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QUANTITATIVE KNOWLEDGE ACQUISITION FOR EXPERT SYSTEMS

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ABSTRACT

A common problem in the design of expert systems is the definition of rules from data obtained in system operation or simulation. While it is relatively easy to collect data and to log the comments of human operators engaged in experiments, generalizing such information to a set of rules has not previously been a straightforward task. This paper presents a statistical method for generating rule bases from numerical data, motivated by an example based on aircraft navigation with multiple sensors. The specific objective is to design an expert system that selects a satisfactory suite of measurements from a dissimilar, redundant set, given an arbitrary navigation geometry and possible sensor failures. This paper describes the systematic development of a Navigation Sensor Management (NSM) Expert System from Kalman Filter covariance data. The development method invokes two statistical techniques: *Analysis of Variance (ANOVA)* and the *ID3 algorithm*. The ANOVA technique indicates whether variations of problem parameters give *statistically* different covariance results, and the ID3 algorithm identifies the *relationships* between the problem parameters using probabilistic knowledge extracted from a simulation example set. ANOVA results show that statistically different position accuracies are obtained when different navigation aids are used, the number of navigation aids is changed, the trajectory is varied, or the performance history is altered. By indicating that these four factors significantly affect the decision metric, an appropriate parameter framework was designed, and a simulation example base was created. The example base contained over 900 training examples from nearly 300 simulations. The ID3 algorithm then was applied to the example base, yielding classification "rules" in the form of *decision trees*. The NSM expert system consists of seventeen decision trees that predict the performance of a specified integrated navigation sensor configuration. The performance of these decision trees was assessed on two arbitrary trajectories, and the performance results are presented using a predictive metric. The test trajectories used to evaluate the system's performance show that the NSM Expert adapts to new situations and provides reasonable estimates of sensor configuration performance.

INTRODUCTION

Knowledge acquisition is a major problem in the development of rule-based systems. The tools developed to date are not designed to extract information from data for which no generalizations are known *a priori*. Instead, these tools either rely on the expert to provide examples from which rules are generated or try to capture the expert's problem-solving methodology with interviewing techniques [1]. Unfortunately, it often is difficult for experts to describe their problem-solving methods or to detail the factors that come into play during the resolution of a problem. It is exactly this type of knowledge that is needed to design rule-based systems.

Since the early 1970's adaptive navigation has been viewed as a highly desirable candidate for development in next-generation aircraft [2]. It is envisioned that future aircraft will have multi-sensor capability for navigation tasks requiring high reliability, optimal performance, and increased automation. With multi-sensor capability, the task of sensor configuration selection and management will become an additional pilot burden.

The performance of multi-sensor navigation systems (more commonly known as "integrated" or "hybrid" systems) has been explored since the late 1960's when results from modern control theory provided techniques for sensor mixing and optimal state estimation [3]. Hybrid systems refer to externally referenced navigation systems that "aid" an on-board inertial navigation system (INS) using an optimal state estimation mechanization. Hybrid navigation systems combine the high- and low-frequency accuracy properties of INSs and external navigation aids (navaids) respectively. Many radio navigation and on-board systems aiding INS have been modelled and their performance covariance results obtained [4-8]. When radio navigation systems are only partially operational, results show that improved navigation performance is obtained over that of the pure INS [4]. Therefore it becomes advantageous to keep partially operational systems as candidates for integrated sensor mixing purposes.

With a large number of available navaids, choosing an optimal or near-optimal sensor set becomes a large combinatorial problem. Convergence towards an optimal sensor configuration requires an exhaustive computer search utilizing simulation results as the basis for selection. In contrast, a small number of available navaids reduces the decision space considerably. Hence, a dilemma occurs; increasing sensor capability (and thus reliability and performance) increases decision-making complexity.

The selection of an optimal configuration requires the application of some decision criteria. Most often, designers choose between navaids based on the relative accuracies of each system using a hierarchical approach [9]. This approach is "knowledge-based" in the sense that the nominal performance of the systems is well-known and that this knowledge is built into the sensor hierarchy. The current hierarchical designs are not as "robust" with respect to sensor availability and performance changes as is necessary for future sensor management systems [10]. Instead, these hierarchies represent "rules-of-thumb" that

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are useful in only the simplest cases. They do not resolve sensor configuration problems when more detailed information must be considered – for example when the number of each available navaid is specified, when partially operational systems remain viable candidates, and when trajectory effects degrade system performance. It becomes necessary to explore factors other than the performance of nominally operating navaids to determine how these factors affect the decision-making process, and to exploit the potential of hybrid systems.

The statistical technique Analysis of Variance (ANOVA) [11] was used to identify the factors that cause variation in navigation performance. Once the important factors were identified, the relationships between them were determined. The ID3 algorithm [12,13], an inductive inference technique based on the probabilistic occurrence of events, was used to find these attribute relationships.

The development of a navigation sensor management expert system using the ANOVA/ID3 technique [14] is described in this paper. The NSM system controls the selection of multi-sensor configurations. The methodology is applicable to any problem where the development of knowledge bases from multi-factor data studies is desired.

