ROUTE PLANNING USING PATTERN CLASSIFICATION AND SEARCH TECHNIQUES

Douglas M. Rouse, 1st Lt, USAF

Wright Research and Development Center (WRDC/KTA)
Wright-Patterson Air Force Base, OH

ABSTRACT

A prototype route planner was developed as part of a master's thesis at the Air Force Institute of Technology. The context for development was the domain of mission planning for air interdiction. A representative geographical scenario was divided into a rectangular grid, with each intersection having nine characteristics associated with it. These characteristics form a pattern vector which describes the attributes of each intersection. A representative sample of these vectors was rated by pilots as to the desirability of overflying points with those particular characteristics. A minimum-distance pattern classifier was constructed using this data. A route planner was then constructed using an "algorithm A" search routine. The route planner attempts to find a "low cost" path to a target by using a heuristic combining distance and pattern classifier output.

INTRODUCTION

The goal of knowledge-based system development is to capture a human expert's reasoning and evaluation skills and reproduce the expert's performance with an automated system. The current design of these systems involves coding the expert's knowledge explicitly in the form of production rules. One problem with this approach is that when a situation arises which cannot be directly addressed with existing rules, the system is unable to respond or is "brittle". In other words, the system cannot make an "educated guess" based on the information already available to it. Another problem is that as more rules are added to encompass a larger range of situations, the system generally becomes increasingly slow and cumbersome. Clearly, these problems may limit the capability of conventional systems.

In the effort described, a prototype route-planning system was constructed for the air interdiction mission. The system relies on the combination of a pilot preference database, a pattern classifier, and a heuristic search routine to identify desirable routes to a designated target. Within this combination, the pattern classifier is examined to see if it may be appropriate in addressing the problems of speed and graceful degradation.

KNOWLEDGE-ACQUISITION

The first step in constructing the route planner was obtaining general knowledge on the domain and collecting data to build the pattern classifier. The air interdiction mission was chosen as the context for development of the system. "Air interdiction mission objectives are to delay, neutralize, or destroy the military potential of the enemy before it can be effectively used against our own forces" (Bahnij, 1985:II-3). The purpose of the route planner is to find a low risk route to accomplish these objectives.

Following discussions with pilots and weapon systems officers (WSOs) of the 89th Tactical Fighter Squadron, a subset of characteristics and characteristic values were chosen as determinants of waypoint desirability in route planning (Table 1). Arbitrary numbers were assigned to each characteristic value for later mathematical manipulation in the pattern classifier. This is not an all-inclusive set, nor is it likely the "best" set. It is, however, a representative collection of the variables considered when planning a route.

These variables form a pattern vector which is input to the pattern classifier. Once the elements of this pattern vector were derived, the goal was to have pilots rate the desirability of as many combinations of pattern vector values as possible. The total number of possible patterns is 9,216, making it impractical to obtain a rating of every one. The question now was to determine how many different samples should be included in the survey of pilots and how many redundant ratings of each sample should be done. This is a form of fractional factorial experiment.

The collection of ratings and corresponding pattern vectors form a training set for the pattern classifier. The minimum number of patterns in this set must be at least twice the dimension of the pattern vector for meaningful results (Cover, 1965:326-334). A good rule of thumb is to use a training set with the number of patterns on the order of ten times this amount (Gonzalez and Tou, 1974:187). This would mean approximately 180 unique pattern vectors where each vector has nine dimensions. (These guidelines are based on vectors whose variables have only two possible values. In this case, the number of values per variable range from two to four. Thus, the actual recommended sample should be even larger than 180.) The problem in obtaining this quantity was the limited number of pilots/WSOs available and the number of patterns each could rate.

