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APPLICATION OF PATTERN RECOGNITION TECHNIQUES TO THE
IDENTIFICATION OF AEROSPACE ACOUSTIC SOURCES

Annual Report : Year one

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INTRODUCTION and THEORY

A pattern recognition system has been developed to recognize simulated aerospace acoustic sources. This paper describes the theory and operation of the system and the results obtained. A more complete description of pattern recognition techniques and their applications can be found in ref 1.

Fig 1 shows a general pattern recognition system. Recognition of a pattern consists of data acquisition, pre-processing, transformation of the pattern, then training or classifying, depending on the mode of operation. In the training mode the system learns to discriminate between the different classes of patterns, while in the classification mode the learned information is used to classify unknown patterns.

The pattern recognition system uses pattern descriptors or features to represent the patterns and these features make up each pattern's feature vector. The feature vector's dimensionality is equal to the number of features, so the greater the dimensionality the more complete the description but more features add to the complexity and expense of data acquisition and processing. A two dimensional example is shown in figure 2, where the x and y axes represent values of feature 1 and feature 2, respectively. A pattern's feature vector locates it in feature space and patterns of similar classes will cluster about the same area if the features are well chosen.

An example of such a feature space is the space containing the heights and weights of basketball player and jockeys. The x axis could be height values and the y axis weight values, making the class of basketball players cluster toward the upper right due to their higher weights and heights while the jockeys would cluster at the lower left.

Features useful in the recognition of acoustic emission signals can be extracted from both the time and frequency domains. Examples of such features are the standard deviation of the signal, the rise time for the biggest time domain pulse, partial power in various frequency bands, and the number of peaks exceeding a preset threshold [2].

If the features are well chosen for a particular problem the different classes will separate into clusters and a surface can be put between the classes. Figure 3 illustrates a two