INTEGRATED NAVIGATION SYSTEMS

Optimal estimation techniques are used to combine inertial and radio navigational systems in order to provide stable continuous inertial navigation information [15]. The errors exhibited by these "hybrid" systems depend on the accuracy of the aiding system, and navaid accuracies are functions of many factors such as navaid type, number of similar navaids, and trajectory parameters such as distance from the navaid and whether the aircraft is approaching or receding from the station. The sensor selection criteria depend on the relative importance of these factors. Five external radio navigation and two on-board navaids were used to update a medium-accuracy (10 N. Mi/hr) INS. Hybrid system performance was simulated using the linearized inertial navigation error model and navaid measurement models as inputs into the optimal estimation filter. The hybrid errors were updated at a specified navaid fix rate. The systems simulated were (1) Global Positioning System (GPS), (2) Long-Range Navigation System (LORAN), (3) Tactical Navigation System (TACAN), (4) Distance Measuring Equipment (DME), (5) VHF Omnidirectional Range (VOR), (6) Doppler radar, and (7) air data sensor. The operational theory and the mathematical models used to simulate the navaids and the inertial navigation error model are discussed in detail in [14].

The numerically-stable discrete-time U-D implementation of the Kalman Filter equations was used to mix the inertial system and navaid information optimally, providing covariance estimates of the navigation errors (e.g., north/east position) [14,17]. Each nonlinear measurement equation was linearized with respect to the inertial navigation states to obtain the observation matrix used in the U-D measurement update equations. Since sensor errors were taken into consideration in the measurement models, the inertial error state vector was augmented with the sensor shaping filter dynamics (e.g., random bias, first-order Markov model) to formulate the hybrid navigation model. Additionally, the measurement noise time history was simulated. As the aircraft moves along its trajectory relative to ground-based navaid stations, the measurement noise characteristics change. Therefore an equation for a distance- or time-varying measurement covariance matrix was found in order to realistically model ground-based radio navigation systems. According to Ref. 17, GPS measurement noise increases in a similar way; as the satellite descends near the aircraft's horizon, the noise increases. To simulate time-varying measurement noise for the ground- and satellite-based navigation systems, each noise variance was modelled as the sum of initial and range-dependent variances. The latter component increases linearly with the square of the distance from the station or satellite.

Position accuracy was selected for the rule-based system decision metric. Here, position accuracy is defined as the root sum of squares (RSS) of the north and east component errors. The RSS decision metric provides sufficiently consistent quantities to compare hybrid performances. For a detailed discussion of the RSS decision metric, the reader is directed to Ref. 14.

HYBRID NAVIGATION SIMULATION RESULTS

Using the RSS position error metric to measure hybrid system performance, the following U-D filter simulations were performed:

1. Single-type hybrids: GPS, LORAN, TACAN, DME, VOR, Doppler Radar, or Air Data Sensor aiding an INS
2. Number of stations used in a single-type hybrid
3. Multi-type hybrids: Combinations of different navaid types aiding an INS
4. Aircraft trajectories simulated: High-performance, commercial, general aviation

Comparisons of Single-Type Hybrid Performance

Consider the four ground stations A, B, C, and D spatially oriented with respect to the high-performance, commercial, and general aviation trajectories in Fig. 1. The four ground stations are simulated as LORAN slaves, TACAN, DME, or VOR stations. Figure 2 shows the performance differences of ground-based, GPS, and on-board type hybrid systems. When the results from all ground station A types (LORAN, TACAN, DME, VOR) are compared on the high-performance trajectory, the relative performance from best to worst may be listed as follows: (1) LORAN, (2) TACAN, (3) DME, and (4) VOR. For example, a hybrid system utilizing LORAN slave station A provides better performance than a hybrid system utilizing TACAN A; a TACAN A hybrid in turn outperforms a DME A hybrid which in turn outperforms a VOR A hybrid. This pattern is repeated for stations B, C, and D [14]. The best hybrid performance was obtained from three GPS satellites aiding the INS. Figure 2 also shows how the performances of the Doppler radar hybrid and the air data sensor hybrid compare with the GPS and ground-based navaid hybrids.

Referring to the LORAN results in Fig. 3, there is a striking variation in the performance of the individual Stations A-D; this figure reveals that single stations of the same type aiding an INS give highly variable performance results. The same variability in performance of the remaining ground-based single-station navaids was found [14]. From Fig. 3, the variation in Station A-D's performances is attributed to the position of each ground station relative to the aircraft's trajectory. For example, LORAN Slave A gives the smallest position error of the four stations; referring to Fig. 1, the aircraft makes a close approach to Slave A on the trajectory's second leg. Hence the RSS error becomes very small. These errors begin to increase towards the end of the trajectory leg, due to the increasingly uncertain north component. In contrast, LORAN Slaves B, C, and D are farther from the aircraft's trajectory. The first trajectory leg results in good relative north information to B, C, and D, whereas the east component uncertainty grows due to the lack of relative east information. The variations in performance observed from Stations A-D are due to trajectory effects; using Station B instead of A to update

