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UTILIZATION OF EXPERT KNOWLEDGE IN AUTOMATIC CLASSIFIERS OF NOISE SOURCES

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1. INTRODUCTION

Due to the progress in micro-processor and digital signal processing technologies, modern noise monitoring equipment offers increased performance. Current "sound-level meters" provide much more sophisticated measurements than old-fashioned sound-levels, like statistical and spectral analysis, or noise event recording. Moreover, there is actually a trend toward integrating noise monitoring systems (NMS) with personal computers to add further processing and memory capabilities. If this increased sophistication is generally welcomed, it has also some drawbacks. The noise control expert is provided with an ever growing wealth of information, and extracting the relevant features from the data becomes more and more difficult. Consequently, there are current research interests in the development of "intelligent" noise monitoring equipments, in order to simplify and automate as much as possible the data analysis task. One current research thread concerns the automatic recognition of environmental noise sources.

In automatic recognition of environmental noise sources, the goal is to classify a noise event based on its acoustic signature [1]. That is, it is expected that the NMS will provide, in addition to the level and time of occurrence of a noise event, some information on the *nature* of its source (e.g., train passing by, airplane flying over,...). Such noise recognition capabilities can be obtained by adding a sound recognition subsystem to a classical NMS. Various classification approaches have been considered for the realization of this subsystem, including neural networks, statistical classifiers, and ad-hoc methods. Preliminary studies have shown the feasibility of automatic noise recognition [2][3][4]. In these studies, standard pattern classification methods were applied straightforwardly without reference to the specificities of the noise recognition problem or to the environmental acoustics framework in which it takes place. We believe that utilization of acoustical-domain knowledge in an environmental noise recognition would be beneficial . Therefore, in this paper, we try to answer the following question, "what are the desirable properties of an automatic noise recognition system?" from the point of view of the noise control practician. A method for implementing such properties in a practical system is then suggested.

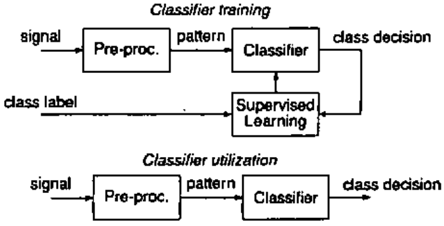


Fig. 1. Supervised pattern recognition.

2. NOISE CONTROL EXPERT KNOWLEDGE AND PATTERN RECOGNITION

The standard supervised pattern recognition paradigm is described in Figure 1. A pre-processor uses signal processing techniques to generate a set of features characteristic of the signal to be classified, for example, a sequence of short-time spectra or the average spectrum, in noise recognition. These features form a *pattern* (or *feature vector*). The classifier utilizes then some decision logic to assign the pattern to a particular *class,* e.g., train, aircraft, car, ... for the classification of environmental noise sources. During the supervised training or learning phase, class labels identifying the *training patterns* or *training samples* are provided to the system so that it can adjust the parameters of the classifier to obtain optimum performance according to some criterion, usually the minimization of the error rate. Once the system has been trained for a particular pattern recognition application, no more modifications are performed, and the classifier is put into service. Note that no use is made of acoustical-domain knowledge in the training of the classifier except in the selection of the pre-processor and the classification algorithm. It is expected that all the necessary information for the classification task is extracted from the training samples during the learning phase.

If the classifiers designed in the standard approach just described are adequate in many pattern recognition situations, they also lack some useful features that are desirable in an environmental noise recognition system. By nature, noise monitoring systems are frequently moved from one location to another where they encounter many different types of noise sources and many different observation conditions of these noise sources. It is theoretically possible to train a classifier for a large number of noise sources and observation conditions, but such training is not practical: it requires an enormous amount of training data if the training data is to be representative of the variability of the patterns. It is also possible to use features that are less sensitive to variations. However, insensitivity to the variations in observation conditions will often be obtained at the cost of a loss in classification power because features that are less sensitive to variations are also often less discriminant. In short, exhaustiveness and generality of a classifier are generally obtained to the detriment of its performance on specific cases. Possible solutions are *adaptable* classifiers which are trained in a particular situation but can be adapted to a different one by tuning some parameters, and *adaptive* classifiers, which can perform the adaptation automatically.

Classifiers are usually trained to minimize the error rate. That is, to commit a minimal number of classification errors. If the minimization of the error rate is commonly a desirable goal, there are situations in which other performance criteria are better suited. Not all classification errors may have the same importance and different costs may be assigned to different types of errors. For example, in some noise monitoring applications, it may be more important to precisely *detect* one particular type of event (e.g., airplane) against all the other types of events than to provide a classification for all types of noise sources. It may also be advantageous to integrate in the system a no-decision or "reject" option for the ambiguous patterns, if the absence of a decision is preferable to a possibly wrong one. Clearly, the choice of performance criterion should be left to the noise control expert, who can take adequate decisions in a particular noise monitoring situation based on his experience.

