Detection of Helicopters Using Neural Nets

Sohail Akhtar, Moustafa Elshafei-Ahmed, *Member, IEEE*, and Mohammed Shahgir Ahmed, *Senior Member, IEEE*

***Abstract*—Artificial neural networks (ANNs), in combination with parametric spectral representation techniques, are applied for the detection of helicopter sound. Training of the ANN detectors was based on simulated helicopter sound from four helicopters and a variety of nonhelicopter sounds. Coding techniques based on linear prediction coefficients (LPCs) have been applied to obtain spectral estimates of the acoustic signals. Other forms of the LPC parameters such as reflection coefficients, cepstrum coefficients, and line spectral pairs (LSPs) have also been used as feature vectors for the training and testing of the ANN detectors. We have also investigated the use of wavelet transform for signal de-noising prior to feature extraction. The performance of various feature extraction techniques is evaluated in terms of their detection accuracy.**

***Index Terms*—Helicopter detection, linear prediction coefficient (LPC), line spectral pair (LSP), neural networks (NNs).**

I. Introduction

HELICOPTERS are highly mobile tactical weapon platforms. A helicopter can be used as an intruder's transport, and as an escape vehicle after an intrusion has been committed. The low-flying ability of such aircraft enables them to penetrate the defense system, undetected by conventional radar. Building a system of remote sensors to detect and track single and multiple very low-flying helicopters is an important defense problem. Detection of helicopters using their sound signatures has been a focus of a number of recent research works [1]–[8]. The conventional method for helicopter sound detection uses the ratio of the main and tail rotor frequencies and their harmonics as the key helicopter noise features. However, most of the helicopter sound detection studies have used simulated spectrums based on only a fixed discrete spectrum from the rotors. In this paper, we propose an artifical neural network (ANN)-based helicopter sound detection system. The detection study of this paper is based on a helicopter sound simulator designed to produce more realistic sound characteristics of the helicopter's rotors, including the effect of aerodynamic vortex shedding, blade thickness noise, Doppler effect, as well as the atmospheric attenuation, and terrain effects [9].

Mori *et al.* [1], [2] investigated the use of a network of remote sound sensors to detect and track single and multiple very low-flying helicopters where information from different sensor nodes was exchanged to improve the resolution of the sound detectors. Feder [3] studied the problem of estimation of the fundamental frequency of the helicopter rotor in the presence of a wide band interfering signal, e.g., generated from a nearby jet engine. The aperiodic nature of the helicopter signal is modeled as a strictly periodic component with an interfering Gaussian noise with unknown spectrum. The parameters of the model are estimated using a likelihood function. Zhiping [4] applied cyclostationary estimation techniques for helicopter signal detection subject to time-varying Doppler shift and in the presence of possibly nonstationary background noise. He also used a cyclic frequency smoothing method to have a better estimate of the average fundamental frequency of the time-variant Doppler shifted helicopter acoustic signal. Cabell *et al.* [5], [6] proposed two pattern classifiers: 1) a statistically based Bayes classifier and 2) an ANN classifier. Selected peaks of spectral amplitudes of the fundamental and first seven harmonics are fitted to least square regressions and used as features for the ANN classifier. The Bayes classifier identified 67% of the audio segments of three helicopters while the ANN classifier was correct 65% of the time. The results suggested that additional features covering more about signal generation and propagation should be included in the ANN training to improve the performance.

Elshafei and Ahmed [7] used a recorded helicopter sound and a number of nonhelicopter sounds to train their ANN detector. They utilized feature vectors based on the main spectral peaks and other components in the frequency band from 150 Hz to 350 Hz. The Goertzel algorithm (GFFT) was used for evaluating the spectrum. Feature vectors of length 30 were used as input vectors for the training and testing of the classifier. The ANN classifier with one hidden layer of neurons was used. The results obtained have shown 99.5% correct detection of helicopter over test samples.

In this paper, different spectral parameters, such as linear prediction coefficients (LPCs), reflection coefficients (RCs), LPC cepstrum coefficients (CCs), and line spectral pairs (LSPs) are investigated.

In the following section, we briefly give an overview of the structure of the ANN- based pattern classification procedure as used for helicopter sound detection. The third section outlines the key features of the simulator used to generate the helicopter acoustic signal. Extraction of the feature vectors using the LPC-based techniques is given in Section IV. The simulation results are given in Section V. Finally, Section VI addresses some possible strategies for improving the detection performance in the presence of noise.

II. Detection Using Pattern Classification

A pattern classification system aims to classify an object based on its previous knowledge of it. Such a system operates in three phases: a training phase, a testing phase and a

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S. Akhtar and M. Elshafei-Ahmed are with the Department of Systems Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia.

M. S. Ahmed was with the Department of Systems Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia. He is now with E/E Engineering, DaimlerChrysler Corporation, Auburn Hills, MI 48326 USA.