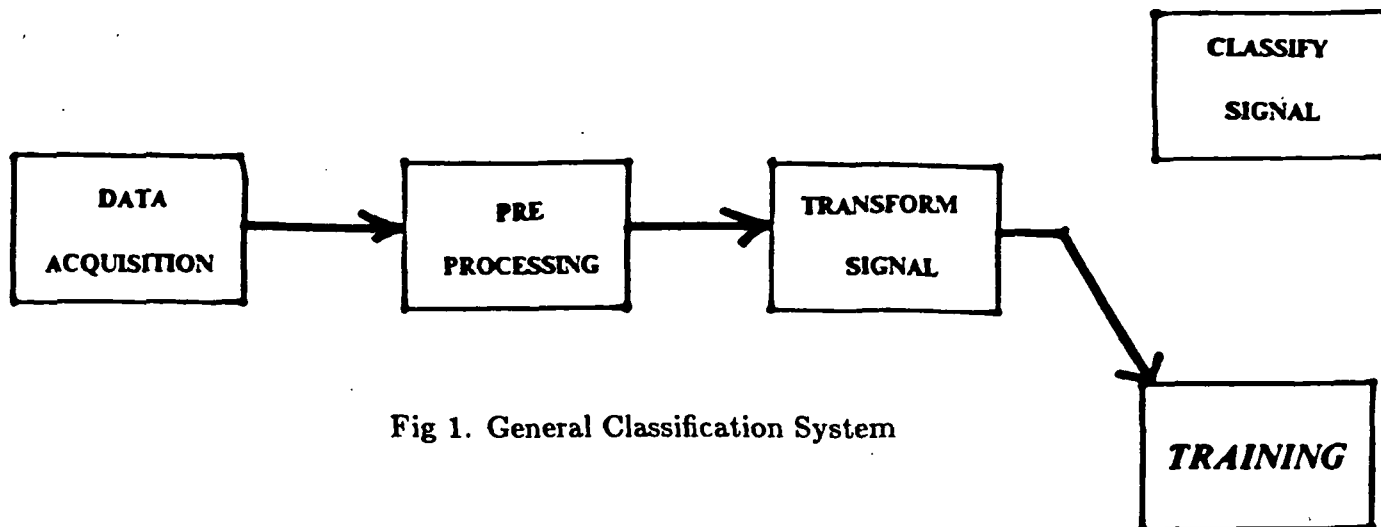


Fig 1. General Classification System

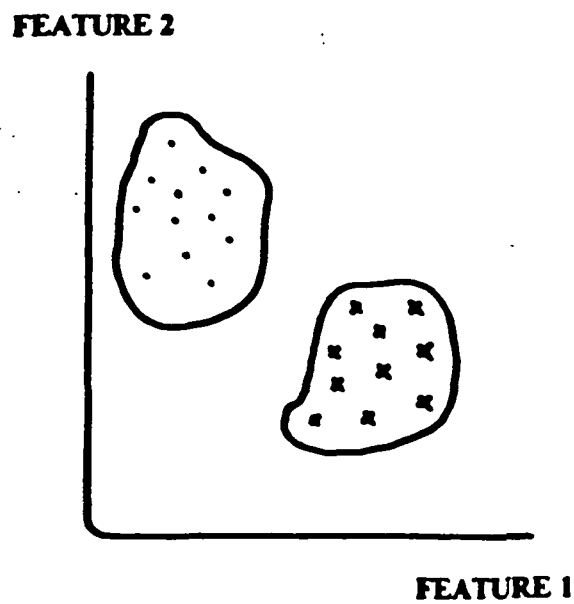


Fig 2. 2-D Feature Space

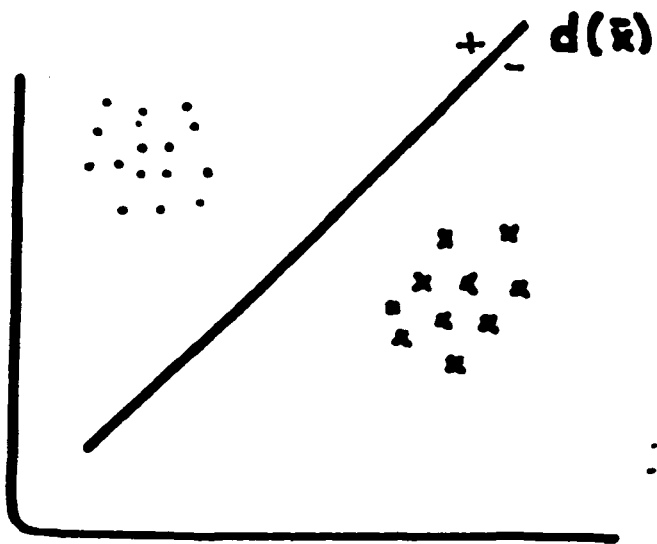


Fig 3. Linear Decision Function

dimensional case where a line separates classes 1 and 2. The separating surface could be more complicated than a simple line and in higher dimensional spaces a simple line becomes a hyperplane.

The classification system we have developed uses a hyperplane as a decision function given by the equation

$$d(\mathbf{x}) = \mathbf{w}'\mathbf{x}$$

where \mathbf{w} , the weight vector, and \mathbf{x} , the pattern vector, are n dimensional. There is one such decision function for each class and a particular pattern is classified by evaluating each decision function and assigning the pattern to the class of the highest valued decision function.

The location of these decision function is not always intuitively obvious, especially in higher dimensional spaces, so the surfaces must be constructed in a training mode. In the training mode known patterns are presented to the classifier and the decision functions evaluated and adjusted. The algorithm we used is based on a reward punishment concept described below.

At the k th iteration a pattern $\mathbf{x}(k)$ is presented to the classifier, where $\mathbf{x}(k)$ is a member of class ω_i . If

$$d_i[\mathbf{x}(k)] > d_j[\mathbf{x}(k)]$$

for all j , j not equal to i , then the pattern has been classified correctly and no adjustment is made. However, if for some l ,

$$d_l[\mathbf{x}(k)] > d_i[\mathbf{x}(k)]$$

then

$$\mathbf{w}_i(k+1) = \mathbf{w}_i(k) + \mathbf{x}(k)$$

$$\mathbf{w}_l(k+1) = \mathbf{w}_l(k) - \mathbf{x}(k)$$

$$\mathbf{w}_j(k+1) = \mathbf{w}_j(k)$$

for all j , j not equal to i or l

where w_i is the weight vector for the i th class.

