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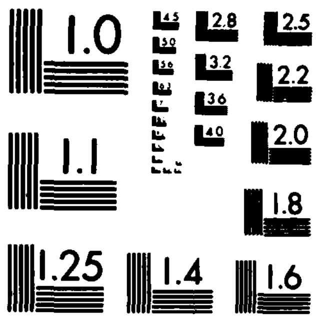

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CONCEPTUAL STRUCTURES IN FIGHTER PILOTS

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This paper reviews continuing work on defining and measuring conceptual structures of critical flight information in fighter pilots. Psychometric methods are used to describe conceptual structures, and experimental tasks and discriminant analyses are used to validate the results of the psychometric procedures. Network structures allow for reliable classification of subjects into groups with different flying experiences. The networks also allow information to be organized into lists that are easy to remember in order. Multidimensional spatial structures also allow for reliable classification of individuals into groups. The optimum dimensionality of the Multidimensional Scaling solutions was studied and found to be four dimensions. Procedures for reducing the amount of data necessary to define

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distinguishable conceptual structures were investigated, and substantial reduction appears to be possible without appreciable loss of information. The findings from this research are relevant to training-program design.

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PREFACE

The central goal of this project is to demonstrate the existence and utility of a systematic structure of flight-related concepts of Air Force fighter pilots. This paper reviews work on defining and measuring conceptual structures and on assessing the reliability, validity, and utility of particular structural descriptions. This work is part of 6.1 basic research that is intended to advance the understanding of basic cognitive dimensions as represented in flying behavior.

Several individuals, in addition to the authors, have made important contributions to this work. At New Mexico State University, Karen Preuss has assisted with the project in countless ways, and Don Dearholt provided valuable advice on properties of networks.

The cooperation of many pilots and other Air Force personnel is gratefully acknowledged.

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CONCEPTUAL STRUCTURES IN FIGHTER PILOTS

INTRODUCTION

The central goal of this project is to demonstrate the existence and utility of a systematic structure of flight-related concepts in the memory systems of Air Force fighter pilots. This paper constitutes the second annual report on the project. First, the major findings from the first year of the project (Schvaneveldt, Goldsmith, Durso, Maxwell, Acosta, & Tucker, 1982) will be summarized, and then an overview of the work accomplished this year will be presented. Background information relevant to each aspect of the overall project is presented in the appropriate sections.

The first year of the project was devoted to the task of defining and measuring conceptual structures and to assessing the reliability, validity, and utility of particular structural descriptions. The assessment of conceptual structures required a data base that could be used in our efforts to develop reliable and valid techniques for describing the psychological organization of flight-related concepts.

The stimulus material for the project was provided by 30 concepts relating to split-plane maneuvers and 30 concepts relating to the low angle strafe maneuver. These concepts were selected with the assistance of senior instructor pilots (IPs) at Holloman AFB. Ratings of the psychological similarity of the concepts were obtained from four groups of officers: Air National Guard Pilots (GPs), Fighter Lead-In Instructor Pilots (IPs), recent Undergraduate Pilot Training graduates (UPs), and Instructor Weapons Systems Officers (IWs). Cognitive structures were defined by two analytic procedures: multidimensional scaling (MDS) and general weighted networks (GWNs). The GWN algorithm was developed as part of the project. The MDS solutions represent concepts as points in multidimensional space. The GWN networks represent concepts as nodes and relations as links connecting the nodes.

Three dimensions in the MDS solutions were identified: the order in which concepts are considered in an air-to-air encounter, a contrast between lead and lag pursuit, and the temporal order of events in a training sequence. A pattern recognition algorithm was applied to the similarity ratings and MDS solutions. This analysis showed that group membership can be predicted from a person's conceptual structure. Reliable predictions were made when a subset of the members of each group was used to define the pattern classifier, and the remaining individuals were classified. Classification was significantly better with MDS results than with raw similarity ratings.

The networks produced by the GWN algorithm were analyzed using various constructs from graph theory. Minimum cycles in the IP network corresponded to clusters of interrelated concepts. Nine substructures were defined by the agreement in the IP and GP networks. Finally, the UP network was compared to the IP and GP networks, resulting in the identification of specific points of agreement and disagreement in the conceptual organization of novice and expert pilots.

On the basis of the initial year of the project, it was concluded that pilots do have measurable cognitive structures for organizing flight-related information. These structures are measurably different for individuals with differing flight experience. The IPs exhibit more efficient and economical structures than do UPs. The techniques employed in the research produce descriptions of conceptual structure that may have application in the training program of fighter pilots and in assessing individual differences in the development of appropriate conceptual structures. The specific differences between novice and expert pilots should provide assistance in planning training programs for fighter pilots.

In the second year of the project, investigation continued into the properties of multidimensional scaling and network representations of conceptual structure. These efforts have included further development of the GWN algorithm. A procedure to obtain metric information from a network has been developed, and several options for defining path length in a network have been added and related to assumptions about properties of data used in constructing the network. The ability to discriminate between individuals in different groups, given the network structures for individuals, was also examined. The discrimination possible with networks was compared to the discrimination obtained with MDS and the original rating data. The relations represented by the links in the IP network have been identified.

A new procedure for determining the optimum number of dimensions to use in MDS was developed and used to examine the data collected last year. Also, a multidimensional representation of individuals was derived that located each individual from each group as a point in two-dimensional space. This procedure can be used to determine how well individuals from different groups are aligned with other members of their group.

Two experiments, comparing the structures derived with MDS and GWN, were conducted. One of them suggested that GWN better captures the relationships between pairs of concepts. This result would be expected on the basis of the differences in the two scaling procedures. The other experiment revealed some methodological problems that accompany the use of "priming" techniques in investigating the structure of a small set of concepts. Finally, a new analysis of the individual concepts further defines which concepts are critical to distinguishing between novices and experts.

NETWORKS

A GWN is a configuration where concepts are depicted by nodes and relations are depicted by links connecting the nodes. The links are assigned a value or weight that reflects the strength of the relationship between the nodes. The value indicates the distance from one node to another along that link and is an index of the psychological proximity or relatedness of the concepts represented by the nodes.

During the previous reporting period, an algorithm was developed and implemented which constructed GWNs from empirical similarity judgments (Schvaneveldt, et al., 1982). The algorithm, GWN, was applied to judgments taken from UPs, IPs, and GPs and produced networks for each of these groups. GWN supplies several important pieces of information. First, like the other scaling techniques, GWN summarizes the data to a considerable extent. The results of GWN are often considerably more interpretable than other scaling techniques, and in addition, GWN offers options (e.g., minimally connected networks) that allow for even further data reduction. Second, GWN captures the local relationships among the concepts. Unlike MDS, GWN focuses on the item-to-item relations in constructing the network. This had both adva ges (e.g., keeping close to the data) and disadvantages (e.g., li was dependent on a small portion of the data).

During the current reporting period, a metric that was developed GWN uses more information from the network to derive weights for the s between concepts. The metric information may be more useful th e empirical judgments for the purpose of identifying the experience of pilots. It will also be interesting to compare the network metric to the MDS metric. The appropriate metric for a network depends on the scale properties of the original similarity judgments. Most scaling procedures assume that the original judgments are ordinal (i.e., the numbers contain information about the ranks of the concepts). The GWN allows the user to specify different definitions of minimum path length depending on the scale properties of the data. Finally, GWN produces networks that can be decomposed into substructures (e.g., cycles, trees, assemblies). The substructures are useful in gaining a further understanding of the network. These substructures were used in the last reporting period to determine which concepts held by the UPs were not well defined relative to the experts.

Analytic Work on General Weighted Networks

There have been two central thrusts in the development of network analyses of conceptual structures. First, the definition of path length in a network has been generalized to take considerations of levels of measurement into account. Second, a metric that was developed for the network maximizes the fit of the network model to the empirical proximities. Each of these efforts is presented in this section.

Path Length and Levels of Measurement

The definition of the length of a path in a network has been one of the central problems in developing methods for deriving networks from psychological proximity data. Recent efforts on this problem have attempted to relate the definition of path length to the information contained in the data.

Stevens (1951) proposed a measurement scales taxonomy that has been widely used over the years. His taxonomy includes nominal scales that simply identify the category appropriate for each element, ordinal scales that have the property of ordering the elements without providing information about the distance between elements, interval scales that have both order and distances information, and ratio scales that have a meaningful zero point in addition to the order and interval information. One useful perspective on levels of measurement is found in the class of transformations that can be applied to the data without losing information of various sorts. Nominal scales permit any-one-to-one transformation without loss of nominal information. Ordinal scales permit any (positive) monotonic transformation without loss of ordinal information. Interval scales permit only (positive) linear transformations, and ratio scales permit only multiplication by a (positive) constant.

For purposes of this study, the ordinal and interval scales hold the most interest since it is assumed that data of interest would convey at least the appropriate order of elements. Whether the data also have interval properties is open to question. The current version of the algorithm has three definitions of path length that require different assumptions about the data. The algorithm also yields a minimal connected network (MCN) that requires only ordinal properties in the data. Only the elaborated networks are affected by the presence or absence of interval information in the data.

The additive definition of path length involves simply adding the values of the links in the path to arrive at the length of the path. The operation of addition and the comparison of a sum to another data point require interval data. In practice, the additive rule produces networks with many links, which is not necessarily bad, but it represents the data as concisely as do the other rules. Networks resulting from application of the additive rule are invariant over linear transformations of the data. Thus, if only ordinal information is provided by the data, the additive rule is not appropriate.

The maximum definition of path length involves using the value of the maximum link in a path as the length of the path. This rule uses only ordinal properties of the data, and the network resulting from applications of the maximum rule is invariant with any (positive) monotonic transformation of the data. The maximum rule also produces the minimal unique network. The MCN is not necessarily unique when there are ties in the data. Since these ties are included using the maximum rule, the resulting network is unique.

Another definition of path length that requires only ordinal properties of the data is the use of ranks rather than data values. When these ranks are used with the additive rule, the resulting network is invariant with (positive) monotonic transformations of the data. Some properties of these "rank" networks are currently being investigated.

Metric Procedure for Networks

Once the structure of the network is determined by the GWN algorithm, the link weights can be adjusted by a linear regression procedure. This adjustment produces the best fit between the network and the original data by regressing the links in the network on the original data. Each pair of items from the distance matrix has an associated empirical distance as well as a minimum path in the network that is defined by the GWN algorithm. The metric procedure essentially allows the value of each link to be determined by its role in each minimum path of which it is a member. The metric procedure uses an additive definition of path length where the length of a path is the sum of the weights for the links constituting the path.

The metric weights are produced by a regression analysis that treats each pair of terms as a case, the links as independent variables, and the empirical distances as the dependent variable. The values of the independent variables (links) are 1 for those links in the minimum path for each pair of terms and 0 for the links not in the minimum path for the pair. The metricized weights are given by the beta values (the regression coefficients) that result from the regression analysis.

Networks represent useful structures for analyzing the conceptual organizations in various domains. An attempt is being made to place the network algorithms on a firm footing to support the use of them in this project and to provide an analytical tool that should prove to be generally useful. During the past year, theoretical efforts have concentrated on developing the network algorithm. Now comparison can be made between the performance of networks and MDS using metric information from each method. The following study reports some initial work on evaluating the network without using metric information. Studies using the metric are currently underway.

Classification of Individuals Using Networks

Similarity ratings between pairs of concepts related to a particular knowledge domain and MDSs of these ratings both are ways of describing conceptual structures. These conceptual structures provide relational and organizational information about the concepts within a domain of knowledge. Networks also provide this type of information. The comparison of structures across groups of individuals allows for the determination of qualitative differences between groups. This qualitative comparison is important for revealing how different groups view a particular set of concepts.

The purpose of this phase of the project is to determine the quantitative differences between the representations of concepts in the networks of individuals as well as groups. The previous accomplishment of developing pattern recognition programs for determining quantitative differences has allowed for groups of subjects to be classified based on similarity ratings and distances in MDS. The success of pattern recognition techniques in classifying individuals into groups pro...ded validation for the data and the derived MDS representations. Using the pattern classification technique with network representations provides a test of the validity of networks for representing the structure of flight-related concepts.

