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TARGET RECOGNITION USING MULTIPLE DISCRIMINANTS FROM AN INFRARE--ETC(U)
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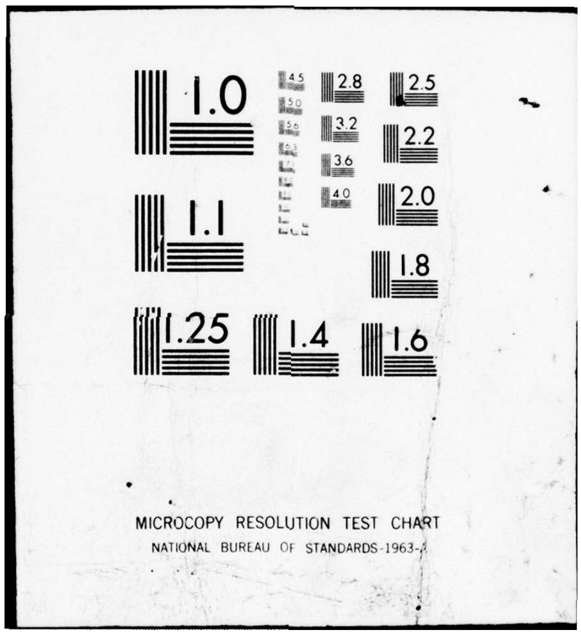
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TECHNICAL REPORT TE-77-16

TARGET RECOGNITION USING MULTIPLE DISCRIMINANTS FROM AN INFRARED SENSOR

U.S. ARMY MISSILE RESEARCH AND DEVELOPMENT COMMAND

Advanced Sensors Directorate
Technology Laboratory

24 June 1977

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Redstone Arsenal, Alabama 35809

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It has been suggested that a laser designator could be adapted to measure certain characteristics of the object being designated and that these measurements could be a useful aid in target recognition and/or identification. Characteristics that could be measured include size, motion (speed), vibration, and quantities relating to the target surface such as reflectance, depolarization, etc. Unfortunately, it appears unlikely that any single target over

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ABSTRACT (Continued)

characteristic will be sufficiently unique to provide an unequivocal identification.

In this report, consideration is given to statistical methods for combining several target characteristics to enhance the identification capability. The technique studied involves using multivariate statistical analysis to construct a linear or quadratic discriminant function on the various measured quantities. It is shown that using this approach, an automatic target recognition feature could be implemented at very small additional cost.

The final section of this report details the experimental data needed to assess completely the feasibility of the proposed identification aid and recommends an experimental program for collecting these data.

CONTENTS

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I. INTRODUCTION

It is well established that long wavelength infrared radiations are better able to penetrate rain, smoke, and haze than are either visible or near infrared radiations. Because of the greater penetrating power at the longer wavelength, it appears likely that future laser terminal homing systems may operate either in the 3- to 5-μm, or the 8- to 14-μm regions of the spectrum [1]. Furthermore, it seems likely that under conditions of reduced visibility, the effective range of these systems may be determined by the operator's ability to locate and designate a target rather than by the ability of the homing seeker to track through smoke or fog [1,2,3,4]. For this reason, it seems desirable that the designator operator be provided with some means of target location and recognition other than visual sighting.

Recently, studies have been conducted to determine the technical feasibility of incorporating a recognition aid directly into a terminal homing laser designator [5,6]. It has been shown that the reflected laser beam contains a considerable amount of information about the reflecting object which, with proper processing, could be used to distinguish a military target from an extraneous or militarily unimportant object. Among the characteristics of the reflected laser beam which could be used as target discriminant are the following:

a) Moving Target Indicator (MTI) — Laser radiation reflected from a moving target experiences a frequency shift (Doppler shift) proportional to the radial speed of the target. By using heterodyne detection, this frequency shift can be measured, thus providing a measurement of the target's speed toward or away from the designator.

b) Vibration Signatures — Vibration of the target will produce a Doppler shift in the reflected laser beam. The frequency spreading associated with the vibratory motion could provide a characteristic signature from which the target could be recognized. It is believed that the vibration signature may prove to be the most useful discriminant [6].

c) Size Estimation — By scanning the designator beam across the target, it is possible to estimate the target's size. The accuracy of this estimation is determined by the width of the laser beam at the target and the contrast between target and background.

d) Other Discriminants — Other target discriminants which might be used include the strength of the reflected signal, degree of depolarization of the reflected radiation, and laser speckle effects.