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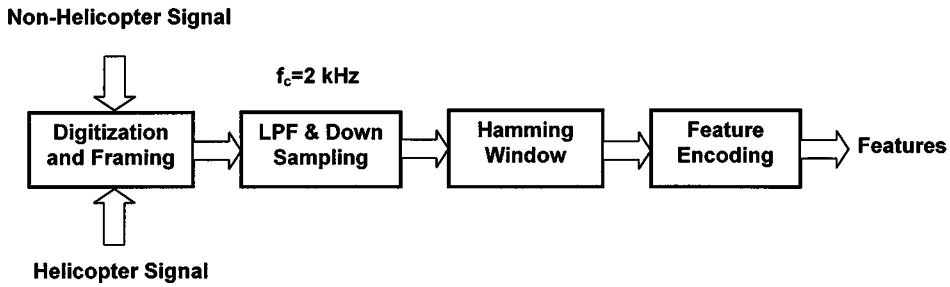

Fig. 1. Feature extraction steps.

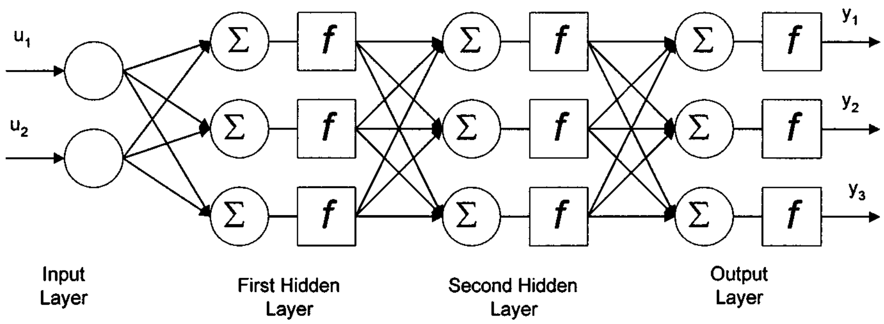

Fig. 2. Multilayer FFANN.

classification phase. A pattern classification system consists of a feature extractor and a classifier. The feature extractor normalizes the collected data, removes irrelevant information, enhances interclass similarities and transforms them to the feature space. The classifier takes these features and attempts to draw a clear distinction among objects from different classes. The sequence of operations in converting the helicopter/non-helicopter acoustic signals into a set of parameters suitable for the classification process is shown in Fig. 1.

The first function of the front-end parameterization stage is to divide the input audio signal into frames, which are digitized prior to analysis. The characteristics of helicopter sound can be considered stationary over time frames of 0.05–0.5 s. On the other hand, the dominant components of the helicopter signal are located in the freqency range below 2 kHz. Therefore, a low-pass filter of cut-off frequency 2 kHz is utilized to filter the signal. This pre-processing step removes some irrelevant information and enables us to down sample the signal to 4 k sps. The next step involves the multiplication of the signal by a finite-duration smoothing window. The type of window chosen (shape and duration) influences the time and frequency resolution. The feature vectors, obtained from this windowed signal, affect directly the complexity and effectiveness of the subsequent stages. The paper investigates several parametric representations of the helicopter spectrum, e.g., LPC [10], [11], and a number of other additional transformations, such as, RC, CC, and LSP [12]. Wavelet transform [13] is also evaluated for signal de-noising prior to feature extraction.

The classifier is chosen here to be a feed forward artificial neural network (FFANN). The capability of learning from examples, the ability of reproducing arbitrary nonlinear functions of input, and the highly parallel and regular structure of ANN make them especially suitable for pattern classification [14], [15]. ANN is also superior in situations where it is difficult to quantify the statistical properties of the phenomena as in the case of helicopter signal.

The feature vectors are applied as input to the network. At the training stage, the network adjusts its variable parameters (synaptic weights) to capture the features of the object. A FFANN consists of simple processing elements called neurons. Each neuron is basically a weighted summation node followed by a scalar nondecreasing output function $f(\cdot)$ called the *activation function*. These neurons are arranged and interconnected in multilayer structures, as shown in Fig. 2.

The back propagation (BP) algorithm is usually used for network training [14], [15]. Although BP is simple, it requires a lot of experimenting to choose a good learning rate. A slow learning rate will result in a long convergence time, whereas fast learning rate will possibly lead to oscillations, preventing the error from falling below a certain value, and remaining at a local minimum. The algorithm in general does not guarantee convergence to the global minimum. To solve these problems, several variants of the BP algorithms were proposed in the literature, e.g., [16]–[18].

Radial basis function networks (RBFNs) [15] offer a viable alternative to the two-layer FFANN. RBFN uses hybrid unsupervised and supervised learning schemes. RBFN can be trained several orders of magnitude faster than the BP FFANN. However, in general it cannot quite achieve the accuracy of the BP networks. Moreover, if RBFN is purely trained in supervised mode with BP learning, it does not learn appreciably faster than the BP FFANNs [15, Sec. 12.6].