Pattern recognition analysis provides information about the degree to which individuals are associated with each group. The analysis reveals how close an individual is to the prototype of the individual's group. Also, the distance from an individual to the decision surface separating two groups reveals how close that person is to being classified as a member of another group of individuals. Both indices provide information about the strength of the association of each individual with various groups.

Method

A pattern was formed for each individual tested by taking the presence or absence of links in the network for each pair of concepts. All the concepts have potential links to all other concepts. The network solution for each subject yields links between concepts which were represented as being present or absent in the network by a 1 or a 0, respectively. An MDS solution yields a metric formed by taking the distance between each pair of concepts in a multidimensional space. Thus, an MDS pattern may be created by viewing the attributes of the pattern as values of the metric. This allows the pattern for the MDS solution to preserve the structural properties inherent in the MDS solution. While the pattern for the network solution does not contain a metric for the length of a link, the attributes of the pattern do retain some of the structural properties of the network through the presence or absence of links.

A third type of pattern may be generated by considering the similarity rating for each pair of concepts as a feature of a pattern. This pattern, containing the individual similarity ratings, lacks the structural properties imposed by the network and MDS scaling techniques. However, the pattern for similarity ratings would possess more scaling information about the degree of relatedness of any two concepts than would the network pattern. This sets up an interesting comparison to determine if there are beneficial aspects in having a structural representation of knowledge over a non-structural one, even when the latter contains scaling information and the former does not. All three methods resulted in patterns with 435 features corresponding to all the possible pairs of 30 concepts.

The first analysis consisted of applying a minimum-distance classifier to all pairs of groups of pilots for both the split-plane and low angle strafe maneuvers. Prototype points for all groups and decision surfaces for separating all pairs of groups were generated. In each application of the minimum-distance classifier, all members of the two groups were used. This provided information about both group and individual differences. The distances from each individual to a decision surface and from each individual to the group prototypes were computed along with the distances between group prototypes.

The second analysis involved computing a decision surface that separated a training set consisting of a limited number of members from two groups and then applying the decision surface to the remaining members of the groups. Decision surfaces were computed with a training algorithm if a minimum-distance classifier did not separate the training sets. Weight vectors were initialized to the weights produced by a minimum-distance classification of the individuals in the limited training set. This minimized the number of iterations needed to produce a solution when the minimum distance classifier failed and also kept the final weight vector as close to the minimum-distance decision surface as possible. The first analysis showed that the classes clustered tightly, indicating that when the minimum-distance weights failed to separate the classes, a solution close to these weights was likely. A small correction increment ($c = .01$) was also used to produce minimal change from the minimum-distance weights.

For each pair of pilot groups, a training set of a particular size was randomly chosen, and a decision surface was computed to separate the members of the training set into their respective classes. In the case where a minimum-distance classifier correctly separated the members of the training sets, the resulting discriminant function was then applied to the remaining members of the two groups. If no solution was found with the minimum-distance classifier, the training algorithm was applied to the subset of selected group members to generate a decision surface. This discriminant function was then applied to the remaining members. This procedure was repeated 100 times for each training set size. The training sets consisted of equal numbers of individuals from each group. The size of the training sets was increased until the size of the smaller group was reached.

Results and Discussion

The results of the pattern recognition analyses performed indicate that it is possible to discriminate classes of flying personnel based on their network representations of critical flight information for both split-plane and low angle strafe maneuvers. Also significant was the result that patterns represented by the networks produced better group separation than did patterns based upon similarity ratings.

Table 1 shows that a minimum-distance classifier applied to each pair of groups resulted in well separated groups with no erroneous classifications for the network patterns. The same results occurred for the patterns representing distances in an MDS solution, whereas the decision surface generated for separating groups on the basis of similarity ratings misclassified some individuals. Even with the simplicity of the decision surface generated by the minimum-distance classifier, the results indicate very distinct classes, especially in the case of IPs and UPs where no IPs were classified as UPs and no UPs were classified as IPs for either maneuver with any of the three pattern types.

Table 1

Classifications Based on Group Separation

with a Minimum-Distance Classifier

Split-Plane Maneuvers

	Ratings				MDS Distances				Networks			
	IP	GP	IW	UP	IP	GP	IW	UP	IP	GP	IW	UP
IPs classified as	3	2	2	0	7	0	0	0	7	0	0	0
GPs classified as	0	9	0	0	0	9	0	0	0	9	0	0
IWs classified as	0	0	4	0	0	0	4	0	0	0	4	0
UPs classified as	0	4	1	12	0	0	0	17	0	0	0	17

Low Angle Strafe

	Ratings			MDS Distances			Networks		
	IP	IW	UP	IP	IW	UP	IP	IW	UP
IPs classified as	6	0	0	6	0	0	6	0	0
IWs classified as	0	6	1	0	7	0	0	7	0
UPs classified as	0	3	13	0	0	16	0	0	16

It is important to note that there was perfect separation of groups using both the patterns from MDS and the network solutions. The structural information supplied by both these patterns appears to maximize the class differences. This information provides support to the claim that both the MDS and network solutions extract important structural information from similarity ratings.

Similarity between groups may be measured by the distance between group prototypes, as shorter distances would suggest greater similarity between the conceptual structures of the groups. Table 2 contains the distances for all pairs of groups and a ranking of these distances. The relatively smaller distances between prototypes for the networks is due to the fact that they are determined from patterns of ones and zeros, whereas distances between group prototypes for ratings and MDS distances are each on a different scale. Direct comparison across the three pattern types of the distance between prototypes would, therefore, not be very useful. The rankings of the distances between prototypes, however, does provide information about the similarity of group conceptual structures. As it turns out, the distances between prototypes for the MDS distances and networks are assumed to be most valid, because the only misclassifications occurred for patterns using the ratings information. Table 2 shows that the most similar groups are IPs and GPs for the split-plane maneuvers, and IPs and IWs for the low angle strafe. Consistent with the finding that no misclassifications occurred between IPs and UPs, it can be seen that these two groups form dissimilar classes.

Table 2 - Distances Between Group Prototypes

Split-Plane Maneuvers

	Ratings	Rank	Distances in MDS	Rank	Networks	Rank
IP-GP	33.36	2	81.30	1	4.24	1
IP-IW	38.02	4	82.96	2	5.13	4
GP-UP	37.90	3	91.31	3	4.35	2
GP-IW	30.72	1	92.56	4	5.51	5
IP-UP	39.14	5	106.29	5	4.98	3
IW-UP	49.41	6	111.96	6	5.72	6

Low Angle Strafe

	Ratings	Rank	Distances in MDS	Rank	Networks	Rank
IP-IW	25.95	1	76.32	1	4.41	1
IW-UP	36.10	2	95.87	2	4.94	2
IP-UP	38.97	3	120.83	3	5.15	3

In addition to providing information about differences between groups, pattern classification analyses also make available information on individual members of the groups that have been classified. Each individual is represented as a point in the pattern space. This makes it possible to provide the distance of individuals from both the group prototype points and the decision surface separating groups. The distance between an individual and the decision surface separating that person's group from another reflects the degree to which that individual belongs to the group. Large distances from the decision surface would reflect strong identification of the individual with the group. The closer the individual is to the decision surface, the more similar that person is to the other group. Negative distances from the decision surface indicate that the individual is on the wrong side of the decision surface and therefore, misclassified. The distance between an individual and the class prototype indicates the degree to which that person represents the average features of that class.

The distances from an individual to both the decision surface and the group prototypes for the network solutions of all individuals are given in Tables 3 through 7. Information based on classification of ratings and MDS patterns is available in an earlier report (Schvaneveldt et al., 1982). It should be noted that there are no negative distances from any individual to the decision surfaces for each of the network classifications; consequently, there were no misclassifications of individuals from any of the groups.

It appears that, even without a metric for link length, the network solutions still provide enough structural information to separate groups with a great deal of accuracy. This is indicated by the 100 percent correct classification of all individuals in their respective groups. On the average, individuals also were closest to their own group prototypes compared to the prototypes of the other groups. The average distance from the class prototype to each class member given in Tables 3 through 7 provides a measure for the degree of class clustering. Shorter distances suggest more homogeneous classes with greater consistency in the individual conceptual structures. For each group this measure is found in the table corresponding to that group's individual distances. It is the average distance from the individuals to their own group prototype and is the value underlined in the tables. For both manuevers it was found that IPs cluster most tightly while UPs are the most variable. This seems logical considering that IPs follow standardized procedures for presenting the maneuvers and have probably developed similar ways of thinking about them. The UPs, on the other hand, are still learning the material and have various ways of thinking about the relationships among these concepts.

Table 3

Separation of IPs from Other Groups
Based on a Minimum-Distance Classifier
of Network Solutions

Split-Plane Maneuvers

I1 through I7 are individual IPs

	Distances from Decision Surface			Distances from Group Prototypes			
	GP	IW	UP	IP	GP	IW	UP
I1	1.71	2.48	1.86	6.86	7.84	8.51	8.09
I2	2.42	2.75	2.80	7.26	8.56	9.00	8.98
I3	2.28	2.94	2.80	7.16	8.40	9.03	8.90
I4	1.72	2.69	1.97	7.45	8.37	9.11	8.67
I5	1.89	2.30	1.80	7.27	8.30	8.75	8.41
I6	2.40	2.32	3.28	6.54	7.94	8.15	8.68
I7	2.44	2.48	2.92	8.00	9.20	9.46	9.65
Average from group prototypes:				7.22	8.37	8.86	8.77

Low Angle Strafe

I1 through I6 are individual IPs

	Distances from Decision Surface		Distances from Group Prototypes		
	IW	UP	IP	IW	UP
I1	2.63	2.82	6.56	8.13	8.49
I2	2.83	2.47	7.19	8.75	8.78
I3	1.65	2.31	6.24	7.32	7.93
I4	2.53	2.44	6.53	8.06	8.24
I5	1.73	2.20	7.37	8.34	8.77
I6	1.85	3.22	7.66	8.66	9.58
Average from group prototype:			6.92	8.21	8.63

* Each row of the table represents one IP. Decision surfaces were computed for separating IPs from the three remaining groups. The distance from each IP to a decision surface is shown along with the distance from each IP to each group prototype. Misclassifications would be indicated by negative distances to the decision surface; however, there were no misclassifications in this case.

Table 4

Separation of GPs from Other Groups
Based on a Minimum-Distance Classifier
of Network Solutions

Split-Plane Maneuvers

G1 through G9 are individual GPs

	Distances from Decision Surface			Distances from Group Prototypes			
	IP	IW	UP	IP	GP	IW	UP
G1	2.02	2.03	1.98	8.56	7.49	8.86	8.57
G2	1.86	2.73	2.29	8.43	7.44	9.25	8.68
G3	1.15	1.96	1.58	7.82	7.17	8.54	8.07
G4	2.21	3.59	1.84	8.87	7.74	9.97	8.72
G5	2.50	3.08	1.75	9.32	8.10	9.97	8.99
G6	3.37	3.83	2.51	9.58	7.95	10.27	9.23
G7	1.90	3.12	2.79	8.11	7.04	9.17	8.60
G8	2.86	2.57	2.29	9.56	8.20	9.77	9.33
G9	1.24	1.86	2.55	8.69	8.07	9.25	9.34
Average from group prototypes:				8.77	7.69	9.45	8.84

* Each row of the table represents one GP. Decision surfaces were computed for separating GPs from the three remaining groups. The distance from each GP to a decision surface is shown along with the distance from each GP to each group prototype. Misclassifications would be indicated by negative distances to the decision surface; however, there were no misclassifications in this case.