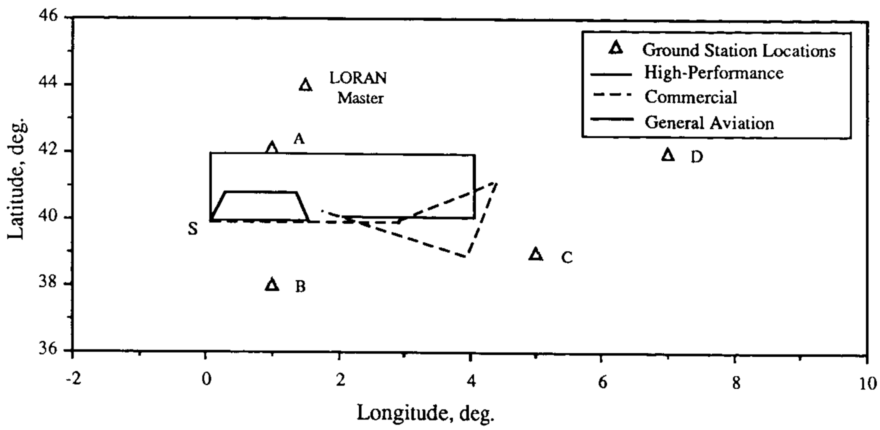


Figure 1. Aircraft Trajectories Used in Simulations

the INS is equivalent to using A and changing the aircraft's trajectory.

Effect of Increasing the Number of Navaids in a Hybrid System

Next, the effect of the number of ground stations was studied by simulating all possible combinations of single, double, and triple stations formed from stations A-D. There are six possible combinations of two stations and four combinations of three stations that may be integrated to aid the INS. These simulations were carried out for LORAN, TACAN, DME and VOR.

Referring to the LORAN results in Fig. 4, the performance variation among the double station combinations and triple station combinations is less pronounced than the single station variations. The magnitude of the RSS errors decreases dramatically when two stations are used instead of one station. The RSS errors decrease further when three stations are used, although the magnitude differences are not as great. The reason why the RSS magnitudes of the double- and triple-station combinations are much lower is that the aircraft receives the best navigation information available. This also explains why there is much more variation in the results for the double station combinations than for the triple stations. Similar performance trends were observed for GPS, TACAN, DME, and VOR [14].

Effect of Trajectory on Hybrid Performance

It already has been shown that an aircraft's trajectory relative to a single ground station hybrid plays an important role in the estimator's performance. The RSS results in Fig. 5 illustrate the performance differences of the LORAN Slave A hybrid on the high-performance, commercial transport, and general aviation trajectories. Two parameters that contribute to these performance differences are distance to a station and heading with respect to a station. A third trajectory parameter that contributes to a hybrid system's performance is the number of heading changes along the trajectory. The effect of heading changes is discussed in more detail in [14]. Trajectory factors affect the INS dynamics, which in turn affects the error estimation performance. The trajectory factors also change the measurement dynamics since the measurements are dependent on the trajectory's geometric properties and aircraft states (such as velocity). The results in Fig. 5 clearly show that when the trajectory changes, the navaid selection decision most likely changes as well since the relative accuracies of the navaids change.

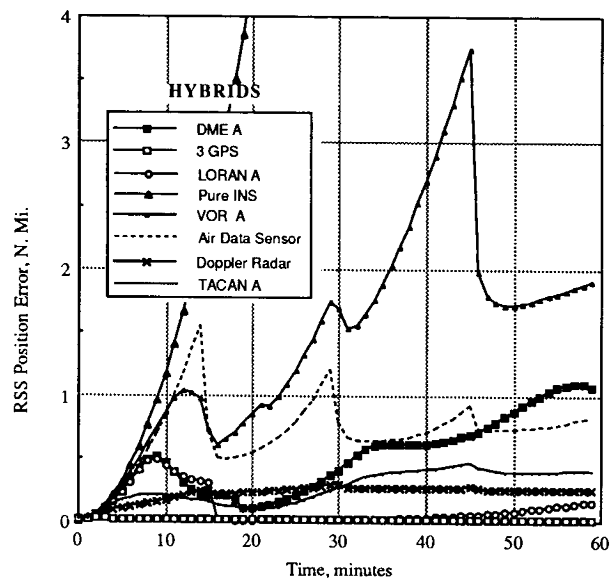


Figure 2. Performance of Satellite, Ground Station-Based and On-Board Hybrid Navigation Systems

Hybrid Performance of Mixed Navaids

Figure 6 shows various combinations of integrated navaids. The individual performances of LORAN Slave B, Doppler radar, and Air Data hybrids are shown in Fig. 6 along the high-performance trajectory. The LORAN/Doppler and LORAN/Air data hybrids also are plotted in this figure for comparison. Both combinations gave better results than their individual components operating alone. For example, the LORAN/Doppler combination outperformed the LORAN hybrid and the Doppler hybrid; similarly, the LORAN/Air Data combination gave better results than did the LORAN alone or the Air Data sensors alone. The latter combination did slightly better than Doppler hybrid on this trajectory after the initial transient period. These results show that good navigation performance is still obtainable when a "failed" LORAN system (only one slave station operational) is integrated with an on-board navaid such as Doppler radar or a standard equipment air data sensor.