III. Simulation of Helicopter Acoustic Signal

Training of the ANN detection system using recorded sound of various helicopters and under every possible flight condition is neither economical nor practically possible. An alternative practical approach is to utilize a reliable simulator based on theoretical and empirical prediction studies [19]–[23].

The simulator used in this work consists of the following four parts [9]:

1) Helicopter database, which contains the key physical parameters of each helicopter.
2) Flight trip simulator, which includes such variable parameters as speed, initial observation point, and 3-D flight path with respect to the observer.
3) Disturbance model, which includes fading, Doppler shift due to wind gusts, and sound interference, e.g., jet engine noise.
4) Sound production model.

A typical section of a helicopter acoustic signal, a real sound recording of UH-1, is shown in Fig. 3. It consists of a tonal signature, a combination of tones from the main rotor (3–40 Hz), the relatively higher tones due to the tail rotor (25–110 Hz), a broad-band noise generated from the laminar flow and vortex wakes (120–600 Hz), noise emitted by the engine drive train components (60–100 Hz), power turbine shaft and the gas generator/compressor turbine (900–2000 Hz), in addition to the effect of ground reflection and the atmospheric attenuation which are significant above 500 Hz [also see (4)]. Fig. 4 shows all of these distinct frequency components separately and the resultant narrow-band spectrum of a typical helicopter sound signature.

A. Rotor Noise

Rotor noise is a sum of the noise generated by the main rotor and tail rotor. The rotor noise is a combination of the rotational noise, vortex noise and discrete frequency noise known as "blade slap" [19], [21]. The amplitude of each blade-passing harmonic may be approximated by [24]

$$p_{mB}(R,\theta_0) = \frac{mB^2\Omega}{4\pi R c_0}\left(L_0\cos\theta_0 - \frac{D_0}{M_s}\right) \cdot J_{mB}(mBM_s\sin\theta_0) \quad (1)$$

where

B	number of blades;
R	distance between the axis of blade rotation and the observer;
Ω	angular velocity of the rotor;
m	harmonic number;
M_S	Mach number of the blade tip velocity;
$J(\cdot)$	Bessel function;
θ_0	angle between the observer and the axis of rotation of the blades;
L_0 and D_0	lift and drag components, respectively;
c_0	speed of sound.

Equation (1) assumes steady blade loading and neglects the rotor loading harmonics. In our simulation the tip velocity of the blades is taken also to be constant (about 0.6 Mach). A refined blade noise formula based on the Quadruple theory has been suggested in [21], but requires more involved computation. The broad-band noise is due to the vortex shedding at the airfoil trailing edge [24]–[27]. The vortex shedding broadband noise spectrum is approximated by a bell-shaped spectrum [26], [27], defined in terms of peak frequency "f_p." The peak frequency depends upon Strouhal number S_t

$$f_p = S_t\frac{V_T}{c} \quad (2)$$

where c is the chord length and V_T is blade tip velocity.

The cutoff frequency is taken as $f_L = f_p/Q$ and higher cutoff frequency is $f_H = f_pQ$ with $f_{\max} = f_p$ where Q is the called quality or shape factor. The broadband noise intensity is estimated using the empirical formula proposed in [28]. The vortex shedding noise is received modulated by the periodic blade passing waveform.

The effect of the rear rotor is usually much less than that of the main rotor. Moreover, it is highly sensitive to the aircraft orientation with respect to the observer. Because of its smaller diameter, the tail rotor runs at a much higher angular speed than the main rotor. As illustrated in Fig. 4, it produces a series of harmonics in a similar manner to the main rotor, but it has a higher fundamental frequency (40–120 Hz). The effect of the rear rotor is assumed to follow a cardioid directivity pattern with its peak in the direction of its wake.

B. Doppler Effect

The time-varying mth harmonic component at the observer can be expressed as

$$\hat{p}_{mB}(R,\theta_0,t) = \alpha p_{mB}(R,\theta_0)e^{-i(mB)\Omega(1-v/c_0)} \quad (3)$$

where α accounts for the path and atmospheric attenuation as it will be discussed shortly, and v is the component of the helicopter velocity in the direction of the observer. The above equation shows that the movement of the helicopter induces a Doppler effect in the form of a frequency shift in the observed spectrum. This change of mth harmonic is given by $\Delta f_m = mB\Omega v/2\pi c_0$. The change in the orientation of the helicopter with respect to the observer causes a continuous fluctuation in frequency and the relative magnitude of each of the harmonic components of the received signal.

