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TITLE: THE REAL-TIME LEARNING MECHANISM OF THE SCIENTIFIC RESEARCH ASSOCIATES ADVANCED ROBOTIC SYSTEM (SRAARS)

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ABSTRACT

SRAARS is an intelligent robotic system which has autonomous learning capability in geometric reasoning. The system is equipped with one Global Intelligence Center (GIC) and eight Local Intelligence Centers (LICs). It controls mainly sixteen links with fourteen active joints, which constitute two articulated arms, an extensible lower body, a vision system with two CCD cameras and a mobile base. The on-board knowledge-based system supports the learning controller with model representations of both the robot and the working environment. By consecutive verifying and planning procedures, hypothesis-and-test routines and learning-by-analogy paradigm, the system would autonomously build up its own understanding of the relationship between itself (i.e. the robot) and the focused environment for the purposes of collision avoidance, motion analysis and object manipulation. The intelligence of SRAARS presents a valuable technical advantage to implement robotic systems for space exploration and space station operations.

I. INTRODUCTION

While the control engineers are concentrating on the relationship between actions and responses, the artificial intelligence discipline is emphasizing mainly on understanding the processes and the descriptions of the knowledge formation. Learning is one of the major items within the overlapped area of these two disciplines. As mentioned in Reference 2, learning can be divided into a high-level symbolic category and a lower-level numeric variety. However, a complete learning mechanism will employ symbolic knowledge to instruct the numerical control system, and the information of sensor inputs will be processed to update or upgrade the symbolic knowledge base. The integrated structure of both quantitative descriptions and qualitative descriptions stands for a more appropriate interpretation of the human learning function.

In order to maintain the learning procedure as a progressively improving process, the parallel coherency of both the short term memory (STM) and the long term memory (LTM) is necessary. There are several approaches in maintaining this kind of operation, e.g. using neural networks (Ref. 5), or employing schemata (Ref. 6). Furthermore, for a real-time expert controlled system, STM should directly interact with the control scheme and LTM would serve as the supervisor (or teacher) (Ref. 3). Then, the resulting learning mechanism can fulfill the six-step knowledge acquisition procedure: perception, strategy, decision making, execution, result and evaluation. As shown in Figure 1, this closed-loop operation would eventually develop a certain extent of understanding which can be expressed as the integral of perceptions and the corresponded evaluations. That is,

$$\text{UNDERSTANDING} = \int \text{PERCEPTION} \wedge \text{EVALUATION} \tag{1}$$

The perceptions can be regarded as the qualitative descriptions of the event, and the evaluations would be the quantitative interpretations of the system's states. Therefore, a generic knowledge representation can be expressed as a set of tuples. That is,

$$\text{KNOWLEDGE} = \{(\text{Qualifier}[i], \text{Quantifier}[i]),\ i = 1,2,\ldots.\} \tag{2}$$

For a specific section of knowledge (e.g. automobile repair), the formation may not be unique, but the utilization of the knowledge base would have an objective standard to qualify the specific knowledge representation as an expert system. This concept is adopted as SRAARS' fundamental principle of establishing the real-time learning mechanism.

Not every quantitative representation has its corresponded wualitative description; also, not every qualitative description can be expressed in quantity. However, it is perceived that those situations which can not be depicted as a tuple of qualifier and quantifier are normally handled without explicit knowledge. In other words, they are termed as unreasonable or illogical such that improving the system performance with learning is uncertain. Therefore, excluding those cases will not affect the generality of the learning mechanism. It is then assumed that every piece of meaningful knowledge can be expressed in a tuple of (Qualifier, Quantifier). When the process of understanding reaches the predetermined level, the evaluated system performance would converge to the designated standard and the machine intelligence will be regarded as an expert. Then the system behavior under the expert controller without closed-loop updating will be just as good as that of the feedback closed-loop in Figure 1. For safety reasons, the feedback closed-loop may still need to be maintained for responding to the potentially changing environment. However, the frequency of processing the understanding procedure can be reduced from real-time to on-line supervising.