CHARACTERISTIC	VALUE	
	SYMBOLIC	NUMERIC
SAM Threat AAA Threat Enemy Fighter	great moderate small none	0 1 2 3
Weather	bad marginal good	0 1 2
Terrain	flat hilly mountains	0 1 2
Landmarks	not prom. prominent	0 1
Availability of: Wild Weasel EF111 ECM Fighter Escort	 no yes	 0 1

Table 1: Waypoint Characteristics

The desirability ratings given to pattern vectors were integers between one and ten, with ten being the most desirable and one being the least desirable. A representative sample of 40 patterns was created and divided into two sets of 20 patterns each. A group of ten pilots/WSOs was divided into two groups of five, each group rating one of the 20 pattern sets. This yielded a total sample of 40 rated patterns, each with a rating redundancy of five. These patterns were stored in a pilot preference database for use by the pattern classifier. The total number of rated patterns is not the desired 180 patterns, but it is more than twice the minimum number required.

PATTERN CLASSIFIER

The pattern classifier models pilot discriminatory capability with respect to varying combinations of pattern vector characteristic values. It evaluates pattern vectors and returns a desirability rating based on the information stored in the pilot preference database (Figure 1).

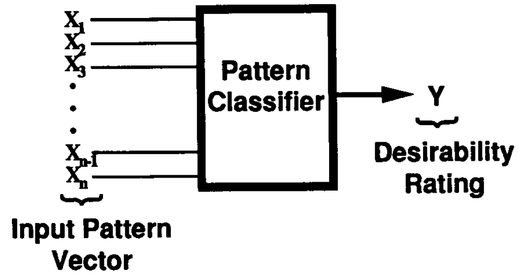

Figure 1: Pattern Classifier

The knowledge acquisition process yielded nine factors used in planning a route to a target. This set is by no means a complete list, but it represents an estimate of what some of the most important characteristics are in comparing the desirability of overflying one area as opposed to another. These characteristics form a nine element pattern vector. Each of the samples collected from the pilots in the knowledge acquisition process represents a specific instance of this vector with a corresponding pilot desirability rating. Thus, the pattern classifier reproduces a pilot's mental mapping of a specific pattern vector into a desirability rating.

A minimum-distance or "nearest-neighbor" method of classification was used to accomplish this mapping. This type of classification scheme is appropriate where vectors with similar ratings tend to cluster together (Tau and Gonzalez:77). A pattern vector is fed to the pattern classifier and compared to all of the previously rated vectors in the database. The input vector is then assigned the rating of the stored vector closest to it in terms of Euclidean distance. For two pattern vectors X and Y, the Euclidean distance between them is:

$$| X - Y | = \text{sqrt} [(X - Y)' (X - Y)] \quad (1)$$

This allows any pattern vector to be rated, even if it is not explicitly represented in the database.

SEARCH ALGORITHM

Search techniques are used to find paths from some beginning state to a goal state. In a best-first or ordered search, the successor state which appears most promising in terms of leading to the goal state is examined first. The heuristic which determines which successor state is most desirable is referred to as an evaluation function (Nilsson, 1980:73). In this effort, a form of best-first search called Algorithm A was used. The evaluation function for Algorithm A is of the form:

$$f = g + h \qquad (2)$$

The "g" term in the equation represents an estimate of the minimal cost path from the start state to an intermediate state. The "h" term represents an estimate of the minimal cost path from the intermediate state to the goal state. Details of the implementation will be discussed in the Route Planner section.

SCENARIO DESIGN

The scenario used in testing the route planner is shown in Figure 2. It consists of a coarse grain, 17 by 28 grid of "nodes" which are used as waypoints in forming a route. A small arrow at the left of the display indicates the general region where the attacking flight of planes will approach the forward edge of the battle area (FEBA). The FEBA itself is shown as a vertical dashed line just inside the left border of the display. A "T" enclosed by a small circle at the far right center of the display represents the target. The dark circles represent either surface-to-air missile threats (SAMs) or anti-aircraft artillery threats (AAAs). The black circles represent areas of "great" threat. The area between the first concentric circles and the black circles represent areas of "moderate" threat. The area between the first and second concentric circles represent areas of "small" threat. All other areas have a SAM or AAA threat value of "none". Note that the areas of highest ground threat concentration are at the FEBA and surrounding the target. Areas of enemy fighter threat are not explicitly shown, but are stored as attributes of the affected nodes. The weather conditions are indicated by letters just below the nodes affected. A "B" means "bad" weather such as an embedded thunderstorm with high winds and poor visibility. An "F" means "marginal" weather such as a low ceiling, high winds, and/or poor visibility. The letter "F" was chosen instead of "M" to avoid confusion with the terrain indication for mountains. If there are no letters below a node, then the weather is considered "good". A storm front is visible at the top center of the scenario. The terrain is either mountainous, hilly, or flat. Mountains are indicated by two

