsequent processing and analysis the user wishes to do.

Figure 4.1-2 shows the various elements of the IAS ground segment and Figure 4.1-3 shows the elements of the flight segment as described in above paragraphs.

It is generally not the intent of IAS to completely process the data. IAS merely performs those processing functions which are generic enough in nature that they would be applicable to the needs of many users. However, there are enough standardized algorithms required for almost all information extraction needs that the ultimate processing burden which must be handled by the users themselves will be dramatically reduced.

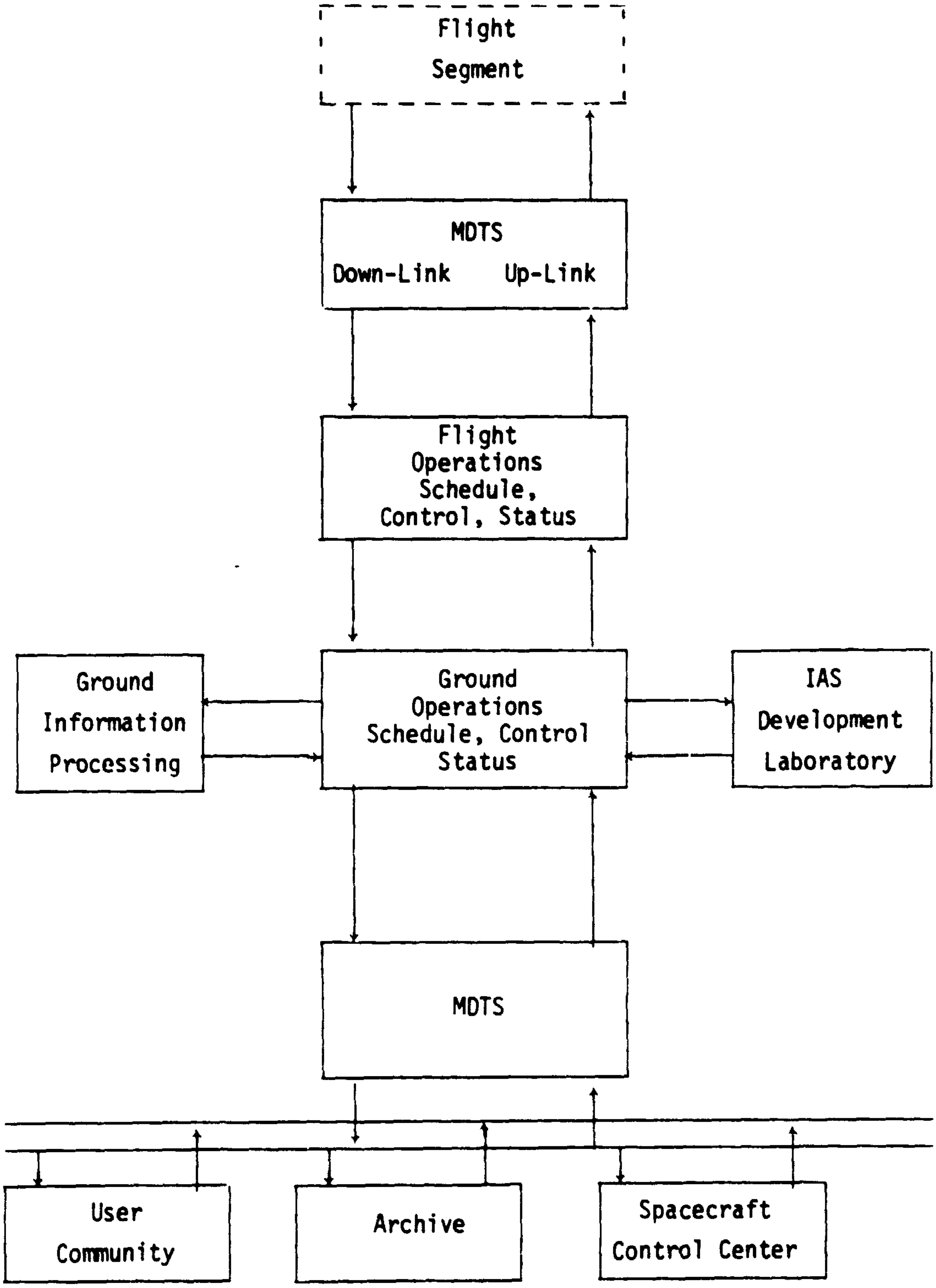

Figure 4.1-2 Generic Block Diagram - IAS Ground Segment

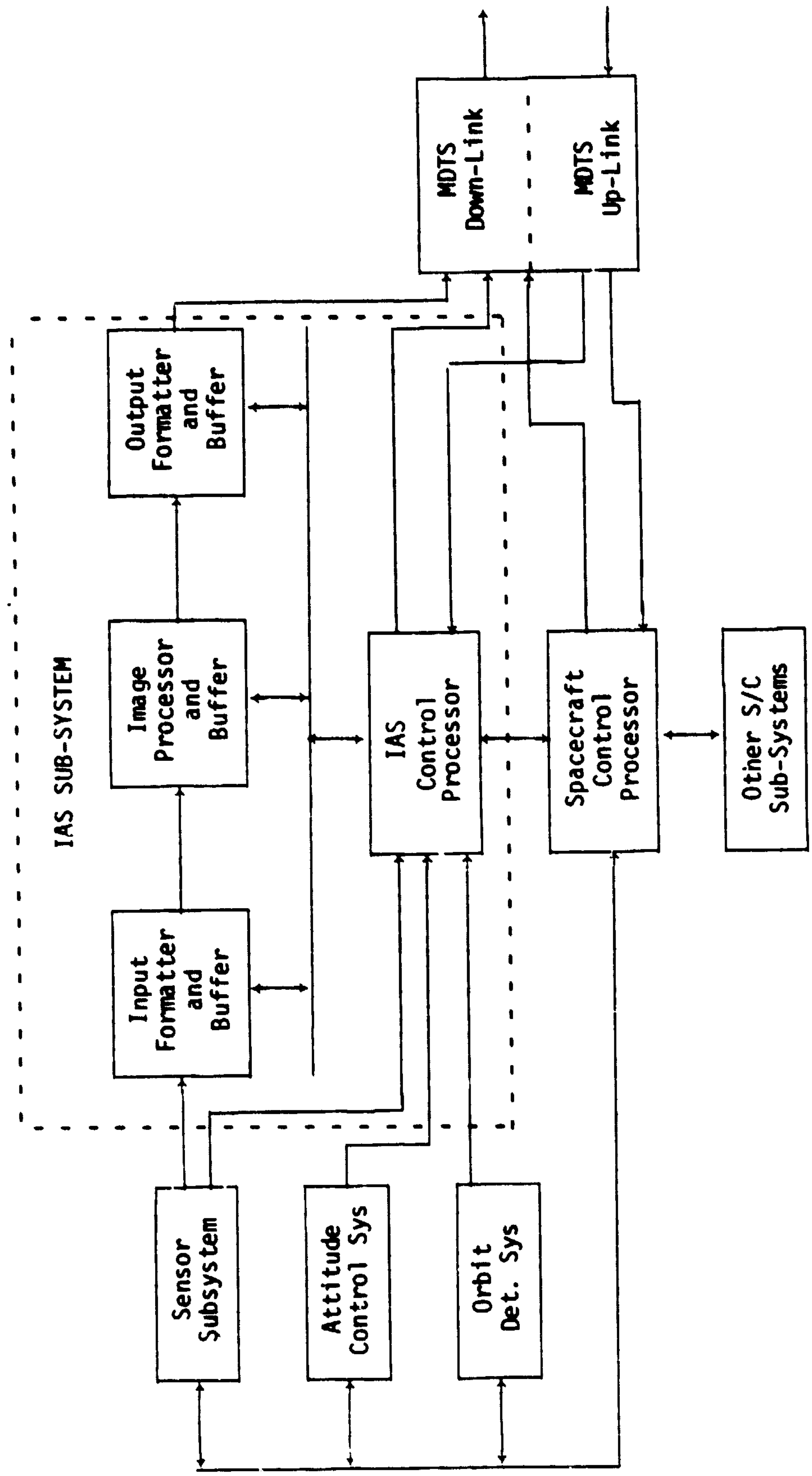

Figure 4.1-3 Generic Block Diagram - IAS Flight Segment

4.1.1 User Interface

Since this data acquisition system exists to service the needs of the user community, the development of a flexible, user friendly, reliable, human interface is of primary importance. The interface should be designed in such a manner that the processing steps required in extracting the information is transparent to the user.

To accomplish the decoupling of the user from the physical system, it will be necessary to develop a language which allows the user to define his information products in terms meaningful to him and which allows the control system for IAS to translate these requests into a detailed processing scenario to be performed by the functional IAS modules. One of the major obstacles is that the language will, of necessity, be evolutionary. The reason is that it is extremely unlikely that, at any given point in time, all of the user requests could be conceived of and incorporated into the language. Thus, the language itself will be dynamic and new phrases and constructs will be added to the language as required. This allows the language to adapt as the user needs develop.

For example, the FORTRAN language typifies the ideas envisioned for the user interface language. FORTRAN has been in existance for well over two decades. There are approximately seven major formal revisions to the language and virtually every computer manufacturer who has implemented a FORTRAN compiler has a unique "dialect". While for marketing reasons these changes to the language are described as "enhancements", it does indicate that the language as spoken within the user community at a particular location is not exactly the same as the language spoken at other locations. Unfortunately, the development of these various "dialects" of FORTRAN has been such that the transportability of programs from one computer system to another is extremely limited even though both computer manufacturers advertise their FORTRAN as being the ANSI standard FORTRAN.

Ideally, the development of the user interface language should avoid these obstacles. Obviously, there will be user facility dependent dialects which are not readily transportable. For example, a particular user location may have an image generation system which does not exist at other locations. The user interface language will have to differ in that regard among the various locations.

However, the application dependent dialects should be as transportable as possible. One way to achieve that is to store within the data base the description of the various dialects. As a user moves to a different location, he need only define the specific dialect he is speaking and the system should be able to recover the description of that dialect from the data base. This has the added advantage that the developments of the numerous users will be shared. There is perhaps an unwillingness on the part of many users to share their developments, free of charge, with others, and some means will have to be made available to satisfy such constraints. However, it is generally felt that the development of scientific principles and practices should be accessible to everyone.

While the concept of an image processing language is certainly valid, there will be an ever increasing group of users who lack the expertise to communicate with the system in such a language. For such users, a "menu driven" interface should exist which will give them easy access to system measures.

The menu should be presented in the form of a check-list phrased in user-relevant terms, which allows the user to select his desired output products. The system will elect the necessary processing scenarios from the data base to correspond to the specific items checked.

In addition, explanatory text will be stored in the data base to achieve a "self-teaching" mode of operation. Such provisions will give totally unskilled individuals the means for applying remote sensing and sophisticated information processing techniques to their problems. It would be reasonable to conceive of terminals located even in County Planning Commission offices.

Development of detailed processing scenarios should be left to experts. However, the casual user should be permitted to develop at a higher level a "processing function" unique to his needs. Using the menu-check-list method, a user could define and store his own processing and extraction sequence for repeated future use. This item would then be added to his menu.

4.1.2 Development Laboratory

Provisions must be made for the development of system compatible algorithms and for their incorporation into a library. To accomplish this with minimum risk to the system, a "pseudo off-line" development laboratory must be present so that users may develop their algorithms. The users should have available to them hardware and software support tools which will adequately emulate the operational environment. There should be little, if any, algorithm "translation" required to transfer an algorithm from the laboratory to the operational system. Any such translation must be transparent to the user.