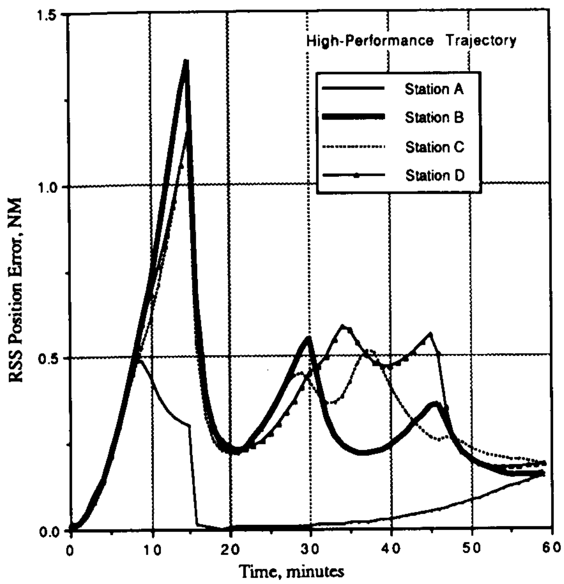


Figure 3. Performance of Single-Station LORAN Navaids Aiding an INS.

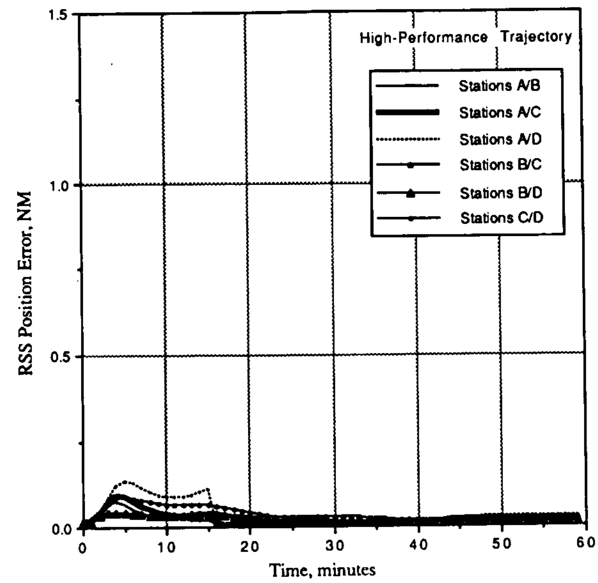


Figure 4. Performance of Double-Station LORAN Navaids Aiding an INS

DEVELOPMENT OF A NAVIGATION SENSOR MANAGEMENT EXPERT SYSTEM

This section describes a novel methodology that uses established statistical techniques to develop the NSM expert from the simulation data. The primary function of this expert system is to select the external navaid sensors that provide the smallest possible RSS position error from a large set of available sensors. The Analysis of Variance (ANOVA) technique [11] is used to identify the factors that make statistically significant contributions to the decision metric. Then, the ID3 algorithm determines the relationships between these factors [11,13].

Identifying Important Factors Using ANOVA

The ANOVA technique was applied as follows: first, the mean value of the RSS position error and the variance for all the simulations were computed. The ANOVA model decomposes the variance into a sum of variances, each associated with a potentially contributing factor. Over two hundred simulations were performed, and the data were used in a four-factor navaid experiment. The goal of the experiment was to identify which of the factors (navaid type, number of ground stations, trajectory effects, performance history) and their interactions had statistically significant impacts on the RSS position error. The factor states used in the ANOVA experiment were: Navaids={VOR, DME, LORAN, TACAN, GPS}; Number of Ground Stations={One, Two, Three}; Trajectory Type={High-Performance, Commercial Transport, General Aviation, from Fig. 1}; Time Interval = {I, II, III, IV}. Since each trajectory consists of four, fifteen-minute legs, the "Time Interval" factor refers to the RSS performance obtained within each fifteen minute time frame. Four single-station, six double-station, and four triple-station hybrids were simulated using combinations of Stations A-D in Fig. 1.

The ANOVA results [14] show that three of the four factors are strongly significant with 99% confidence; the fourth factor, trajectory, was shown to be weakly significant (90% confidence). The latter result suggested that additional investigation into the effect of trajectory on RSS position error is necessary for more specific trends to be observed. Indeed the term "trajectory" is extremely vague; the results from Scheffé comparison tests suggest that "trajectory" should be decomposed into attributes that describe, in better detail, what these effects really are. For example, some trajectory attributes include distance from a station, airspeed, and whether the aircraft is approaching or receding from the station. Scheffé multiple comparison tests were applied to the navaid and number of ground station factors to identify the specific differences within each groups; for example, the RSS performance difference between GPS and TACAN, all other factors being equal, was statistically significant. On the other hand, the RSS performance difference between LORAN and TACAN with all other factors being equal, was not statistically significant. This means that a LORAN hybrid could perform better or worse than a TACAN hybrid, depending on the values of the other factors (e.g., number of ground stations). The multiple comparison test results yielded the same performance ranking depicted in the graphical results (e.g., Fig. 2), while utilizing the information content of a large number of independent simulations. Further investigation into the ANOVA interaction effects revealed that the ranking should be cautiously applied to single-station hybrids, since these are highly-sensitive to trajectory effects. The complete factor analysis results are given in Ref. 14. In summary, the ANOVA and Scheffé methods systematically identified trends in the simulation data without recourse to tedious graphical analysis.