Table 5

Separation of IWs from Other Groups
Based on a Minimum-Distance Classifier
of Network Solutions

Split-Plane Maneuvers

W1 through W4 are individual IWs

	Distances from Decision Surface			Distances from Group Prototypes			
	IP	GP	UP	IP	GP	IW	UP
W1	2.91	3.02	3.20	9.16	9.34	7.35	9.52
W2	4.17	3.74	3.36	10.36	10.28	8.03	10.14
W3	1.75	2.45	2.23	7.94	8.48	6.71	8.40
W4	1.44	1.81	2.66	7.83	8.15	6.82	8.77
Average from group prototypes:				8.82	9.06	<u>7.23</u>	9.21

Low Angle Strafe

W1 through W7 are individual INs

	Distances from Decision Surface		Distances from Group Prototypes		
	IP	UP	IP	IW	UP
W1	3.01	3.34	8.94	7.31	9.30
W2	2.00	2.63	7.91	6.71	8.42
W3	1.19	2.18	7.79	7.08	8.47
W4	1.30	1.52	8.12	7.39	8.34
W5	3.82	2.41	10.58	8.85	10.10
W6	1.74	1.83	8.14	7.14	8.31
W7	2.36	3.40	8.46	7.13	9.19
Average from group prototypes:			8.56	<u>7.37</u>	8.88

* Each row of the table represents one IW. Decision surfaces were computed for separating IWs from the three remaining groups. The distance from each IW to a decision surface is shown along with the distance from each IW to each group prototype. Misclassifications would be indicated by negative distances to the decision surface; however, there were no misclassifications in this case.

Table 6

Separation of UPs from Other Groups
Based on a Minimum-Distance Classifier
of Network Solutions

Split-Plane Maneuvers

U1 through U17 are individual UPs

	Distances from Decision Surface			Distances from Group Prototypes			
	IP	GP	IW	IP	GP	IW	UP
U1	3.09	2.63	2.25	9.52	9.09	9.25	7.73
U2	2.59	1.95	3.41	10.13	9.69	10.77	8.77
U3	2.10	1.89	3.28	11.33	11.13	12.04	10.37
U4	2.75	2.20	2.94	9.17	8.71	9.51	7.54
U5	2.27	1.83	3.37	8.69	8.30	9.57	7.27
U6	2.95	2.63	2.99	10.96	10.66	11.18	9.53
U7	2.70	2.15	2.02	9.52	9.09	9.33	7.99
U8	2.18	1.77	2.59	8.75	8.38	9.19	7.41
U9	2.54	2.09	3.21	8.60	8.18	9.25	6.98
U10	2.27	2.13	2.98	9.41	9.19	10.00	8.12
U11	2.71	2.51	3.45	9.03	8.74	9.70	7.39
U12	2.31	2.08	2.78	8.95	8.68	9.43	7.56
U13	2.65	1.84	2.36	9.53	8.97	9.57	8.03
U14	1.31	2.15	2.03	7.86	8.22	8.49	6.99
U15	2.84	2.06	3.06	9.99	9.45	10.32	8.45
U16	1.52	2.25	2.59	9.33	9.57	10.07	8.48
U17	3.56	2.84	3.33	11.19	10.71	11.31	9.48
Average from group prototypes:				9.53	9.22	9.94	8.12

* Each row of the table represents one UP. Decision surfaces were computed for separating UPs from the three remaining groups. The distance from each UP to a decision surface is shown along with the distance from each UP to each group prototype. Misclassifications would be indicated by negative distances to the decision surface; however, there were no misclassifications in this case.

Table 7

Separation of UPs from Other Groups
Based on a Minimum-Distance Classifier
of Network Solutions

Low Angle Strafe

U1 through U16 are individual UPs

	Distances from Decision Surface		Distances from Group Prototypes		
	IP	IW	IP	IW	UP
U1	4.06	3.90	12.50	12.37	10.70
U2	2.88	3.60	10.68	10.95	9.18
U3	2.92	2.43	9.49	9.16	7.73
U4	1.74	1.74	8.79	8.75	7.70
U5	3.89	3.36	12.35	12.08	10.61
J6	1.68	1.26	9.16	8.90	8.17
U7	2.00	1.84	8.77	8.63	7.51
U8	3.01	2.86	10.13	9.99	8.46
U9	1.72	2.19	8.96	9.18	7.91
U10	2.96	3.23	10.47	10.53	8.89
U11	2.94	2.79	9.64	9.50	7.92
U12	1.87	1.59	9.02	8.82	7.88
U13	1.71	1.69	8.74	8.68	7.66
U14	1.70	1.91	8.85	8.93	7.80
U15	2.17	1.97	9.56	9.40	8.30
U16	4.00	3.21	11.57	11.15	9.63
Average from group prototypes:			9.92	9.81	8.50

* Each row of the table represents one UP. Decision surfaces were computed for separating UPs from the three remaining groups. The distance from each UP to a decision surface is shown along with the distance from each UP to each group prototype. Misclassifications would be indicated by negative distances to the decision surface; however, there were no misclassifications in this case.

The classification data discussed so far have resulted from applying discriminant functions to members of classes from which the discriminant functions were originally derived. Although this provides useful information about class and individual differences, it is not a direct test of the ability of discriminant functions to categorize members of unknown classes. The second analysis involved generating a discriminant function on the basis of a limited training set from two classes and then using the function to place new and unknown members into one of the two classes.

The results of this analysis are given in Tables 8 and 9 for the split-plane maneuvers and Table 10 for the low angle strafe maneuver. The tables give the total number of individuals for which classification was attempted, followed by the percentage of those correctly classified for the ratings, MDS, and network patterns. Since 100 different randomly chosen training sets were used for each training set size, the number of classifications attempted is always 100 times the number of remaining members in the two classes. The probability of randomly classifying correctly at least the obtained number of correct classifications for each training set size was less than .01 for all but two instances for the split-plane maneuver. The two exceptions had a probability less than .05 and occurred when the training set size was 1 and 1. This probability is associated with the comparison of IPs and GPs and the comparison of IPs and IWs. For the low angle strafe maneuver the probabilities were less than .01 for the comparison of IPs and UPs and the comparison of IWs and UPs. For the comparison of IPs and IWs, probabilities were less than .05 for all training set sizes, except when the training set size was 1 and 1, in which case the probability was less than .10.

Pattern classification with networks was successful. Table 8 shows that with only one member each from the IPs and GPs on which to base a decision surface, 742 out of 1400 remaining IPs were classified correctly. With only three members each from the IPs and UPs it is possible to classify correctly the remaining 18 members with an 88 percent accuracy rate. Table 10 shows that the classification was poorest for IPs and IWs with the low angle strafe maneuver. Table 2 shows that the distance between group prototypes is shortest for IPs and IWs, indicating that they are the most similar pair of groups in viewing this maneuver. This points out that, in general, classification improves as the distance between classes in the pattern space increases.

Classification generally improves also as the size of the training set increases. With larger training sets, the discriminant function is derived from a larger, more representative sample. Exceptions to this sometimes occur when a few members in one class strongly resemble members of the other class. In this case, the decrease in percent correct is probably due to the difficulty in classifying these outliers.

Table 8

Classification of Group Members Using Limited Training Sets

Split-Plane Maneuver Concepts

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
IPs	GPs				
1	1	1400	57	68	53
2	2	1200	67	77	56
3	3	1000	67	82	60
4	4	800	68	84	62
5	5	600	62	87	64
6	6	400	52	87	64
7	7	200	51	84	66
		Average:	63	79	61

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
IPs	IWs				
1	1	900	53	56	53
2	2	700	57	60	61
3	3	500	61	63	64
4	4	300	71	67	72
		Average:	58	60	63

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
IPs	UPs				
1	1	2200	65	79	70
2	2	2000	77	95	80
3	3	1800	78	98	88
4	4	1600	83	100	89
5	5	1400	89	100	91
6	6	1200	91	100	94
7	7	1000	96	100	94
		Average:	80	94	87

Table 9

Classification of Group Members Using Limited Training Sets

Split-Plane Maneuver Concepts

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
GPs	IWs				
1	1	1100	58	62	62
2	2	900	64	71	70
3	3	700	65	76	74
4	4	500	70	76	74
		Average:	63	70	70

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
GPs	UPs				
1	1	2400	62	79	67
2	2	2200	70	89	76
3	3	2000	74	93	82
4	4	1800	76	95	89
5	5	1600	76	95	90
6	6	1400	76	95	94
7	7	1200	73	95	95
8	8	1000	73	96	96
9	9	800	72	98	97
		Average:	72	92	87

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
UPs	IWs				
1	1	1900	68	76	65
2	2	1700	81	93	84
3	3	1500	81	94	90
4	4	1300	78	95	94
		Average:	76	89	83

Table 10

Classification of Group Members Using Limited Training Sets

Low Angle Strafe

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
IPs	IWs				
1	1	1100	49	56	48
2	2	900	43	54	51
3	3	700	45	53	55
4	4	500	47	55	55
5	5	300	43	53	57
6	6	100	56	56	60
		Average:	46	55	54

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
IPs	UPs				
1	1	2000	59	84	59
2	2	1800	72	96	67
3	3	1600	73	96	73
4	4	1400	81	97	76
5	5	1200	79	97	79
6	6	1000	80	95	86
		Average:	73	94	73

Training Set Size		Number Classified	Percent Correct of Classifications		
			Ratings	Distance in MDS	Network
UPs	IWs				
1	1	2100	58	69	53
2	2	1900	62	88	71
3	3	1700	65	91	74
4	4	1500	67	92	80
5	5	1300	67	93	78
6	6	1100	60	93	86
7	7	900	54	87	85
		Average:	62	87	77

The discriminant functions based on the network patterns resulted in better classification of unknown members compared to the rating patterns. The average percentage of correct classifications for the network patterns was significantly greater than the average for the ratings ($p<.01$, sign-test, based on the binomial distribution). Apparently, the structural information captured by the networks is superior to the information in the rating data despite the simplicity of the network representation. Only the presence or absence of links was used in the patterns. The MDS patterns resulted in better classification of unknown members compared with the network patterns. The average percentage of correct classifications for the MDS pattern was significantly greater than the average for the network patterns ($p<.01$, sign-test). The superiority of MDS may be due to the metric information it provides. Further work is required to determine whether adding metric information to the networks will improve their ability to classify individuals.

The goal of this phase of the project has been to test the ability of network representations to discriminate between individuals in different groups. In general, the pattern classification techniques appear to provide a sensitive method for detecting differences between the networks of both groups and individuals. The finding that the distance between concepts in an MDS solution allow for more accurate classification than does the network pattern illustrates the need for deriving a metric which describes the length of network links. It would be of interest to examine the results of the classification of a pattern containing the metric for the length of links in a network relative to the classification of the MDS distances.

Identification of Links between Concepts

As seen in several applications of the network algorithm, networks provide useful and interpretable structures. The algorithm itself, however, only indicates where the links are in a set of concepts. The task of identifying the nature of the links is the purpose of the present study. An expert fighter pilot assisted in identifying the nature of the relation represented by the links in the networks of IPs for split plane maneuvers and the low angle strafe (Schvaneveldt et al., 1982). The results of this analysis are presented in Tables 11 and 12. It should be noted that there were many fewer types of links than there were links.

For the split-plane maneuvers, there were seven types of links: AFFECTS (15 links), IS A (11 links), LEADS TO (5 links), DESIRABLE (4 links), ACCEPTABLE (2 links), SELECTS (2 links), and INSTRUMENT OF (1 link). In some cases, a more general relation is used where more specific relations could be specified. In particular, the general relation AFFECTS can be made more specific for some of the links. For example, while quarter plane affects angle off, the specific purpose of the quarter plane is to INCREASE angle off. As an initial classification attempt, however, the fewest possible types of relations were used. The general meaning of the relations is as follows. Let "first" represent the first element of a linked pair of concepts and "second" represent the second element. AFFECTS means that first leads to some change in second. IS A means that first is one member of the category designated by second. LEADS TO means that first produces the result designated by second. DESIRABLE means that first is an optimal or desirable condition for second. ACCEPTABLE means that first is an acceptable (but not optimal) condition for second. SELECTS means that first is involved in choosing or selecting second. INSTRUMENT OF means that first is the instrument of the action designated by second.