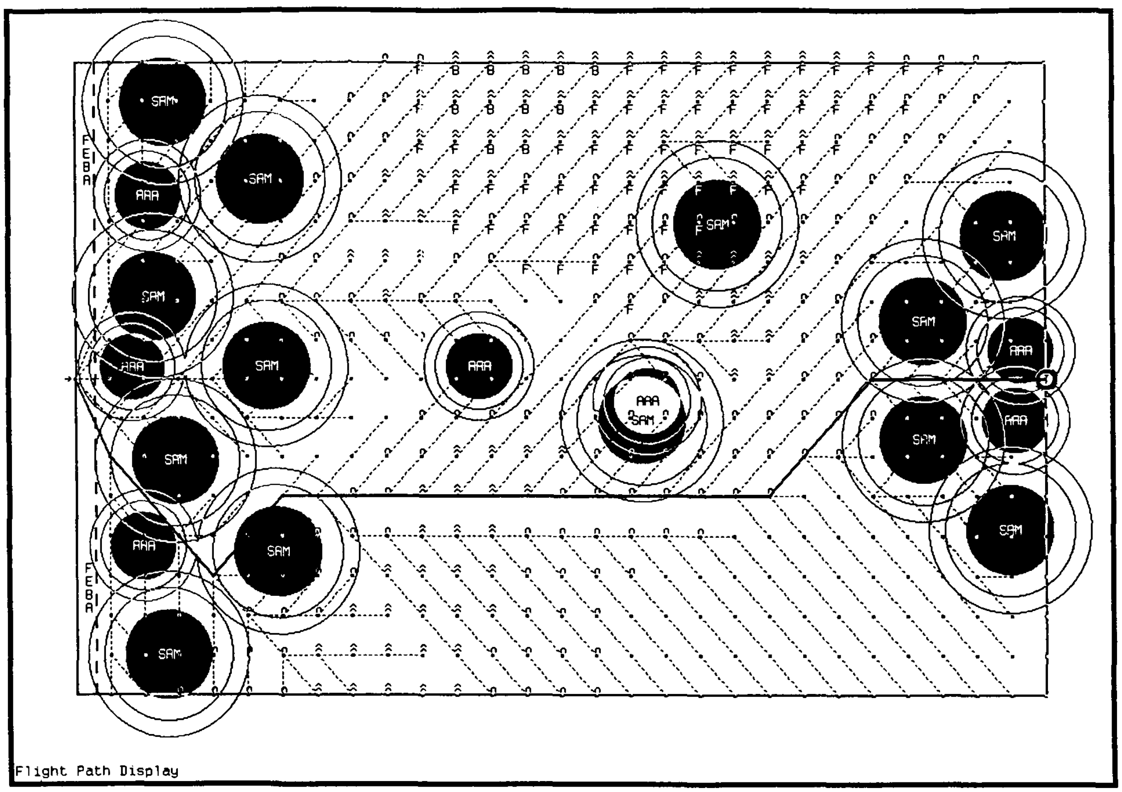

Figure 2: Scenario and Route Example

carats above a node, hills are indicated by an upside down "u" above a node, and all other areas are considered "flat". The landmark and support values are not represented graphically, but are stored as attributes of the affected nodes.

ROUTE PLANNER

The route planning system was implemented in Zetalisp on a LISP Machine Inc. Lambda. Flavors, an object-oriented language with inheritance properties, was used extensively to define the nodes in the scenario and implement many of the procedures used.