As it is presently envisioned, the recognition aid would use the designator to illuminate the target and might, in a lock-before-launch configuration, use the missile tracking system's sensors to measure one of the previously mentioned quantities. If lock-before-launch were not possible, or if the missile were launched from somewhere other than the designator, then an additional sensor would be required. In either case, the recognition aid is conceived as a relatively low cost add-on to the basic designator-guidance system.

It should be emphasized that the system as presently envisioned will not necessarily provide a means of absolute target identification because none of the proposed discriminants are sufficiently unique.* For example, if a system were devised that could measure the size of an object being designated with a fair degree of precision, and if it were found that a suspected target's size were comparable with that of an enemy tank, this would be useful information. However, it would not be sufficient to insure that the suspected target were, in fact, a tank. It could be a large truck, a small building, or even a pile of scrap metal.

It has been proposed that a more positive identification could be obtained by using two or more of the previously mentioned discriminants. To continue this example, if it were known that the tank-size object were moving, the building and scrap heap could be eliminated. The remaining possibilities are a tank, a tank-size truck, or perhaps a small truck viewed from the side which had approximately the same dimension as the frontal aspect of a tank. In any case, the identification is more certain than would be the case with either a size measurement or MTI alone.

This report considers how an identification system might be implemented using two or more discriminants. This problem can be divided into two parts: first, what measurements should be made; second, once the measurements are made, how can they be used in deciding if a suspected target should be attacked? The first question has been addressed elsewhere [5,6]. The second question is basically a problem in multivariate statistical analysis, and will be the principle subject of this report.

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*The possible exception to this statement is vibration signatures which may or may not be sufficiently unique to provide a means of positive identification. At the present time, information is not sufficient concerning the actual signatures of military vehicles and the precision with which they can be measured optically to assess their usefulness fully in target identification. However, on the basis of the available data, there is considerable optimism about the possibility that they may provide a practical means of positive target identification.

II. STATEMENT OF THE PROBLEM

It is assumed that a laser designator-system is instrumented to measure a number of quantities (X_1, X_2, X_3, ..., X_n). For example, X_1 might be the horizontal dimension of the target, X_2 the radial component of the target's speed, etc. If target vibration measurements are included, then some of the quantities might be derived from the audio spectrum of the target. One possibility would be to let X_k be the fraction of the total audio power in the frequency bandwidth f_k to $f_k + \Delta f_k$. Other possibilities also exist and will be discussed later; for now, it is assumed that the quantities to be measured have been selected and that the instrumentation for making the measurements is in hand. A little reflection will show that the X's are a set of random variables. Randomness is introduced into the measurements for two reasons. First, there are random errors in all measurements and, as shown by analysis in previous reports, these may be considerable for the measurements being considered here. Secondly, even if there were no measurement errors, some of the quantities would still be random variables due to changes in the conditions under which the measurements are made. For example, the apparent size of a tank will depend on the aspect angle. The vibration will depend upon the target's speed or it may vary from one vehicle to another of the same type. Furthermore, it is clear that, in general, the X's will not be statistically independent.

Now, the problem may be stated as follows: Given a set of measurements (X_1, X_2, ..., X_n) made on a suspected target, a decision must be made in some optimum fashion whether the object is an actual target or not. There is a standard problem in statistical decision theory, a solution of which will be presented in the following section.

III. STATISTICAL CLASSIFICATION

It is assumed that a set of measurements (X_1, X_2, ..., X_x) has been made on an object which is known to be a member of one of two populations; T a target or $\overline{T}$, a nontarget. For convenience the measurements will be denoted by a point

$$\vec{X} = (X_1, X_2, X_3, \ldots, X_N) \tag{1}$$

in an n-dimensional measurement space M. Furthermore, M is divided into two regions R_T and $R_{\overline{T}}$ such that if $\vec{X} \varepsilon R_T$ the object will be considered a target, and if $\vec{X} \varepsilon R_{\overline{T}}$, the object will be considered a nontarget. Clearly, the union $R_T \cap R_{\overline{T}}$ must be M. Also, it is assumed that $P_T(\bar{x})$ and $P_{\bar{T}}(x)$ are the population densities of targets and nontargets. The following conditional probabilities may then be defined:

a) The probability of correctly classifying a target:

$$P(T|T,R) = \int_{R_T} P_T(\vec{x})\, d\vec{x} \quad . \tag{2}$$

b) The probability of correctly classifying a nontarget:

$$P(\bar{T}|\bar{T},R) = \int_{R_{\bar{T}}} P_{\bar{T}}(\vec{x})\, d\vec{x} \tag{3}$$

c) The probabilities of incorrectly classifying a target and a nontarget:

$$P(\bar{T}|T,R) = \int_{R_{\bar{T}}} P_T(\vec{x})\, d\vec{x} \tag{4}$$

$$P(T|\bar{T},R) = \int_{R_T} R_{\bar{T}}(\vec{x})\, d\vec{x} \quad . \tag{5}$$

Now it is assumed that there is a cost of $C(T|\bar{T})$ associated with classifying a nontarget as a target and a cost $C(\bar{T}|T)$ associated with calling a target a nontarget. Then, the expected loss due to misclassification is

$$L = C(\bar{T}|T)P(\bar{T}|T,R)P(T) + C(T|\bar{T})P(T|\bar{T},R)P(\bar{T}) \tag{6}$$

where $P(T)$ and $P(\bar{T})$ are the a priori probabilities of the object being a target or a nontarget, respectively. The optimum decision procedure is the one which minimizes this loss. Such a procedure is called a Bayes procedure. Clearly, the mathematical problem is to choose R_T such that L is minimum. This problem has been treated in the literature [7,8]. It can be shown that the regions of classification which minimize L are:

$$R_T : \frac{P_T(\overline{x})}{P_{\overline{T}}(\overrightarrow{x})} > k \qquad (7)$$

where

$$k = P(\overline{T})C(T|\overline{T})/P(\overline{T})C(\overline{T}|T) \qquad (8)$$

That is to say that if for a given $\overline{X}$ the ratio $P_T/P_{\overline{T}}$ is greater than k, **the object is classified as a target and not otherwise.**

The treatment to this point has been quite general. Now, it is necessary to make some assumptions concerning the probabilities $P_T(\overline{X})$ and $P_{\overline{T}}(\overline{X})$. The common, but often questionable, assumption is that of multivariate normal populations. With this assumption, the following equation can be written:

$$P_i(\overrightarrow{X}) = (2\pi)^{-N/2} \; |\Sigma|^{-1/2} \; \exp\left[-\frac{1}{2}\left(x - \mu^{(i)}\right)' \; \Sigma^{-1}\left(x - \mu^{(i)}\right)\right] \qquad (9)$$

where $\mu^{(i)}$ is the vector of means of the i^{th} population, and Σ is the covariance matrix, i.e.,

$$\overrightarrow{\mu}^{(i)} = (\mu_1, \mu_2, \ldots, \mu_N) \qquad (10)$$

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 & \ldots \\ \rho_{21}\;\sigma_1\;\sigma_2 & \sigma_2^2 & \ldots \end{pmatrix} . \qquad (11)$$

Here, σ_1, σ_2, ... are the variance of the X's and ρ_{ij} is the correlation coefficient between X_1 and X_j. Σ is assumed to be the same for both targets and nontargets populations. Finally, i may take on the values 1 or 2 corresponding to the target and nontarget populations, respectively. Substituting Equation (9) into Equation (7) and taking the logarithm of both sides, the following is obtained:

$$-\frac{1}{2}\left[\left(\overline{X} - \overline{\mu}^{(1)}\right)' \; \Sigma^{-1} \; (\overline{X} - \overline{\mu}') - \left(\overline{X} - \overline{\mu}^{(2)}\right)' \; \Sigma^{-1}\left(\overline{X} - \overline{\mu}^{(2)}\right)\right] \geq \ell n \; k \qquad (12)$$

for the region of classification as a target. On expanding the left side and rearranging terms, this becomes

$$\overline{X}' \; \Sigma^{-1}\left(\overline{\mu}^{(1)} - \overline{\mu}^{(2)}\right) - \frac{1}{2}\left(\mu^{(1)} + \mu^{(2)}\right)' \; \Sigma^{-1}\left(\mu^{(1)} - \mu^{(2)}\right) \geq \ell n \; k \quad . \tag{13}$$

