DEVELOPMENT OF AN AIRCRAFT OPERATION CLASSIFICATION SYSTEM FOR LOUISIANA'S AIRPORTS

by

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ABSTRACT

In this project the development and deployment of systems measuring aircraft activity at airports is considered. This includes determining the type of aircraft and the type of aircraft activity. The type of aircraft is basic such as helicopter, single engine, multiengine, and jet aircraft. The different aircraft activities at airports include take-offs, landings, touch and go and low approach. Accurate counts of aircraft operations are important because the number and types of aircraft operations are related to airport planning and operation. The objective of this project was to investigate the feasibility of developing an automatic aircraft operation monitoring system. This involved investigating candidate technologies and developing a prototype system for monitoring aircraft operations.

In large airports with control tower operations, one can readily determine aircraft operations because the towers are always manned and logs are kept of all operations. This is not true at smaller and rural airports that may be only manned during certain hours. Some of the issues involved in deploying technologies for monitoring aircraft operations include: the system must be cost-effective, reliable portable, must operate self-contained in the field for two weeks, and must be acceptable at airports.

ACKNOWLEDGMENTS

IMPLEMENTATION STATEMENT

The system for monitoring aircraft operations is based on hardware and data acquisition software developed by Larson Davis. A flexible software system has been developed for aircraft operations classification. The software was made the software flexible so that it could be used in the future with any data collection system. The software performs well with the data from this study. Larson Davis has recently agreed to supply their latest hardware and software. The next step in the development is to utilize the Larson Davis 824 system with the software. This would allow further testing and tuning of the software. It would only require some personnel costs to visit airports and operate the system. If this is successful, then vendors such as Larson Davis will be interested in the system as a product.

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INTRODUCTION

A multimedia database was established for the study. The information contained in the database consists of airport information, runway information, acoustic records, photographic records, a description of the event (take-off, landing), aircraft type, and environmental information. The information is stored in a relational database.

Features were extracted from the acoustic time signal and the frequency content of the signal. Often data obtained from portable spectral analyzers are collected in octave filters or 1/3 octave filters. The 1/3-octave frequency measures were also used as features. A multi-layer feed-forward neural network was chosen as the classifier. Training and testing results were obtained for the data in our database. Classification results of over 95 percent for training and testing were obtained. A flexible software system implemented in Matlab was developed for the classification software. This software system can be used with any acoustic data collection equipment suitable for operation at airports. The study indicates the feasibility of developing an acoustic system for monitoring aircraft operations.

OBJECTIVE

The objective of this project was to investigate the feasibility of developing an automatic aircraft operations monitoring system. This involved investigating candidate technologies, determining candidate technologies, and developing a prototype system for monitoring aircraft operations.

SCOPE

The scope of the project involved the determination of a prototype system for aircraft monitoring. It did not cover the area of developing the system to the level of a commercial product or forming the necessary links with a commercial partner for the commercial development of the system.

METHODOLOGY

This section describes the methods used in the project. This includes sections on database formation, feature extraction, classification, and software development.

Aircraft Operations Database Formation

In order to develop algorithms and evaluate the developed system for characterizing aircraft operations, a database of aircraft operations was created. The information contained in the database consists of airport information, runway information, acoustic records, photographic records, a description of the event (take-off, landing) aircraft type, and environmental information.

Description of Equipment used for Data Collection

The equipment used in the field for data collection consisted of a digital camera, sound recording equipment, and a form to manually enter information related to the aircraft operation. The camera was used for a photographic record of the aircraft operation. A Kodak digital camera was used. The acoustic equipment was used to record the sound records of the aircraft operations. This equipment consisted of: a Larson-Davis Model 712 Sound Level Meter, Electro-Voice RE55 Microphones, and a Sony TCD-D8 DAT Walkman. The data were collected at 44.1kHz on the DAT tapes. It was processed at 22.05 kHz, because this speed proved sufficient for the application.

Data Collection

The airports were selected in order to have some variety from large to small airports while still enabling the collection of a good number of aircraft operations. Before visiting any airport, the airport manager was notified days in advance of the visit. Permission to visit the airport and have access to the operations areas of the airport was obtained from the airport manager. Instructions were also obtained as to where the crew could assemble and the conditions under which the team could move about the airport operations area. At times, an escort was necessary. Whenever possible a transmitter was obtained so that the data collection team could communicate with the tower or other appropriated airport operations personnel. This allowed the team to know about incoming traffic and be given any updated instructions from operations personnel.