Figure 3 shows an overview of the implemented system. Conceptually, it represents an automated knowledge pipeline. The first link is the knowledge acquisition tool (KAT). The KAT is designed to prompt the domain expert with random combinations of pattern vector characteristics. The expert then enters a desirability rating which is stored in a raw data file with the corresponding pattern vector. The information in the raw data file is preprocessed and the average desirability ratings for duplicate pattern vector entries are stored with the variance, standard deviation, number of ratings for that pattern, and the ratings themselves in the compiled data file. This file is what the pattern classifier uses to determine the desirability rating of an input pattern vector.

The planning process begins when a starting node and a goal node are provided to the route planner. The nodes adjacent to the starting node (or current node) are examined and compared for their desirability. The pattern vector describing the characteristics of each adjacent node is fed to the pattern classifier which then assigns them desirability ratings. The algorithm A "f" function for each adjacent node N is then calculated. The "g" term is defined as the weighted sum of three variables: 1) The straight line distance from the current node to adjacent node N; 2) The classification rating of adjacent node N (inversely weighted); and 3) The "g" value of the current node. The "h" term is defined as a constant times the straight line distance from adjacent node N to the goal node. Adjustment of the coefficients for these variables tune the search, forcing it to push more directly toward the goal, or expand breadth-wise, examining more nodes. This process of expanding the path and examining adjacent nodes continues until the goal node (the target) is reached.

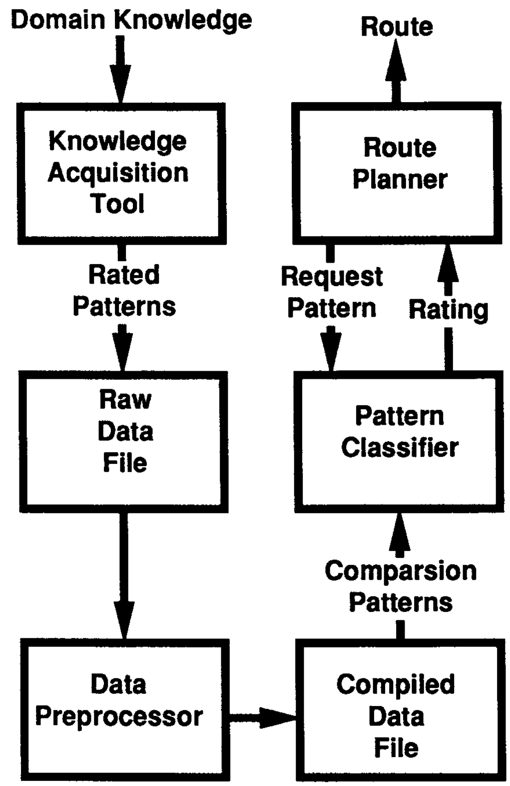

Figure 3: System Design Overview

RESULTS

Table 2 gives a statistical compilation of the knowledge acquisition results. The numbers in the pattern vector correspond in order to the characteristics listed in Table 1. In general, the results were favorable. The average overall rating was 5.23, which is what might be expected for a normal distribution, assuming a representative sample of pattern vectors were used. The average standard deviation was 1.32. This indicates that most of the ratings for each pattern vector were within approximately $\pm$ 2.6 points of the average rating for that vector.

The desirability rating data in Table 2 was divided and manipulated to form sets for training and testing the effectiveness of the pattern classifier. Thirty of the patterns were used to "train" the pattern classifier and ten patterns were used to test it. This procedure was performed a total of four times by partitioning the forty patterns into four sets of ten and then combining the sets in four combinations of three and