Equation (13) is a linear equation in the X_j. Therefore, it may be written in the form

$$a_1 x_1 + a_2 x_2 + \ldots + a_N x_N \geq \ell n \; k + \frac{1}{2} b \tag{14}$$

where a_j is the j^{th} component of the vector

$$\Sigma^{-1}\left(\overline{\mu}^{(1)} - \overline{\mu}^{(2)}\right)$$

and b is

$$\left(\overline{\mu}^{(1)} + \overline{\mu}^{(2)}\right)' \; \Sigma^{-1}\left(\overline{\mu}^{(1)} - \overline{\mu}^{(2)}\right) \quad .$$

The left side of the equation is called the discriminant function. If the population means ($\overline{\mu}_1$ and $\overline{\mu}_2$) and the covariance matrix Σ are known, it is merely necessary to evaluate the discriminant function; then, if the inequality of Equation (14) is satisfied, the object is classified as having come from Population 1 (target); if not, it is classified as having come from Population 2 (nontarget).

The previously outlined procedure can be generalized to allow classification into more than two populations. If n - 1 different types of targets are to be considered, i = 1 represents targets of the first type; i = 2, targets of the second type; and so on to i = n - 1. Nontargets are then represented by i = n. Then, proceeding as before, a system of linear discriminate functions $\mu_j(x)$ can be constructed as follows:

$$\mu_{ij} = \frac{P_i(x)}{P_j(x)} \tag{15}$$

from which a system of inequalities of the form

$$\mu_{ij} > \text{constants} \tag{16}$$

is obtained. Classification can be made on the basis of this system. In the remainder of this report, classification into more than two populations will not be considered.

The probability of classification errors using this procedure has been extensively investigated [7,9,10]. It can be shown that the probability of misclassification can be computed in terms of Hotelling's T^2 statistic; however, a discussion of this aspect of the problem is beyond the scope of this report.

IV. CASE OF UNEQUAL COVARIANCE MATRICES

The discussions of classification by means of multivariate statistical analyzes that are found in the literature assume equal covariance matrices for the different populations. This assumption is convenient in that it leads to a linear discriminant function. However, it is difficult to justify at best. In many cases, it is obviously wrong. In this section, a discriminant function is derived under the assumption $\Sigma^{(1)} \neq \Sigma^{(2)}$ where $\Sigma^{(1)}$ and $\Sigma^{(2)}$ are the covariance matrices of the target and nontarget populations.

For the case of unequal covariance matrices, Equation (12) becomes

$$\frac{1}{2}\left[\left(\overline{X} - \overline{\mu}^{(1)}\right)' \, {\Sigma^{(1)}}^{-1} \left(\overline{X} - \overline{\mu}^{(1)}\right) - \left(\overline{X} - \overline{\mu}^{(2)}\right)' \, {\Sigma^{(2)}}^{-1} \left(\overline{X} - \overline{\mu}^{(2)}\right)\right] \geq \ln k \qquad (17)$$

or

$$\begin{aligned} -\frac{1}{2}\Big[& X' \, {\Sigma^{(1)}}^{-1} X - X' \, {\Sigma^{(1)}}^{-1} \mu^{(1)} - \mu^{(1)'} \, {\Sigma^{(1)}}^{-1} X \\ & + \mu'^{(1)} \, {\Sigma^{(1)}}^{-1} \mu^{(1)} - X' \, {\Sigma^{(2)}}^{-1} X \\ & + X' \, {\Sigma^{(2)}}^{-1} \mu^{(2)} + \mu^{(2)'} \, {\Sigma^{(2)}}^{-1} X \\ & - \mu^{(2)'} \, {\Sigma^{(2)}}^{-1} \mu^{(2)} \Big] \geq \ln k \; ; \end{aligned} \qquad (18)$$

hence, the discriminate function:

$$\frac{1}{2} X' \left(\Sigma^{(1)^{-1}} - \Sigma^{(2)^{-1}} \right) X - X' \left(\Sigma^{(1)^{-1}} \mu^{(1)} - \Sigma^{(2)^{-1}} \mu^{(2)} \right)$$

$$+ \frac{1}{2} \left(\mu^{(1)'} \Sigma^{(1)^{-1}} \mu^{(2)'} - \mu^{(2)'} \Sigma^{(2)^{-1}} \mu^{(1)} \right) \geq \ell n\, k \quad . \tag{19}$$

For unequal variances, the discriminate function is quadratic. In principle, this should cause no difficulty except for an increase in the computational effort required to evaluate the function. The classification errors arising from the application of quadratic forms has not been extensively studied [11].