A common problem encountered at all the airports is inclement weather. In Louisiana, thunderstorms and lightning can occur suddenly and frequently. This often necessitated the interruption of data collection. The airport personnel usually have a general idea of the aircraft activity during any day. This helps to estimate how much data will be collected. They can also indicate the runways being used for take-offs and landings at the current time. Knowledge of the specific airport is important so that the units are placed in the best location for recording acoustic signals of aircraft operations. One needs to be on the right runway and select the best location on the runway to receive good information. If one is located too far at the end of a runway, some airplanes will be airborne well before they get to the unit on take-off. The aircraft may exit on a taxiway before they arrive at the unit on landings.

Database

This section describes the database collected for the study. It is important to collect a variety of data describing the conditions under which the sound event was recorded. For example, pavement type, wind speed and direction, aircraft type, microphone configuration, and aircraft operation are important pieces of data. A relational database schemes was developed. Figure 1 shows an example data entry screen that is used for entering the data. Notice the screen displays a photograph of the operation, details of the airport and runway, as well as other data. The user can also listen to the sound by clicking on the speaker icon. Consequently, this form provides a mechanism for integrating the multi-media data (sound, photo, data attributes). Since all of this information is stored in a relational database, it is very easy to construct free-form queries and reports to summarize data. Figure 2 shows a tabulation of the various sounds recorded.
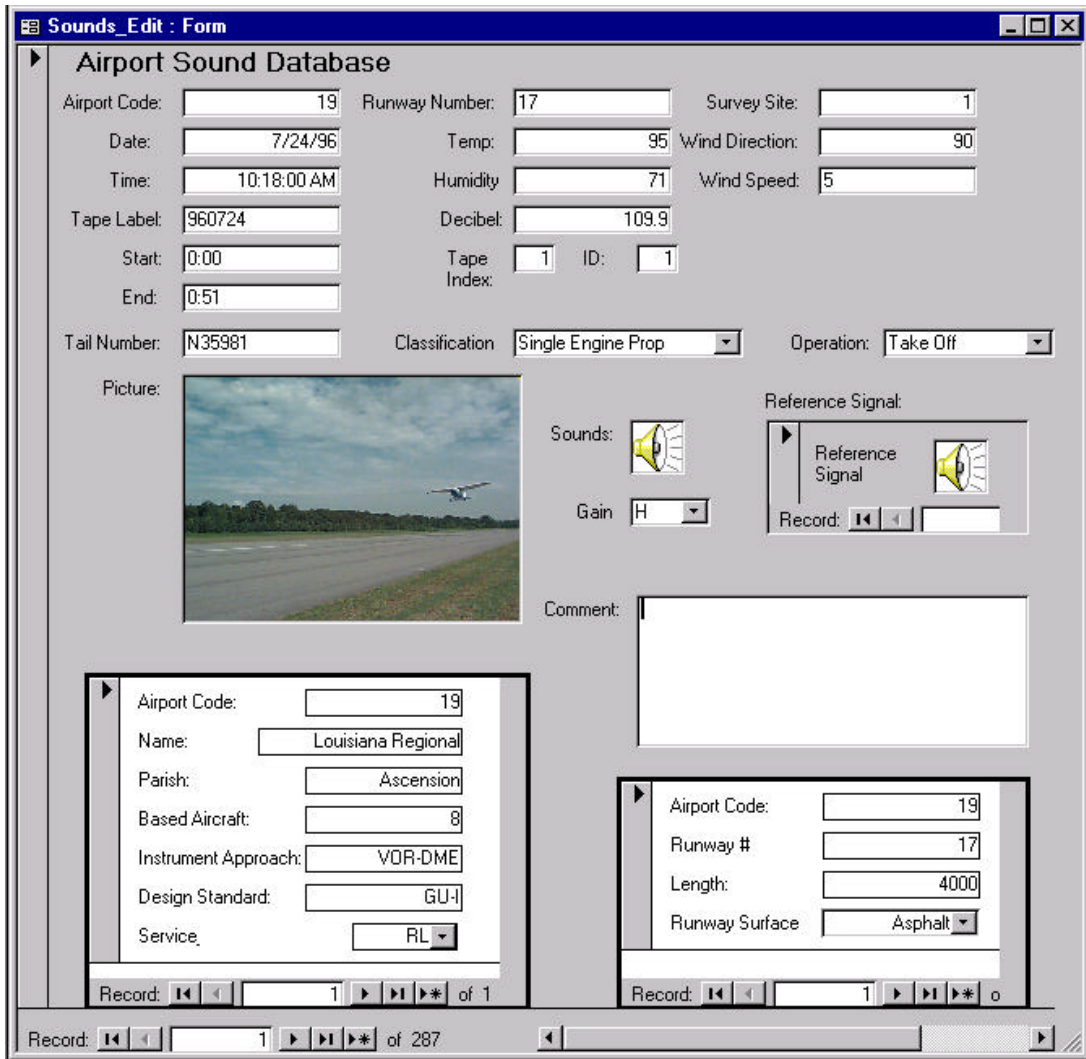
Figure 1
Database screen