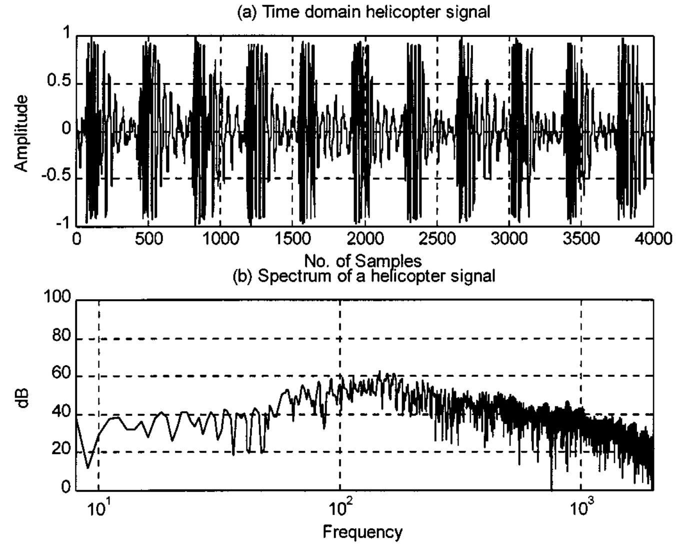

Fig. 3. (a) Time domain of a helicopter signal. (b) Spectrum of a helicopter signal.

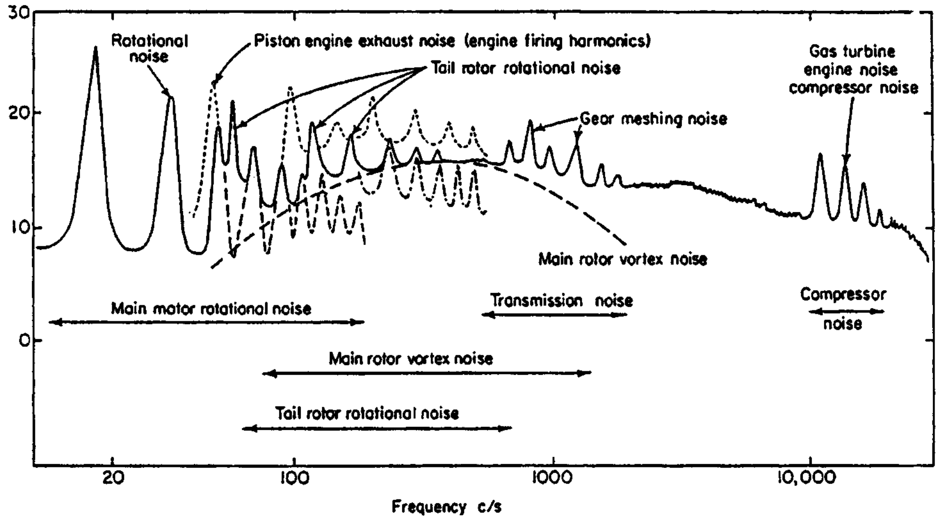

Fig. 4. Helicopter noise narrow-band spectrum [29].

C. Engine Noise

The noise emitted by the engine drive train components, power turbine shaft (N2), and the gas generator/compressor turbine (N1) are in the range of 900–2000 Hz [29]. Due to lack of real data, the two vibration frequencies (N1and N2) of the engine were fixed in this first version of the simulator. The received engine noise is modulated by the blade passing pressure, and Doppler shifted due to the motion of the helicopter.

D. Attenuation by Air Absorption

Atmospheric attenuation at a temperature of 20 °C may be calculated from [30]

$$A_e = 7.4\frac{f^2R}{h_{\%}}10^{-8}\ \text{dB} \tag{4}$$

where

- f geometric-mean frequency of the band (Hz);
- $h_{\%}$ percentage of relative humidity;
- R distance between source and receiver (m).

E. Flight Mission

In the simulation, we have considered a helicopter flying at a constant height and speed. The initial position and the forward velocity can be selected to simulate varying levels of Doppler shift and orientation effects.

IV. Feature Vectors

In designing a classifier, the choice of feature parameters of data is very important, since it greatly affects the overall performance of the system. The method of linear prediction analysis has been very successful for speech analysis, speech compression, and speech recognition systems. The importance of the method lies in its ability to provide an accurate estimate of spectral parameters, and its computational efficiency. This section presents a brief account of the parametric spectral representation techniques, which are used as feature vectors in this paper, specifically, LPC, RC, LSP, and CC.

A. Linear Predictive Coding of the Acoustic Signals

The linear prediction technique has proven to be very useful in providing an efficient representation of the speech signals [10], [11]. The signal s_n is considered to be wide sense stationary during a window or frame of length N. The signal s_n can be predicted approximately from only a linearly weighted summation of past samples. Let this approximation of s_n be $\hat{s}_n$, where

$$\hat{s}_n = -\sum_{k=1}^{M} a_k s_{n-k}. \tag{5}$$

The coefficients a_k can then be obtained through minimization of the mean squared prediction error with respect to each of these parameters. The polynomial

$$A(z) = 1 + \sum_{k=1}^{M} a_k z^{-k} \tag{6}$$

is called the LP polynomial, and the spectrum of the filter

$$H(z) = \frac{1}{1 + \sum_{k=1}^{M} a_k z^{-k}} \tag{7}$$

approximates the spectral envelope of the original signal. The linear prediction coefficients obtained by the autocorrelation method guarantee the stability of this all-pole filter.