The main objective of the real-time learning of SRAARS is geometric reasoning. Therefore, the perception is the geometric interpretation. The strategy is to move the robotic system in an effective way such that the unwanted collision can be avoided and the assigned object manipulation can be achieved. Decision making would determine the strategy selection based upon given knowledge of the physical correlation of the environment and the robot. The execution would then carry out the decision in a model-referenced adaptive control. The result would decide the termination of the action; and the evaluation will praise the system performance based upon the chosen criteria such as the difference between the desired design and the actual accomplishment, the execution time and the repeatability, etc. In the next section, these functions will be explained in detail. The third section will introduce the actual implementation plan. A prototype of SRAARS is under development. The anticipated results are discussed in the final conclusion section.

II. THE FRAMEWORK OF SRAARS INTELLIGENCE

SRAARS is a general purpose mobile manipulator. Its real-time learning mechanism can be applied to any specific target domain. The only limitation is the memory size. Three sets of representation elements would require user input for qualitative expression, quantitative description and relational specification, respectively. The knowledge system has a library of inference tools (e.g. forward chaining and backward chaining, induction and deduction) and a set of strategies for heuristics and hypothesizing. The knowledge base is designed with the basic format of Equation 2. The overall learning/control system of SRAARS is illustrated in Figure 2.

The user input set of qualitative expressions would be the entire set of vocabulary which the system can accept and utilize. The current level of the system intelligence does not have the capability of generating any new expressions by itself. The set of quantitative descriptions has two subsets: one contains the symbolic specifications of variables, parameters and constants, such as ranges (e.g. minimum, maximum), types (e.g. integer, real, or boolean), and formats (e.g. scalar, vector or matrix); another is comprised of the corresponded numerical values of each entity specified in the previous subset. Every symbolic entity can represent only one item throughout the entire learning/control process to eliminate unnecessary internal conflict. The third input set of relational specification would provide the initial system knowledge in linking and grouping all the available qualifiers and quantifiers. Some examples of relational specifications are formula or equations among symbolic quantities, rules of thumb among qualitative terms or certain production rules which relate both qualitative and quantitative items.

II.1 KNOWLEDGE UTILIZATION

Most currently available expert systems require a certain extent of human involvement (Ref. 7). Ranging from off-line query format man-machine interface to on-line process advisory, the developed knowledge systems are designated as an auxiliary component in the real world operations, which is because the knowledge programming is still confined to the level of managing the expressiveness of various knowledge representations, and the methodology for actually utilizing the digested information is not available. The knowledge evolution is basically a dynamic process. Since there are quite a few methods to express the understanding of one particular issue, and a major proportion of knowledge of understanding does not have a direct connection to the necessary action. Therefore, knowledge utilization itself becomes a rather ambiguous phenomenon. Fortunately, it is less ambiguous in those occasions of skill learning (Ref. 2). The knowledge utilization of SRAARS will serve two purposes: improving the understanding of the working environment and employing the updated geometric knowledge of both the robot and its surroundings to execute the given assignment.

In the field of robotics, problems such as the reachability analysis of articulated mechanical systems with redundancy, the collision avoidance problem of mobile robots and the object extraction of robot vision are very difficult to solve in a general platform. The human approach of dealing with these problems is through a long period of learning. Therefore, the knowledge system of SRAARS is regarded as the core solution of mobile manipulation of the robot in general environments.

II.2 STRATEGY GENERATION

The system is initiated with knowledge of models of both the robot and the environment. The strategy at the beginning would be assuming these models are correct and plan the action accordingly to perform the given task. The decision maker then takes this strategy to execute the user commands. Some possible commands are "find object A in location C", "find object B in location D", "insert object A into object B, then place the sub-assembly on the conveyer belt", etc. The user commands would be translated into a sequence of actions for the controller to execute. The controller would employ a model-referenced adaptive scheme to plan the motion trajectory based upon the models and the assignment. Then, the actuating systems will be directed to realize the planned actions.

At the same time, an initial sensing action with default frequency is issued to monitor the robot motion and the changing environment. Therefore, both the vision system and other sensors such as ultrasonic sensors, proximity sensors or laser range finders, are sending data back to the brain. The data processor then converts the data into two formats. A direct conversion of input data to the values of system variables will be sent to the controller to serve as the output feedback of the control law. It will still maintain the data format. Another more complicated conversion will examine the input data with the existing knowledge base. The result is converted into an information format. The result will then be processed through the inference engine to conclude as knowledge verification and validation.