The steps above are repeated for each pattern until either all training patterns are correctly classified or an acceptable error rate is reached.

The performance of the algorithm is dependant on the discriminatory power of the features because poorly chosen features won't separate the classes thereby preventing the algorithm from reaching a satisfactory solution. It would seem that increasing the number of features would solve this problem but this increases computation time and reduces performance on classification data. An optimal set of features is needed, but such a set is difficult to specify *a priori* without extensive system specific knowledge. Our system has a feature selection capability to solve this problem.

Feature selection means a user can input numerous features without worrying about their discriminatory power and the system will search the list and select the set of features that performs best. The selection is done independent of the user, who only needs to specify the desired number of features in the final set. The interested reader is referred to ref 4, which outlines the feature selection algorithm.

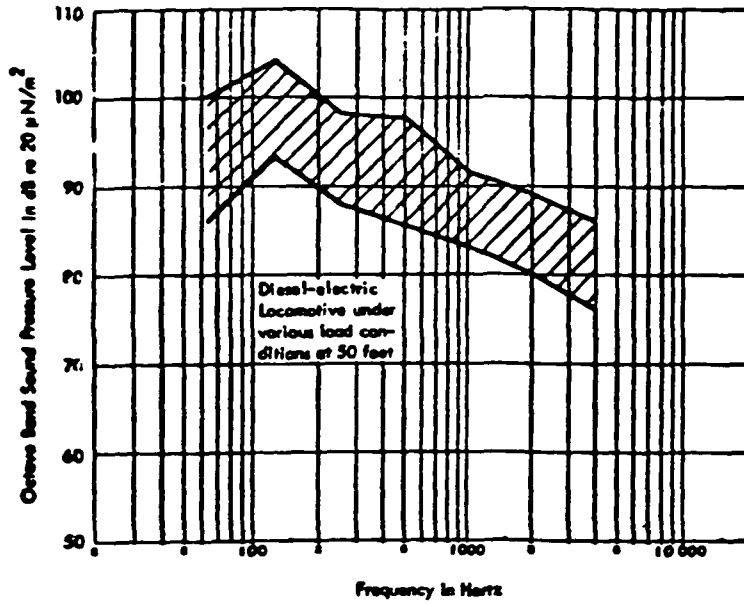
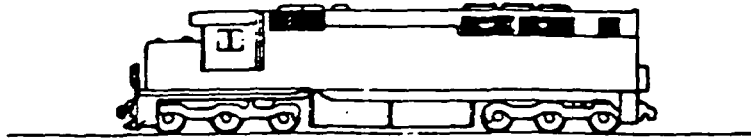
RESULTS

The system was tested on SPL data from five different sources. The data was derived from SPL curves for a prop plane, jet aircraft, automobile, train, and helicopter, shown in figure 4. The percent of energy in each of 8 octave bands makes up an 8 dimensional feature vector for each pattern. The classifier was trained with three patterns from each class with minor variations between patterns of the same class. One unknown from each class was also fed to the classifier.