B. Reflection Coefficients

Reflection coefficients, usually denoted by $\{k_i\}$, are LP filter representations in an orthogonal system of coordinates. This makes these coefficients desirable in pattern matching tasks as speech recognition systems. The value of the reflection coefficients does not change as the order of the filter is varied. Among the important advantages of the reflection coefficients, are their finite dynamic range, $|k_i| < 1$, and natural ordering of the reflection coefficients. The reflection coefficients can be obtained directly and efficiently from the signal autocorrelation using, for example, Burg's algorithm [11].

C. Line Spectral Pairs

The concept of the LSP was first introduced by Sugamura and Itakura [12]. LSPs encode acoustic signal information more efficiently than other spectral parameters (log-area ratio, inverse sine transform) due to the intimate relationship between LSP and the spectral peaks. The computation of LSP starts from the LPCs. A new polynomial known as the backward polynomial can be represented as

$$B(z) = z^{-(M+1)} A(z^{-1}). \tag{8}$$

Using $A(z)$ and $B(z)$, the following two auxiliary polynomials can be constructed:

$$P(z) = A(z) + B(z) \tag{9}$$

$$Q(z) = A(z) - B(z) \tag{10}$$

while $P(z)$ is symmetric, $Q(z)$ is antisymmetric. Furthermore, all the roots of the two polynomials occur on the unit circle, and the LSP are the angular positions of the roots $0 < \omega_i < \pi$. If the roots of $A(z)$ are inside the unit circle, then the roots of $P(z)$ and $Q(z)$ lie on the unit circle and are interlaced, starting with a root of $P(z)$ [12].

D. Cepstrum Coefficients

The LPC cepstrum is defined as the Fourier representation of the logarithmic amplitude spectrum based on LPC modeling. For a minimum phase LP filter, the LPC cepstral coefficients c_n are defined as

$$\log |H(e^{j\omega})| = \sum_{n=0}^{\infty} c_n e^{-j\omega n}. \tag{11}$$

A recursive algorithm for computing the cepstrum coefficients from the LP coefficients can be found in [10]. Cepstrum analysis is another alternative for obtaining the spectral feature vector. Cepstrum coefficients have the advantage that frequency response distortions introduced by the transmission system are removed [10].

V. Simulation Studies

In this study, the ANN detection system was trained on helicopter and nonhelicopter sounds. Four different helicopters (S-67, H500, CH-47C, and MI-HIND) were considered in this problem. Each of these helicopters has a different characteristic sound due to different rotor blade diameters, number of rotor blades, chord length, engine power, disc loading factor, etc. The helicopter sounds were obtained using the simulator described in Section III. Helicopters were assumed to pass by a stationary observer. A 28-s simulated sound for each helicopter was obtained at 11 025 samples per second, and using 16 bits per sample. Nonhelicopter sounds such as music, conversations, sound of crossing vehicles, running automobile engine sound, motor car horns, and motor boat sounds were included in the training. Helicopter and nonhelicopter acoustic signals were divided into 0.1-s frames as discussed before. Alternate frames were selected for the training purpose. A new set of helicopter acoustic signals with different flight conditions was simulated to be used later to evaluate the performance of various classifiers.

TABLE I
PERFORMANCE OF DIFFERENT FEATURE BASED CLASSIFIERS

Parametric model used	Detection Results of	SNR			
		Clean	18dB	12dB	9dB
LPC	Helicopter	100%	71.5%	25%	9%
	Non-helicopter	95%	98.4%	99%	100%
	False Alarm	5%	1.6%	1%	0%
	Miss	0%	28.5%	75%	91%
RC	Helicopter	100%	80%	48%	33%
	Non-helicopter	96.2%	99%	100%	100%
	False Alarm	3.8%	1%	0%	0%
	Miss	0%	20%	52%	67%
CC	Helicopter	98.9%	84.7%	41.5%	10.3%
	Non-helicopter	100%	100%	100%	100%
	False Alarm	0%	0%	0%	0%
	Miss	1.1%	15.3%	58.5%	89.7%
LSP	Helicopter	100%	95%	60%	47%
	Non-helicopter	97%	99%	100%	99%
	False Alarm	3%	1%	0%	1%
	Miss	0%	5%	40%	53%

The helicopter signals and the nonhelicopter signals are analyzed and encoded following the steps in Fig. 1. A sigmoidal tangent function $f(\cdot)$ was used in the hidden layers of the constructed neural networks, and a linear function was assumed in the output layer. Helicopter signals were assigned a target of 0.9, while nonhelicopter signals were assigned a target of 0.1. In the testing phase, a threshold of 0.5 is used for deciding a helicopter or nonhelicopter signal. The training set consists of 700 frames, including 550 helicopter sound frames and 150 nonhelicopter sound frames. All of the ANN simulation has been carried out in MATLAB, using the fast-training BP algorithm proposed in [16].