V. APPLICATION TO A LASER IDENTIFICATION AID

The Bayes procedure in the previous sections provides a formal solution to the problem of target classification; however, the question of its applicability to a laser identification aid remains. In this section, some of the problems in applying this technique will be discussed.

A. Mathematical Assumptions

The Bayes procedure is based on two assumptions: (1) the explicit assumption of multivariate normal populations, and (2) a tacit assumption that the population means are sufficiently different to allow classification at all. The assumption of normal populations is commonly made in most classification problems, although it is often questionable. For many of the discriminants considered here, it seems likely that they will not be normal variables. However, it is not known at this time what distribution should be used. If it were known, it is likely that any other distribution function would lead to intractible mathematics. It seems, therefore, that the assumption of normal statistics must be used by default, at least for the present. Fortunately, it has been found that in many cases (drawn mostly from the behavioral and life sciences) that the assumption of a multivariate normal distribution often yields satisfactory results even when it is known that the true population densities are not normal.

The validity of the second assumption, namely, that the population means are sufficiently different to allow classification, is also difficult to assess at this time. If for any one discriminant variable the difference in means between target and nontarget populations is sufficiently large (several times the variance), then this variable alone would be sufficient for classification. However, if the differences in means of all variables are very small, then the use of multivariate analysis will not be of much value. It is in the intermediate case, (i.e., when there is a significant difference in the means, but this difference is still not large enough to allow accurate classification with a single variable) that the multivariate approach is useful. Thus, a knowledge of the mean and variances of both target and nontarget populations is needed to assess whether or not classification by discriminant function is appropriate. This information is not available at the present time.

B. Selection of Measurements to be Used for Classification

Although any of the measurements discussed in Section I could be used for target identification, it is clear that the minimum number consistent with accurate classification should be used. Which measurements are chosen will depend upon the effectiveness of the variable in classification and the difficulty of implementing the measurement. A considerable amount of experimental data will be required before this choice can be made with certainty.

C. Determination of the Population Means and the Covariance Matrix

To construct the discriminant function, it will be necessary to determine accurately the mean and variance of each variable used in the classification. This must be done for both target and nontarget populations. Furthermore, it will be necessary to determine the correlation coefficients for those variables that are not statistically independent. In principle, these quantities can be estimated by making a large number of measurements on typical targets and nontargets. If N_T measurements $\left(\vec{X}_i^{(1)}\right)$ from targets and $N_{\bar{T}}$ measurement $\left(X_j^{(2)}\right)$ from nontargets are used; then the mean vectors $\vec{\mu}^{(1)}$, and $\vec{\mu}^{(2)}$ would be estimated by $\langle\vec{X}^{(1)}\rangle$ and $\langle\vec{X}^{(2)}\rangle$ where

$$\langle\vec{X}^{(1)}\rangle = \frac{1}{N_T}\sum_{\alpha=1}^{N_T} \vec{X}_\alpha^{(1)} \tag{20}$$

$$\langle\vec{X}^{(2)}\rangle = \frac{1}{N_{\bar{T}}}\sum_{\alpha=1}^{N_{\bar{T}}} \vec{X}_\alpha^{(2)} \quad . \tag{21}$$

The covariance matrix would be estimated by S given by

$$(N_T + N_{\overline{T}} - 2)S = \sum_{\alpha=1}^{N_T} \left(\vec{X}_\alpha^{(1)} - \langle\vec{X}^{(1)}\rangle\right)\left(\vec{X}_\alpha^{(1)} - \langle\vec{X}^{(1)}\rangle\right)'$$

$$+ \sum_{\alpha=1}^{N_{\overline{T}}} \left(\vec{X}_\alpha^{(2)} - \langle\vec{X}^{(2)}\rangle\right)\left(\vec{X}_\alpha^{(2)} - \langle\vec{X}^{(2)}\rangle\right)' \quad . \qquad (22)$$

Clearly, this will require a very large amount of experimental data. Furthermore, the nontarget population presents a particular problem because it will be necessary to insure that the objects used in estimating the statistical parameters are representative of nontargets that will be encountered in an actual battlefield situation.