If there is a certain unacceptable inconsistency detected, then other strategy generation will be activated. The activation and the termination of different strategies are embedded in the kernel of the knowledge base which the user will not be able to access. However, users can change the level of acceptable inconsistency which triggers the activation and the termination of certain strategies, and increase or alter the strategy library. There are essentially two types of alternative strategies: heuristic approaches or hypothesis-and-test. The heuristic strategies are particularly suitable for object searching. When a segment of the environment model is detected to be incorrect (e.g. the original model does not have an object in that segment and current information indicates there is something in that area, or the previous model shows that there should be an object in that segment but the current sensor information cannot verify the existence of the object), a heuristic search strategy can be issued to take certain actions to modify the current model.

The hypothesis-and-test strategy can be utilized to resolve the potential reachability problem of the robot. The relationship between the robot model and the environment model can be very delicate when certain compliance activity is required. The articulated robot with many redundant degrees of freedom has a better chance to perform difficult interior operations. However, a general solution may require substantial computational effort (Ref. 4). Employing the knowledge engineering technique with an adequate hypothesis-and-test strategy is a practical solution to resolve these types of problems. For this particular situation, there may not be any inconsistencies in modeling; instead, the maneuverability of the robot is the main focal point. If the robot has n degrees of freedom, then the projection of n dimensional joint space to the three-dimensional world coordinates present a very complicated combinatorial problem, especially when the topological structure contains tree branches or closed-loops. This type of knowledge system application will be the first step of utilizing artificial intelligence to solve some problems which even human beings cannot provide a definite solution.

III. THE SYSTEM DESIGN OF SRAARS

The realization of SRAARS emphasizes more on the system feasibility than on the utilization of the state-of-the-art microprocessor technology. It is fully aware that an adequate integration of both CISC and RISC architectures, such as Intel 80486 and 80860, Motorola 68040 and 88000 series, may provide a more powerful platform within a miniature form factor for intelligent robot development. However, this technology is not yet matured. It is therefore considered as the system design platform of the next generation of SRAARS. Intel 80386 is selected as the main processor for current SRAARS development. The major bus connection between GIC and LICs is determined to be VME bus.

The Global Intelligence Center is regarded as the brain and the central neural system of SRAARS. It has the following major features:

- Multitasking with virtual 8086 mode;
- Asynchronous processing of memory management, computation, inference and I/O interface;
- Hierarchical interrupt control; and
- Real-time kernel with concurrent programming constructs.

The functional diagram of SRAARS's brain is shown in Figure 3. Each individual modular functionality is listed as follows:

C3BUS:

- Mother-daughter communication handshake
- Command send out to designated LICs
- Receive status reports from LICs
- Network management and control
- Record update and archive

RVR:

- Image coprocessor communication
- Frame buffer management
- Image analysis, including edge detection, motion detection and object extraction

SANE:

- Sensor sampling and data acquisition control
- Sensor/actuator network management
- Device-independent database management
- Input buffer update
- Limited sensor fusion and impulsive reactions

EAN:

- Environment model formulation and update
- Consistency analysis
- Map formulation, revision and interpretation

KBL:

- Knowledge base formulation
- Knowledge utilization including rule extraction, rule-data association, and strategy generation
- Knowledge base/data base integration
- Knowledge input processing

MSM:

- Memory management among various devices (e.g. ROM, RAM, or disks)
- Memory initialization and reboot sequence
- Memory swap, cache and page
- Backup routine
- Memory status update

SPE:

- Model-based control monitoring
- Self-correction and self-calibration
- System power monitoring
- System performance record

MMI:

- Human operator input interrupt handling
- Panel-driven task assignment input
- Task analysis
- Task recording and retrieving
- Task planning
- Task status update

There are eight Local Intelligence Centers. Six of them are employed for controlling the mechanical linkage manipulation. Every one of the six LICs would control two to three degrees of freedom of the robot. The decentralized control systems would carry out the spatial planning commands under AISP (Ref. 1). The seventh LIC is a dedicated machine vision system which would control two CCD cameras and two to three degrees of freedom of motion to manipulate the orientations of cameras. Lower level image processing will be accomplished in this LIC as well. The eighth LIC is utilized to control the mobility of the base which includes the driving, steering, braking and backup operations. Some major features of LICs are listed below:

- Mother-daughter interactive communication
- Local trajectory planning and execution
- Status report back to GIC
- Impulsive response override

The connection between GIC and LICs basically follows the VME specification. GIC and Four LICs, including vision and base control, are located at the mobile base compartment. The rest of LICs will be located at the central portion of the lower body. There is a dedicated cable to connect the "head", which contains cameras and the corresponded positioning mechanism, to the seventh LIC situated at the base. A general mockup of SRAARS is shown in Figure 4.