For the case of LPC, RC, and CC, 20-point feature vectors were used. For the LSP- based model, a 14-point feature vector was constructed due to the limitations of the root finding algorithm. All four classifiers have 14 neurons in a single hidden layer. Input neurons were equal to the input features (20 in the case of LPC, RC, CC, and 14 in the case of LSP) and a single neuron was used in the output layer. During training a sum square error (SSE) goal of 0.01 was assigned initially. After every fixed number of training epochs, the performance of the classifiers was evaluated for a test data. At a point where performance degradation was observed, training was terminated. After training, the performances of the classifiers were checked on test patterns without noise and patterns corrupted by a background noise of 18 dB, 12 dB, and 9 dB signal-to-noise ratio (SNR). Table I summarizes the performance of the four parametric model-based classifiers at different noise levels. In the case of LPC when the conditions were identical to those encountered in the training set, i.e., no noise was added to the test patterns, there was a small drop in recognition performance. This indicates that the training data has accounted for most of the variability in the test data. When the test frames were corrupted

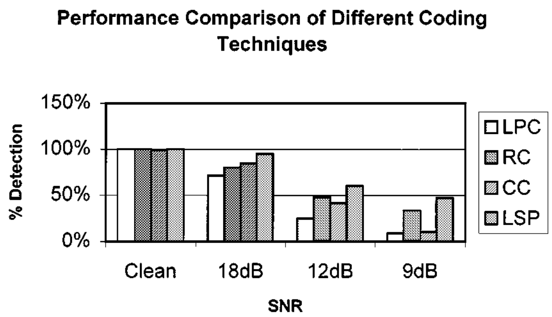

Fig. 5. Performance comparison of the feature vectors.

by a white Gaussian noise, the simulation indicated that as the SNR decreases, the noise distorts the spectral peaks, causing a rapid deterioration in performance. The noise tends to reduce the dynamic range of the resulting LP coefficients. The peaks and valleys of the spectrum become blurred [10], [11].

Due to the finite dynamic range $|k_i| < 1$ of the reflection coefficients, the RC-based classifier has shown much faster convergence than the LP coefficients-based scheme. The results for clean and noisy test data have shown that the classifier has produced 100% correct detection when no noise was added. Due to the relatively small dynamic range of the reflection coefficients, additive noises of relatively low power produce small variations in the reflection coefficients resulting in satisfactory performance. However, at higher noise levels, a poor detection rate was observed.

The CC performance results are also indicative of the fact that for clean data the detection accuracy has been 100%. However, the nonlinear log operation has the potential for improper emphasis of the low-level noisy portion of the acoustic spectrum [10]. This fact has caused a severe and rapid degradation of the performance of the ANN detection based on the CC.

The LSP parameters have both well-behaved dynamic range and filter stability preservation property. The LSP parameters are interpretable in terms of the spectral peak frequencies. The zeros of the LSP polynomials lie on the unit circle, and the roots of the symmetric and anti-symmetric polynomial are interlaced. The detection results on clean test data are found to be not much better than the previous methods. However, LSP feature vectors have shown in general much better robustness against noise than the other feature vectors. Fig. 5 shows a composite performance comparison of different ANN classifiers based on different feature extraction techniques.

VI. Strategies for Improving Performance

It is clear from the previous simulation results that the presence of background noise in the helicopter signal could cause unacceptable degradation in the detection performance. To counteract the effect of noise, two approaches were investigated:

2) De-noising of the signal prior to feature extraction
3) Training the system in an environment similar to the test conditions

On the other hand, the reported identification results are all based on a frame-by-frame test. Substantial improvement can be achieved if we utilize the fact that helicopter sound extends over a long sequence of frames. A simple post-processing technique to improve detection performance based on a moving average of the ANN decisions will also be discussed.

TABLE II
Correct Detection Using DeNoised Signal

Detection Results of	SNR			
	Clean	18 dB	12 dB	9 dB
Helicopter	100%	96.2%	70.3%	58.5%
Non-helicopter	95%	98%	99%	100%
False Alarm	5%	2%	1%	0%
Miss	0%	3.8%	29.7%	41.5%

A. Denoising of the Signal Prior to Feature Extraction

Substantial research in the signal processing area has recently been focused on the wavelet analysis technique. This technique is applied here for de-noising of the acoustic signal prior to the feature extraction stage. The wavelet transform partitioned the data into two half bands, namely, a low-frequency band and a high-frequency band [13]. These bands can be further partitioned into two half bands, and so on. In this way, the signal can be resolved at various resolutions. In our application, a three-level decomposition of the signal is performed. Compactly supported orthonormal wavelet "db3" was used in the analysis. Entropy-based criteria are adopted for selection of the de-noising threshold.