The problem of obtaining representative populations for parameter estimation can be simplified if it can be assumed that in practice the designator operator will exercise a certain amount of judgment and not simply designate objects at random. It would then be possible to restrict the class of nontargets to certain well-defined objects. For example, it might be assumed in a certain situation that the target would be a tank or a armored personnel carrier (APC) and that a non-target would always be another vehicle.

D. Estimation of A Priori Probabilities and Misclassification Cost

The discriminant function involves both the a priori probabilities that an object being designated is a target and a misclassification cost factor, neither of which are known accurately. The determination of the cost (or expected loss) associated with attacking a false target, or failing to attack a real target, is largely a matter of military judgment; as such it is outside the scope of this report.

There are several possible ways in which an estimation of the a priori probability of designating a target might be made. The simplest way (and one frequently used when the actual probabilities are unknown) is to assume that the probabilities of designating a target or a nontarget are equal, i.e.,

$$P(T) = P(\overline{T}) = \frac{1}{2} \quad . \qquad (23)$$

Although this assumption has some validity, Anderson [7] has shown by an example that the probability of misclassification will be much greater than it would be the case if the actual a priori probabilities were known.

In some cases, it may be possible to improve upon the assumption of equal probabilities by postulating the tactical situation in which the identification aid will be used. As a hypothetical example, it is assumed that the designator is being used in a defensive position under attack by enemy armor. As before, it is assumed that the suspected target will be a vehicle and that only tanks are to be attacked. The problem is then simplified to distinguishing between tanks and other vehicles. Now, if there is information concerning the mix of tanks and other vehicles in a typical enemy armor attack, it would be reasonable to use this ratio for the a priori probability that a vehicle being designated is a tank.

A third method of determining the a priori probabilities would be by observing designator operators under simulated battlefield conditions and counting the number of times they designated actual targets and the number of times they designated false targets.

Finally, two comments on the a priori probabilities and misclassification cost seem in order. First, both the probabilities and cost are likely to depend on the tactical situation in which the identification aid is being used. Secondly, because the cost and probabilities enter into the discriminant function as products, it is not necessary to know the probabilities more accurately than the misclassified cost. Because the costs are estimates, the rough estimates of the probabilities should also be sufficient.

E. Advantages of the Discriminant Function

The chief advantage in using the discriminant function for target classification is the ease with which it can be implemented. Although a considerable amount of data and extensive computations are required to construct the discriminant function, this computation can be performed on a high-speed computer. Once the discriminant function has been found and programmed into the identification aid, all that remains is the evaluation of a linear (or, at worst, quadratic) function and comparing the value of the function with a constant. Thus, "on board" computation is kept to a minimum. In fact, the entire decision process can probably be implemented in a single microcircuit.

VI. RECOMMENDATIONS FOR AN EXPERIMENTAL RESEARCH PROGRAM

It is clear from the preceding discussion that a considerable amount of experimental data is needed before the feasibility of a laser target identification system can be fully assessed. Even more data will be required to implement such a system. In this section, recommendations are presented for an experimental program which is considered to be the logical next step in the development of a laser designator target identification aid. Recommendations are made in the following paragraphs.

Initial effort should be directed toward the use of vibration signatures for target identification. Additional discriminants can be considered later. The reason for recommending that vibration signatures be given first consideration is that previous analyses [5,6] indicate that they are the most likely to provide a positive means of target identification. Furthermore, the US Army Missile Research and Development Command (MIRADCOM) will have in the near future a CO_2 laser heterodyne detector system capable of sensing target vibrations. This measuring system can readily be adapted for studying target classification techniques.

The first step in the experimental program must be to provide a means of processing the audio output of the heterodyne detector to obtain quantities suitable for discriminant variables. An appropriate choice of variables would be to let X_i be the fraction of the total audio power in the frequency intervals from f_i to $f_i + \Delta f_i$. Note that it is not necessary for the frequency intervals to cover the entire spectrum. Also, it is permissible for them to overlap. There are several ways in which the power in a given frequency interval could be measured as follows:

a) Using a spectrum analyzer.

b) By means of a Doppler filter bank.

c) By recording the audio, converting from analog to digital format, and then using a fast Fourier transform (FFT) algorithm to obtain the power spectrum.