IV. THE CONCLUSION

The real-time learning mechanism of SRAARS is one of the innovative ideas which are incorporated into the development of SRAARS. It takes a plain and straightforward approach to integrate the knowledge system into the real world applications. The developed learning capability will move the knowledge engineering into the central arena of operating a complex dynamic system and perform as a decision maker. It would be interesting to see the comparative analysis with other conventional approaches if the explicit general solution may one day become available.

ACKNOWLEDGEMENTS

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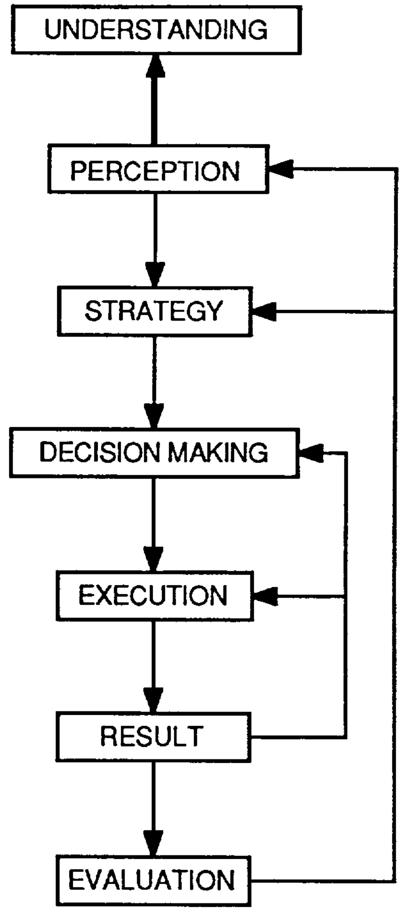

Figure 1. The Evolution Process of Understanding.