The task of developing an algorithm will also require a set of bench mark data acquired by the operational system and not processed beyond the point allowed by the algorithm input requirements. This data could be stored in the data base sub-system so as to minimize the load on the spacecraft and, most important, mimimize the response time to the developer.

This base of test data should have sufficient "ground truth" information available to allow assessment of the algorithm. In addition, the test data base should be sufficiently comprehensive that the algorithm can be evaluated in as many of the "real life" environments as possible. For example, a crop classification algorithm should be tested using data with various degrees of haze, sun angles, etc., before being declared "operational". This could very well indicate that the operational system will be called upon to retrieve additional data with specific amounts and types of contamination.

To provide maximum versatility to the algorithm developer, use of the laboratory by remotely located users should be provided. In this way, travel to GSFC (or any other central laboratory) with its attendant costs, scheduling and logistics problems will be avoided. Users with direct data links to the system could use their links to develop their own algorithms interactively, much as they now do using standard time share computer networks.

The development laboratory should serve to simulate the functions of all of the available elements of the IAS. It should draw upon raw data as needed from the data base and thereby simulate the sensing of a scene by a spacecraft.

The development laboratory should be available to at least some of the users for purposes of testing and demonstrating the processing techniques which will ultimately be included in the IAS repertoire. Ideally, techniques which have been developed in the laboratory will be transportable to the operational system with no translation steps required. To permit this, it is necessary that the development laboratory effectively duplicate the functional characteristics and procedures which exist for each spacecraft.

In addition to providing a simulation capability, the development laboratory should be equipped with analysis tools -- primarily software programs -- which can be used to aid in the analysis of processing algorithms. Generally, the software would take the form of "comparator" programs which would be used to compare the output product of a developmental algorithm with the ground truth data provided as an input to that algorithm. In many cases, the only viable method for conducting such comparisons would be through the production of image overlays. Such an overlay would depict the source data with the corresponding output image in such a way that the user could relate the output results to the input. Other programs capable of performing a variety of statistical analysis operations on the algorithm output would be of substantial benefit.

4.1.3 Data Base

The data base depicted is used for the storage of user developed processing scenarios, system standard processing scenarios, and all data acquired by the system. There is now considerable effort going on to develop data base technology to the point where a data base of 10^{15} bits can be handled efficiently. It is felt that such a large data base will be of considerable benefit to IAS (NASA, 1977).

However, a data base of this size indicates a capacity of approximately 27 years of storage at today's ingest rate (approximately 10^{11} bits per day). If IAS does achieve its objectives in terms of dramatically reducing the volume of data, a data base of 10^{15} bits would conceivably hold one or more centuries of acquired data. It is not unreasonable to assume that well before such a data base were filled, further technological advancements would make it posssible to achieve virtually unlimited data accumulation.

A major difficulty with a data base of this size is the problem of efficiently retrieving related data records. It is reasonable to assume that the information content of each record has been used at the time that that record was initially entered into the data base. If this is true, then the only subsequent value which that record may have is its ability to be combined with other records in new ways to explore broader relationships.

This implies that the access method for this data base should be relational in nature. That is, rather than accessing data solely on geographic location, or orbit number, or other such information independent parameters, the data should be accessible based on its relationship to other records. For example, a useful access request might be to gather all data classed as wheat which has been observed during a specific season over a number of years. When satisfied, this request would produce data from numerous spacecraft, over widely dispersed geographic regions over a number of years in spectral signature, areas under cultivation, seasonal trends, etc.

4.1.4 Control System

The heart of the ultimate information adaptive system lies in the control algorithms. To be of significant benefit to the user community, the control algorithms should free the individual users of the burden of having detailed knowledge about the ensemble of spacecraft available to provide the data and the detailed characteristics of each of the spacecraft. Further, the user should be allowed to define his requests in terms which are meaningful to him. For example, if he is interested in acquiring data about wheat, he should be able to express his request in terms of wheat rather than in terms of relative spectral intensities or other units which possess an obscure relationship to wheat.

The control system should have the capability of translating into user units or other descriptors the data types generated by the appropriate spacecraft. It is expected that the data acquired by different sensors would also be normalized in spatial resolution.

It is assumed that there will be a moderate number of spacecraft with different characteristics available to the system for scene sensing. The control system should have the capability of selecting from the ensemble of spacecraft the one or combination best suited to the particular user request. This would involve such considerations as the time required for a spacecraft to observe the scene, as well as the suitability of the sensors to the task at hand. Should it later develop that the assigned spacecraft is unable to carry out its mission due to cloud cover or other disturbing influences, the control system should reschedule the mission for the next available opportunity. The control system should keep the user advised of the status of his request. This status report should include, at a minimum, the acceptability of the request, the estimated time of completion, and any charges which will be incurred in satisfying the request. It is possible that there would be alternative means for satisfying the user request. For example, there may be data available in the data base which would avoid the need to sense the scenes at all. If such is the case, the user should be afforded the option of using historical information. This would avoid the time involved in waiting for a new sensing of the scene and the related costs.

In addition to providing a user friendly, flexible interface to the user community, the control system should create its own requests for sensing missions. Generally, these requests would be to update the data base periodically. These updates would be at a frequency substantially lower than what is now current practice and would employ some intelligence in the request. For example, certain geographic areas are more interesting in terms of their relationship to daily life. It is quite likely that, in the future, crop quality and a detailed analysis of the global harvest will be maintained. To be of value, agricultural regions would have to be examined with a reasonably high frequency. However, remote barren regions, forest lands, and perhaps even range lands, would not have the same need for frequent observation. The control system would, therefore, generate update missions for the data base which would be tailored to the frequency of observation requirements for the specific regions. With such a process in operation, it is quite likely that a normal user request would not result in a sensing mission by a spacecraft at all but, rather it would result in an access to the data base with some attendant processing of that data.

The control system will initially be provided with an estimate of the interest in certain scenes or scene classes in terms of a data base update schedule. To achieve maximum utility, the update schedule should modifiy autonomously to reflect evolutionary changes in user interest. This can be accomplished by analyzing user request to deduce user interests, and modifying the schedule as indicated.

4.2 Long Term Development Schedule

This section will attempt to predict the long term IAS schedule. In doing this, the common denominator for capabilities appears to be the number of basic processing instructions per second which are required to accomplish a given task in real time. We have predicted the speed improvements of electronic hardware using the sound assumption that speed will increase by a factor of 10 every five years (NASA, 1973). Obviously, this does not mean that the speed of a specific processor will behave in this fashion. It merely means that for a certain amount of volume and power, electronic hardware will be available to produce a given number of instructions per second.

One factor not shown in Figure 4.2 is that of algorithmic improvement. We have assumed that more efficient computational algorithms will be developed as time goes on. This would have the affect of increasing the effective computational power of the processing hardware thereby reducing the time lapse between the various milestones indicated. The four image processing techniques covered by the graph are radiometric correction, haze removal, geometric correction, and spectral classification. The three sensors of interest are the multispectral scanner, flown on LANDSAT's I, II and III, the thematic mapper proposed for LANDSAT D and the synthetic apperature radar flown on the SEASAT spacecraft.

The chart is vertically calibrated according to the logarithm of the number of millions of instructions per second required to implement the indicated function using current techniques. Horizontally, it is calibrated in years. Along the implementation line are shown the points which represent the achievement of these various characteristics. We are assuming that there is approximately a five year delay between the time at which a given technology is commonly available and the time at which it can be flown operationally. That is, there is roughly a five year lag between a technology in reasonable commercial use and the appearance of that technology in a spacecraft.

4.3 Requirements and Recommendations for IAS Development

Table 4.3-1 lists the four dominant requirements for the long term development of IAS. These four requirements are rather all encompassing in their scope and will be further defined, to a large extent, only as the future unfolds. We shall, however, present a few comments on each of these at this time.

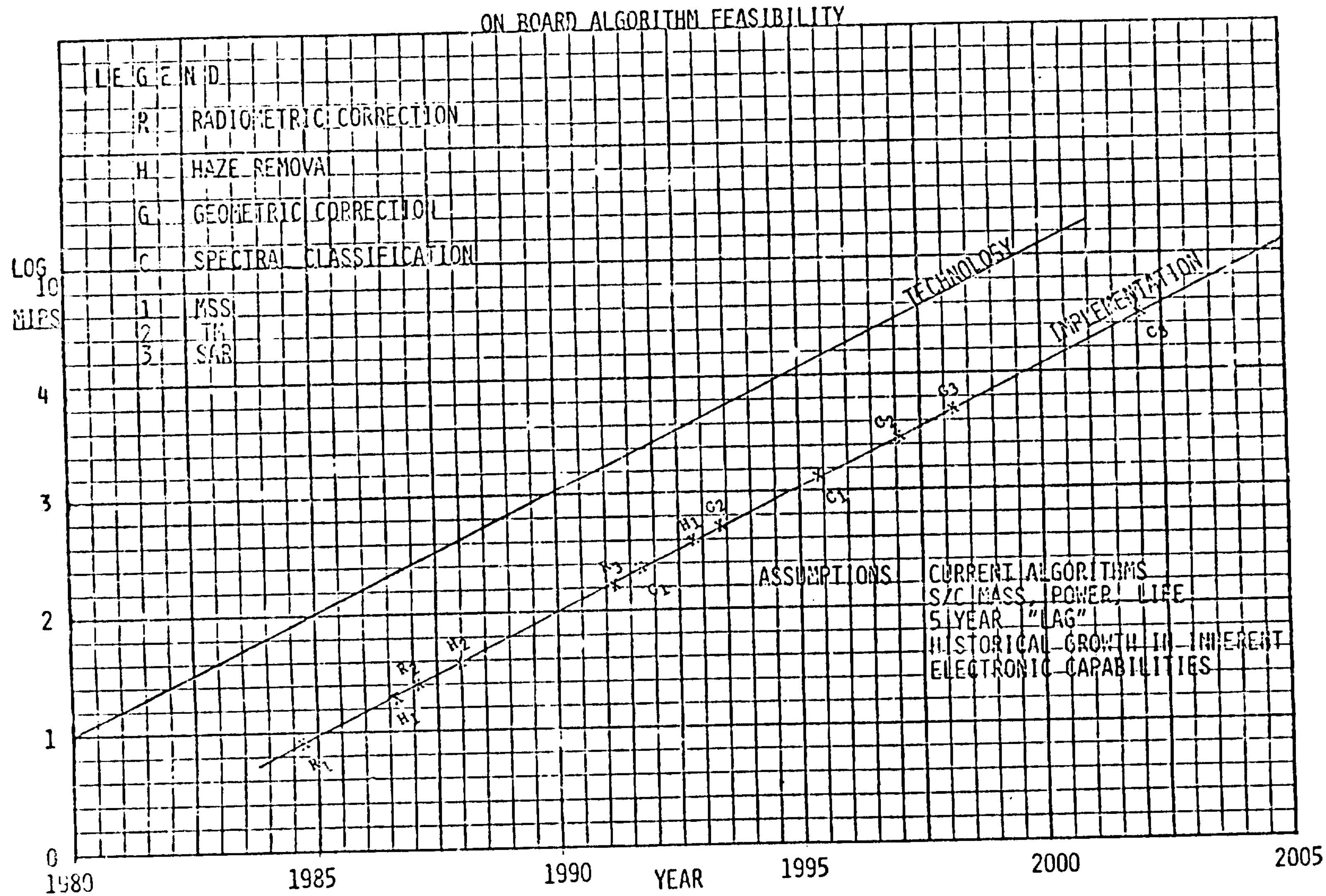

Figure 4.2-1 IAS Long Term Schedule

(1)	Adaptive Resolution sensor
(2)	Efficient autonomous image processing algorithms
(3)	Relational data base management system to support a base of 10^{15} bits
(4)	Dialect tolerant image processing language

Table 4.3-1 Long Term IAS Requirements

4.3.1 Adaptive Resolution Sensor System

The current technology for sensor systems is relatively primitive in many respects. The two major deficiencies are the lack of geometric accuracy in the generated image and the "fixed" resolution of each individual pixel. The lack of geometric accuracy produces a significant computational work load currently handled by ground processing. The burden is two-fold in that the pixels must be resampled by some technique in order to introduce geometric accuracy and the information required to control the resampling process does not coexist with the image data itself. The spacecraft attitude and emphemeris information all arrive at the resampling system by a path separate from the image data itself, hence there is a correlation process which must take place first, followed by a massive geometric resampling process.