Using a spectrum analyzer is impractical for mass data recording because its output will be in the form of a photograph of an oscilloscopal trace or a strip chart recording. Taking the data from the photograph and computing the power in various frequency intervals will involve an excessive amount of work.

The bank of Doppler filters is probably the simplest way to extract the data and is probably what would be used in an actual identification aid. But for experimental work, it has the disadvantage that the effect of changing the frequency intervals is to be investigated, the measurement must be repeated. This difficulty is avoided by use of the FFT because once the power spectrum has been computed and stored, it is a simple matter to have the computer compute as many different sets of (X_j) (corresponding to different frequency bands) as desired. Ideally, all three systems should be available: a spectrum analyzer for "quick look" data, digital data for the bulk of the data collection, and a Doppler filter bank for implementing a prototype.

The first data collected should be a "quick look" at the vibration spectrum of a number of vehicles in order to determine the range of frequencies which will be encountered and to obtain a general impression of the shape of the power spectral density curves. These data could be collected using a spectrum analyzer.

On the basis of the observed power spectra, a number of frequency bands should be selected for further study. These bands should be chosen in that region of the spectra where there appears to be the greatest difference between different types of vehicles. Now, a large number of measurements should be made on two or three different vehicle types and the power in each band recorded. These data should be analyzed to determine the following:

a) The average ($\overline{X}_j$) in each frequency band.

b) The variance of the X_i.

c) The probability density function of each X_i in order to verify the assumption of normal distribution.

The last of these can be done using a chi-square test or, more crudely, by plotting the cumulative distribution function on probability paper.

The purpose of these measurements is (1) to verify (or reject) the assumption of normal distributions; (2) to test the assumption that the covariance matrix will be the same for targets and nontargets (the assumption is supported if the variances are the same for different type vehicles); and (3) to determine if the discriminant variable is likely to be useful for classification. This is done by comparing the difference in means for various vehicle types with the variance. The larger the difference in means, the more likely the variable is to be effective in classification. Conversely, if there is no detectable difference in the mean from one type vehicle to another, then the variable is useless for classification.

The objectives of these measurements can be accomplished by using only a small number of frequency bands (two to five) and a few vehicle types (two to three). However, to obtain reasonable statistics, a large number of individual measurements (at least 50 and preferably 100) should be made on each vehicle.

The next step should be to repeat the preceding measurement using different frequency bands, and various bandwidths. If the original probability density functions (PDF) have been stored in a computer, the frequency bands can be changed without actually repeating the measurement. After a number of bands have been investigated, there should be a reasonably good indication whether or not there is a sufficient difference in the vibration spectra to allow classification, and if so, what frequency band should be used.

Assuming that frequency bands have been found in which there is a significant difference in target and nontarget means, an attempt can now be made to construct a discriminant function and perform target classifications. This can best be done by means of a computer simulation. The procedure is as follows:

a) On the basis of the previous results, a set of frequency bands are selected. Then, using the available data (and additional data, if needed), the coefficients of the discriminant function are computed.

b) A computer is programmed to evaluate the discriminant function and make the classification decision. The computer is then given sets of data taken from both targets and nontargets; the number of misclassifications is determined. If the data consist of N_1 targets and N_2 nontargets, the a-priori probabilities are taken as follows

$$P_T = \frac{N_1}{N_1 + N_2}$$

and

$$P_{\overline{T}} = \frac{N_2}{N_1 + N_2}$$

and the misclassification costs are assumed to be equal. The misclassification error rate (MER) is then

$$MER = \frac{N_{mc}}{N_1 + N_2}$$

where N_{mc} is the number of incorrect classifications.

c) The computer simulation can be used to investigate the effect of varying the number, center frequency and bandwidth of the frequency bands used to obtain the discriminant variables.

Once an adequate discriminant function is found, it will remain only to implement and test a prototype identification aid. The circuitry required is shown in the Figure. The output of the optical heterodyne detector is demodulated and passed through a bank of Doppler filters. The input of the filter bank is held constant by an automatic gain control (AGC) circuit so that the rectified outputs of the filters are proportional to the variables X_j. Each output is amplified by an amount proportional to its coefficient in the discriminant function. The output of the amplifier is then summed to yield the discriminant function. Classification is then performed by a threshold detector which determines if the discriminant function exceeds a preset level. This circuitry is very simple and could easily be constructed in hours.