Signal spectral estimates were then obtained from the de-noised signals in the form of a 14-point LSP. An ANN classifier having 14 hidden neurons was trained. The results obtained are shown in Table II. The detection results are better by 1.2%, 10.3%, and 11.5% for 18 dB, 12 dB, and 9 dB SNR test signals, as compared to the previously results that were not de-noised.

B. Training the System in an Environment Similar to Test Conditions

Another way to make the ANN less sensitive to changes in spectral shapes due to additive background noise is to train the network using templates created with background noise. This conjecture has been tested through simulation study. In this simulation, an ANN classifier was trained on 1400 frames, 700 frames without noise, and 700 frames with an additive noise level of 9 dB SNR. The ANN had one hidden layer of neurons having 14 neurons. The feature vector is obtained in the form of 14-point LSP. The performance of the classifier is shown in Table III. The results indicate a noticeably improved performance even in the case of heavy background noise.

Fig. 6 compares the detection performance of the best coding technique (LSP) trained on the clean signal only, the wavelet de-noised technique, and the performance of classifiers trained on the noisy as well as the clean signal. The observed trend in our simulation study consistently indicates that training under noisy feature vectors gives the best robustness against noise. The use of pre-filtering increases the complexity of the detector and does not produce better results. The ANN performs the noise filtering itself with the proper training strategy.

TABLE III
CORRECT DETECTION USING CLEAN AND NOISY DATA FOR TRAINING

Detection Results of	SNR			
	Clean	18 dB	12 dB	9 dB
Helicopter	100%	97.3%	81.2%	71.4%
Non-helicopter	98%	99%	100%	100%
False Alarm	2%	1%	0%	0%
Miss	0%	2.7%	18.8%	28.6%

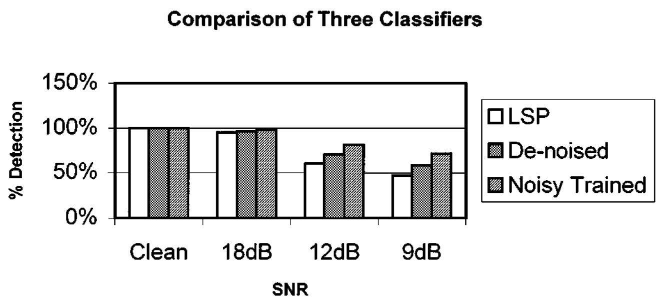

Fig. 6. Performance comparison of three LSP-based classifiers.

C. Improving the Detector Performance Using Post-filtering

A simple post-processing technique to improve detection decisions is to use a moving average based on the time series observations, $u_t, t = 0, 1, 2, \cdots$, of the memoryless ANN detector. Let H be a random variable which takes the value of one if a helicopter is present and zero if it is not. We assume that detection is not exact and the following conditional probabilities are known:

$$P(ut = 1|H = 1) = p; \quad P(ut = 0|H = 1) = 1 - p;$$
$$P(ut = 1|H = 0) = 1 - q; \quad P(ut = 0|H = 0) = q.$$

Let us assume that the output of the post-processor is the random variable $v_t, t = 1, 2, \cdots$, where $v_t = 1$ indicates that a helicopter is present and $v_t = 0$ indicates that the rotor craft is absent. The objective of the post-processing stage is to bring the probability of false alarm (POFA) $P_F = P(v_t = 1|H = 0)$, and the probability of missing (POM) $P_M = P(v_t = 0|H = 1)$ to within prespecified limits.

Let us consider the simple moving average

$$x_t = \sum_{k=0}^{n-1} u_{t-k}. \tag{12}$$

The new decision variable v_t is then defined such that $v_t = 1$ if $x_t \leq r$, and $v_t = 0$ if $x_t > r$; where r is a threshold value $r \leq n$.

In this case, the POFA and POM are given by

$$P_M = P\left(\sum_{k=0}^{n-1} u_{t-k} \leq r|H = 1\right) = \sum_{\ell=0}^{r} \binom{n}{\ell} p^\ell (1-p)^{n-\ell} \tag{13}$$

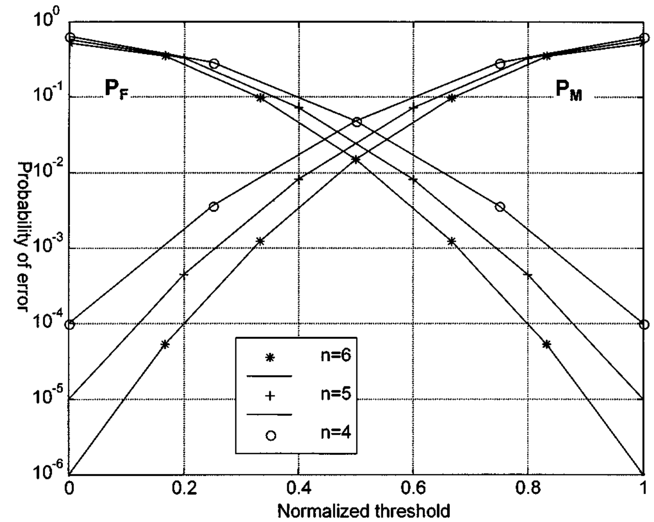

Fig. 7. P_M and P_F as function of n and r at $p = q = 0.9$.