The second deficiency that a fixed resolution generates is a massive quantity of data which is essentially redundant. While it is true that there are scenes requiring fine resolution, it is also true that large areas of user interest could be satisfied by course resolution sensors. For example, observing mile after square mile of corn fields at a rate of 1600 mss pixels per square mile seems excessive especially if the pixel values themselves differ primarily by small amounts of quantization error.

To provide for the ultimate needs of IAS, new sensor sytems are required. The first enhancement to be made in these systems should be that of generating geometrically correct data. This in itself would open the door to a much broader IAS capability on-board the spacecraft, since data generated by such a sensor could be directly referenced in terms of geographic coordinates.

By adaptive resolution, we imply that the sensor should produce pixels of varying size. Conceptually, this amounts to a variable band pass filter whose band width fluctuates to accommodate the signals present. It is envisioned that the sensor system could produce a stream of high resolution pixels which would be processed to yield the desired characteristics. Along feature boundaries, such as the edge between a corn field and a soy bean field, a number of full resolution pixels would be provided; over the bulk of the areas low resolution pixels would be provided. Ultimately, this would greatly enhance the process of classification since greater precision could be provided for the low resolution pixels and the boundary pixels should normally not be classified at all since their signature is a mixture and does not properly belong in either of the adjacent region classes. This would contribute significantly to a reduction in transmission band width and storage requirements while increasing classification accuracy, and feature recognition.

4.3.2 Autonomous Processing Algorithms

Current techniques for image processing include a high degree of human interaction, particularly after the geometric and radiometric correction phases have been completed. The interaction is particularly obvious when multispectral classification is being performed. Generally, what the operator does during such interactive sessions is to introduce his knowledge about ground truth and then evaluate the classification process from an esthetic standpoint; that is he concludes that the classification is sufficient when the picture "looks good".

What is needed is a study effort which examines, in detail, those properties of images which do not "look good". By so doing, it can be determined what factors contribute to the esthetic problem and a means can be developed to avoid these problems while operating in an autonomous mode. Such processing algorithms must also take into consideration ground truth and signature tracking.

Current techniques for multispectral classification are computationally intensive. While it is conceivable that the hardware could be designed to do the classification task in real time, the hardware design effort would be enhanced considerably if the classification algorithms were improved with regard to their computational efficiency. One possible method for doing this would be to classify a large number of pixels at one time by partitioning the image into regions which had spectrally similar characteristics. This could be done by identifying boundaries around regions in a relatively straight forward fashion and is far less computationally intensive than the classification process. Having isolated the boundaries, the areas within the boundaries could then be classified with the assumption that since there were no boundaries within an area, all of the pixels within that area were of the same class.

4.3.3 Relational Data Base Management System

It has already been indicated that the future data bases in remote sensing systems will be of the order of 10^{15} bits in size. While it is possible to retrieve data from such a base using current DBM techniques, it is felt that the major benefit of such a data base could be achieved only when retrievals of a relational nature are permitted. In many cases, the value of the information acquired in the data base is enhanced significantly when diverse data records are brought together, records which share certain common relationships.

Such relationships could be multispectral classification, geography, time of year, time of day, amount of haze, etc. It is felt that more information could be extracted from the data when such relationships are exploited and correlations established. To do this, a powerful tool for retrieving related data records from the data base is required.

Efforts are currently under way to develop a relational data base management system (RDBMS). Such efforts should be continued with a eye toward their application in future IAS systems. It should be assured that the domain of such RDBMS software is at least 10^{15} bits and probably more.

4.3.4 Dialect Tolerant Image Processing Language

To enhance the overall performance of the IAS, as well as to make possible the interchange of techniques and algorithms among the user community, a dialect tolerant image processing language is needed. Such a language will require precise definition for all of the various techniques and features which are elements of generic image processing (Wolfe, Chern, and Stokes, 1978).

The different areas of interest represented by the members of the user community can be thought of as individual dialects. While a certain terminology is used by geologists, a somewhat different terminology is used by agricultural analysts, etc. Yet, when the language differences are swept away, there remains considerable commonality in terms of the actual processing techniques being employed. To facilitate a sharing of such information, the language processing software which supports the various user interfaces should have the ability to see through the language differences used by various members of the user community and extract the common meaning. In such an environment, new developments will spread throughout the overall user community with great speed and afford all users with the maximum benefit which the system can deliver.

It is certainly advantageous from a user standpoint that the system be configured in a very flexible manner. It is not the intent to develop a system which is relatively immutable. To give the users the flexibility they would like to see, it will be necessary to have the capabilities of IAS available in what amounts to a "subroutine call" fashion as opposed to a main program fashion. This will allow each user to tailor a processing scenario to suit his needs without unduly constraining him. During the next portion of the IAS study, the primitives needed to provide a comprehensive solution to these two applications will be explored, and specified. However, the system, as a whole, will be tailored to allow the inclusion of additional processing primitives as needs dictate in the future.

APPENDIX A

Minutes of Meeting for Pre-Study

Minutes of the Meeting

Subject: Kick-off meeting for IAS

Date: Thursday, May 17, 1979

Present:

Peter Van Wie	(GSFC)
Paul Beaudet	BTS
Paul Maresca	BTS
John Morone	BTS
Bruce Gibbs	BTS

Purpose:

Introduce the IAS team to the NASA Technical Monitor and discuss other aspects of IAS.

Topics discussed:

- John Morone gave a presentation of his concept of the IAS job and how his background could be used advantageously in conducting the study.
- Identified the need to establish study assumptions as we go along and we discussed a few of them.
- Discussed the communications concepts of using 2-D representations for communications. In particular, the notion of Data products - vs - User characteristics were discussed.
- The need to have an initial system concept was established.
- A list of potential NEEDS elements and associated NASA personnel were identified for IAS Technical Exchanges.

Action Items:

- Determine a viable schedule for IAS Technical Exchange meetings (Paul Beaudet).

Sincerely submitted:

Paul R. Beaudet

Minutes of the Meeting

Subject: Review Table of Contents and Study Assumptions

Date: May 25, 1979

Present:

Peter Van Wie	GSFC
Paul Beaudet	BTS

Purpose:

To review the work done to date and to approve/modify the Table of Contents for the final report.

Topics discussed:

- Lee Holcomb from NASA Headquarters (OAST) would like a meeting on The IAS approach and assumptions of this study. NASA officials have strong feelings about what IAS should contain.
  - Bill Shaffer
  - Pitt Thorne
- Two dimensional Classification concepts and the relationship of IAS with Peter Argentero's work.
- Examined and approved our potential list of Study Assumptions.
- Reviewed Table of Contents and decided that it was inappropriate to ascertain what the final document should be like before the design was initiated. We postponed the review until after the pre-design effort.
- We agreed on a 'Document as you go approach' to the study for ease in generating final documentation.
- Discussed a Tree structure for classification and agreed to document the concept.
- Discussed list of applications - vs - algorithms and established approval of our approach to the pre-study tasks.
- Delineated our approach to establishing Feasibility Measures for algorithms.
- Gave a list of Feasibility Criteria and discussed a Feasibility - vs - algorit   -gram.

- Discussed the need to have a meeting with Fred Wulff on MDTS.
- Discussed the assumptions and philosophy of trying to adapt MPP for IAS before considering other concepts such as P^3 or CCD pipeline processors.
- Discussed on-board Image connections and the need to interface with Art Fuchs.
- Presented some documentations of work performed during the first two weeks of the IAS study.

Action Items:

- Document Tree structure concept for classification (Paul Beaudet).
- Set up meeting with Fred Wulff (Peter Van Wie).

Sincerely submitted:

Paul R. Beaudet

Minutes of the Meeting:

Subject: Technical Exchanges for IAS
Date: Friday, June 1, 1979

Present:

Peter Van Wie	GSFC
Fred Wulff	GSFC
Paul Beaudet	BTS
John Morone	BTS
Bruce Gibbs	BTS

Purpose:

To extract Format information with viable output lengths for IAS/MDTS interface.

Topics discussed:

- Distinction between Transport frames and Source Packet. We agreed to call our image 'packet' an image array so as not to confuse it with a 'Source Packet'.
- Ed Greene Standards from JPL was discussed - a 4600 bit packet with fixed length was not viable.
- The notion of 'Transparency' was discussed in which data from an instrument would remain uncontaminated by the communications process. (This is quite different from the IAS concept but can be made compatible if IAS has a 'Transparent' mode.)
- Forward Error Protection concepts were discussed and the reasons for them.
- Variable Bandwidths for MDTS 90 - 100%) with two modes:
  - Packet switching mode < 1Mb/sec.
  - Dedicated line mode > 1Mb/sec.
- Each channel will be capable of somewhere between 50 - 300 Mb/sec. (requirement).
- Source Packet Format

  See Bill Poland for Data Systems Requirement document or "Packet Standards".

- Philosophy of Secondary header

  Time • Attitude • Orbit
- He (FW) will not be available for MDTS discussions suggest seeing Mr. Sos.
- JPL has a document discussing IAS as an "on the Bus" distributed processing system.

Action Items:

- To retrieve "Packet Standards" from Bill Poland. (Peter Van Wie).

Sincerely submitted;

Paul R. Beaudet

MINUTES OF THE MEETING

SUBJECT: IAS Application Feasibility Review Meeting

DATE: Tuesday, June 19, 1979

PRESENT: Peter Van Wie, GSFC
David Fischel, GSFC
James Strong, GSFC
Paul Beaudet, BTS
John Morone, BTS

PURPOSE: To present the BTS approach for selecting *a priori* feasible sets of application for further study.

Topics Discussed:

- IAS block diagram
- Algorithm filtering
- Algorithm feasibilities
- Application costs
- Application pre-selection
- IAS desires
- IAS concepts
- Measures of feasibility
- IAS H/W system concepts

Action Items:

- Get 3 copies of presentation to Peter Van Wie (Paul Beaudet).
- Number of micro-operations/iteration was changed to number of micro-operations/algorithm (Paul R. Beaudet)

Sincerely submitted:

Paul R. Beaudet

MINUTES OF THE MEETING

Subject: IAS Technical Review

Date: Friday, August 24, 1979

Present: Peter van Wie, GSFC; David Fishel, GSFC; Paul Beaudet, BTS; John Morone, BTS; William Ataras, BTS

Purpose: To present this month's study results for the pre-study and attributes/selection tasks of IAS.