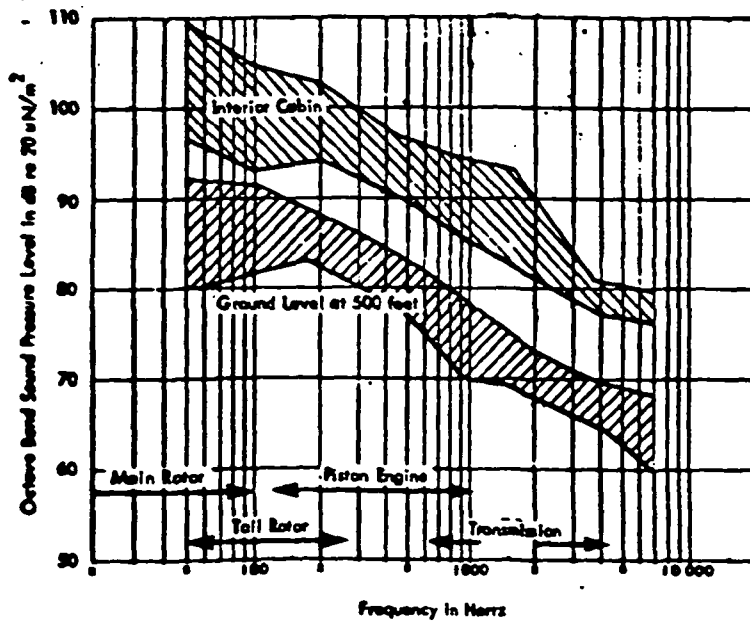
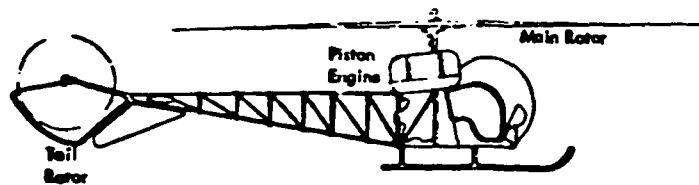
The system successfully separated the five classes and correctly classified the unknown patterns.

The feature selector was used to reduce the features from 8 to 3 or 4 best, resulting in faster convergence to a working classifier during the training stage. When compared visually, the features from the chosen best set of features differentiated between classes much better than those left out as poor features.

NOISE DATA



SPL CURVE FOR TRAIN

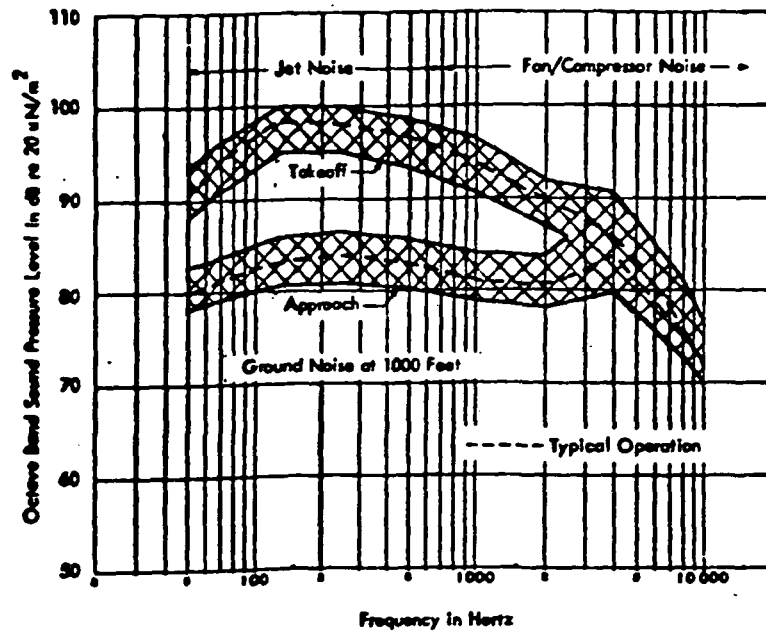
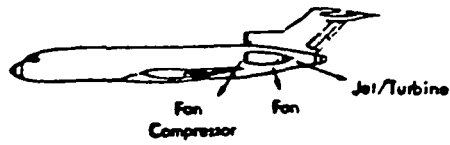