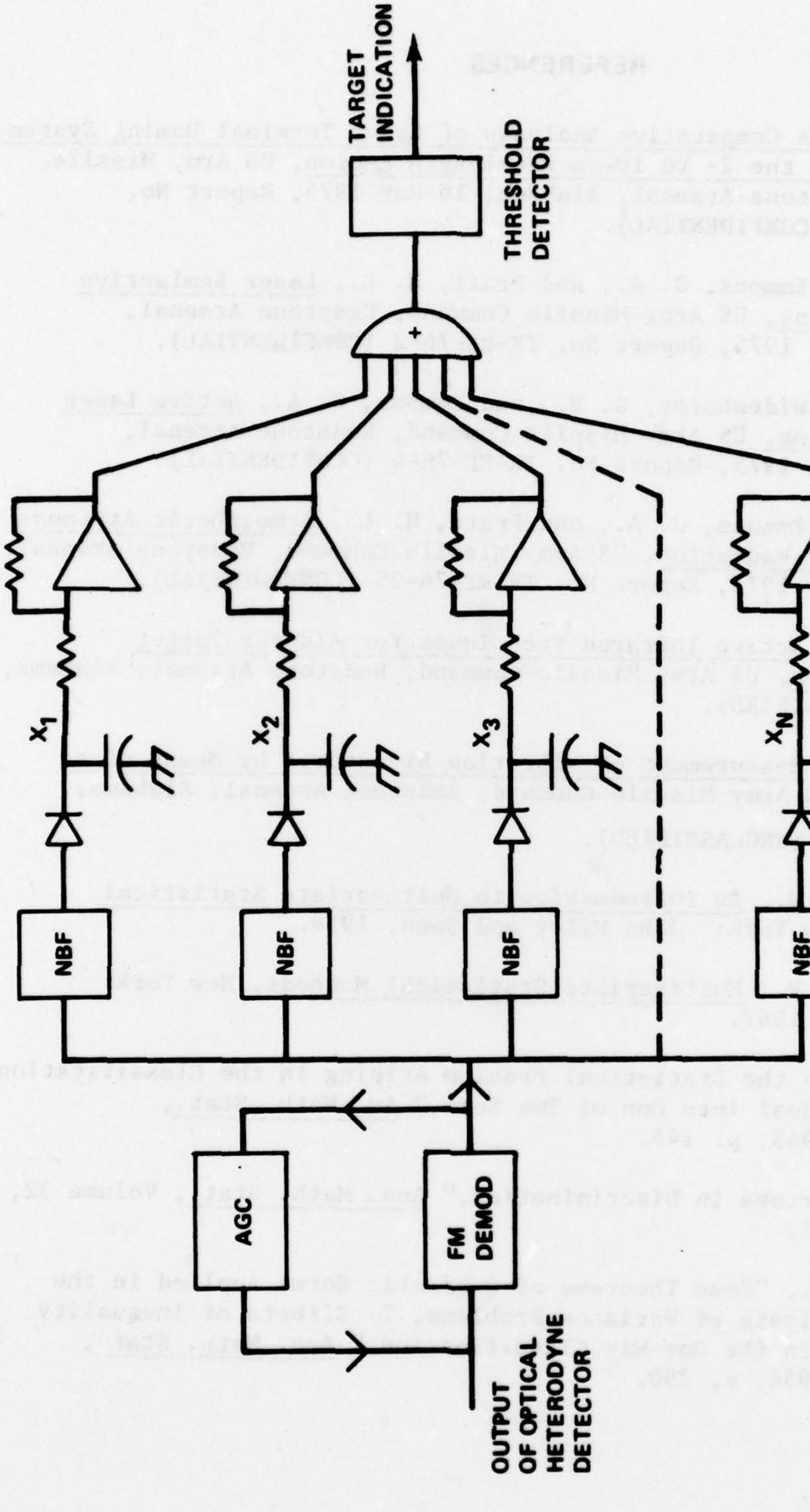

Figure. Filter bank detectors.

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