Row\Column	1	2	3	4	5	6
1	(2 0 3 2 1 1 0 0 1)	7.40	1.04	1.02	5	(7 8 9 7 6)
2	(1 1 2 0 0 1 1 1 1)	5.00	3.60	1.90	5	(4 2 7 7 5)
3	(1 2 3 0 0 0 0 1 1)	4.60	2.24	1.50	5	(6 2 6 5 4)
4	(3 3 1 2 2 1 1 1 1)	9.00	0.00	0.00	5	(9 9 9 9 9)
5	(1 2 2 0 0 0 0 0 1)	4.00	3.20	1.79	5	(3 2 5 3 7)
6	(2 0 0 1 2 1 0 0 1)	5.60	9.04	3.01	5	(3 1 8 8 8)
7	(1 3 3 2 2 1 1 1 1)	8.80	0.56	0.75	5	(8 8 10 9 9)
8	(1 1 2 1 2 1 1 1 1)	7.00	4.40	2.10	5	(7 3 8 9 8)
9	(3 1 0 2 2 0 1 0 1)	6.60	2.24	1.50	5	(4 8 8 7 6)
10	(1 3 0 0 1 0 0 1 1)	4.20	0.96	0.98	5	(3 4 6 4 4)
11	(2 1 0 1 2 0 0 0 0)	3.40	1.84	1.36	5	(1 3 4 4 5)
12	(3 2 1 1 1 0 0 1 0)	5.20	0.96	0.98	5	(5 5 5 4 7)
13	(2 1 3 2 1 0 1 0 0)	7.40	0.24	0.49	5	(8 7 7 7 8)
14	(1 3 0 2 0 1 1 1 1)	6.80	1.76	1.33	5	(6 9 7 5 7)
15	(2 1 2 0 1 1 0 1 0)	3.60	0.64	0.80	5	(3 3 5 4 3)
16	(3 2 1 2 2 0 0 0 0)	5.60	2.24	1.50	5	(4 8 6 4 6)
17	(0 3 3 2 1 1 1 0 1)	7.80	2.56	1.60	5	(6 9 10 6 8)
18	(0 1 2 0 2 0 1 1 0)	4.00	4.80	2.19	5	(2 2 8 4 4)
19	(3 3 0 0 2 0 0 0 1)	4.80	6.16	2.48	5	(7 2 8 5 2)
20	(1 2 2 1 2 0 0 1 1)	5.40	1.84	1.36	5	(5 4 8 5 5)
21	(1 3 1 2 1 1 0 1 1)	8.40	0.64	0.80	5	(7 9 8 9 9)
22	(2 2 0 0 1 0 0 0 1)	5.00	0.80	0.89	5	(6 4 6 5 4)
23	(0 1 1 1 0 1 0 1 1)	4.20	2.16	1.47	5	(3 3 6 3 6)
24	(0 0 3 2 2 0 0 1 1)	5.60	1.04	1.02	5	(5 7 6 6 4)
25	(0 2 2 2 1 1 1 1 1)	9.00	2.40	1.55	5	(6 10 9 10 10)
26	(2 1 0 0 0 1 0 0 1)	6.00	2.80	1.67	5	(7 4 4 7 8)
27	(0 0 3 1 1 1 0 0 1)	3.80	2.96	1.72	5	(4 3 3 2 7)
28	(1 0 1 1 0 0 0 1 1)	3.60	0.64	0.80	5	(5 4 3 3 3)
29	(1 3 0 0 1 0 0 1 0)	3.40	1.04	1.02	5	(4 2 3 5 3)
30	(3 1 3 1 2 0 1 1 0)	5.00	1.60	1.26	5	(3 7 5 5 5)
31	(1 2 1 2 1 1 1 0 0)	6.60	1.84	1.36	5	(5 5 7 8 8)
32	(1 0 1 1 1 0 1 1 0)	3.60	0.64	0.80	5	(5 4 3 3 3)
33	(0 2 0 0 0 0 1 0 1)	3.00	2.40	1.55	5	(2 3 2 6 2)
34	(3 1 0 0 2 0 0 1 1)	2.60	0.64	0.80	5	(4 2 2 3 2)
35	(2 0 1 0 2 0 1 1 1)	3.40	1.44	1.20	5	(5 4 2 2 4)
36	(1 0 3 0 2 0 0 1 1)	2.40	1.04	1.02	5	(4 2 2 1 3)
37	(3 0 0 2 1 0 1 1 0)	4.80	0.56	0.75	5	(6 4 5 4 5)
38	(1 1 1 1 1 0 0 0 0)	3.80	1.36	1.17	5	(5 5 4 2 3)
39	(2 2 3 0 0 0 0 1 1)	6.00	4.80	2.19	5	(7 7 3 9 4)
40	(0 1 0 1 0 0 0 1 0)	2.80	1.36	1.17	5	(4 4 3 1 2)