For the low angle strafe, there were also seven types of links: AFFECTS (12 links), DETERMINES (11 links), IS POINT OF REFERENCE FOR (5 links), DESIRABLE (5 links), IS (3 links), AVOIDS (2 links), and INSTRUMENT OF (1 link). Not surprisingly, some of the relations occur in both sets of concepts. The relations AFFECTS, DESIRABLE, and INSTRUMENT OF seem to be natural relations in the domain of fighter maneuvers. There are also various ways of describing categorical relationships. These appear as IS A in the split-plane concepts and as IS POINT OF REFERENCE FOR and IS in the low angle strafe concepts. The relation DETERMINES represents a stronger version of the relation AFFECTS. DETERMINES means that the first element leads to the second, regardless of other factors. AFFECTS means that the first element can lead to the second depending on other factors.

With the addition of information about the identity of the relations represented by links in the network, the network representation becomes a more complete representation of the conceptual structure of IPs. As such, it may be useful in communicating some of the important conceptual relations to trainees. The network with labelled links should also prove useful in further attempts to define conceptual structure and to relate these structures to actual performance in the aircraft.

Table 11 - Concept LINKS - Split Plane Maneuvers

AFFECTS	IS A
low yo yo-acceleration	quarter plane-vertical maneuvering
quarter plane-angle off	barrel roll-vertical maneuvering
lag roll-relative energy	cutoff-overtake
lag roll-aspect angle	smash-overtake
barrel roll-aspect angle	airspeed-acceleration
weapons parameters-guns	smash-airspeed
weapons parameters-heat	G loading-weapons parameters
airspeed-vertical maneuvering	smash-relative energy
airspeed-corner velocity	3-9 line-aspect angle
acceleration-G loading	aspect angle-weapons parameters
radial G-G loading	high yo yo-quarter plane
power setting-smash	
power setting-extension	
lift vector-radial G	
lift vector-vertical maneuvering	

LEADS TO	DESIRABLE
quarter plane-lag pursuit	lead pursuit-guns
lag roll-lag pursuit	airspeed-pure pursuit
angle off-snapshot	6 O'Clock-heat
lead pursuit-cutoff	3-9 line-quarter plane
acceleration-extension	

ACCEPTABLE	SELECTS
lag pursuit-heat	switchology-guns
pure pursuit-heat	switchology-heat

INSTRUMENT OF
guns-snapshot

Table 12 - Concept LINKS - Low Angle Strafe

AFFECTS

drift-bullet impact
dive angle-recovery
bunt-glide path
airspeed-closure
closure-foul
bank-tracking
pipper fixation-foul
pull up-walking
yaw-tracking
range-bullet impact
pipper placement-bullet impact
pipper placement-aim point

DETERMINES

bank-drift
aim off point-glide path
aim off point-pipper placement
dive angle-glide path
foul line-foul
altitude-foul
walking-bullet impact
trigger-fire
pipper placement-tracking
bunt-pipper placement
pull up-recovery

IS POINT OF REFERENCE FOR

foul line-recovery
foul line-fire
run in line-final
aim point-pipper fixation
final-tracking

DESIRABLE

stabilize-airspeed
stabilize-trim
stabilize-tracking
tracking-fire

IS

glide path-final
burst-fire
foul line-range

AVOIDS

pull up-ricochet
pull up-foul

INSTRUMENT OF

guns-fire

MULTIDIMENSIONAL SCALING

Multidimensional scaling is a powerful technique for producing structural descriptions of empirical similarity judgments. The technique arranges the judged concepts in an N-dimensional space where the Euclidean distances between points reflect the psychological proximity of the concepts. The MDS supplies several important pieces of information. First, it summarizes the data into a spatial configuration, which though at times complex, is considerably more informative than are the empirical similarity judgments. Second, MDS captures the global relations among the concepts. That is, MDS considers the relationship of each concept to all other concepts and places the concepts along the dimensions of the space in a way that reflects these relations. Although such a procedure can distort local relationships, the procedure is unsurpassed at revealing global structure. While identifying the dimensions of the space may, at times, prove problematic, successful identification supplies information about conceptual structure that cannot be gleaned from the original ratings nor from other scaling techniques. Finally, MDS supplies a metric (distance between concepts in multidimensional space) that has some useful applications.

Optimal Dimensionality in Representing Concepts

Most MDS programs require the user to specify the number of dimensions to be used in scaling the input data. In representing a specific conceptual structure, determining the number of dimensions that best describes the conceptual space may be somewhat problematic. The use of too few dimensions will result in the loss of potentially important information about the interrelationships among concepts. In contrast, uncovering the relationships between concepts becomes increasingly complex as the number of dimensions used to describe the conceptual structure increases. Thus, using too many dimensions will result in an unnecessarily complex representation of the conceptual structure. The goal then is to use the minimum number of dimensions that will preserve meaningful relationships between concepts in representations of a conceptual space.

The earlier approach (Schvaneveldt et al., 1982) to determining the appropriate number of dimensions was to increase systematically the number of dimensions in the scaling program and to plot the amount of variance in the IPs data which was accounted for by MDS solutions. The point at which the function began to level off was selected as the appropriate dimensionality for that set of concepts. For the split plane maneuvers, a five-dimensional solution accounted for 80 percent of the variance in the input data (similarity ratings) and was selected as the appropriate dimensionality for the split-plane data. Two of these dimensions were associated with temporal factors, and a third dimension with distinguishing maneuvers appropriate with lead pursuit as opposed to lag pursuit. The other two dimensions have not yet been identified.

It was discovered that the distances recovered from MDS scaling solutions were better at discriminating between individuals in different groups (IPs, GPs, UPs, and IWs) than were the rating data on which the MDS solutions were based. This result led to reexamination of the issue of optimal dimensionality from a different perspective. If MDS distances are superior to ratings and the two correlate highly, perhaps the superiority of MDS was constrained by using as many as five dimensions. Since the correlations between MDS distances and ratings necessarily increase as the number of dimensions increases, possibly MDS distances were been artificially constrained to correspond to the ratings. To verify that the conceptual space for split plane maneuvers is best represented with a minimum of five dimensions, conceptual structures derived from multi-dimensional scaling output using two, three, and four dimensions were compared with the five-dimensional structures.

Table 13 shows the average correlations between the MDS distances for pairs of individual subjects. The distances were derived from multi-dimensional scaling using two, three, four, and five dimensions. Notice that the correlations obtained using four dimensions are comparable to those obtained using five dimensions, and even slightly higher in some cases. The correlations within and between the IP and GP groups using three dimensions are also quite similar to the four- and five-dimensional correlations. Apparently, little information about the conceptual structure of these concepts is lost when dropping one and possibly two dimensions from the conceptual space. The two-dimensional correlations are somewhat lower, and in fact, are comparable to those obtained using the raw data, or rating scores.

Perhaps a more salient indication of the importance in the way this conceptual space is represented is the ability of pattern recognition techniques to discriminate between groups of flying personnel based on conceptual structures represented in two, three, four, and five dimensions. Four groups were examined: GPs, IPs, IWs and UPs. Each individual is represented as a distance vector consisting of the 435 distances between concepts (30 concepts taken two at-a-time) in the MDS spatial structure. The classification of individuals into groups will be more successful when the groups are more highly separable. Further, assuming that the number of dimensions used to represent a conceptual space has some effect on the degree of group differentiation, the optimal number of dimensions used to represent the conceptual space is the number at which groups of flying personnel are most highly separable.

Table 13

Average Correlations Within Groups and Between Groups for Split-Plane Maneuvers

Two Dimensions

	IP	GP
IP	.42	.34
GP	.34	.36

Three Dimensions

	IP	GP
IP	.45	.39
GP	.39	.42

Four Dimensions

	IP	GP	IW	UP	Average
IP	.46	.38	.41	.22	.37
GP	.38	.40	.34	.24	.34
IW	.41	.34	.37	.20	.33
UP	.22	.24	.20	.30	.24

Five Dimensions

	IP	GP	IW	UP	Average
IP	.45	.37	.40	.22	.36
GP	.37	.39	.34	.24	.34
IW	.40	.34	.38	.20	.33
UP	.22	.24	.20	.29	.24

Table 14 compares the performance of a training algorithm in discriminating between IPs and GPs. The training algorithm takes some number of individuals (shown in the left-most columns) from each of two groups, develops a classifier that sucessfully discriminates between those individuals in the two groups, and then applies the classifier to the other members of the groups. The percent correct assignments are shown for 100 iterations for each size of initial group. Each iteration randomly selects the initial individuals. Classification performance using distances derived from four-dimensional solutions compared well with performance using distances derived from five-dimensional solutions. Slightly poorer performance occurred with two- and three-dimensional distances.

Table 14

Training Algorithm Classification Performance of IPs and GPs Using Distances Derived From Two, Three, Four, and Five Dimensions

Training Set Size		Percent Correct			
IP	GP	2D	3D	4D	5D
1	1	61	62	70	68
2	2	68	70	75	77
3	3	69	76	80	82
4	4	72	79	83	84
5	5	73	82	85	87
6	6	80	84	84	87
7	7	85	80	81	84
Mean		69	73	78	79

Further comparisons involving all other groups of pilots (Table 15) revealed that, in general, the training algorithm can discriminate between groups equally well with MDS solutions with four or five dimensions. These comparisons suggest that little is gained from increasing the conceptual space from four to five dimensions and that some information is lost by confining the space to less than four dimensions.

Table 15 - Training Algorithm Classification Performance

Training Set Size		Percent Correct	
IP	IW	4D	5D
1	1	54	56
2	2	61	60
3	3	64	63
4	4	71	67
Mean		60	60

Training Set Size		Percent Correct	
IP	UP	4D	5D
1	1	80	79
2	2	94	95
3	3	96	98
4	4	98	100
5	5	99	100
6	6	99	100
7	7	100	100
Mean		94	94

Training Set Size		Percent Correct	
IW	UP	4D	5D
1	1	80	76
2	2	91	93
3	3	93	94
4	4	93	95
Mean		89	89

Training Set Size		Percent Correct	
GP	IW	4D	5D
1	1	65	62
2	2	72	71
3	3	79	76
4	4	80	76
Mean		72	70

Training Set Size		Percent Correct	
GP	UP	4D	5D
1	1	76	79
2	2	89	89
3	3	93	93
4	4	94	95
5	5	94	95
6	6	95	95
7	7	95	95
8	8	94	96
9	9	95	98
Mean		90	92

	4D	5D
Grand Mean	87.3	86.8

Still another way of comparing representations of concepts using various numbers of dimensions can be obtained from a minimum-distance classifier. The minimum-distance classifier is a pattern recognition technique that calculates a prototype for each group by averaging feature values (distances between concepts in this case) and calculates the distance between each prototype and each pattern. Patterns are placed into the group that is represented by the closest prototype. Given the distances between patterns of a group and their prototype, and the distances between those same patterns and the prototypes of other groups, a measure of group differentiation can be obtained. For example, let Dw be the sum of the distances of patterns within a group to the group prototype, and Db be the sum of the distances between those patterns and the prototypes of contrasting groups. The ratio Dw/Db is essentially the degree to which patterns of a group cluster around their own prototype, divided by the degree to which those patterns are separated from prototypes of contrasting groups. Lower ratios would mean that patterns of the same group are close to their prototype relative to prototypes of other groups. Consequently, the group would be highly differentiated from other groups. Higher ratios would mean either that patterns within a group are far away from their group prototype, or that patterns within a group are relatively close to prototypes of contrasting groups, or both. The average ratio for a set of groups would give an indication of overall group differentiation.

Table 16 shows that overall, groups were most differentiated (had lower structural ratios) when represented as distances derived from four-dimensional scaling solutions. This suggests that pattern recognition techniques should be able to classify different groups of pilots more accurately when their conceptual structures are represented as distances derived from MDS solutions using four dimensions.