	Take-off	Landing	Touch & Go	Low Approach	Other	Reference	Total
Helicopter	0	6	0	1	10	0	17
Single Engine	55	45	17	4	20	0	141
Multi-Engine	28	31	6	0	1	0	66
Jet	13	7	1	0	4	0	25
Other	0	0	0	0	10	0	10
Reference	0	0	0	0	0	23	23
Total	96	89	24	5	45	23	282

Figure 2
Summary report

Acoustic Concepts

There are some terms need to be defined. Sound data are often processed in the root mean square of the sound signal pressure, p(t). The form is $p_{rms} = \sqrt{\dfrac{1}{T_2 - T_1} \int_{T_1}^{T_2} p^2(t)dt}$ [1]. The units are Pascals. The interval over which p_{rms} is computed is a function of the sample rate of the sound power meter. The term L_p refers to the logarithmic form $L_p = 20\log_{10}\left(\dfrac{p}{p_0}\right)$ with units of dB or decibels. This is the sound pressure level (SPL). The quantity p_0 is 20 micro Pascal's, mPa , which is the perception threshold at 10 [2]. The sound pressure level, L_p , varies too quickly for interpretation and often generates too much data for storage. An average is performed over some interval to reduce the amount of data. The equivalent continuous sound level over a specified time interval is the equivalent steady level that would have the same RMS value over that time interval [2]. It is defined as $L_{eq} = 20\log_{10}\left(\dfrac{p_{rms}}{p_0}\right)$.

When the intervals are one second or less they may be called L_{eq} short.

The human ear does not have a uniform sensitivity to sound as the frequency is varied. A unit of loudness is the one which is defined to be the loudness of a pure tone with a sound pressure level of 40dB at 1000Hz [3]. A sound that is twice as loud has a loudness of 2 sones. The loudness level of a 1000 Hz pure tone of 40dB is defined as 40 phons. If it is raised in level by 10dB, it is twice as loud to a listener. A doubling of loudness is equivalent to an increase of loudness level by 10 phons. If S is loudness in sones and P is loudness level in phons, then $S = 2^{\frac{(P-40)}{10}}$.

Because of the sensitivity of the human ear, often frequency weighting is used. The most common weightings are A-frequency weighting, C-frequency weighting, and LIN-frequency weighting. LIN-weighting signifies, indicates no weighting [2]. A-weighting is widely used because it correlates with the human response to sound. It is intended to simulate a human ear at 40 phons. Sound level meters, (SLM), sound exposure meters, and noise dosimeters use A -weighting to measure the effects of noise on humans. This type of weighting is widely used to measure community noise. B-weighting is meant to simulate the human ear at 70 phons. It is not widely used. The C-weighted filter is meant to simulate the human ear at 100 phons. It is flat over most of the audible frequencies and is down 3dB at 31.6 Hz and 8000Hz. This

filter often used to measure the acoustic emissions of machinery. The weighting terms are [3]:

$$W_C = 20\log_{10}\left(\frac{A_1(fF_4)^2}{(f^2 + F_1^2)(f^2 + F_4^2)}\right),$$ (1)

$$W_A = W_C + 20\log_{10}\left(\frac{A_2 f^2}{\sqrt{(f^2 + F_2^2)(f^2 + F_3^2)}}\right), \text{ and}$$ (2)

$$W_B = W_A + 20\log_{10}\left(\frac{A_3 f}{\sqrt{(f^2 + F_5^2)}}\right)$$ (3)

where $A_1 = 1.007152$, $A_2 = 1.249936$, $A_3 = 1.012482$, $F_1 = 20.598997\ Hz$, $F_2 = 107.65265\ Hz$, $F_3 = 737.86223\ Hz$, $F_4 = 12194.217\ Hz$, and $F_5 = 158.48932\ Hz$.

The following plots are for these frequency weighting functions (Figure 3).