The desirable properties of a pattern recognition system for noise monitoring application can be summarized as follows:

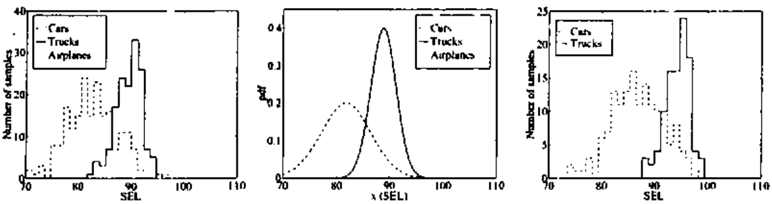
1. adaptableness and adaptiveness to different situations,
2. flexibility of the performance criterion,
3. integration of acoustical-domain expert knowledge.

In the present state of pattern recognition technology, it is clear that a monolithic "black box" approach to the conception of the noise recognition system will not meet all these requirements. To attain this objective, a better approach is the constitution of a noise classification "toolbox" with a library of classifier elements which can be easily selected and tuned by the noise control expert to provide an ad-hoc system for the noise control situation. Additional adaptive capabilities for on-site fine-tuning of the resulting classifier are also desirable.

3. STATISTICAL DECISION FRAMEWORK

The statistical paradigm for pattern recognition provides a framework for the realization of the noise classification "toolbox" and for the implementation of the desirable adaptation mechanisms. Moreover, Bayesian learning methods offer the possibility of integrating *a priori* acoustical knowledge in the classifier design. The statistical decision theory framework for the classification of environmental noise sources will be presented on a notional example. The reader should be aware, however, that the methodology described does apply to problems more complex than our trivial application. Complete description of the statistical decision theory framework can be found in the companion papers [1][5] and references therein. Note that the statistical approach is not the only possible one, but it is, in our opinion, powerful and rigorous yet flexible.

Let us assume that the only feature available for the classification of a noise event is its sound exposure level (SEL). Let us further assume that there are only three possible types of sources for the noise events: cars, trucks, and airplanes. A histogram of the training data is given in Figure 2 (a). A statistical model can be assumed for the data, for example, a Gaussian model as in Figure 2 (b). Let $\{\omega_1 = \text{"Car"}, \omega_1 = \text{"Truck"}, \omega_1 = \text{"Airplane"}\}$ denote the set of three possible noise source classes, let $P(\omega_i)$, $i = 1,2,3$, denote their *a priori* probabilities, and let $p(x|\omega_i)$, $i = 1,2,3$, denote the class conditional pdfs, where x stands for the SEL. Under the Gaussian hypothesis, we have $p(x|\omega_i) = \frac{1}{\sqrt{2\pi}\sigma_i}\exp\left[-\frac{1}{2}\left(\frac{x-\mu_i}{\sigma_i}\right)^2\right]$. The parameters of



(a) (b) (c)

Fig. 2. Histograms and model distributions for the SEL feature: (a) and (b) training situation, (c) utilization situation.

the distributions (means and variances) can be estimated from the training samples by the usual methods. Once the pdfs $p(x|\omega_i)$ are available, classifiers can be easily constructed. For example, it can be shown that the classifier minimizing the error rate (the Bayes classifier) is obtained by assigning to a new pattern y the class maximizing the *a posteriori* probability $P(\omega|y) = p(y|\omega_i)P(\omega_i)/\sum_{i=1}^{3} p(y|\omega_i)P(\omega_i)$. Similarly, it can be shown that the optimal detector for "airplane" events against "car" or "truck" events is given by the comparison of the likelihood ratio $p(y|\omega_3)/p(y|\omega_1 \vee \omega_2)$ to a threshold T selected to obtain adequate "miss" and "false alarm" probabilities according to the Neyman-Pearson criterion. Note that both decision tests can be obtained straightforwardly from the set of pdfs $\{p(x|\omega_i)\}$. Now, let us assume that the NMS has to be put into service at a location where only traffic noise (cars and trucks) can be encountered. Let us further assume that the distance between the NMS and the road on which the traffic is located is different from that in the training conditions. The observed SEL will be modified accordingly for both types of noise sources. A histogram of the SEL data in this case is given in Figure 2 (c). Clearly, the classification tests designed for the original situation will perform poorly. It is necessary to design a new classifier from the library of pdfs for this two-class case in similar fashion to that for the three-class case. The change in distance can be taken care of by accordingly modifying the parameters of the pdfs: the effect of the distance variation on the SEL can be easily modeled and the means and variances of the pdfs can be correspondingly adapted. Furthermore, on-site fine-tuning of the parameters of the pdfs can be obtained without the intervention of an external supervisor by mixture density estimation methods such as the EM algorithm [5].

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