Table 16

Structural Ratios (Dw/Db) of Classes of Pilots Using
Two, Three, Four, and Five Dimensions

Class	2D	3D	4D	5D
IP	.803	.815	.769	.772
GP	.836	.836	.802	.810
IW			.761	.759
UP			.783	.797
Mean	.820	.825	.779	.785

In summary, the minimum number of dimensions that would optimally describe a conceptual space representing split-plane concepts was investigated. Within and between group correlations suggested that four and possibly three dimensions were adequate to describe the conceptual space. Other measures, however, proved to be more highly predictive of classification performance using pattern recognition techniques. Structural ratios, which measure the amount of group differentiation, suggested that pattern recognition techniques would perform optimally when conceptual structures were represented as distances derived from MDS solutions using a minimum of four dimensions. This was verified by comparing the classification performance of a training algorithm using two, three, four, and five dimensions.

Spatial Representations of Individuals and Groups

Previously in this project, MDS techniques have been used to derive spatial representations of various flight-related concepts. These MDS representations are useful in that they (a) illustrate conceptual relations in a concrete manner, (b) depict global relations and dimensions among the concepts, and (c) produce measures of spatial distance which are useful in comparing different representations. While these MDS solutions illustrate relations among concepts in an individual's cognitive organization, information about the relations among individuals can also be derived. For instance, within and between group correlations of these solutions indicate degree of agreement between and within groups of individuals. Pattern classification techniques use the MDS solution to compare an individual to that person's group in terms of distance from decision surfaces and prototypes. The information from these techniques, however, lacks the concrete spatial representation and the relational and dimensional information of the MDS solution. Thus, it would be useful to use scaling techniques to produce a spatial representation of individuals, just as was done with flight-related concepts.

The purpose of this phase of the project is to derive MDS representations of individuals. Not only should these representations illustrate differences between and within groups of individuals, but they should also provide an indication of global dimensions that separate individuals into these groups. This dimensional information has practical applications in terms of training and selection. For instance, if undergraduate pilots that were closer to a particular end of a dimension were also more likely to succeed as fighter pilots, then separation of individuals along this dimension could be used as a predictor for future success. Also, the closer that an individual is in the MDS solution to one particular group of pilots, the more similar that person's cognitive representation of flight-related information is to other pilots of this experience level.

There are several ways of generating MDS solutions for individuals. McKeithen, Reitman, Rueter, and Hirtle (1981) investigated the differences among computer programmers of differing levels of expertise. Subjects recalled a list of ALGOL W reserved words, and based on the order that each subject recalled the words, a tree structure was generated. The number of chunks in common within these tree structures was used as a measure of similarity between individuals. These similarity values were then arranged in a matrix and scaled using MDS techniques. In this way, individuals were plotted in multidimensional space. Adelson (1981), in a similar experiment with computer programmers, derived an MDS solution for individuals by correlating distance matrices for each subject. From these correlations, an intersubject correlation matrix was constructed, to which the MDS technique was applied.

An additional technique that seems to capture the distance information inherent in MDS involves the calculation of distances between each person using the distances derived from their individual MDS solutions. In this case, the individual can be thought of as a point in "n-dimensional" space (n = 435 dimensions based on the 435 distances for all pairs of 30 terms). The distance between two individuals would take into account the difference in distance for each of the 435 pairs of points for the two individuals. This "distance" technique will be used in this project to derive a measure of intersubject similarity, since distance measures have proven useful in pattern recognition analyses of individual and group differences.

Method

Distance vectors produced from four-dimensional MDS solutions of both Split and Strafe concepts were used to compare individual pilots. Four dimensions were chosen since this number of dimensions has been found to be optimal, as mentioned in the preceding section of this report. Results from split-plane and low angle strafe concepts were analyzed separately. The distance vectors for each subject consisted of 435 distances between pairs of 30 concepts. Thus, each individual pilot can be thought of as a point in 435-dimensional space.

Distances between individuals were taken as the Euclidean distance between the points representing the individuals in the 435-dimensional space. These distances resulted in a matrix of distances with individuals as rows and columns. These distance values were then scaled in multidimensional space using one and two dimensions for both the split-plane and strafe concepts. Also, in order to focus on differences among experts, two-dimensional representations were derived, excluding UPs.

Results and Conclusions

The two-dimensional solutions for all subjects can be seen in Figures 1 and 2. In both representations, the undergraduate pilot trainees are linearly separable from the more experienced subjects (IPs, GPs, and IWs). In the split-plane representation, the GPs tend to be separated from the other experienced subjects (IWs and IPs) on the vertical dimension. Data from GPs were not available for the strafe concepts, but in that representation, a slight separation of IPs and IWs is evident. Therefore, the two-dimensional MDS solutions of individuals provide excellent illustrations of organization of individuals along an "expertise" dimension. For both representations, this is the horizontal dimension which plots less experienced subjects to the left and more experienced pilots to the right. The vertical dimension is not as clearly defined, although it does tend to separate the different groups of experts.

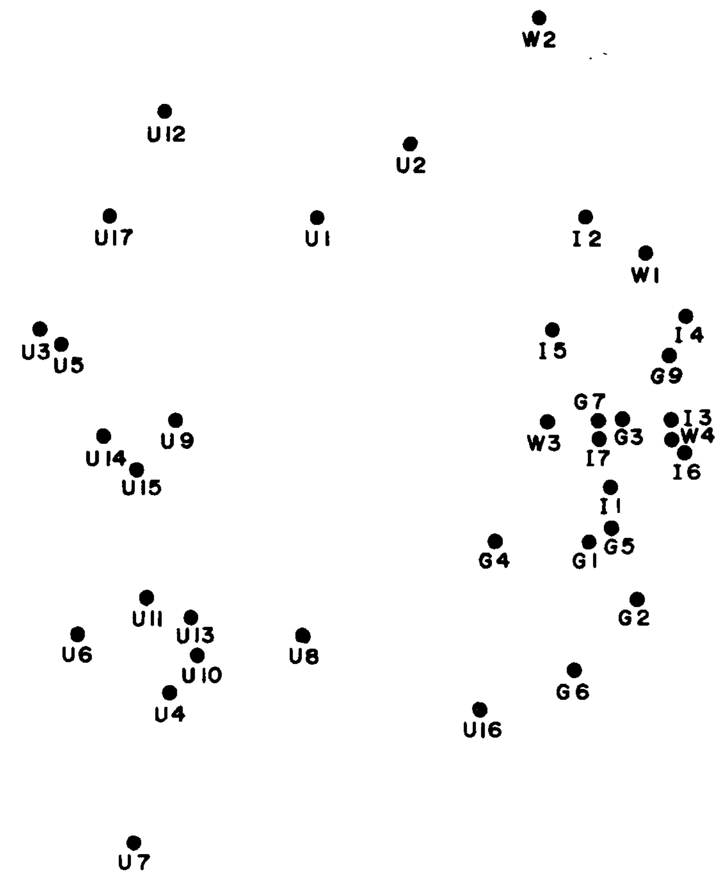

Figure 1. Two-dimensional MDS solution for all subjects for split-plane concepts. I - Instructor Pilots, G - Air National Guard Pilots, U - Undergraduate Pilot Trainees, W - Instructor Weapons Systems Officers.

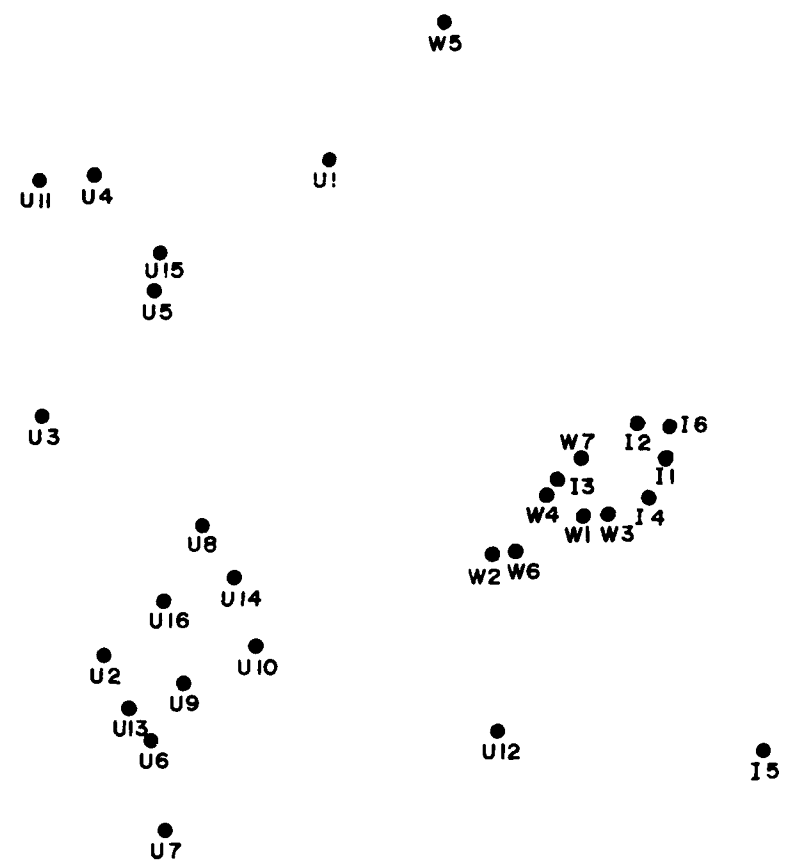

Figure 2. Two-dimensional MDS solution for all subjects for strafe concepts. I - Instructor Pilots, U - Undergraduate Pilot Trainees, W - Instructor Weapons Systems Officers.

In an attempt to further delineate the different groups of experts in an MDS representation, an inter-subject distance matrix was derived using data from only the expert pilots. The two-dimensional MDS solutions for the expert subset are presented in Figures 3 and 4. In the split-plane representation, IPs and IWs are nearly linearly separable from GPs. This might be expected, based on the fact that IPs and IWs are involved in teaching, whereas GPs are not. Therefore, this dimension could be labeled "teaching experience," with the GPs being located on the lower end of the continuum and the IPs and IWs on the upper end. The second dimension is not as clear in this case. In the strafe representation, the horizontal dimension tends to separate the IWs from IPs, with a few exceptions. Apparently, the IWs and IPs are not as easily separated as other groups.

Table 17 shows the one-dimensional MDS solutions. A one-dimensional solution should extract the one dimension that accounts for the most variance. In Table 17, subjects are presented in order of occurrence in the MDS solution. Values assigned to each pilot are transformed coordinate values and are an indication of the relative distance from one individual to another. In both split-plane and strafe solutions, the largest distance interval occurs between the group of UPs and experienced subjects. There is one exception in each case, however. In the split-plane solution, UP-16 is in the expert group and in the strafe solution, UP-12 is in the expert group. This is not surprising because these two individuals also appear closer to the expert groups in the two-dimensional solutions. Thus, it seems that the one-dimensional solutions ordered individuals along the expertise dimension.

The results from the MDS of individual subjects clearly help to define the separate groups of subjects and the locations of individuals in relation to the groups. The previous finding that the more experienced pilots agree more with each other and have well defined conceptual structures is supported by Figures 1 and 2, in which expert groups tend to form tighter clusters than do UPs. From these scaling solutions, two dimensions have been labeled. The "expertise" dimension separates UPs from all other groups, and the "teaching experience" dimension separates GPs from IWs and IPs. Also, if the individuals in the one-dimensional solutions are ordered along the "expertise" dimension, then this ordering may prove to be a possible means of predicting success as a pilot or in simply determining a student's cognitive "status" in relation to other students as training progresses. For instance, if expertise is the appropriate label for the single dimension in the one-dimensional solution, individuals that are close to the expert end of the continuum should have organizations of flight-related information that are similar to those of experts. In general, representation of individual pilots in multidimensional space provides a concrete illustration of relations among individuals and groups, as well as an indication of possible dimensions which separate these individuals and groups.