A-weighted filter
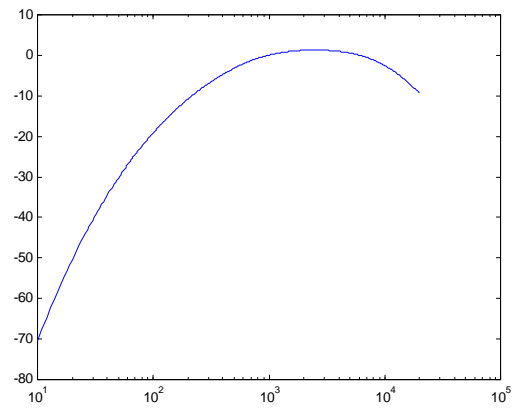
B-weighted filter
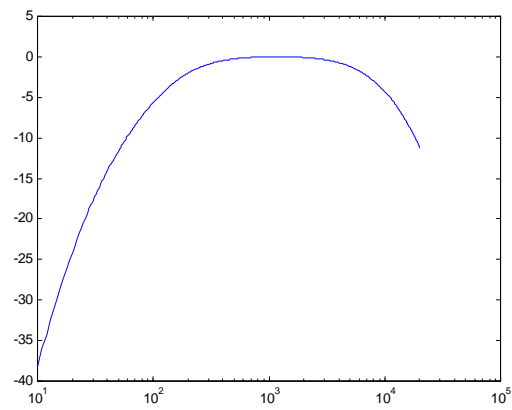
C-weighted filter
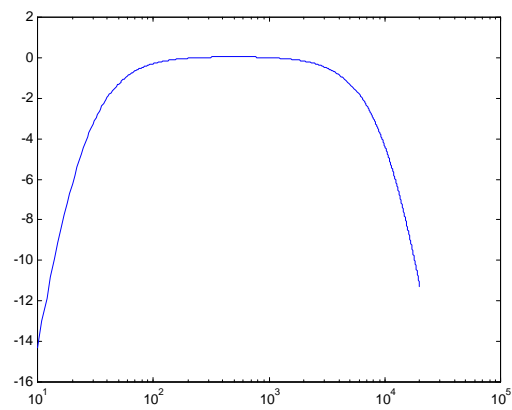
Figure 3
Weighted filters

Sound level meters equipped with filters are called spectrum analyzers. Often data are collected in octave filters or 1/3 octave filters. An octave band pass filter is a filter where the upper cutoff frequency is twice the lower cutoff frequency. An octave is a doubling of frequency. This filter can be subdivided into 1/3 octave filters with three bands per octave. The center frequencies for octave filters increase by a factor of two. Since the 1/3 octave filters divide this range into three parts, each 1/3 octave center frequency increases by a factor of $r = 2^{\frac{1}{3}}$. The following table gives the center frequencies of these filters. Let r be the ratio of the frequencies between adjacent filters. Then r is two for an octave filter and for a 1/3 octave filter $r = 2^{\frac{1}{3}}$. In order to get the low and high cutoff frequencies for a given center frequency one observes that,

$$f_c + \frac{f_h - f_l}{2} = f_h \Rightarrow f_c = \frac{f_h + f_l}{2} \text{ and } f_h = r * f_l \Rightarrow f_l = \frac{2 f_c}{r + 1}. \text{ If r is two and } f_c \text{ is 31.5}$$

then f_l is 21 and f_h is 42. For the 1/3 octave filter $r = 2^{\frac{1}{3}}$ and if $f_c = 20$ is a center frequency, the corresponding cutoff frequencies are $f_l = 17.7$ and $f_h = 22.3$ Hz. The bandwidth is

$$BW = f_h - f_{l.} = r * f_l - f_l = f_l (r - 1) = \frac{2 f_c (r - 1)}{(r + 1)} = 2 f_c \frac{(r - 1)}{(r + 1)}. \text{ For the (1/3) octave filter}$$

with

$f_c = 20$ then r = 1.2599 and BW = 4.6Hz.

Feature Extraction

In the application of acoustics to aircraft counting and classification, we are interested in identifying aircraft from one-dimensional (1-D) sound signals collected over time. This problem may be stated as an object identification problem, where the objects are the different types of aircraft. An audio sensor can generate a significant amount of data in a few seconds. An important step in object identification is to obtain information suitable for modeling the object to the automated recognition system. Objects can often be identified with samples as short at 20ms, which for convenience is called a frame of the signal [4]. It is desirable to reduce this data for object recognition. This process of reducing the amount of data while retaining the ability to recognize the object is called feature extraction. The features will be represented as vectors, and it is necessary, if each object is to be identified, to have distinguishable feature vectors.