$$P_F = P\left(\sum_{k=0}^{n-1} u_{t-k} > r|H = 0\right) = \sum_{\ell=r+1}^{n} \binom{n}{\ell} (1-q)^\ell q^{n-\ell}. \tag{14}$$

For a given p and q, the post-processing design problem is then equivalent to selecting the integers n and r such that $P_M \leq \alpha$ and $P_F \leq \beta$, where α and β are sufficiently small probabilities, selected by the decision maker. Fig. 7 shows the P_M and P_F for $n = 4,\ 5$, and 6 as a function of the threshold r, when $p = q = 0.9$. For example, at $n = 6$ and a threshold of 0.4, the MA post-processor would achieve $P_M \leq 0.002$, and $P_F \leq 0.03$, while at a threshold of 0.6 it would achieve $P_M \leq 0.03$, and $P_F \leq 0.002$.

Other techniques can also be employed, e.g., autoregressive post-processor, or a recurrent ANN detector, however, with substantially more complex training procedure.

VII. CONCLUSION

In this paper, we have evaluated the performance of ANN-based helicopter sound detection systems. Different LPC parametric modeling techniques were applied for parametric representation of helicopter spectrum features. The detection performance of these parametric features in the presence of noise is presented. Reflection coefficients are simple to calculate and require minimum ANN training time. On the other hand, LSP give the best robustness performance in the presence of noise, but require complex front end computation and show slow ANN training. The paper showed also that the performance of the ANN detectors can be improved if the wavelet transform is applied for de-noising the signal prior to the feature extraction stage, or if the detection system is trained using a combination of clean as well as noisy signals.

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Sohail Akhtar received the B.Sc. degree in electrical (communication) engineering from the University of Engineering and Technology, Lahore, Pakistan, in 1993, and the M.S. degree in systems (control) engineering from King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, in 1998.

He was an Instrument/Control Engineer at a chemical plant for three years. He is currently a Lecturer at King Fahd University of Petroleum and Minerals. His research interests include pattern recognition, and neural and fuzzy techniques for control and measurement.

Moustafa Elshafei-Ahmed (S'73–M'76) was born in Egypt in 1952. He received the B.Sc. degree (with honor) from Cairo University, Cairo, Egypt, in 1975, and the M.Eng. and Ph.D. degrees (with honors) from McGill University, Montreal, QC, Canada, in 1979 and 1982, respectively.

In 1982, he was Research Associate at the Canadian Institute of Guided Ground Transport, Queens University. From October 1982 to June 1985, he was Assistant Professor at the Electrical Engineering Department of Worcester Polytechnic Institute, Worcester, MA, where he supervised a number of projects which led to the development of several high-tech products and patent applications. In June of 1985, he left his academic career to assume full charge of the engineering operations at TechMan Corporation, Brookfield, MA, to develop a spread spectrum local area network. From September 1987 to September 1993, he was an Assistant, then Associate, Professor in the Systems Engineering Department, King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia. From September 1993 to August 1996, he was a Consultant Engineer at HOSTEK, Egypt. He rejoined the Systems Engineering Department at KFUPM in September 1996. He is the sole inventor and coinventor of a number of U.S. patents. He has also published numerous papers in many international journals and conferences, and taught many graduate courses and professional short courses. He has been the Principal Investigator of many government and industrial projects.

Dr. Elshafei is a member of the Instrument Society of America and the International Society of Computer Simulation. He received the Award of Distinguished Services from the city of Worcester.

Mohammed Shahgir Ahmed (S'75–M'78–SM'89) was born in Faridpur, Bangladesh. He received the B.S. degree from University of Engineering and Technology, Dhaka, Bangladesh, in 1973, and the M.S. and Ph.D. degrees from the University of Windsor, Windsor, ON, Canada, in 1975 and 1978, respectively, all in electrical engineering.

From 1978 to 1999, he was with the King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, where he was a Professor. He also held faculty positions at Carnegie Mellon University, Pittsburgh, PA, University of Michigan, Dearborn, and Purdue University, Fort Wayne, IN. Since October 1999, he has been working with the Core Networking Group, DaimlerChrysler Corporation, Auburn Hills, MI, where he is responsible for the network simulation and validation. His research interest includes signal processing, control systems, simulation, and neural networks, and he has numerous publications in these areas.