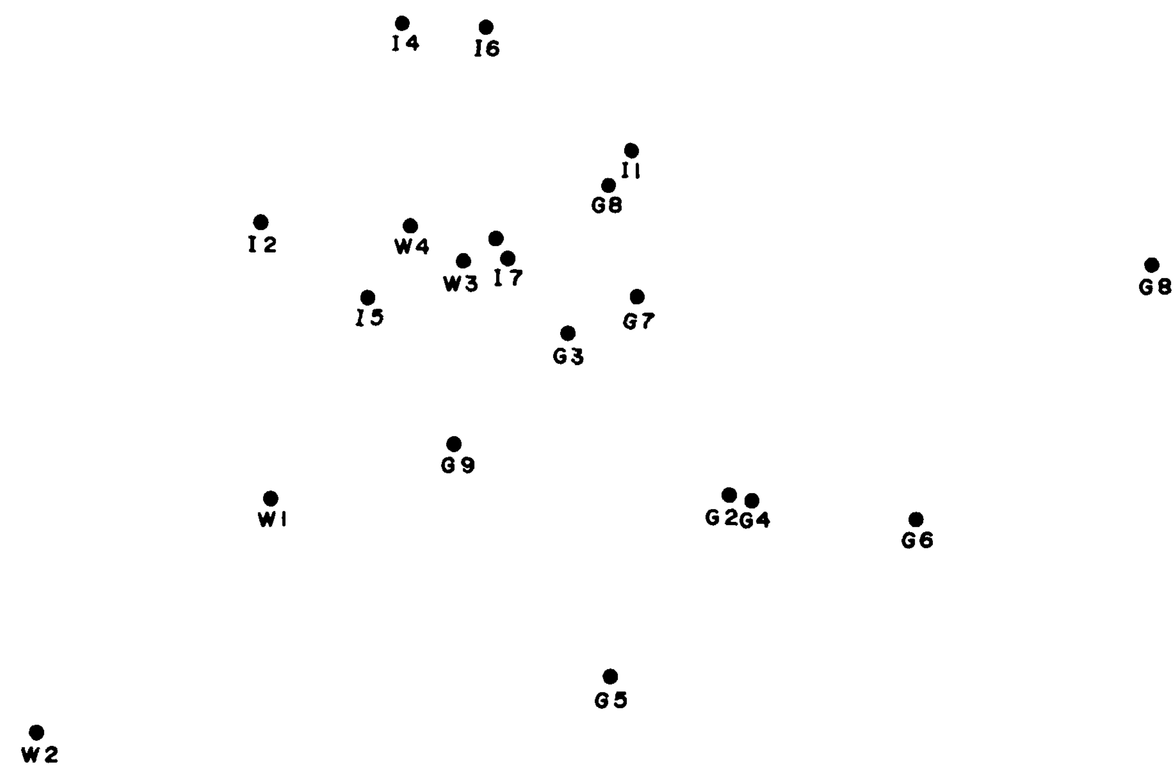

Figure 3. Two-dimensional MDS solution for experienced subjects for split-plane concepts. I - Instructor Pilots, G - Air National Guard Pilots, W - Instructor Weapons Systems Officers.

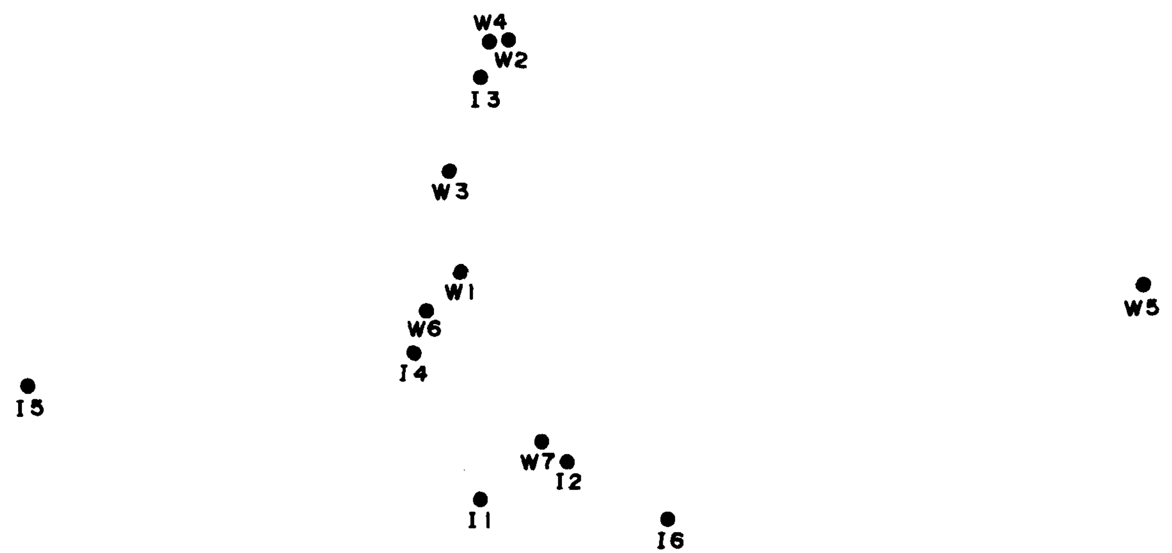

Figure 4. Two-dimensional MDS solution for experienced subjects for strafe concepts.
I - Instructor Pilots, W - Instructor Weapons Systems Officers.

Table 17 - One-Dimensional MDS Solutions for Individuals

Split-Plane Maneuvers		Low Angle Strafe	
Individual	Position on Dimension	Individual	Position on Dimension
GP 8	0	IP 5	0
IW 2	3	IW 5	26
IP 4	29	IP 6	51
IP 6	36	IP 1	52
IP 3	38	IP 4	60
IW 1	40	IP 2	62
GP 9	42	IW 3	88
GP 2	43	UP 12	91
IP 2	46	IP 3	94
IW 4	48	IW 1	96
GP 6	50	IW 7	98
GP 3	59	IW 4	111
IP 1	61	IW 6	119
GP 5	62	IW 2	123
GP 1	66	UP 14	202
GP 7	67	UP 10	218
IP 7	69	UP 8	230
IP 5	75	UP 16	246
UP 16	91	UP 9	249
IW 3	92	UP 1	256
GP 4	103	UP 15	260
UP 2	184	UP 5	267
UP 1	198	UP 13	273
UP 8	198	UP 2	274
UP 9	227	UP 6	278
UP 13	235	UP 3	286
UP 15	236	UP 7	300
UP 10	241	UP 4	310
UP 11	247	UP 11	326
UP 14	251		
UP 4	256		
UP 17	268		
UP 5	271		
UP 6	273		
UP 12	278		
UP 3	281		
UP 7	304		

Note.
IP-Instructor Pilots
GP-Air National Guard Pilots
UP-Undergraduate Pilot Trainees
IW-Instructor Weapons Systems Officers

EXPERIMENTAL ANALYSES OF CONCEPTUAL STRUCTURE

Ordered Recall: A Comparison of Networks and MDS

The MDS techniques and the recently developed scaling technique that produces a GWN have been used extensively throughout this project to investigate the organization of critical flight-related concepts in memory. Structural representations of memory have been generated using these techniques. The MDS techniques produce spatial representations of memory in various dimensions, whereas the GWN technique produces a structural representation consisting of nodes and links, representing concepts and their relationships, respectively.

As previously mentioned, these scaling techniques and their representations differ in several ways. The MDS techniques involve the "fitting" of a set of psychological distances, such as those derived from similarity ratings, into a space consisting of a predetermined number of dimensions. This process of manipulating the data to fit the dimensionality results in a loss of some information. In general, the information lost is that concerning specific or local relationships among concepts. On the other hand, global information, such as clusters of several concepts, is augmented through this technique. Also, from a MDS spatial representation, dimensions in which concepts are organized can be discovered (e.g., temporal or procedural dimensions). Another advantage of the MDS technique is that from the solution, a distance metric can be derived. These distances are useful in comparing organizations across individuals or groups.

The GWN provides local information that the MDS representation lacks. Schvaneveldt et al. (1982) developed the GWN algorithm, and Schvaneveldt and Durso (1981) used the algorithm to scale a set of natural concepts such as plants, animals, and their features. To illustrate the difference between the network and MDS solutions, they positioned the nodes in the network according to the two-dimensional MDS solution. The concept, FEATHERS, illustrates the fact that networks are better able to represent concepts that are connected to many diverse concepts. In the MDS solution, FEATHERS is closely related to the concepts CHICKEN, FROG, and ROBIN in terms of distance in space, while it is distant to concepts such as HAIR and BIRD. In the network, however, FEATHERS is linked to CHICKEN, as well as HAIR and BIRD, but not to FROG or ROBIN. Thus the GWN captures these additional relationships that are absent in the MDS solution. Also, in the GWN, atypical category members are not connected, whereas they may be close in an MDS representation.

In general then, the MDS provides global information, while the GWN provides local information. An important issue, however, involves the validation of one of these structural descriptions. That is, which scaling technique produces a representation that is most similar to actual memory structure? To compare these two techniques, an ordered recall task can be used in which the order of the list is derived from either MDS or GWN representations.

Recall order has been used frequently to generate representations similar to those produced by relatedness ratings (Adelson, 1981; Chase & Simon, 1973; McKeithen, et al., 1981). In order to compare memory stuctures of expert and novice computer programmers, Adelson(1981) presented lines of Polymorphic Programming Language "(PPL)" code to subjects in a random fashion. Subjects were asked to recall the lines of code. Psychological distance, in this case, was defined as the number of intervening items in a recalled list. Resulting MDS representations showed that novice programmers organize according to syntax, whereas experts organize according to procedure or function. In general, it is assumed in these studies that the order in which a list of randomly presented concepts is remembered corresponds to the organization of those concepts in memory.

Chase and Simon (1973) investigated the differences between chess players of different skill levels in a memory task and a perception task. In the memory task, subjects had to reproduce the pieces and their locations on a chessboard after viewing the setup for 5 seconds. They found that for expert chess players, recall of the board was superior when the pieces were arranged in a meaningful fashion than when the pieces were arranged randomly. Novices, however, did not benefit from a meaningful organization. This finding has been replicated in several studies (Engle & Bukstel, 1978; McKeithen, et al., 1981), suggesting that experts benefit from meaningful organizations as opposed to random arrangements.

According to the findings of these studies, a meaningful organization is beneficial to recall for expert subjects, and the organization that corresponds most closely to actual memory should produce superior recall. Along this line of reasoning, a list of words or concepts, organized in a meaningful fashion should facilitate recall over a random or nonmeaningful organization, when the subject has to recall the words in the order in which they are presented. Also, the more meaningful the organization is to the subject (the more similar to actual memory structure), the less time it should take for perfect ordered recall.

To compare the MDS and GWN representations, recall performance can be compared using lists of concepts generated from either MDS or GWN representations. The MDS list would consist of terms ordered in such a way that each term is spatially close to the following term according to MDS, but is not linked to the following term in the network. The opposite would be the case for the GWN lists. Each concept would be linked to the following concept in the network, but the terms would be distant according to MDS. If one list is recalled in significantly fewer trials than the other, then it is likely that the representation from which it was derived should correspond more closely to the actual organization of those concepts in memory.

An initial study was done using introductory psychology students and natural concepts. These concepts were chosen because MDS and GWN solutions were already available for these concepts (Schvaneveldt & Durso, 1981).

Method

Subjects. The subjects for the pilot study were 54 undergraduates from New Mexico State University, enrolled in an introductory psychology class. The subjects volunteered for the experiment in order to fulfill course requirements.

Apparatus. The stimulus lists were presented to the subjects on a TERAK screen. Subjects also typed their responses using the TERAK keyboard, positioned below the screen.

Materials. Nine stimulus lists (three for each condition) consisting of 12 words each were used in this experiment. Concepts were identical to those used by Schvaneveldt & Durso (1981), and the GWN and MDS representations derived in their study were used to order the lists. The nine lists are reproduced in Table 18. In the MDS-related condition, lists were derived by locating chains of concepts that were close to each other in the MDS solution, but not linked in the network. Network-related lists were generated by selecting chains of concepts that were linked to each other in the network, but were distant in the MDS solution. Finally, non-related lists were chains of concepts that were neither linked to each other nor closely related in the MDS solution. The three lists within each condition differed in terms of alternate ways of generating the lists (i.e., different starting concepts in the chain or a choice between two equally distant concepts).