Extracting Rules Using Induction: The ID3 Algorithm

The ID3 Algorithm uses inductive inference to extract rules [13] from a training set of examples. The problem space is described in terms of attributes, where each attribute is characterized by a set of values that define the possible "states." For example, in the previous section, the navaid type and number of ground stations were shown to be attributes affecting RSS position error. The attribute values for the factor "navaid

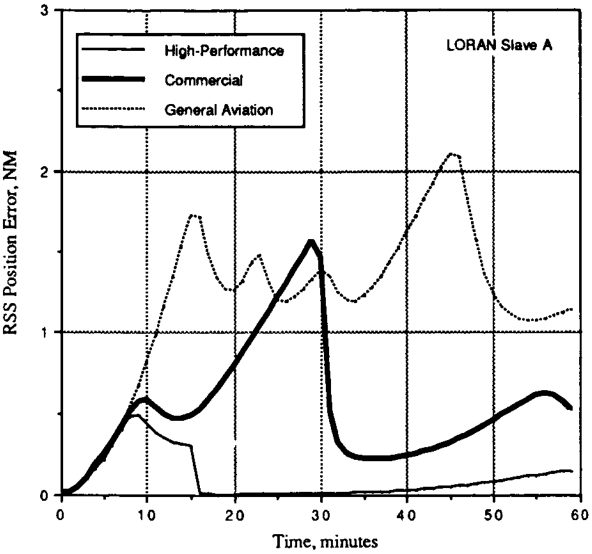


Figure 5. Comparison of RSS Results for LORAN Hybrids on Three Different Trajectories

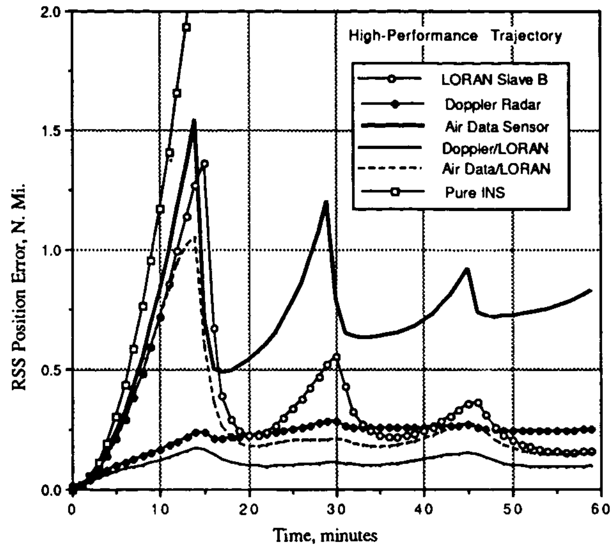


Figure 6. Comparison of RSS Results with LORAN, Doppler Radar, and Air Data Sensor Hybrid Combinations

type" were {GPS, LORAN, TACAN, DME, VOR}, and the attribute values for the factor "number of stations" were {One, Two, Three}. Hence there is a clear connection between ANOVA and ID3 problem structures. ANOVA factors are ID3 attributes, and ANOVA factor levels are ID3 attribute values.

An important problem in designing an inductive inference algorithm is identifying the attributes that span the problem space most efficiently, so that the resulting decision tree is as compact as possible. The ID3 algorithm selects the most important attributes using an information-theoretic measure (ITM) that minimizes the number of tests (attribute nodes) necessary to classify a problem. The ID3 algorithm utilizes a splitting strategy [12] to decide which attribute provides the most information from the example set. A detailed example illustrating how the splitting strategy is used to construct classification rules is given in [14].

Developing the ID3 Attribute Framework Using ANOVA Results

Up to three ground stations (four GPS satellites) were included as possible configurations. Time-weighted measurement effects are included in the attribute framework using RSS position error classification codes representing the hybrid's performance on a preceding trajectory leg. The trajectory effects were separated into the following attributes: geodetic distance from a ground station, line-of-sight angle from the station, and the direction of flight (approaching or receding) relative to a ground station. The distance from a ground station is an important attribute since the signal-to-noise ratio decreases as the distance to the station increases. The direction of flight with respect to the station influences position accuracy through its effect on the line-of-sight angle. The trajectory parameters were computed for each of the high-performance, jet transport, and general aviation trajectories on each trajectory leg. The maximum and minimum distances to the aiding station were also determined on each trajectory leg, in addition to the difference between the maximum and minimum distances.

When more than one station was used, the attributes were redefined slightly. The maximum and minimum distances then referred to the closest and farthest distances computed to the stations. The distance difference is the algebraic difference between the farthest and closest distances determined on the trajectory leg. A similar definition was applied to the line-of-sight angle; from the angles computed to each station, the largest and smallest were selected. The ID3 algorithm's task was then to determine how these attributes were related to each other and to the RSS performance.

The classification scheme chosen to represent the RSS position error endnode in the decision trees is depicted in Table I. Since an approximate prediction of the RSS position error was of interest, it was appropriate to represent the RSS performance in terms of an error range.