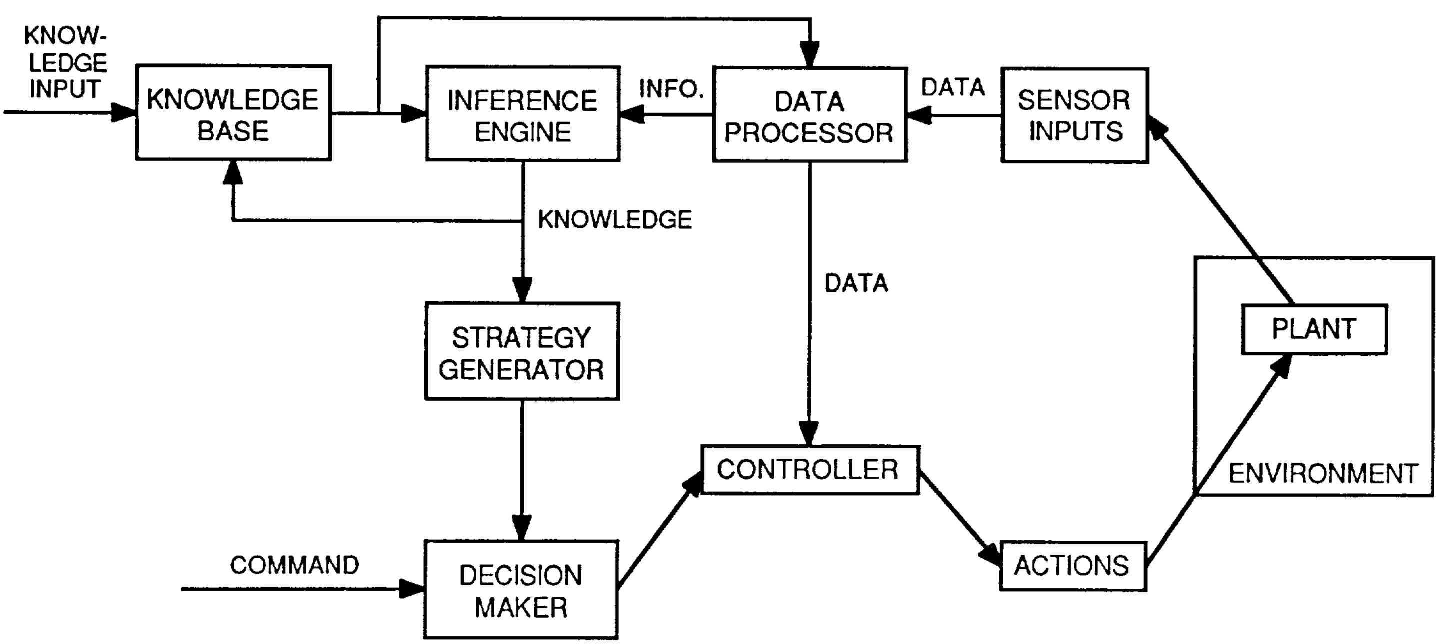

Figure 2. The Functional Diagram of the Learning Control System of SRAARS.

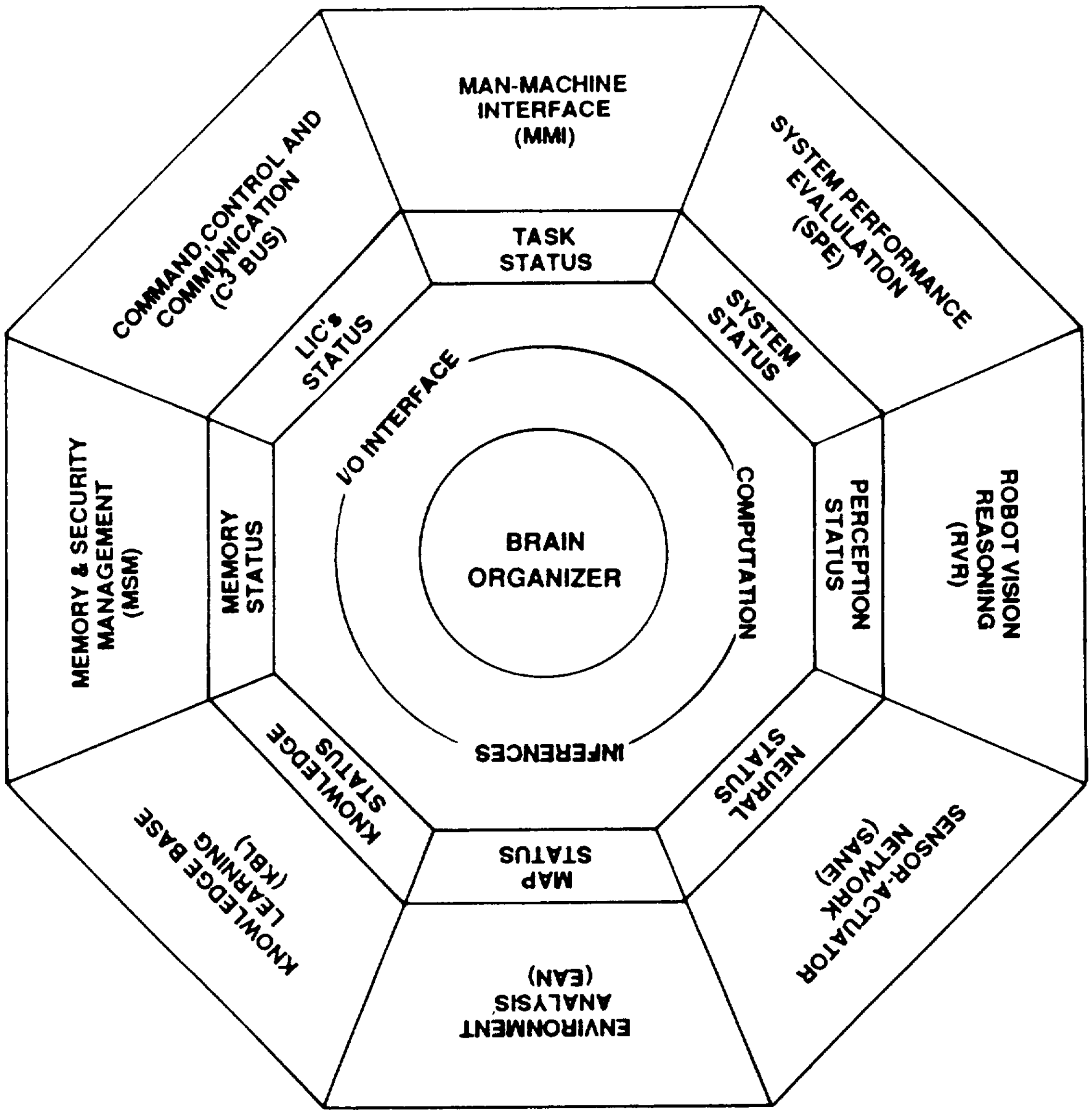

Figure 3. Functional Diagram of SRAARS's Brain.