Procedure. Subjects were randomly assigned to one of three conditions: (a) GWN-related list, (b) MDS-related list or (c) non-related list. Within conditions, subjects were randomly assigned to one of three lists. The purpose of using three different lists in each condition was to determine if idiosyncracies inherent in specific lists affects time to recall the lists. The subject was seated in front of a TERAK screen and presented with the instructions. Then, the ordered list of 12 words was presented, one word at a time. The words in the list were always presented in the same fixed order. Each word appeared on the screen for 1.5 seconds.

After all words were presented, the subject was instructed to type as many words as could be recalled in the same order as they had been presented. A program was written in PASCAL to control the experiment. Spelling and typographical errors were scored as correct as long as the words were sufficiently close to the target words to be recognized by the scoring program. Interresponse times were also recorded. When the subject finished the list or could recall no more, the words were checked by the computer. If all 12 words were not recalled, or if the order of words was incorrect, another trial would begin, and the words would be presented again. This procedure continued until all 12 words were recalled in the correct order. The total number of trials to recall the list was recorded. The maximum possible number of trials was 12.

Table 18 - Ordered Lists Derived for Each Condition

Network-related Lists (linked but far apart)

LIST 1	LIST 2	LIST 3
tree	color	frog
robin	hair	living thing
bird	feathers	animal
feathers	bird	dog
hair	robin	hair
color	tree	feathers
green	leaves	bird
frog	green	bat
living thing	frog	blood
bat	living thing	red
mammal	bat	rose
animal	mammal	flower

MDS-related Lists (Close but not linked)

LIST 1	LIST 2	LIST 3
hoof	cottonwood	feathers
antler	daisy	frog
hair	plant	robin
deer	leaves	chicken
mammal	flower	blood
dog	tree	bird
living thing	rose	animal
rose	living thing	color
tree	mammal	rose
flower	dog	green
leaves	bird	flower
plant	animal	tree

Non-related Lists (not linked and far apart)

LIST 1	LIST 2	LIST 3
cottonwood	dog	chicken
chicken	green	leaves
antler	hoof	hoof
leaves	feathers	bird
blood	daisy	green
green	bat	mammal
hair	leaves	plant
frog	mammal	feathers
daisy	red	deer
feathers	antler	color
deer	robin	dog
red	hair	frog

Results and Discussion

Mean interresponse time was calculated for each subject on the last trial. The mean interresponse times for each condition are shown in Table 19. These differences, however, are not significant. On the other hand, mean number of trials for each of the main conditions (See Table 19) do differ significantly, $F(2,45) = 10.019$, $p<.001$. The effect of different lists within conditions on number of trials was not significant, suggesting that the idiosyncracies within a particular list were not the cause of differences found between conditions. Linear contrasts done on mean number of trials showed that the differences between the GWN and MDS conditions ($F(1,34) = 17.772$, $p<.001$) and between the GWN and non-related conditions ($F(1,34) = 24.322$, $p<.001$) were significant. The differences between the MDS and non-related conditions were not significant.

Table 19 - Performance Data from Ordered Recall Task

Mean Interresponse Time (sec)

	Network	MDS	Non-Related
List 1	1.76	1.84	1.65
List 2	2.91	1.63	2.04
List 3	3.21	1.97	2.87
Mean	2.63	1.81	2.19

Mean Number of Trials to Perfect Recall

	Network	MDS	Non-Related
List 1	3.50	5.67	6.50
List 2	4.17	7.67	7.00
List 3	3.67	5.83	9.16
Mean	3.78	6.39	7.55

In general, the results of this study suggest that GWN better captures the aspects of memory structure responsible for aiding ordered recall. Subjects in the GWN condition took an average of 3.78 trials to recall the lists perfectly, while mean number of trials for the MDS condition (6.39) did not differ significantly from the mean number of trials for non-related lists (7.55).

The lists organized according to the MDS solution were no easier to recall than were the nonmeaningful lists. This finding suggests that the MDS representation did not capture the aspects of memory structure that facilitate ordered recall. The superiority of the GWN list can be explained based on the properties inherent in the network. In a task such as this, in which concepts have to be recalled in a particular order, local relations should aid recall more than global relations. For instance, three concepts found in the GWN lists, TREE, ROBIN, and BIRD are concepts that are linked in the network, but are distant in the MDS solution. On the other hand, HOOF, ANTLER, and HAIR are three concepts from the MDS lists. These latter concepts are globally related in that they are mammal body parts, but are not linked to each other in the network. Intuitively, it appears that network-related words would be easier to remember in a list that is made up of a series of chains or links of concepts because this mimics the structure of a network.

While the GWN structure was superior to the MDS structure in this particular task, other tasks that require global information for good performance may show different results. Further research would determine whether MDS structures are superior in other situations.

Priming: A Comparison of Similarity Ratings and MDS

Previous studies have indicated that visual word recognition is performed more quickly when a word to be recognized is preceded by the presentation of an associated word. Meyer, Schvaneveldt, and Ruddy (1975) performed a series of studies that showed that a target string of letters can be recognized more quickly as a word when it is preceded by a word that is associated with it. For instance, the string of letters DOCTOR could be recognized as a word more quickly if it were preceded by the word NURSE than if it were preceded by the word BREAD. This contextual effect in the "lexical-decision" task (in which strings of letters are classified as words or non-words) was described in terms of a word-processing model where the stimulus letter string is graphemically encoded and transformed into a phonemic representation through the "grapheme-phoneme correspondence rules" of the English language. Following the encoding of the stimulus string, lexical memory is accessed to check for a match between the phonemic representation and some item stored there. Based on the result of the retrieval process, the stimulus is recognized as a word or non-word and a yes/no response is executed. The influence of the semantic context was shown to affect the encoding operation as opposed to the retrieval process. This was indicated when the contextual effect was shown to be larger for visually degraded letter strings than for letter strings of unimpaired visual quality.

A "spreading activation" theory provides an explanation of the semantic context effect displayed in a word recognition task. According to this theory, individual concepts in lexical memory are represented as nodes in a network structure. The activation of a node in the lexical network leads to a spread of activation to other nodes that are near the activated node. The organization of the network ensures that nearby nodes are semantically (meaningfully) related. In this way, spreading activation may facilitate the accessing of related concepts once a particular node has been activated.

Studies conducted last year produced a list of concepts relating to flight maneuvers. These concepts were used to construct various representations of the organization of the concepts. An MDS analysis of similarity ratings for pairs of the concepts resulted in a spatial structure. The present study was undertaken to evaluate the MDS representations using a priming procedure. From earlier analyses of the MDS solutions (Schvaneveldt, et al., 1982), it appears that MDS solutions contain more information than do the ratings from which they were constructed. For both the MDS solutions and the original ratings, some pairs of concepts are more closely related than are other pairs. Since priming presumably reflects underlying memory structure, this study was designed to determine whether pairs derived from MDS solutions would lead to more or less priming than would pairs derived from the original ratings.

The effect of semantic context has been shown to generalize across tasks, as subjects were consistently faster at pronouncing words when the words were preceded by associated words rather than unassociated words (see Meyer et al., 1974). In this study, subjects performed a similar pronunciation task in which they vocalized target words that followed a word prime. The effect of the word pair relationship (between the target word and the word prime) on reaction time was examined. The relationship between words in a pair varied in two ways. The words could be similar or dissimilar based on similarity rating averages, or the words could be near to or far from each other according to distances derived from the MDS scaling solution.

Method

There are 435 word pairs in all possible combinations of words from a list of 30 split-plane manuever or 30 strafe manuever concepts. The terms from each pair were rated for similarity on a scale from 0 to 9 by seven instructor pilots. From the averages of these ratings, an MDS solution was obtained that produced relative distances between concepts, representing the strength of the relationship between the concepts as seen by the pilots. In this way, highly related words were given shorter MDS distance values, while less strongly related concepts were given larger MDS distance values.

From the similarity rating averages and the MDS distances, concept pairs that are near or far in MDS distance and high or low in similarity were determined. Pairs of concepts that had a high similarity rating and were near to each other in the network solution derived from MDS were selected as "High-Near" (H-N) pairs. Word pairs that had low similarity ratings on the average and were most distant from each other made up the set of "Low-Far" (L-F) pairs. The similarity ratings were based on the average ratings from the eight IPs. The MDS distance pairs were based on the distances determined from a MDS solution along five dimensions for the averaged ratings.

Concept pairs could be one of four types: (a) H-N: high in similarity and near in MDS distance, (b) L-F: low in similarity (dissimilar) and far in MDS distance, (c) H-F: high in similarity and far in MDS distance, or (d) L-N: low in similarity and near in MDS distance.

Procedure. Eight instructor pilots served as subjects (s) and were presented with two terms, one at a time, on a CRT screen. The terms were selected from a list of 30 split-plane manuever concepts for five of the subjects and 30 low-angle strafe concepts for three of the subjects. The subjects' task was to read aloud the second concept accurately and as quickly as possible. The vocal response time was measured to the nearest millisecond from the time the target word was presented until the subjects read the target word aloud. The subjects were presented with each of the 30 concepts as targets following each of the four types of primes. The targets were also presented following the prime, NOTHING, to establish a neutral baseline for assessing priming effects.

A single trial proceeded as follows. A warning tone alerted the subjects to fix their gaze on the CRT screen for the start of a trial. A word prime followed the offset of the tone and was displayed for 0.5 second. The screen was then cleared, and there was a 1.0-second delay prior to the presentation of the target word. The target word remained on the screen until a verbal response was made. The subjects spoke into a microphone situated 7.5 to 10 centimeters from their mouth. A delay of 0.1 second preceded the warning tone for the next trial.

Each subject was presented with 150 concept pairs presented in a random ordering. The 150 pairs consisted of all 30 concepts paired with the five different prime types. The subjects completed two blocks of trials, with each block having a different random ordering of the 150 concept pairs. Response times were recorded by the computer program that controlled the experiment.

Results

The mean response times in each condition are shown in Table 20. An analysis of variance was performed on the pronunciation response times and revealed no significance for the priming effect, $F(4,28)=0.86$. Apparently the subjects were able to improve their performance with practice as they progressed through the experiment. This practice effect is indicated by the response times for the second block of trials being significantly lower than the response times for the first block of trials, $\underline{F}(1,7)=84.9$, $\underline{p}<.001$.

Table 20 - Mean Response Times (msec) for Each Priming Condition.

Priming Condition (Similarity - MDS Distance)	Block 1	Block 2	Condition Mean
High-Near	461	439	450
High-Far	465	438	452
Low-Near	460	444	452
Low-Far	455	442	448
Neutral	469	443	456
Block Means	462	441	

Discussion

As indicated by the average response times in Table 20, the effect of semantic context in a word pronunciation task was not replicated in this study. One explanation for the lack of facilitation with related primes may be provided by the spreading activation theory. Each subject saw each of the 30 concepts 10 times as a target and several times as a prime. The resulting spread of activation from activating each of these concepts this frequently may be so large that all of these concepts are highly activated in memory, and the primes on individual trials do not lead to any further activation of the targets. Some support for this interpretation comes from analysis of the first few trials in the experiment. The expected priming effects were present, but with so few trials, there were no significant effects.

The one lesson to be learned from this study appears to be that priming studies cannot use procedures that require extensive repetition of stimulus materials. With a limited set of items such as those from an earlier work, it will be very difficult to evaluate memory structure using priming methodology. Other tasks, such as the ordered recall task, appear to be more promising.

CRITICAL CONCEPTS

An ongoing concern in this project is identifying critical concepts that distinguish expert pilots (instructors) and novice pilots (undergraduate trainees). Earlier work on this problem (Schvaneveldt et al. 1982) used network representations to compare different classes of pilots. In network representations, concepts are depicted by nodes, and relations are depicted as links connecting nodes. The links are assigned values which reflect the strength of the relationship between the nodes. Network representations, as mentioned before, are extremely useful in representing local relationships among concepts. The networks enabled identification of pairs of concepts that distinguished experts (instructor and guard pilots) and novices (undergraduate trainees). Pairs of concepts that were found to discriminate expert and novice pilots were basically of two types: pairs between which there existed a critical association for experts but not for novices (the pair was linked in the network representation for experts but not in network representation for novices) and pairs between which there existed a critical association for novices but not for experts.