Table I RSS Position Error Classification Scheme

[High]		Accuracy [Medium]		[Low]	
Error (N. Mi.)	**Code**	**Error (N. Mi.)**	**Code**	**Error (N. Mi.)**	**Code**
0.00-0.02	c-1	0.10-0.20	c-6	1.0-1.5	c-15
0.02-0.04	c-2	0.20-0.30	c-7	1.5-2.0	c-16
0.04-0.06	c-3	0.30-0.40	c-8	2.0-2.5	c-17
0.06-0.08	c-4	0.40-0.50	c-9	2.5-3.0	c-18
0.08-0.10	c-5	0.50-0.60	c-10	3.0-3.5	c-19
		0.60-0.70	c-11	3.5-4.0	c-20
		0.70-0.80	c-12	4.0-4.5	c-21
		0.80-0.90	c-13	4.5-5.0	c-22
		0.90-1.00	c-14	> 5.00	c-23

The velocity, distance, and line-of-sight angles were expressed in terms of ranges instead of individual values, so that the expert system weights trends more heavily than specific examples. This renders the expert system more adaptable to new conditions, because matches between the actual and knowledge-base cases could be obtained more frequently.

The example set was developed using the attribute framework described above. The RSS position errors for each simulation were classified on each trajectory leg using the scheme in Table I. The ID3 example base was then created from each single-, double-, and triple-station simulation.

NSM Decision Trees

The NSM example set was divided into seventeen smaller example sets. The GPS and on-board navaid examples were grouped into one expert, whereas the ground-based navaid examples were divided according to navaid type and time (15-minute intervals). The ID3 algorithm constructed decision trees for each of the seventeen small expert systems that comprise the larger NSM Expert. The breakdown of the NSM Expert into smaller systems provides greater manageability of the training example base. The total number of examples used to develop the NSM Expert System was nine hundred and thirty-two. In total, two hundred and sixty Kalman Filter covariance simulations were performed to formulate the complete NSM example set. An additional thirty-seven simulations were performed to obtain a decision tree to estimate RSS performance when different navaid types are combined. The NSM expert system prompts the user for a set of flight conditions commensurate with the attribute/value lists used in the example set, and the resulting RSS classification code is returned to the user from the decision tree.

A typical decision tree obtained for the ground-based navaids is exemplified by the TACAN results. Figure 7 presents the decision trees for single-, double-, and triple-station combinations on the first fifteen-minute trajectory leg. Here, the majority of the testing nodes are trajectory parameters (distance, LOS angle, direction of flight with respect to the station(s)). The top or root node in Fig. 7 is the aircraft's direction of flight. This is expected because the distance and LOS angle attributes are dependent on directional motion. Distance, LOS angle, and groundspeed are results of the aircraft's motion, and hence, represent more specific problem parameters; therefore it is expected that these parameters appear at a lower depth in the decision tree. Figure 7 also shows that distance, ground velocity, LOS angle, and hybrid performance history are significant factors that enable a prediction of the RSS error to be made. The RSS classification results verify that the closer the aircraft is to a station(s), the smaller is the RSS error; other results show that the larger is the LOS angle, the smaller is the RSS error [14].

The expected performance of the GPS system on each trajectory leg is shown in Fig. 8. Note that the aircraft's groundspeed plays an important role in the GPS hybrid's performance. Velocity affects the measurement dynamics (history) and is therefore classified as a trajectory effect. From Fig. 8, the two-satellite hybrids are more sensitive to these velocity effects than are the three- and four-satellite hybrids.

Finally, the decision tree showing what position error range is expected when different navaid types are integrated in a hybrid system is presented in Fig. 9. Note that the decision tree is not specified for a given trajectory leg. The RSS position errors for these simulations were averaged over the entire flight time for the high-performance trajectory. The tree is organized in terms of the navigation method used: (1) Distance-Velocity (ρ-V), (2) Bearing-Velocity (θ-V), (3) Distance-Bearing (ρ–θ), (4) Distance-Distance (ρ–ρ), (5) Bearing-Bearing (θ–θ), and (6) Velocity-Velocity (V-V). These results show that LORAN is a better distance-measuring navaid than DME and that Doppler Radar is a better velocity-measuring system than the Air Data Sensor when ρ-V navigation is used. The ρ–θ results show that it is possible to obtain performance when LORAN and VOR are used. The LORAN/DME hybrid gives better results than two DME stations but worse performance than two LORAN stations. By far the worst results are obtained using two VOR stations. As discussed before, the VOR system is the least accurate measurement device of the seven systems studied, which greatly affects INS-VOR hybrid results.