Topics Discussed:

1) John Morone gave a presentation of work done in the month of August. A copy of the presentation was available and given to all participants.

2) Questions were asked as to the application vs. algorithms chart with regard to the meaning of the numbers therein. John Morone explained that the numbers corresponded to the sequence of algorithms as they should be implemented for each application.

3) It was realized that the application class which had been previously called vegetation classification really corresponded to rangeland classification, and a proposal was put forth to change the name of that application class.

4) The notion of feasibility was clarified in that feasibility involved only the question of <u>algorithms/procedure</u> feasibility for each application.

5) A discussion was also initiated in regard to the use of only existing algorithms for the feasibilities study. It is anticipated that new problem areas for IAS onboard algorithms will be discovered in the algorithm pre-design task.

APPENDIX B

List of Applications Versus Algorithms

C-3

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Other Sources																							•		•		•		•	•										
Ground Processing			14											•																										
Human Interaction/Protation									•	•	•							•					•				•	•	•	•	•	•	•	•	•		•		•	•
Temporal Data									•	•	•		•														•													•
Regression																			•	•				•		•														
Threshold limits					6	11	6								6		8				8						8									7	7	7	7	7
Number (Theme)	11	11	11	11	6	12	6	11	6	6	6	11	11	11	6	11	6	6			6						8	8	8	8	8	8	8	8	8	8	8	8	8	8
Theme mean	12	12	12	12		13		12				12	12	12		12																				9	9	9	9	9
Theme variance	13	13	13	13		14		13				13	13	13		13												9	9	9	9	9	9	9	9	10	10	10	10	10
Ground Truth sampling									11	11	11							11							[illegible]															
Ratios (Spectral)	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4			4	4	4	4													
Mean																																								
Variances																																								
Spectral Weighted Signature	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)			(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)
Histogram Norm. (Haze Cor.)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)			(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Theme Generation																																								
Alligement (Spatial)																																								
Contour Mapping																																								
Moment Description																																								
Chain Encoding																																								
Region Growing																																								
- Point Detection	(5)	(5)	(5)	(5)		(5)		(5)	8	8	8	(5)	(5)	(5)		(5)		8																						
- Line Detection	(6)	(6)	(6)	(6)		(6)		(6)	9	9	9	(6)	(6)	(6)		(6)		9																						
- Corner Detection																																								
- Edge Detection																																								
Cursor Determinator																																								
Edge Detection	(7)	(7)	(7)	(7)		(7)		(7)	10	10	10	(7)	(7)	(7)		(7)		10																						
Karhunen-Loeve Transformation	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)			(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)
Averaging																																								
Relaxation Methods																																								
Curvature Principle Axes																																								
Edge Preserving Smoothing																																								
Hueckle Edge-Line Model																																								
Mixed Pixel Classification																																								
Linear Noise Suppression																																								
Linear Filtering - Smoothing																																								
Linear Filtering - Derivatives																																								
Line Enhancement																																								
FFT - Correlation																																								
FFT - Power Spectral																																								
Statistical Noise Suppression																																								
Curve Length Measurements																																								
Straight Length Measurements																																								
Hierarchical Classifiers																																								
Syntactic Approaches																																								
Perceptron																																								
Nearest Neighbor																																								
N-Dimensional																																								

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APPLICATIONS	Perceptron	Nearest Neighbor	N-Dimensional	2-Dimensional	Saturation	Maximum Likelihood	Texture Recognition	Table Look Up 40	Table Look Up 20	Supervised Training	Non-Supervised Clustering	Non-Parametric Clustering	Parametric Clustering	N Dimensional Histogram	1 Dimensional Histogram	PRODUCT TYPE
A01 Agricultural Crop Inventory (RB)						10				9	8			12		[illegible]
A02 Multi-Date Agricultural Crop Inventory (RB)						10				9	8			12		[illegible]
A03 Monitoring World Wide Food Productivity (RB)						10				9	8			12		[illegible]
A04 Plant Species Identification (RB)						10				9	8			12		[illegible]
A05 Plant Disease Detection (RB)																[illegible]
A06 Stem Inventory/Disease (LB)						10				9	8			12		[illegible]
A07 Plant Stress (due to insects, drought, nutrients) (RB)																[illegible]
A08 Estimation of Winter Wheat Yield (RB)						10				9	8			12		[illegible]
A09 Soil Conservation Practices (R)						13	7			12				5		[illegible]
A10 Soil Diagnosis (R)						13	7			12				5		[illegible]
A11 Soil Surveying (R)						13	7			12				6		[illegible]
A12 Acreage Measurement (LB)						10				9	8			12		[illegible]
A13 Agricultural Preservation (R)						10				9	8			12		[illegible]
A14 Large Area Crop Inventory (RB)						10				9	8			12		[illegible]
A15 Location of Citrus Trees (RB)																[illegible]
A16 Estimating Wheat Acreage (RB)						10				9	8			12		[illegible]
A17 Detection and Classification of Infestations of Crop Insect Pests & Diseases (RB)																[illegible]
A18 Mapping Soil (R)						13	7			12				5		[illegible]
F01 Forestry Classification and Timber Inventory (RB)						8				7	6			5		[illegible]
F02 Forest Typing (RB)						8				7	6			5		[illegible]
F03 Forest-non-Forest Delineation (LB)																[illegible]
F04 Detection of Forest Fires (RB)																[illegible]
F05 SO_2 Damage to Forests (RB)																[illegible]
F06 Forest Quality (RB)						8				7	6			5		[illegible]
F07 Gypsy Moth Defoliation (LB)										6	7		5			[illegible]
F08 Estimating Timber Volume (RB)						8				7	6			6		[illegible]
F09 Plant Stress Detection (RB)																[illegible]
R01 Range Resources Identification (RB)						8				5	4			7		[illegible]
R02 Vegetation Density (R)						6				5	4			7		[illegible]
R03 Estimating Vegetative Biomass for Range Management (LB)						8				5	4			7		[illegible]
R04 Plant Development and Range Conditions (R)						6				5	4			7		[illegible]
R05 Vegetation Conditions for Range Management (R)						6				5	4			7		[illegible]
R06 Classification of Vegetation (RB)						6				5	4			7		[illegible]
RC7 Natural Resource Inventory (RB)						6				5	4			7		[illegible]
R08 Natural Resource Management (RB)						6				5	4			7		[illegible]
L01 Land Use Classification (RB)						11				5	4			6		[illegible]
L02 Site Planning (RB)						11				5	4			6		[illegible]
L03 Large Area Mapping (R)						11				5	4			6		[illegible]
L04 Nuclear Restoration of Land (LB)						11				5	4			6		[illegible]
L05 Urban Growth (R)						11				5	4			6		[illegible]

ALGORITHMS

S - STATISTICAL
M - MULTI-THEMATIC IMAGE
F - FLAG
T - SINGLE THEME IMAGE
H - HEAVY HUMAN INTERPRETATION
- See Note
( ) - Optional

Other Sources	8 8 5	8	8	8 8	8 8		8	8
Ground Processing								
Human Interaction/Protection	8 8 8 8	8 8 8	8 8 8 8	8 8 8	8 8 8 8 8	8 8 8 8	8 8 8 8	8 8 8
Temporal Data		8	8 8			8		8 8
Regression		9	9	9	11			
Threshold limits	7 7 6	6 8 7 7 7	7 7 6	6 7 7 7	6 6 10	7 6	6 6	
Number (Theme)	8 6 8	8 6 8 8	8 8 8	8 8 8 8	6	8		6
Theme mean	9 9	9 9 9	9 9	9 9 9	7	9		
Theme variance	10 10 5	5 10 10 10	10 10	10 10 10	5 5 8	10		6
Ground Truth sampling	8 6	4	8	11	4 4 8 9 8	8	4 4 6 6	5 5
Ratios (Spectral)	4	4	6	4 4				
Mean								
Variances								
Spectral Weighted Signature	(2) (2) (2) (2) (2)	(2) (2) (2) (2) (2)	(2) (2) (2) (2)	(2) (2) (2) (2) (2)	(2) (2) (2) (2) (2)	(2) (2) (2) (2)	(2) (2) (2) (2)	(2) (2)
Histogram Norm. (Haze Cor.)	(1) (1) (1) (1) (1)	(1) (1) (1) (1) (1)	(1) (1) (1) (1)	(1) (1) (1) (1) (1)	(1) (1) (1) (1) (1)	(1) (1) (1) (1)	(1) (1) (1) (1)	(1) (1)
Theme Generation								
Alignment (Spatial)								
Contour Mapping								
Moment Description								
Chain Encoding								
Region Growing					7 7 8 8	5		
- Point Detection	5 7	7	5		8 8			
- Line Detection	8	8			6 6	6		
- Corner Detection	6		6					
- Edge Detection								
Corner Determinator				5	9 9 4 4	4 5	5 5	
Edge Detection	4 9	9	4					
Karhunen-Loeve Transformation	(3) (3) (3) (3) (3)	(3) (3) (3) (3) (3)	(3) (3) (3) (3)	(3) (3) (3) (3) (3)	(3) (3) (3) (3) (3)	(3) (3) (3) (3)	(3) (3) (3) (3)	(3) (3)
Averaging						(8)	(8)	
Relaxation Methods								
Curvature Principle Axes								
Edge Preserving Smoothing	7 (10)	(10)	7		(10) (10) 7 7	7		
Double Edge-Line Model				7		7	7 7	
Mixed Pixel Classification								
Linear Noise Suppression					(12) (12)			
Linear Filtering - Smoothing	(13)	(13)			(13) (13)			
Linear Filtering - Derivatives	(12)	(12)						
Line Enhancement	11	11		6	11 11	6	6 6	
FFT - Correlation								
FFT - Power Spectral								
Statistical Noise Suppression	(14)	(14)			(14) (14) 4			
Curve Length Measurements								
Straight Length Measurements								
Hierarchical Classifiers								
Syntactic Approaches								
Perceptron								8
Nearest Neighbor								