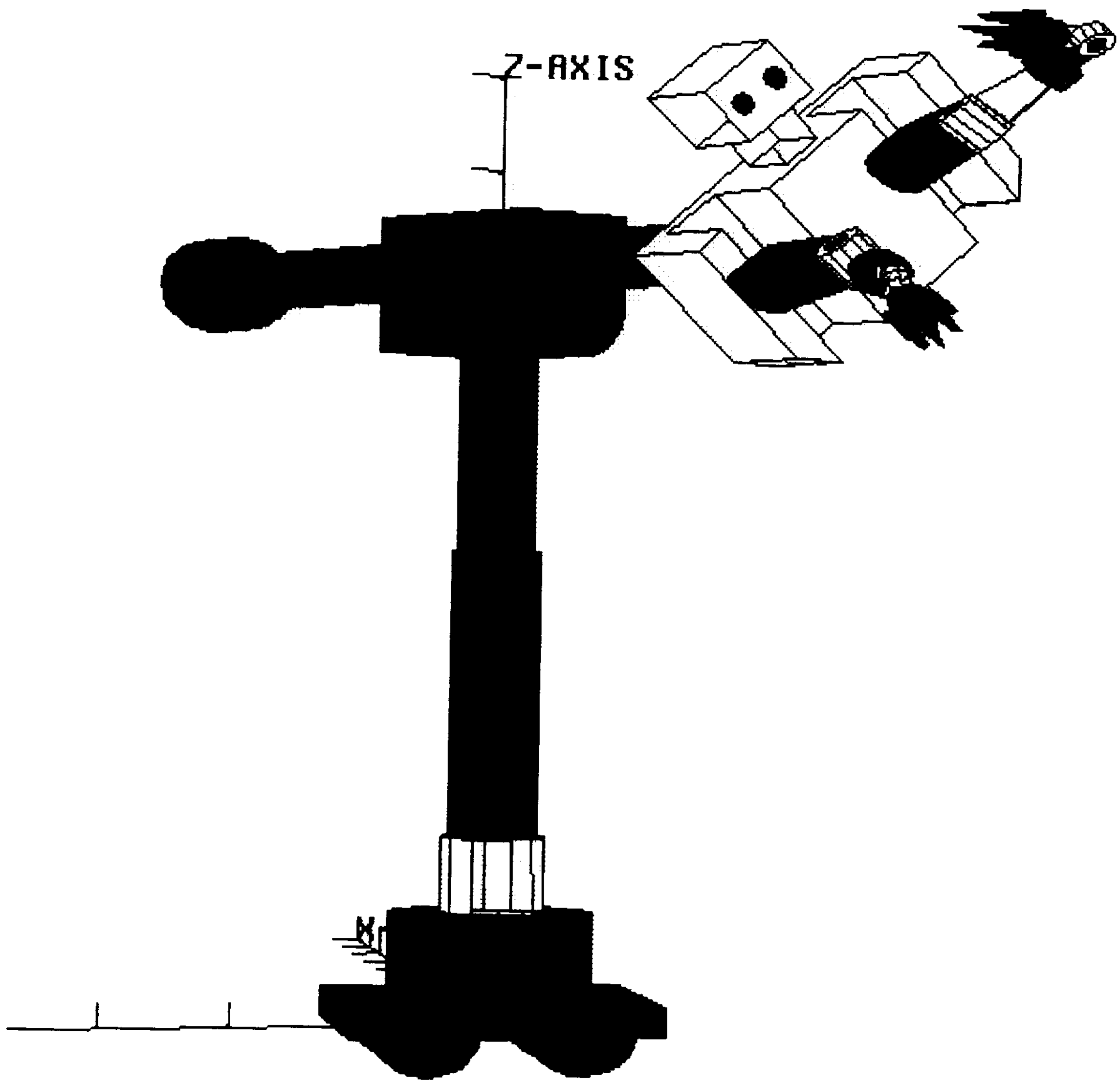

Figure 4. SRAARS Mockup