SPL CURVE FOR HELICOPTER

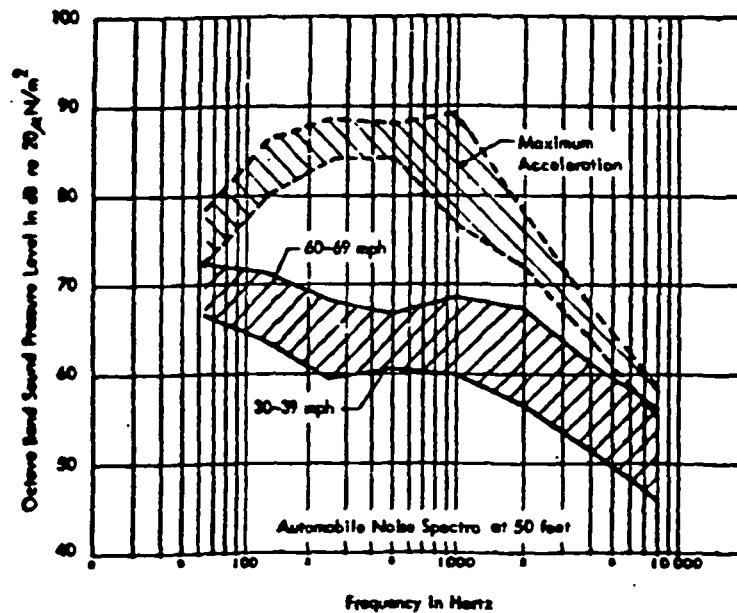
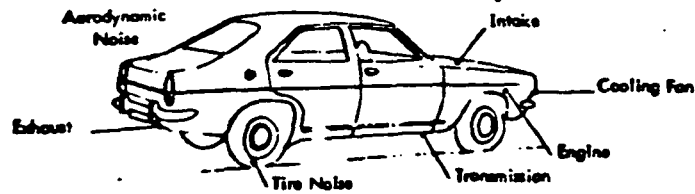
Fig 4. SPL curves

NOISE DATA

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SPL CURVE FOR JET AIRCRAFT

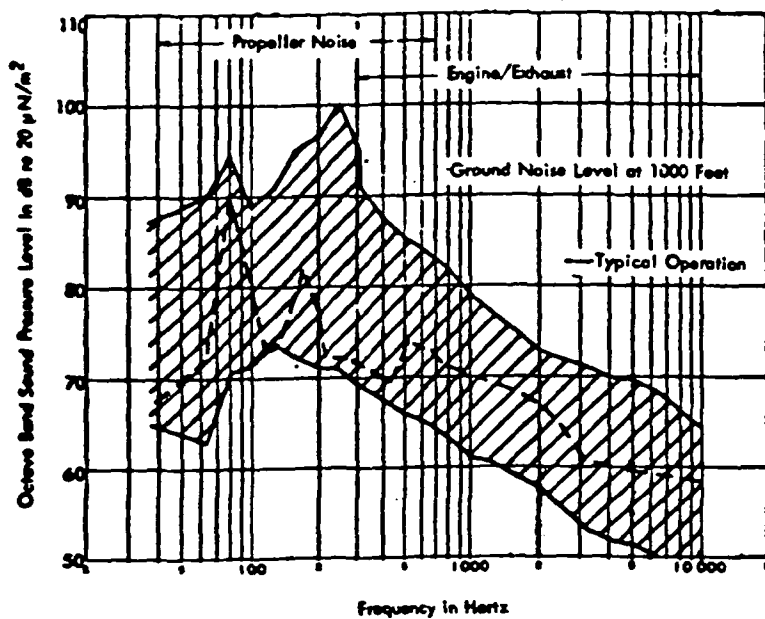
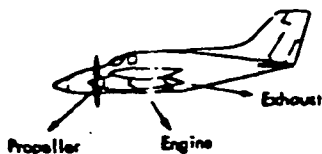


SPL CURVE FOR AUTOMOBILE

Fig 4. SPL curves

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SPL CURVE FOR PROP AIRCRAFT

Fig 4. SPL curves

CONCLUSIONS

A pattern recognition system has been developed that successfully recognizes simulated spectra of five different types of transportation noise sources. The system generates hyperplanes during a training stage to separate the classes and correctly classifies unknown patterns in classification mode. A feature selector in the system reduces a large number of features to a smaller optimal set, maximizing performance and minimizing computation.

Future work will involve testing the system on more realistic signals and studying the effect of perturbations of the signal on the performance of the classifier. Realistic signals will complicate the preprocessing and feature extraction but will yield better results due to increased information content. The overall performance of this initial classifier and the potential for information in realistic signals leads us to believe there is a potential for such a system to identify aerospace acoustic sources.

PATTERN RECOGNITION
NOISE SPECTRA
ACOUSTIC EMISSION
AIRCRAFT NOISE

ALGORITHMS
DISCRIMINATION
AERODYN. NOISE
HYPERPLANES
VECTOR ANALYSIS

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