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ALGORITHMS \ APPLICATIONS	L06 Area Measurements (S)	L07 Power Plant Siting (LS)	L08 Revise Geographic and Road Maps (MS)	L09 Inventory of Ponds (LS)	L10 Petroleum Exploration (HS)	L11 Mineral Exploration (HS)	L12 Monitoring Surface Mines (LS)	L13 Land Use Change (S)	L14 Delineation of Urban/Rural Areas (LS)	L15 Detailed Urban Structure (S)	L16 Traditional Map Preparation (HS)	L17 Changes in U.S. Metropolitan Regions (S)	L18 Regional Planning and Urban Development (S)	L19 Strip Mine Location (LS)	L20 Mapping Acid Mine Drainage (HS)	L21 Inventory of Surface Mined Areas (HS)	L22 Delineating Land Water Cover in Coal Mining Regions (HS)	L23 Classification of Inland Lakes (LS)	L24 Trophic Status of Inland Lakes (LS)	L25 Identification of Potential Recreation Areas (S)	L26 Mineral Exploration (HS)	L27 Base Metal Deposits (HS)	L28 Road Alignment (LS)	L29 Mapping of Wildland Fuel Characterization (HS)	L30 Regional Mapping (HS)	L31 Change Detection (S)	L32 Interpretation of Rivers and Roads (S)	W01 Watershed Management (HS)	W02 Measurement Snow Areas (S)	W03 Turbidity Pattern Identification (HS)	W04 Delineation of Land Water Boundaries (HS)	W05 Delineation of Hydrologically-Related Terrain Features (S)	W06 Hydrodynamics, Including Floods, Reservoirs, Estuaries (HS)	W07 Water Quality Evaluation (HS)	W08 Snow Cover and Evaluation (S)	W09 Dynamics of Playa Lakes (HS)	W10 Water Management (HS)	W11 Measuring Watershed Runoff (S)	W12 Flood Hazards (HS)
Mixed Pixel Classification																			7											7			7	7					
Linear Noise Suppression																																							
Linear Filtering - Smoothing					(13)	(13)															(12)	(12)																	
Linear Filtering - Derivatives					(12)	(12)															(13)	(13)																	
Line Enhancement					11	11													6		11	11								6			6	6					
FFT - Correlation																																							
FFT - Power Spectral																																							
Statistical Noise Suppression					(14)	(14)															(14)	(14)			1														
Curve Length Measurements																																							
Straight Length Measurements																																							
Hierarchical Classifiers																																							
Syntactic Approaches																																							
Perceptron																																							
Nearest Neighbor																																						6	
N-Dimensional																																							
2-Dimensional							7							7		7																							
Bayesian																																							
Maximum Likelihood	11	11		6	16	16		11	11	11		11	11				11	11		11	16	16		11		11													6
Texture Recognition																																							
Table Look Up 40																																							
Table Look Up 20																																							
Supervised Training	5	5					5	5	5	5		5	5	5		5	5	5		5						5													4
Non-Supervised Clustering	4	4		5	15	15		4	4	4		4	4				4	4		4	15	15		4		4													
Non-Parametric Clustering																																							
Parametric Clustering																																							
N Dimensional Histograms	6	6		7				6	6	6		6	6				6	6	6	6				5		6				6			6	6					
1 Dimensional Histograms																													7										
PRODUCT TYPE	S	M	M	MS	MS	MS	M	MS	MS	MS	M	MS	MS	M	M	MS	MS	MS	MS	MS	MS	MS	M	MS	M	MS	MS	M	MS	MS	M	M	MS	MS	MS	M	M	S	MS

S - STATISTICAL
M - MULTI-THEMATIC IMAGE
F - FLAG
T - SINGLE THEME IMAGE
H - HEAVY HUMAN INTERPRETATION
- See Note
( ) - Optional

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Other Sources
Ground Processing
Human Interaction/Prestation
Temporal Data
Regression
Threshold limits
Number (Theme)
Theme mean
Theme variance
Ground Truth sampling
Ratios (Spectral)
Mean
Variances
Spectral Weighted Signature
Histogram Norm. (Norm Cor.)
Theme Generation
Alignment (Spatial)
Contour Mapping
Moment Description
Chain Encoding
Region Growing
- Point Detection
- Line Detection
- Corner Detection
- Edge Detection
Corner Determinator
Edge Detection
Karhunen-Loeve Transformation
Averaging
Relaxation Methods
Curvature Principle Axes
Edge Preserving Smoothing
Hueckle Edge-Line Model
Mixed Pixel Classification
Linear Noise Suppression
Linear Filtering - Smoothing
Linear Filtering - Derivatives
Line Enhancement
FFT - Correlation
FFT - Power Spectral
Statistical Noise Suppression
Curve Length Measurements
Straight Length Measurements
Hierarchical Classifiers
Syntactic Approaches
Perceptron
Nearest Neighbor

FOLDOUT FRAME

FOLDOUT FRAME 2

S - STATISTICAL
M - MULTI-THEMATIC IMAGE
P - PLAN
T - SINGLE THEME IMAGE
H - HEAVY HUMAN INTERPRETATION
* - See Note #4
( ) - Optional

ALGORITHMS

APPLICATIONS	PRODUCT TYPE	1 Dimensional Histograms	N Dimensional Histograms	Parametric Clustering	Non-Parametric Clustering	Non-Supervised Clustering	Supervised Training	Table Look Up 40	Table Look Up 20	Texture Recognition	Maximum Likelihood	Bayesian	2-Dimensional	N-Dimensional	Nearest Neighbor	Perceptron	Syntactic Approaches	Hierarchical Classifiers	Straight Length Measurements	Curve Length Measurements	Statistical Noise Suppression	FFT - Power Spectral	FFT - Correlation	Line Enhancement	Linear Filtering - Derivatives	Linear Filtering - Smoothing	Linear Noise Suppression	Mixed Pixel Classification	Mobile Edge-Line Model
W13 Watershed Wide Evapotranspiration (LB)	M																												
W14 Flood Plain Mapping (HB)	SMH						6				6																		
W15 Snow Mapping (B)	M																												
W16 Mapping of Hydrothermal Alternation Zones (LB)	M																												
E01 Environmental Surveys (VB)	SM		5			4					12																		
E02 Wildlife Habitat Evaluation (HB)	SM		5			4					12																		
E03 Thermal Pollution (HB)	M																												
E04 Air Pollution Studies (VB)	M																												
E05 Measure Atmospheric Aerosol Content (B)	M																												
E06 Strip Mine and Reclamation Maps (LB)	M						5						2																
E07 Environmental Impact of Freeways (LB)	M																												
E08 Grizzly Bear Habitat Analysis (HB)	M																												
E09 Breeding Habitat of Migratory Waterfowl (HB)	M																												
E10 Wildlife Management (VB)	SM		5			4					12																		
E11 Screwworm eradication (HB)	M																												
E12 Defining Salt Marsh Mosquito Breeding Areas (LB)	SM					5	6				7																		
E13 Inventory and Analysis of Environmental Problems (HB)	SM		5			4					12																		
E14 Human Impact on Tropical Vegetation (B)	M																												
E15 Locust Breeding (B)	M																												
C01 Marine Resources (VB)	SMH		8				7				8													6					
C02 Location of Schools of Fish (LB)	MH		8				7				8													6					
C03 Monitor Off-Shore Oil Production (VB)	M																												
C04 Algae Concentration Determination (B)	SMH		8																					6				7	
C05 Coastal Zone Resources (VB)	M																												
C06 Coastal Zone Management (VB)	M																												
C07 Mapping of Shorelines (LB)	MH																												
C08 Mapping of Shoals (HB)	MH					4	5				11																		
C09 Wetlands Inventory (B)	SM		6																										
C10 Bathymetry Determination (B)	SMH		8																					6				7	
C11 Bottom Topography Studies (B)	SMH		8																					6				7	
C12 Mean High/Low Water Line Determination (LB)	M																												
C13 Pollution Detection (HB)	SM		8																					6				7	
C14 Coastal Wetland Detection (HB)	SM		6			4	5				11																		
C15 Wetland Characterization (VB)	SM						3				(4)																		
C16 Availability and Distribution of Living Marine Resources (VB)	MH		8				7				8													6					
C17 Coastal and Navigational Charts (VB)	MH																												
C18 Monitoring Coastal Water Properties and Current Circulation (VB)	MH		8																					6				7	
C19 Estuarine and Coastal Oceanography (VB)	MH																												
C20 Mapping of Sediment Concentration in Tidal Estuaries (LB)	MH		8																					6				7	
C21 Mapping of Coastal Wetlands (VB)	M																												

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Other Sources							x				x				x				x	x		x	x		x	x	x	x		x	x	x	x		x	x	
Ground Processing							x																														
Human Interaction/Protation	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	
Temporal Data				x	x						x				x	x				x								x		x	x	x	x		x	x	
Regression																																					
Threshold limits	6	6	6	6	6	6	6	6	6	6		6	6		6	6	6	6	6		6			6								6				6	
Number (Theme)																													10			7				7	
Theme mean																													11								
Theme variance	5	5	5	5	5	5	5	5	5	5		5	5		5	5	5	5	5										12								
Ground Truth sampling	4	4	4	4	4	4	4	4	4	4		4	4		4	4	4	4	4										9	8	8						
Ratios (Spectral)																					4			4					4			4	4			4	
Mean																																					
Variances																																					
Spectral Weighted Signature	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)		(2)	(2)		(2)	(2)	(2)	(2)	(2)		(2)			(2)					(2)	(2)	(2)	(2)	(2)			(2)	
Histogram Norm. (Haze Cor.)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)		(1)	(1)		(1)	(1)	(1)	(1)	(1)		(1)			(1)					(1)	(1)	(1)	(1)	(1)			(1)	
Theme Generation																																					
Allignment (Spatial)																																					
Contour Mapping																																					
Moment Description																																					
Chain Encoding																																					
Region Growing																																					
- Point Detection	7	7	7	7	7	7	7	7	7	7		7	7		7	7	7	7	7										6	5	5	5				5	
- Line Detection	8	8	8	8	8	8	8	8	8	8		8	8		8	8	8	8	8										(3)			(3)				(3)	
- Corner Detection																														6	6						
- Edge Detection																																					
Corner Determinator																																					
Edge Detection	9	9	9	9	9	9	9	9	9	9		9	9		9	9	9	9	9		6			6						4	4		5				
Karhunen-Loeve Transformation	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)		(3)	(3)		(3)	(3)	(3)	(3)	(3)		(3)			(3)						(3)	(3)		(3)				
Averaging																																					
Relaxation Methods																																					
Curvature Principle Axes																																					
Edge Preserving Smoothing	(10)	(10)	(10)	(10)	(10)	(10)	(10)	(10)	(10)	(10)		(10)	(10)		(10)	(10)	(10)	(10)	(10)											7	7						
Hueckle Edge-Line Model																																					
Mixed Pixel Classification																																					
Linear Noise Suppression																																					
Linear Filtering - Smoothing	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)		(12)	(12)		(12)	(12)	(12)	(12)	(12)																		
Linear Filtering - Derivatives	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)		(13)	(13)		(13)	(13)	(13)	(13)	(13)																		
Line Enhancement	11	11	11	11	11	11	11	11	11	11		11	11		11	11	11	11	11		7			7					7				6				
FFT - Correlation																																					
FFT - Power Spectral																																					
Statistical Noise Suppression	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)	(14)		(14)	(14)		(14)	(14)	(14)	(14)	(14)																		
Curve Length Measurements																																					
Straight Length Measurements																																					
Hierarchical Classifiers																																					
Syntactic Approaches																																					
Perceptron																																					

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S - STATISTICAL
M - MULTI-THEMATIC IMAGE
F - FLAG
T - SINGLE THEME IMAGE
H - HEAVY HUMAN INTERPRETATION
R - See Note #
( ) - Optional