Key: Column 1: Pattern Vector; Column 2: Average Rating; Column 3: Variance; Column 4: Standard Deviation; Column 5: Number of Samples; Column 6: Individual Ratings

Table 2: Pilot Rating Results

one. The average difference between the individual pilot ratings and the average of those same ratings was 1.13. The average difference between the pattern classifier ratings and the average pilot ratings was approximately 1.43. Thus, the level of agreement between the pattern classifier output and the average pilot rating for a particular pattern vector was almost as good as the level of agreement between pilots.

Figure 2 shows a representative route planning result. In this example, the dashed lines show the partial paths expanded during the search and the solid dark line shows the final route. It is a reasonable route, but there appears to be an anomaly at the beginning where the path crosses the highest lethality region of a SAM. If the path had begun turning upward at the previous node it would have missed this region altogether. Upon closer examination though, it is evident that this alternate path would take the aircraft in range of two SAMs. Thus, the system may have "decided" that passing through a high lethality region of one SAM was better than passing through a less lethal region of two SAMs simultaneously. There are a number of factors which may alter the behavior of the system in these situations if desired. These include changing the heuristic, adding or deleting pilot desirability ratings, or adjusting the granularity of the scenario to reduce jaggedness. A system of this type is only as good as the data and heuristics upon which it is built.

CONCLUSION

The goal of this effort was to use route planning as an application to examine the suitability of using pattern classification techniques in knowledge-based system development. Future knowledge based systems are going to require a melding of technologies to progress past the limitations of their present production rule implementations. Pattern classification techniques may be one source for this infusion of technology.

Since a pattern classifier can provide a "best guess" response based on whatever information it has available, it may prove useful in knowledge-based systems by providing graceful degradation at the edges of the domain knowledge. Intuitively, it also seems that pattern classifiers would be faster than a rule-based system, since they generally rely on discriminant functions. The elements of a pattern vector are substituted into the variables of an equation which outputs the class in which the pattern belongs. This would provide an option for obtaining time critical approximate responses.

There are a number of disadvantages with pattern classifiers. The primary disadvantage is the difficulty of obtaining accurate subjective data in sufficient amounts to properly "train" the pattern classifier. Another disadvantage is the problem of verifying that the classifier consistently produces appropriate outputs.

Pattern classifiers do provide an alternative for "reasoning" with limited information. The potential benefits and consequences must be examined to identify appropriate applications.

The material reported herein is based on the author's thesis submitted in partial fulfillment of the requirements for the Master of Science degree at the Air Force Institute of Technology, Wright-Patterson AFB, OH 45433.

REFERENCES

Bahnij, Major Robert B. A Fighter Pilot's Intelligent Aide for Mission Planning. MS Thesis. School of Engineering, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, December 1985 (AD-A163 944).

Cover, T. M., "Geometrical and Statistical Properties of Systems of Linear Inequalities with Applications to Pattern Recognition," IEEE Transactions on Electronic Computers, 14: 326-334 (March 1965).

Gonzalez, Rafael C. and Julius T. Tou. Pattern Recognition Principles. Reading, Massachusetts: Addison-Wessley Publishing Company, 1974.

Nilsson, Nils J. Principles of Artificial Intelligence. Palo Alto, California: Tioga Publishing Company, 1980.

Rouse, Lt Douglas M. Route Planning Using Pattern Classification and Search Techniques. MS Thesis. School of Engineering, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, December 1986 (AD-A177 664).