In contrast to the network representations, MDS provides a more global description of conceptual structure. The problem of identifying the critical concepts that differentiate novices and experts can thus be pursued on a more global level through representations derived from multidimensional scaling. With MDS, concepts are depicted as points in a multidimensional space, where the distance between concepts along a dimension represent psychological distance (i.e., two concepts that are close along a given dimension are similar along that dimension) . A measure of distance between each concept can be derived from the concept coordinates in multidimensional space. Each concept can then be represented as a vector of distances from the concept to every other concept in the representation. With a pool of 30 concepts each from low angle strafe and split-plane maneuvers, each concept can be represented as a vector of 29 (n-1) distances. A measure of the degree to which UPs and IPs agree on these concepts can be calculated by correlating each concept or distance vector from the UPs with the IPs. Tables 21 and 22 show these correlations for the split-plane maneuvers and low angle strafe, respectively. As can be seen from these tables, a wide range of correlations were found. For example, for split-plane maneuvers, high agreement between IPs and UPs was found for the concepts AIRSPEED and RELATIVE ENERGY, while the negative correlations found for ANGLE OFF and EXTENSION reflect extremely low agreement. Similar observations can be made regarding low angle strafe concepts.

Table 21 - Correlations of UPs with IPs

Split-Plane Maneuvers

Concept	r	UP Familiarity Rating 1	2	3
Airspeed	.81	0	0	16
Relative Energy	.81	0	4	12
Smash	.76	1	1	14
Weapons Parameters	.71	4	12	0
Corner Velocity	.70	1	8	7
Power Setting	.70	0	0	16
Guns	.70	1	14	1
Overtake	.69	0	0	16
Acceleration	.69	0	1	15
Switchology	.64	7	5	4
Lift Vector	.62	0	4	12
g Loading	.60	0	1	15
Barrel Roll	.59	0	1	15
Verticle Maneuver	.53	0	2	14
Snapshot	.52	13	3	0
Lag Roll	.47	13	3	0
3-9 Line	.43	12	4	0
Aspect Angle	.43	13	3	0
6 O'clock	.26	0	3	13
Quarter Plane	.25	14	2	0
Lag Pursuit	.22	10	4	2
Cutoff	.20	0	0	16
Low Yo Yo	.19	10	6	0
Pure Pursuit	.16	9	5	2
Lead Pursuit	.15	10	4	2
High Yo Yo	.13	8	8	0
Radial g	.12	12	3	1
Heat	.05	13	3	0
Angle Off	-.04	4	8	4
Extension	-.24	13	3	0

Note. Familiarity rating entries are the number of UPs giving each rating to each concept.
1-Totally unfamiliar
2-Familiar but not used in flying
3-Used in flying

Table 22 - Correlations of UPs with IPs

Low Angle Strafe

Concept	r	UP Familiarity Rating 1	2	3
Drift	.76	0	6	9
Yaw	.73	0	2	13
Fire	.71	1	14	0
Burst	.70	3	12	0
Pipper Placement	.69	6	9	0
Trim	.67	0	1	14
Guns	.65	1	14	0
Trigger	.63	2	13	0
Final	.61	2	4	9
Aim Point	.61	1	7	7
Stabilize	.60	2	6	7
Tracking	.57	1	10	4
Range	.53	1	12	2
Bank	.52	0	1	14
Bullet Impact	.50	3	12	0
Recovery	.49	1	8	6
Glide Path	.47	0	3	12
Run In Line	.44	14	1	0
Pull Up	.44	3	5	7
Closure	.42	0	5	10
Airspeed	.39	0	2	13
Altitude	.37	0	1	14
Pipper Fixation	.37	7	8	0
Dive Angle	.37	1	9	5
Ricochet	.35	6	9	0
Aim Off Point	.34	12	2	1
Foul Line	.26	14	1	0
Foul	.21	14	1	0
Bunt	.00	14	1	0
Walking	-.07	12	3	0

Note. Familiarity rating entries are the number of UPs giving each rating to each concept.
1-Totally Unfamiliar
2-Familiar but not used in flying
3-Used in flying

Concepts that show low correlations are probably those that the UPs have not learned. At any rate, these concepts are not organized for UPs in the same way as for the instructors. The UPs may not have encountered or used these concepts in training. A comparison of the correlations and UP familiarity ratings supports this suggestion. Generally, those concepts that all, or most, UPs have had experience with during training correlate highly, while concepts which have not been encountered correlate relatively low. However, there are exeptions to this rule. For example, all UPs have used the concept CUTOFF in flying (Table 21), yet they correlate relatively low with the IPs. Similarly, all UPs have had either flight or classroom experience with the concept 6 O'CLOCK, and again, they correlate relatively low with IPs. For low angle strafe, similar examples include DIVE ANGLE, AIRSPEED, and ALTITUDE. Although UPs have encountered these concepts in training, their organization of these concepts in memory still greatly differs from that of the IPs. One possible reason is that UPs have not learned the <u>relationships</u> between these concepts and other concepts. During training, they may have encountered these concepts in specific contexts or situations and not in others.

To verify further the critical concepts that separate novice and expert pilots, pattern recognition techniques (the training algorithm described earlier) were applied to subsets of the original distances derived from multidimensional scaling. To reiterate, the training algorithm operates on the distances between concepts. Beginning with a set of 30 concepts, each concept has 29 distances with which it is associated. Distances associated with groups of concepts were systematically removed, starting with those concepts that were most highly correlated. By removing those distances, the remaining subsets contain the information that should be most useful in discriminating between IPs and UPs. The cutoffs used are shown as the dotted lines in Tables 21 and 22. The performance of the training algorithm on subsets of the original distances is shown in Table 23. As can be seen from Table 23, training algorithm performance did not greatly deteriorate with the removal of all concepts that correlated at or above .40. This suggests that those concepts correlating .40 and above did not contribute significantly to the separation of the IP and UP groups, and the concepts that most separate the UPs and IPs are those that correlate below .40. One practical consequence of these findings is that the set of concepts can be considerably reduced without seriously affecting the discrimination power of the task. For each concept eliminated, data collection time is reduced by the number of remaining concepts because of the testing of all pairs of concepts.

Table 23 - Pattern Classification Performance for Various Cutoffs (r)

Split-Plane Maneuvers

Cutoff (r)	% Correct
None	.94
.70	.92
.60	.91
.50	.96
.40	.89
.20	.84

Low Angle Strafe

Cutoff (r)	% Correct
None	.94
.60	.96
.50	.99
.40	.90
.30	.48

CONCLUSIONS AND RECOMMENDATIONS

Primary Accomplishments

This project has produced several interesting and potentially useful findings. The major new theoretical effort being pursued under the contract concerns the development of methods for obtaining and analyzing networks of concepts from empirical data. Networks have been widely postulated as the underlying structure of concepts in semantic memory. Now there are methods for determining the nature of such networks without relying on guesswork and intuitive judgments. These methods should prove to be important in the continuing analysis of structures of knowledge.

In the domain of critical flight-related concepts, it has been shown that systematic methods can yield valid and reliable descriptions of the structure of these concepts. Further, these structures can be used to identify individuals as members of groups with differing training and experience. Of particular interest are the findings showing more accurate classification of individuals into groups using structural representations of concepts than using the original data from which the structures are derived. Multidimensional spatial structures lead to the most accurate classification, but network structures also lead to more accurate classification than do the direct judgments obtained from various groups of flying personnel. Since the network representations are based only on information about which concepts are linked to which other concepts, the classification performance with network structures is particularly noteworthy. Perhaps as the testing of a metric for the network structure proceeds, classification with networks will approach the level of performance found using the MDS structures.

Further specific areas of disagreement have also been identified in the structures possessed by expert and novice pilots. These specific differences may deserve special attention in lead-in fighter training. The structures themselves may also prove to be useful in the academic program since they provide some graphic examples of the differences in the ways novices and experts think about critical flight concepts.

One major area investigated in the past year concerns the experimental verification of the structures that were identified. An ordered recall task was developed to compare MDS and network structures. In the preliminary test, the network representation facilitated recall while the MDS representation did not. Although this finding is suggestive, it should not be taken as definitive for two reasons. First, the ordered recall task itself may be biased in favor of networks because the task requires recalling items in a designated order. Second, further work with the task using fighter pilots is underway, and that test may show different results. At the very least, however, the initial experiment did provide some validation of the network structure in a memory performance test. This validation serves to reinforce earlier findings that the structures being discovered do reflect some important aspects of the underlying organization of flight-related concepts.

A final major accomplishment this year has been the analysis of larger units of conceptual structure in the form of scripts. This work is reported in detail in a separate technical paper (Maxwell & Schvaneveldt, in press). In brief, this work has shown that pilots do have script-like organizations for the particular actions that go together to make up various maneuvers. The experiments showed that expert pilots (fighter lead-in IPs) are able to integrate actions that constitute parts of scripts, and they also show clear evidence of elaborating presented actions with other actions that belong to the script but were not presented. Novice pilots (UPs) show quite different effects. They are not able to integrate actions that belong together as completely as do the experts, and they show no evidence of elaboration of scripted activities. Naive subjects (undergraduate psychology students) show still another pattern of results. As would be expected, they show no integration and no elaboration. Of course, they should have no knowledge of the scripts and, therefore, should not show script effects.

Directions for Future Work

The next reporting period will be devoted to additional work on the scaling procedures used and developed throughout the contract period. Further experimental studies are planned to evaluate the results of the scaling procedures.

One major new analysis is planned for the next year. The new analysis will be concerned with a procedural analysis of decision making in fighter pilots. The intent is to develop a production system model to simulate the decisions made by fighter pilots in particular combat situations and/or in executing particular maneuvers. The rationale behind this project is that a successful simulation of pilot decisions will constitute a model of the decision-making process as well as the knowledge necessary to make such decisions.

Recommendations

The work accomplished under this contract has provided a detailed analysis of the conceptual structure of critical flight information in fighter pilots as well as correlational and experimental verification of the validity of the structures. These structures may be useful in training programs for students attempting to acquire these conceptual structures. Also, the representations themselves may prove to be useful as training aids. The network analysis, for example, shows how expert fighter pilots organize the concepts involved in particular maneuvers. To the extent that the network representation provides an understandable representation of experts' knowledge structures, students may find it useful in learning about the maneuvers.

From a somewhat different angle, specific differences have been identified in the conceptual structures of students and expert fighter pilots. In particular, the differences show, in part, what experts know that students do not and what misconceptions the students may have acquired from earlier training or from other life experiences. These areas of difference should receive special attention in the training program for fighter pilots.

Finally, work in classifying individuals based on their conceptual structure suggests further work in attempting to predict the success of future fighter pilots based on the conceptual structures students demonstrate early in training. It may be necessary to study the structures associated with a different set of concepts than those used in the present investigation. For example, perhaps some concepts relating to attitude and motivation should be included along with concepts relating to the operation of aircraft. The classification techniques developed appear to be very sensitive to differences in cognitive structures, and they may well provide some predictive power for organizing the training program to produce maximum benefit for those who are likely to benefit the most from fighter training.

In a more general vein, attempts to define the cognitive structures involved in successful operation of fighter aircraft should serve to complement other research concerned with perceptual processes and motor skills. The investigation of knowledge organization in pilots seems to have been relatively neglected in attempts to apply psychology to the understanding of the pilot and the pilot's task. Recently, psychologists and workers in the field of artificial intelligence have made some important strides toward a more complete understanding of knowledge representation and the process involved in the use of knowledge. It is believed that this work contributes to the application of these recent developments to the task of understanding the knowledge of fighter pilots. If cognitive skills are found to be at least as important as perceptual-motor skills for successful pilots, it is imperative to continue to advance the understanding of the nature of these cognitive skills.

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