ALGORITHMS

APPLICATIONS	PRODUCT TYPE	1 Dimensional Histogram	N Dimensional Histogram	Parametric Clustering	Non-Parametric Clustering	Non-Supervised Clustering	Supervised Training	Table Look Up 40	Table Look Up 20	Texture Recognition	Maximum Likelihood	Bayesian	2-Dimensional	N-Dimensional	Nearest Neighbor	Perceptron	Syntactic Approaches	Hierarchical Classifiers	Straight Length Measurements	Curve Length Measurements	Statistical Noise Suppression	FFT - Power Spectral	FFT - Convolution	Line Enhancement	Linear Filtering - Derivatives	Linear Filtering - Smoothing	Linear Noise Suppression
G01 Terrain Feature Analysis (VB)	SH					15					16										(14)			11	(13)	(12)	
G02 Structural Geology (Faults, Folds, Lineaments)(HB)	SH					15					16										(14)			11	(13)	(12)	
G03 Geomorphology (Landform Classification) (HB)	SH					15					16										(14)			11	(13)	(12)	
G04 Lithological Mapping (B)	SH					12					16										(14)			11	(13)	(12)	
G05 Geological Hazards (HB)	SH					15					16										(14)			11	(13)	(12)	
G06 Landslides (HB)	SMH					15					16										(14)			11	(13)	(12)	
G07 Volcano Studies (LB)	SMH					15					16										(14)			11	(13)	(12)	
G08 Vehicular Scars (HB)	MH					15					16										(14)			11	(13)	(12)	
G09 Surface Lithologies (HB)	SH					15					16										(14)			11	(13)	(12)	
G10 Stratigraphic Subdivision of the Transvaal Dolomite (HB)	SH					15					16										(14)			11	(13)	(12)	
G11 Major Sand Seas in Desert Areas (LB)	M																										
G12 Monitoring Global Volcanic Activity (B)	SMH					15					16										(14)			11	(13)	(12)	
G13 Spectral Geological Mapping (HB)	SM					15					16										(14)			11	(13)	(12)	
G14 Earthquakes and Tectonic Evolution (B)	M																										
G15 Roof Falls in Underground Coal Mines (HB)	SM					15					16										(14)			11	(13)	(12)	
G16 Geological Significance of Temporal Changes (B)	SMH					15					16										(14)			11	(13)	(12)	
G17 Significance of Selected Lineaments (B)	SMH					15					16										(14)			11	(13)	(12)	
G18 Geomorphical Evolution of Lake Basins (LB)	SMH					15					16										(14)			11	(13)	(12)	
G19 Boundaries of a Buried Pre-Glacial Valley (HB)	MH					15					16										(14)			11	(13)	(12)	
M01 Determination of Wind Fields (VB)	M2																										
M02 Cloud Classification (VB)	SMH		9			5																		7			
M03 Temperature Profiles (VB)	MG																										
M04 Surface Temperatures (HB)	MG																										
M05 Cloud Cover Survey (HB)	SMH		9			5																		7			
M06 Prediction and Assessment of Natural Disasters (LB)	MH				2																						
M07 Freeze Prediction Based on Surface Temperatures (B)	MG																										
M08 Mapping Soil Moisture (B)	MG																										
M09 Mapping Rainfall (VB)	MG																										
O01 Determination of Sea State (VB)	SMH		13			5				8														7			
O02 Chart Unknown Reefs (VB)	MH																										
O03 Assist Navigation (VB)	MH																										
O04 Location of Ice Masses (VB)	MH																										
O05 Study of Biological Processes (HB)	MH		8								7													6			
O06 Study of Current Patterns (VB)	MI																										
O07 Ocean Internal Waves (B)	M																										
O08 Sea Ice Surveillance (VB)	MH																										

N1: Thermal IR Scanner.

N2: Time Lapse Movies of Cloud Trajectories.

N3: Infrared Radiometer centered on a very opaque absorption band of the constituent gases over several wavelengths and opacities.

N4: Geo Stationary satellite to perform many meteorological applications.

N5: Gravimetric Methods or Tensiometers or Neutron Scattering Methods.

N6: Relate cloud area to associated radar echo area and then relate echo area to volumetric rainfall.

APPENDIX C

Rationale for Algorithmic Attribute Measures

In this Appendix, we give our rationale for measures that have been established for the eight attributes associated with the thirty-five algorithms as shown in Table C-1 of this Appendix. This appendix is organized according to the attributes that have been measured and where a value of 0 has been established for the attribute implies that algorithm does not involve the particular attribute being measured; only non-0 attribute measures are discussed in this Appendix. The eight attributes which are called X1 through X8 in the Feasibility Study are:

X1 = degree of human interaction
X2 = algorithmic complexity
X3 = adaptivity
X4 = data storage
X5 = computational requirements
X6 = _a priori_ knowledge
X7 = control requirements
X8 = data structuring.

Degree of Human Interaction

The degreee of human interaction attribute is based on the number of human provided parameters that are required during the execution of the algorithm. The entries in Table C-1 under heading X1 are described herein.

The "regression" algorithm is conceived of as a ground aid for human interaction. The results of any regression analysis is usually a plane in multi-dimensional space. The simplist case is two dimensional regression analysis in which two parameters, slope and intercept must be communicated to the onboard processor. So, an entry of two is provided in Table C-1 For "threshold limits", every limit requires an upper and lower bound threshold. Hence, an entry of two is provided. Six parameters are required for ground truth sampling; they are the latitude and longitude of the center of the ground truth region, the width and length of the region, its orientation and the sixth item defines its signature class. For "spectral ratios", two parameters are required; the delineation of the particular spectral bands to be used as (1) numerators and (2) denominators. For "histogram normalization", it is necessary to communicate the detailed histogram to which normalization is desired. This histogram can be provided in sixty-four relative levels uniformly distributed over radiance values. In order to implement the "Karhunen-Loeve" transformation, used in reducing the dimensionality of the available spectral channels, it is necessary only to decide on how many output channels are desired as a result of the transformation; so, one parameter must be provided. The "averaging" algorithm requires humanly provided information to delineate the size of the region which is desired to be averaged; two parameters are required for this; (1) the number of pixels and (2) the number of lines in the averaging region. In the execution of an "edge preserving smoothing" operator, the variances may be taken about a uniform region, a plane, or a quadratic for <u>various shaped</u> pixel configurations. Decisions are made on the basis of these extracted variances as to the viability of replacing that pixel by the mean of one of these geometric pixel configurations. A single parameter, which we can call the state parameter, is required to delineate which of the edge preserving smoothing algorithms is desired. The "maximum likelihood classifier" requires <u>a priori</u> knowledge about the means and covariances of these classes to be classified. A two dimensional classifier would require two parameters to define a two channel means and three parameters to define the corresponding two dimensional covariance matrix. These five parameters are required for each class of data which is desired. The use of sixteen such classes is being assumed in this case for a total of eight parameters. In "supervised training" it is necessary to give the location, orientation, size, and class of the region in which training is to occur. This information requires six parameters. "Non-supervised clustering" requires one human provided parameter; the initial number of clusters that are desired. "Parametric clustering" also requires this piece of information and the "histogram generation" will require the partitioning of multi-dimensional space into regions required for the histogram. We assumed four spectral bands and a partition of each band into sixty-four regions, giving a total of 256 parameters that are required.

Algorithmic Complexity

The complexity of an algorithm is defined as the number of distinct primitives that must be executed for the specific algorithm. Many of the entries in Table C-1 are 1. For such entries the specific algorithm is, in fact, considered to be a primitive. The "regression" algorithm consists of two primitives. The execution of means and variances needed by the human operator to update his data base in the delivery of new slopes and intercepts resulting from the regression. In the execution of "theme variances", it is necessary to execute two statistical entities the theme mean (averaged radiance) and the theme averaged radiance squared. In the "ground truth sampling" algorithm, three primitives are identified, (1) the development of a ground region theme, the establishment of (2) the theme mean, and of the (3) theme variance. The "line detection algorithm" involves two primitives; (1) the extraction of derivatives and (2) the contraction of the X and Y derivatives in generating a gradient scalar. Corner detection also involves two primitives; (1) the extraction of second derivatives from linear filters for the definition of the curvature tensor and (2) the self contraction of that tensor, i.e., (the determinant) for the generation of a corner detection scalar. The "Karhunen-Loeve" transformation involves three primitives, (1) the product functions between pairs of bands, (2) the means of such over such product functions and (3) the generation of eigen functions associated with the established covariance matrix. "Edge preserving smoothing" involves three primitives, (1) computation of means over a masked theme, (2) computation of the variants about a fixed representation and (3) a selection of the least variance over a set of alternative masks. The "mixed pixel classification" also requires three primitives, two required for the generation of edges, corners, lines, and point masks and a third one for the dissection of the mixed pixel into their relative percentages of neighboring classes. "Straight line measurements" require three primitives; two required for the identification of corners, and line ends, and the third for the computation of the distance between the identified points. "Hierarchical classifiers" require three primitives; (1) the linear combinations of spectral bands are required for the classifier, (2) the generation of an address from the multi-dimensional signatures that have been pre-computed and (3) the looking up of the class as a table look-up process. "Neighborhood clustering" requires four primitives; three are associated with the classifier needed to classify the data and the other is associated with the extraction of the mean of the class. N-dimension classifiers require (1) the combination of multi-spectral channels into an address and (2) the looking up of the class in a table. "Maximum likelihood classifiers" involve three primitives; (1) the dot product of the signature with a constant, (2) the square of the signatures which are then combined into a signature for the lcass, and (3) the choice made by finding the minimum of the resulting likelihood computation. Texture recognition is considered to involve two primitives; (1) the linear filtering for the extraction of texture signatures and (2) the generation of a texture scalar for recognition. "Supervised training" involves (1) the generation of the themed area, (2) the computation of the mean and (3) variance of the supervised region. "Parametric clustering" involves three primitives two for maximum likelihood classification and another for the generation of cluster means. It is assumed here that the a priori covariance matrices will not be recomputed.

Adaptivity

By adaptive algorithms, we mean those that require a specific and perhaps uncertain number of iterations. The amount of adaptivity is defined as the average number of iterations that are expected to occur before convergence. Most of the algorithms that have been defined and delineated in Table C-1 do not require any degress of adaptivity and are assigned a value of 1. However, "nearest neighbor clustering", "non-supervised clustering" and "parametric clustering" will require iteration. It is assumed that the number of iterations needed for convergence will average about four. It is also understood that convergence may not occur in these algorithms and it is expected that after six iterations, a convergence test will delineate the status of the clustering algorithms.

Data Storage

Each of the algorithms require a certain degree of data storage for its execution. These typically involve intermediate storage requirements for the computation to proceed. In particular, the amount of data storage is oriented towards the number of fixed constants that are needed for the specific algorithm, exclusive of values that may be expected to change over the course of time. Such changeable data is considered a separate entity in the study and is associated with a priori knowledge which is the sixth attribute in Table C-1. The measurement of data storage is given in the number of bytes. It also includes storage that may be required for the final answers. For example, in N-dimensional histogramming, it is assumed that 256 bins of information would be required in a two-dimensional histogram involving the dissection of each dimension into 256 parts. It is anticipated that in the execution of this algorithm, a higher dimensional histogram would be generated as a sequence of two dimensional ones so that the amount of storage requirement associated with the algorithm is kept to a minimum. In the ground truth sampling as a second example, 256 elements (again a 16x16 packet) has been assumed in relationship to potential ground truth sample sizes. The storage requirements for other algorithms are estimated on the basis of a practical implementation for onboard processing.

Computational Requirements

The computational requirements for each of the algorithms were computed as the number of micro operations that may be required for one iteration. It is very difficult to assess the exact number of micro operations that may be required, since this delineation would require explicit knowledge of the hardware and software that is involved in their execution. Also, some of the processes may be performed in special purpose hardware and were not considered viable in relationship to this attribute. Three algorithms fall into this class:

Threshold limits
Ground truth sampling
N. D. histograms.

It was felt that the threshold limit algorithm had more to do with the seventh attribute (control requirements) than computational requirements and is addressed more heavily in attribute seven. Ground truth sampling simply provides ground truth information and N. D. histograms involve more intimate connection with the adaptive aspects of IAS that it was felt more likely that special hardware might be built to accommodate these requirements. As such, they were not included in the computatiuonal requirements for information extraction. It is clear that the numbers in Table C-1 are subjective and are guided by a notion that a primitive operation of the simplist type would require approximately 256 operations. Such a primitive as theme mean and number counting constitutes such a primitive. More complex operations involving multi-spectral means, ie., (four channels are scaled up in proportion) take more micro-operations than less complex ones. There is really no significance to the number of decimal places that are in the table other than those which are the integer values that have been estimated on the basis of the algorithmic complexity.