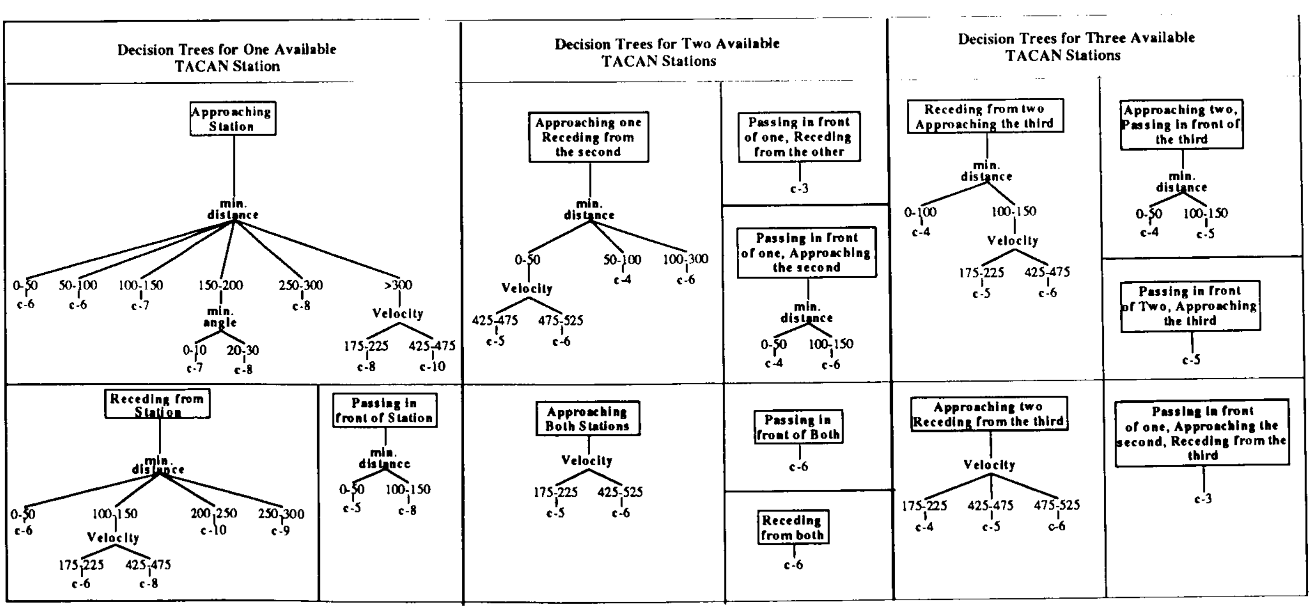


Figure 7. Decision Trees Predicting RSS Position Error Range for an INS Aided by TACAN During the First 15 Minutes of Flight

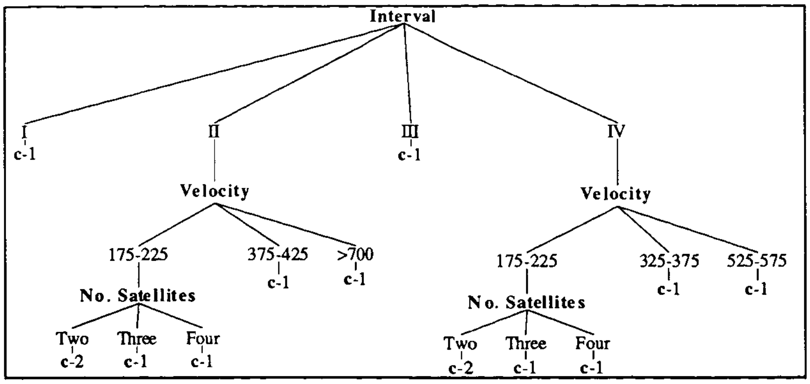


Figure 8 Decision Tree Predicting RSS Performance for an INS Aided by GPS

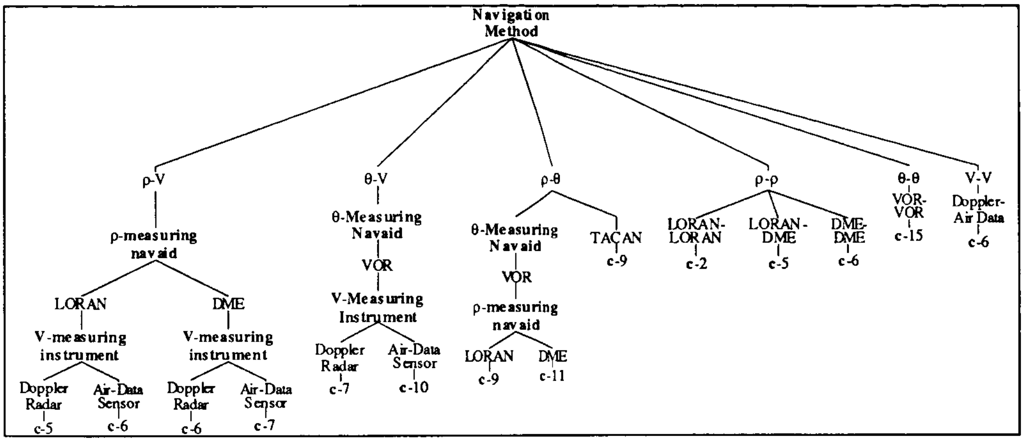


Figure 9 Decision Tree Predicting RSS Performance When Different Navaid Combinations are Used to Aid an INS

PERFORMANCE RESULTS OF NSM EXPERT SYSTEM

It is important to quantify the NSM Expert's performance for several test scenarios, in terms of how well it predicts a given hybrid's RSS position error. It is also important to gain insight into the factors that affect the system's performance, so that these factors can be exploited in future system development.

Two high-performance trajectories were used in the performance evaluation of the NSM Expert. The two trajectories each consist of four fifteen-minute legs. Trajectory #2's flight pattern was in a counter-clockwise direction, whereas clockwise flight patterns were used to develop the NSM Expert (Fig. 1). Additionally, the takeoff point on Trajectory #2 was five degrees farther north than the training trajectories' takeoff points. These trajectory differences change the measurement and INS dynamics, and hence the hybrid performance. Trajectory #2 was designed this way intentionally, so that the NSM Expert System's adaptability could be determined.