A Priori Knowledge

A priori knowledge is information which may be changed on a daily, weekly, or monthly basis and are measured in the number of bytes of knowledge required for the execution of each algorithm. Many of the algorithms do not require a priori knowledge and are not included. A short description of the algorithmic requirements is given. "Regression" requires the polynomial order and the dimensionality required. Threshold limits requires the operational band, "spectral weighted signatures" require 4 weighting coefficients. "Point detection", "line detection", "corner detection" and "edge detection" are similar in that they each require a set of coefficients, their being, a 3x3, 4x4, 4x4 and 4x4 array respectively.The "Karhunen-Loeve" transform needs the number of features required while "averaging" needs to know the selection of bands and possibly some scale factor. "Edge preserving smoothing" requires coefficients for the operators. "Mixed pixel classification" requires the 2D signatures on the right and left of the pixel. "Smoothing" and "derivatives" require a 5x5 and 4x4 array of coefficients while "line enhancement" uses a 7x7 and the selected channel. "Statistical noise suppression" also requires a 7x7 but also needs the channel selection gain. "Straight length measurements" use line end and corner detectors which require 4x4 sets of coefficients. "Hierarchical classifiers" assuming 16 classes require 16 threshold values. "N-D classifiers" require the dimensionality. The "maximum likelihood classifier" utilizes a 16x16 table. "Texture recognition" uses a 4x4 set of coefficients and 4 threshold limit values. "Non-supervised clustering" needs the number of classes while "parametric clustering" requires for 2 dimensions, 2 means and 3 covariance measurements. "N-D histograms" require 256 bin sizes for histogram normalization.

Control Requirements

Control requirements are a measurement of the number of flag tests needed to execute an algorithm. It can be seen that many of the algorithms do not require tests and a value of is entered. The larger values indicate that more flag tests are required. "Number (theme)", "theme mean", "theme variance", "ground truth sampling", "theme generation", "line detection", "statistical noise suppression" and "supervised training" are all procedures which require a single yes or no type operation, therefore the value 1.

"Threshold limits" assuming 16 classes utilizing 2 dimensions will require decision for each upper and lower threshold value. "Karhunen-Loeve" transforms require the choice of the largest eigenvector of 4 possible eigenvactors. "Edge preserving smoothing" must choose one of eight directions (requiring 7 decisions) and it also requires a variance threshold decision. "Mixed pixel classification" needs to decide if the pixel is indeed mixed and if there is a legitimate third signature and it must do a comparison to a threshold value. "Statistical noise suppression" must decide on whether to apply it or not. "Straight length measurements" make decisions on whether it has a line end and a corner for 2 line ends and corners. "Hierarchical classifiers" make up to 16 decisions based on 4 nodes having upper and lower threshold values assuming 2D classification. "Nearest neighbor clustering" must make 15 decisions for 16 classes. "Maximum likelihood classifiers" utilizing table look-up requires 3 decisions on which table to use in a decision tree approach with 16 classes. "Non-supervised clustering" must decide whether to suppress a class or combine classes. "Parametric clustering" must make a maximum likelihood decision based on 16 classes.

Data Structuring

Data structuring refers to the maximum packet dimension required for an algorithm. Many of the algorithms have 4 as this entry and this is because as a base value it was assumed that an algorithm would operate on a 4x4 packet. Algorithms with a 1 value indicate an algorithm's ability to process a single value at a time very easily. Algorithms with larger values (4) indicate a requirement for less local data to execute them accurately. Note that these values are all calculated assuming a Rough Order of Magnitude. For example, "means", "variances", and "histrogram normalization" need to look at data covering a greater extent in order to calculate accurate values. "Straight length measurements" is also an operation covering a much larger region as are "N-D histograms".

Algorithms	Attributes							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Regression	2	2	1	8	1289	2	0	16
Threshold Limits	2	1	1	64	0	1	64	0
Number (Theme)	0	1	1	1	256	0	1	1
Theme Mean	0	1	1	1	256	0	1	1
Theme Variance	0	2	1	1	768	0	1	1
Ground Truth Sampling	6	3	1	256	0	0	1	16
Ratios (Spectral)	2	1	1	16	128	0	0	4
Mean	0	1	1	16	1024	0	0	16
Variances	0	1	1	16	3696	0	0	16
Spectral Weighted Signature	0	1	1	5	7168	4	0	4
Histogram Normalization	64	1	1	68	1024	4	0	16
Theme Generation	0	1	1	256	256	0	1	1
Point Detection	0	1	1	265	2816	9	0	3
Line Detection	0	2	1	272	4864	16	1	4
Corner Detection	0	2	1	272	4864	16	0	4
Edge Detection	0	1	1	272	1536	16	0	4
Karhunen-Loeve Transformation	1	3	1	20	9472	1	3	4
Averaging	2	1	1	258	192	2	0	4
Edge Preserving Smoothing	1	3	1	282	2048	26	8	5
Mixed Pixel Classification	0	3	1	260	320	4	2	4
Smoothing	0	1	1	281	7680	25	0	5
Derivatives	0	1	1	272	4096	16	0	4
Line Enhancement	0	1	1	306	1280	50	0	5
Stat. Noise Suppression	0	1	1	258	14080	51	1	7
Straight Length Measurements	0	3	1	8	2560	50	4	32
Hierarchical Classifiers	0	3	1	272	10752	16	16	4
Nearest Neighbor Clustering	0	4	4	160	229376	0	15	4
N-Dim. Classifier	0	2	1	513	512	1	0	3
2-Dim. Classifier	0	1	1	256	256	0	0	2

Table C-1 Algorithms and their Attributes

Algorithms	Attributes							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Max. Likelihood Classifier	80	3	1	37	1840	256	4	4
Texture Recognition	0	2	1	276	7680	20	0	4
Supervised Training	6	3	1	20	5120	0	1	4
Non-Supervised Clustering	1	1	4	69	4096	1	2	4
Parametric Clustering	1	4	4	165	229376	5	15	4
N-D Histogram	256	1	1	256	0	256	0	256

Table C-1 Algorithms and their Attributes (Continued)

APPENDIX D

Desirability Attributes

The IAS desirability attributes which make up the desirability measure are defined in such a way so as to consider the total requirements needed for an IAS application. For desirability, six attributes (X_i) have been defined. Table D.1 lists the desirability attributes as we see them now. We feel that each attribute will be evaluated on an IAS favorability scale shown in Figure D.1.

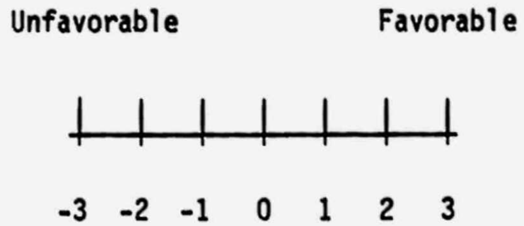


Figure D.1 IAS Favorability Scale

To find an application's total desirability cost, compute:

$$\text{Desirability measure} = \sum_{i=1}^{6} \alpha_i X_i$$

where α_i represents the equivalent cost coefficients. It is anticipated at this time that BTS will interface with the IAS application review committee to determine the appropriate X_i 's and α_i's for desirability measures. It should also be noted that we feel that if the application review committee feels more desirability attributes than have been listed need to be added, they should be added, and if they feel that any of the listed attribute measures should be deleted they, indeed, should be deleted. BTS feels that it is very important to bring the application review committee into the final selection process.

X_1	User Benefit for timely end-to-end information extraction and distribution
X_2	Cost reduction to user for pre-processing
X_3	Cost reduction to user for partial processing
X_4	Cost reduction to user for complete product
X_5	Utility of reduced data volume
X_6	Utility of increased standardization

Table D.1 Desirability Attributes

Maturity Measures

The maturity attributes which make up the maturity measures are associated with the success that have been achieved in specific applications for creating image products for the end user. Table D.2 lists the seven maturity attributes that have been distinguished at this time. As with the desirability measures, BTS expects to interface with the application review team to determine the proper attribute values X_i and the proper cost equivalences α_i in determining the correct maturity measure values $\sum_i \alpha_i X_i$.

Maturity Attributes (X_i)
X_1: Years of experience for application
X_2: Years of development required
X_3: Time to/from pre-operational system
X_4: Relative Ease (Measured on IAS favorability scale, Figure D.1)
X_5: Available funding (measured on IAS favorability scale, Figure D.1)
X_6: Number of distinct technologies
X_7: Application visibility (size of user base measured on IAS favorability scale, Figure D.1)

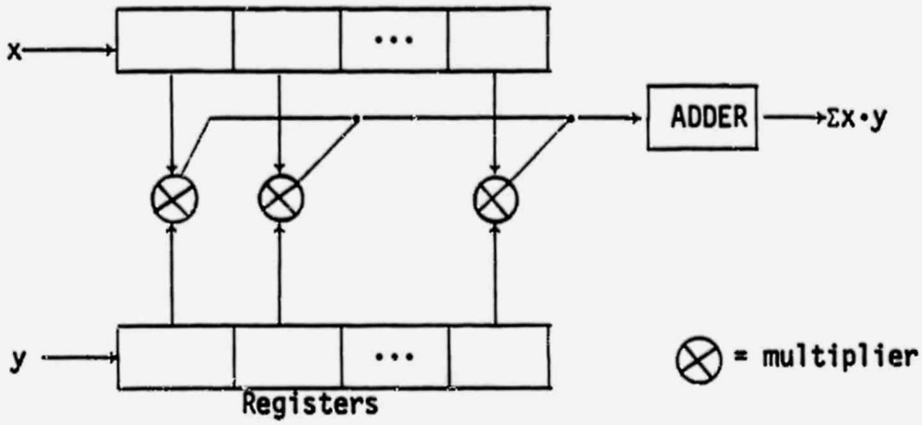
Table D.2 Maturity Attributes

APPENDIX E

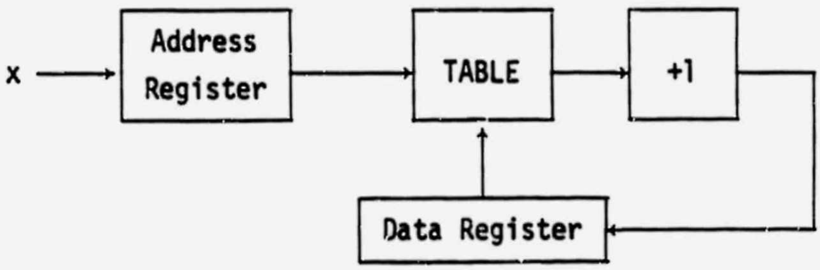
Conceptual Generic Primitives

1. <u>Linear Combinations</u> (Sum of Products)

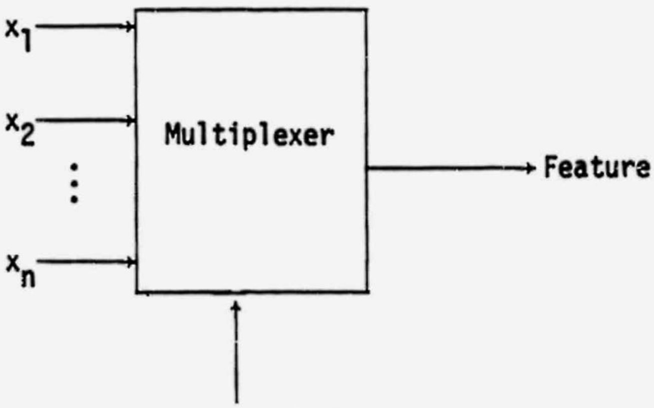
$$\Sigma x \cdot y = x_1 y_1 + x_2 y_2 + \cdots x_n y_n$$



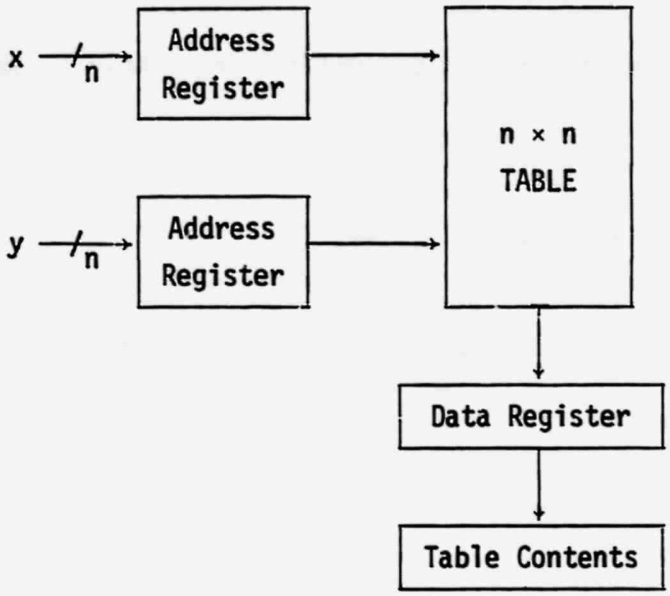
2. <u>Histogram</u> (256 - bin)



3. <u>Feature Selection</u>



4. Table Look-Up (Two-Dimensional)



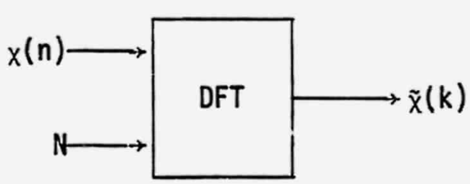
5. Matrix Multiplication

$$A_{m\times n}\, B_{n\times p} = C_{m\times p}$$

Matrix mulitplication involes $m\times p$ dot products, that is, it requires $m\times p$ linear combination operators. The conceptual linear combination operator is described in 1.

6. Discrete Fourier Transform

$$\tilde{x}(k) = \sum_{n=0}^{N-1} \chi(n)\, e^{-j(2\pi/N)nk}$$



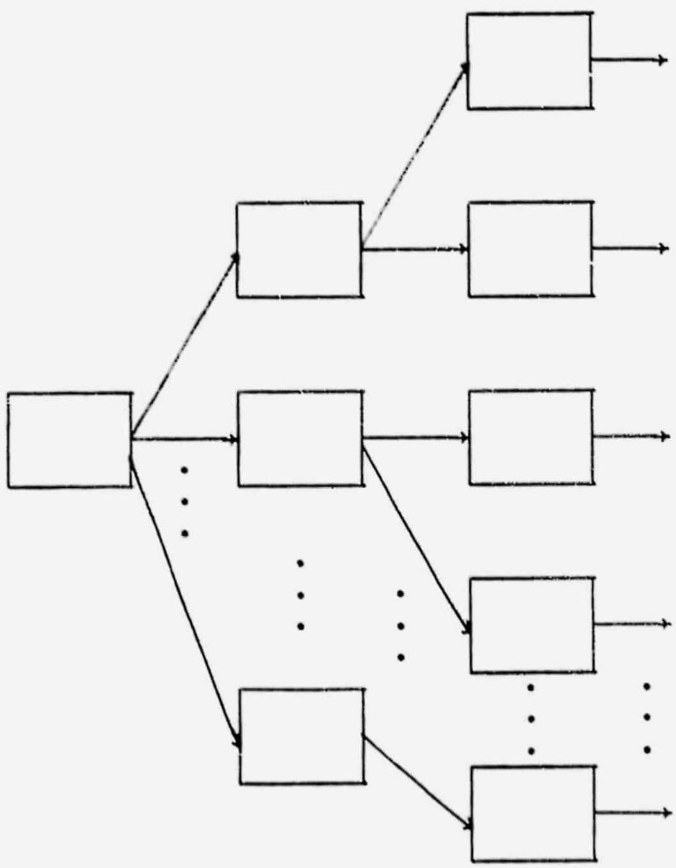
7. Linear Convolution

Let $x_1(n)$ and $x_2(n)$ be two N-point sequences, then, their linear convolution $x_L(n)$ is:

$$x_L(n) = \sum_{m=0}^{N-1} x_1(m)\, x_2(n-m) \; .$$

It is straightforward to implement this operation by using the linear computation device.

8. Tree Structure Processing



Each node processor contains processing functions, branching criteria termination criteria, structural parameters, and data pointers.

APPENDIX F
Geographic Data Selection

GEOGRAPHIC DATA SELECTION

The purpose of geographic data selection is such that the satellite given a set of parameters which describe a geographic area can decide whether the current pixel is either in the area or not. If it is in the specified area it is to transmit else no transmission.

To perform this task certain operations must take place, most of which are ground based activity. The goal being to give the satellite as little responsibility as possible to reduce the real time demands on the overall satellite system.

In all cases the geographic data selection procedure must begin with a circuit of points input by an operator. These points will probably be specified in latitude and longitude but for simplicity we will consider an x, y coordinate system now. In any case the algorithmic techniques apply.

Given a circuit of geographic points $(x_i, y_i) | i=1,\cdots n$ the first task is to generate an extended set of points $(\alpha_j, \beta_j) | j=1\cdots m$. These points are then operated on to determine the on-board geographic description for the satellite.

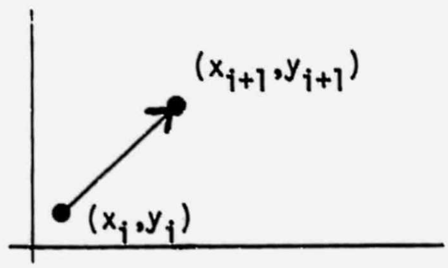
Step 1

A circuit of points $(x_i, y_i) | i = 1 \cdots n$ describe n-1 arcs. The object is to find the best discreet path from point (x_i, y_i) to (x_{i+1}, y_{i+1}) for all i . There are four possible orientations of these paths as described below.

A.

$x_{i+1} > x_i$

$y_{i+1} > y_i$



If Slope > 1 a=0,b=1

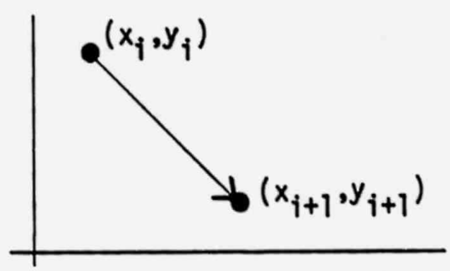
If Slope < 1 a=1,b=0

If Slope = 1 a=1,b=1

B.

$x_{i+1} > x_i$

$y_{i+1} < y_i$



If Slope >-1 a=0,b=-1

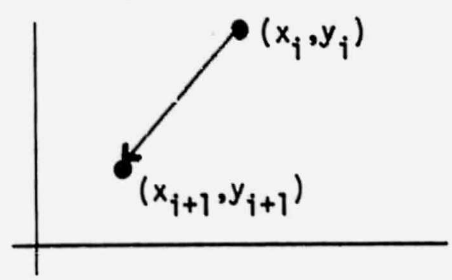
If Slope <-1 a=1,b=0

If Slope =-1 a=1,b=-1

C.

$x_{i+1} < x_i$

$y_{i+1} < y_i$



If Slope > 1 a=0,b=-1

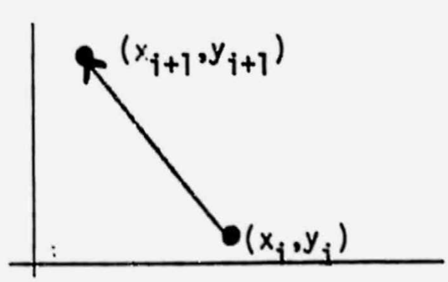
If Slope < 1 a=-1,b=0

If Slope = 1 a=-1,b=-1

D.

$x_{i+1} < x_i$

$y_{i+1} > y_i$



If Slope >-1 a=0,b=1

If Slope <-1 a=-1,b=0

If Slope =-1 a=-1,b=1

To generate the set $(\alpha_j,\beta_j)|j=1,\cdots m$ perform the following for <u>each arc</u> in the circuit:

$i \leftarrow 1$

$j \leftarrow 1$

Loop Until Arc Set Empty

$(x_i',y_i') \leftarrow (x_i,y_i)$

$(\alpha_j,\beta_j) \leftarrow (x_i',y_i')$

Loop Until $(x_i',y_i') = (x_{i+1},y_{i+1})$

Compute Slope from (x_i',y_i') to (x_{i+1},y_{i+1})

$$= \frac{y_{i+1} - y_i'}{x_{i+1} - x_i'}$$

Select Orientation A, B, C, or D and based on computed slope choose a and b

$j \leftarrow j+1$

$(\alpha_j,\beta_j) \leftarrow (x_i'+a,y_i'+b)$

$(x_i',y_i') \quad (\alpha_j,\beta_j)$

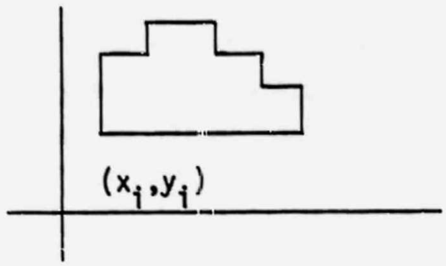
End;

$i \leftarrow i+1$

End

Step 2

Having generated the set $(\alpha_j, \beta_j) | j=1\cdots m$ it is a simple matter to scan these points and transform them to the following description.

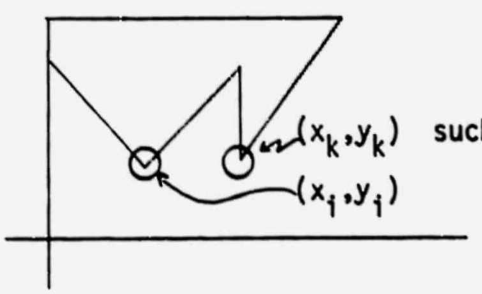


x_i, y_i, Length to the next (x_{i+n}, y_i)

$\vdots$

$i=1,\cdots k$

Note: The following situation must be checked for



such that $y_i = y_k$

Notice that the two circled points can cause the algorithm problems. It is very simple to solve this problem.

If $(x_{i-1}+1, y_{i-1}-1) = (x_i, y_i)$

and $(x_{i+1}-1, y_{i+1}-1) = (x_i, y_i)$ Then length = 0

If $(x_{i-1}-1, y_{i-1}-1) = (x_i, y_i)$

and $(x_{i+1}+1, y_{i+1}-1) = (x_i, y_i)$ Then length = 0

Note that there are other techniques for solving this problem; however, this single technique is illustrated to show that the problem is easily solved.

Having generated this set of points and lengths they can then be given to the satellite. With this detailed description, the satellite can then very easily determine if a pixel is in or not in the selected geographic area.