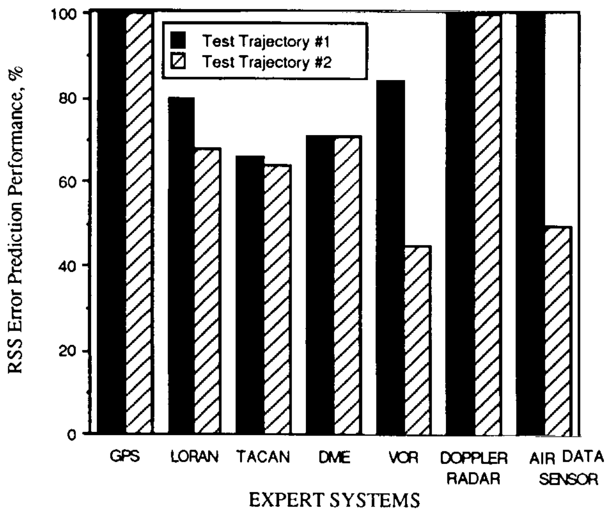
Single-, double-, and triple-station combination hybrids were simulated on each test trajectory for each of the DME, VOR, TACAN, and LORAN systems. The combinations were formed using four ground stations located as in Fig. 1 with respect to each other. Additionally, two-, three-, and four-satellite hybrids were simulated on the test trajectories, as were Doppler Radar and Air Data sensor hybrids. In total, sixty covariance simulations were performed for the two test trajectories.

Test Trajectory Data Preparation, Performance Metrics, and Results

The performance results for each of the sixty simulations were classified on each trajectory leg according to the scheme in Table I. The total number of matches was counted on each leg of each test trajectory for the seven navaid types studied. A match was declared between the actual and predicted RSS classification if and only if the RSS classification codes differed by one or less. For example, if the NSM Expert predicted an RSS classification code of 6 whereas the covariance results determined a performance of Class 7, a match was declared. A match would also have been declared if the actual performance was Class 5. Since the NSM Expert is only expected to *estimate* a hybrid's performance, it is allowed some room for error.

In total, the NSM Expert System was run four hundred and eighty-eight times in order to determine the number of matches for each system on the test trajectories. Figure 10 shows the NSM Expert's performance in predicting the RSS position error for each hybrid configuration. The *predictive performance metric* for each navaid is defined as the percentage of number of matches obtained from the total number of combinations tested for that navaid. The matches on all four trajectory legs are reflected in this figure.

The NSM Expert performed very well on the two test trajectories. Figure 10 shows that the NSM Expert correctly predicts the RSS position error better than 70% of the time on test Trajectory #1. The system required only the trajectory information and its knowledge of hybrid system performance to make these predictions. However, its predictive capability on test Trajectory #2 is slightly worse for the LORAN hybrids, considerably worse for the VOR and Air Data sensor hybrids, and identical for the remaining configurations. Hence, the results from Trajectory #2 suggest that additional investigation into trajectory effects on VOR's and Air Data Sensor's performance may be necessary.



The results in Fig. 10 are truly encouraging for designers of expert systems. We have shown that an expert system can be designed from data, and that good results are obtainable even from relatively small training sets. Recall that the total number of examples used to obtain the NSM decision trees was slightly less than one thousand.

CONCLUSIONS

The performances of seven navigation systems aiding a medium-accuracy INS were investigated using Kalman Filter covariance analyses. Hybrid performance decisions were based on the RSS position error history metric. A NSM Expert was designed from covariance simulation data using a systematic method comprised of the two statistical techniques, the Analysis of Variance (ANOVA) method and the ID3 algorithm.

ANOVA results show that statistically different position accuracies are obtained when different navaids are used, the number of radio navigation ground stations or GPS satellites used to aid the INS is varied, the aircraft's trajectory is varied, and the performance history is varied. By indicating that these four factors significantly affect the decision metric, an appropriate parameter framework was designed, and a simulation example base was created.

The example base was composed of over nine hundred training examples from nearly three hundred simulations. The example base was divided into seventeen smaller groups to enhance manageability. The ID3 algorithm then was used to determine the NSM Expert's classification "rules" in the form of decision trees. The performances of these decision trees were assessed on two arbitrary trajectories, by counting the number of times the rules correctly predicted the RSS position accuracy. These performance results then were presented using a predictive metric.

The ANOVA/ID3 method was very effective for the systematic development of the NSM Expert using simulation data. Results show that the NSM Expert can predict the RSS position accuracy between 65 and 100% of the time for a specified navaid configuration and aircraft trajectory. The test trajectories used to evaluate the system's performance show that the NSM Expert adapts to new situations and provides reasonable estimates of the expected hybrid performance. The system's good performance with relatively few examples clearly shows how the ID3 algorithm maximizes the information content contained in the example base. The performance results strongly suggest that operational systems can be designed from simulation or experimental data using the ANOVA/ID3 method for knowledge acquisition. The systematic nature of the method makes it a useful tool for expert system designers.

Other aerospace applications that are good candidates for the ANOVA/ID3 method are air combat pilot strategies from simulation or flight test data and air traffic control solutions to multi-configuration problems. The expert system design methodology also is pertinent to problems such as nuclear reactor control strategies, chemical process control strategies, automated highway driving, and robotics applications. In each case simulation or operational experiments may be executed for the systematic development of an expert system advisor.

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