There are several factors that complicate the object recognition process. One problem is that the communication channel may vary even if the object is the same. That is, sensors placed in different environments will behave somewhat differently and will produce different signals

for the same aircraft. Different airports and different weather conditions will affect the signals and will distort the feature vectors for the objects. Another complication is the objects in the same class, e.g. aircraft of the same type, will produce somewhat different signals. Finally, noise and multiple signals from different sources will distort the signals. A goal is to develop models of the audio signal in feature space that can be used for object identification. The features will be in the form of an n-dimensional vector, and object identification is accomplished by analyzing the feature vector.

The following two figures (Figures 4 and 5) show the raw sound signals obtained from a jet and a propeller powered aircraft. The sound data is available at 22,050 Hz, which gives a large amount of data that must be reduced to produce features suitable for object classification.
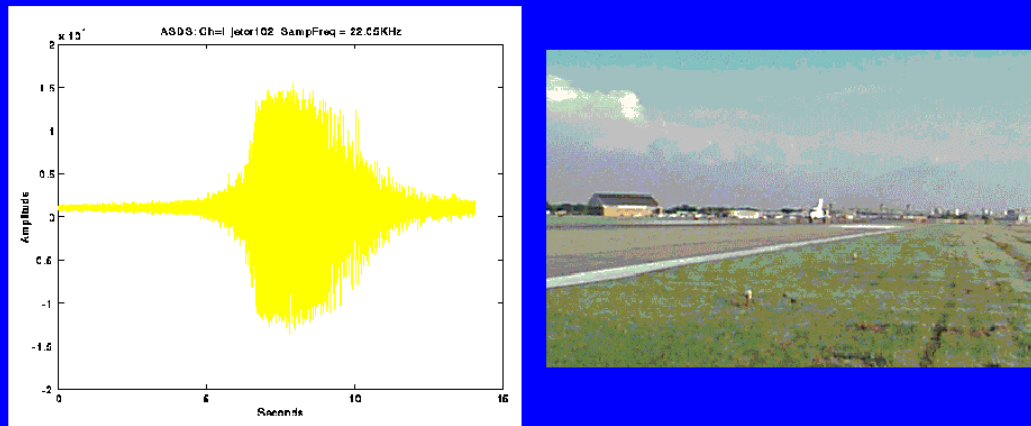
Figure 4
Sound signal for jet aircraft take-off
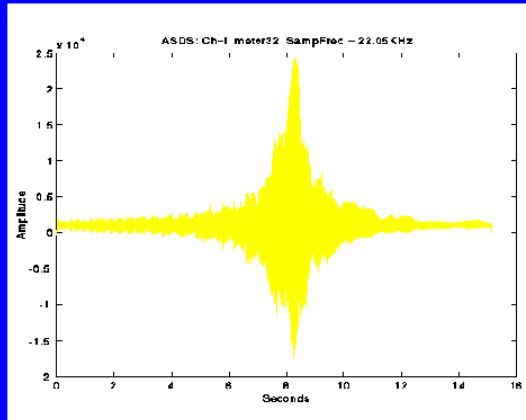
Figure 5
Sound signal for multi engine aircraft take-off

The following figures show the sound power level (SPL) signals or L_{eq} signals and the 1/3 octave filter responses for a typical helicopter, single engine propeller, multi engine propeller, and jet aircraft operation of take-off. On the frequency plots, the frequency data are all normalized to one and the horizontal axis is the measurement number given in Table 1. The data here has been significantly reduced from the raw sound data collected. The L_{eq} signals are taken at 1/8 second intervals. The sound data is available at a sampling rate of 22,050 Hz. This implies that only estimate frequencies up to (22,050/2) Hz can be made without aliasing. For this reason, we limited our frequencies to an 8,000 Hz center frequency. Therefore, 27 frequency measures are taken up to 8000 Hz as shown in the following table of approximate 1/3 octave filters.

Table 1
One-third octave filters

measure	center freq /Hz	bandwidth/BW
1	20	4.6
2	25	5.75
3	31.5	7.245
4	40	9.2
5	50	11.5
6	63	14.49
7	80	18.4
8	100	23
9	125	28.75
10	160	36.8
11	200	46
12	250	57.5
13	315	72.45
14	400	92
15	500	115
16	630	144.9
17	800	184
18	1000	230
19	1250	287.5
20	1600	368
21	2000	460
22	2500	575
23	3150	724.5
23	4000	920
25	5000	1150
26	6300	1449
27	8000	1840
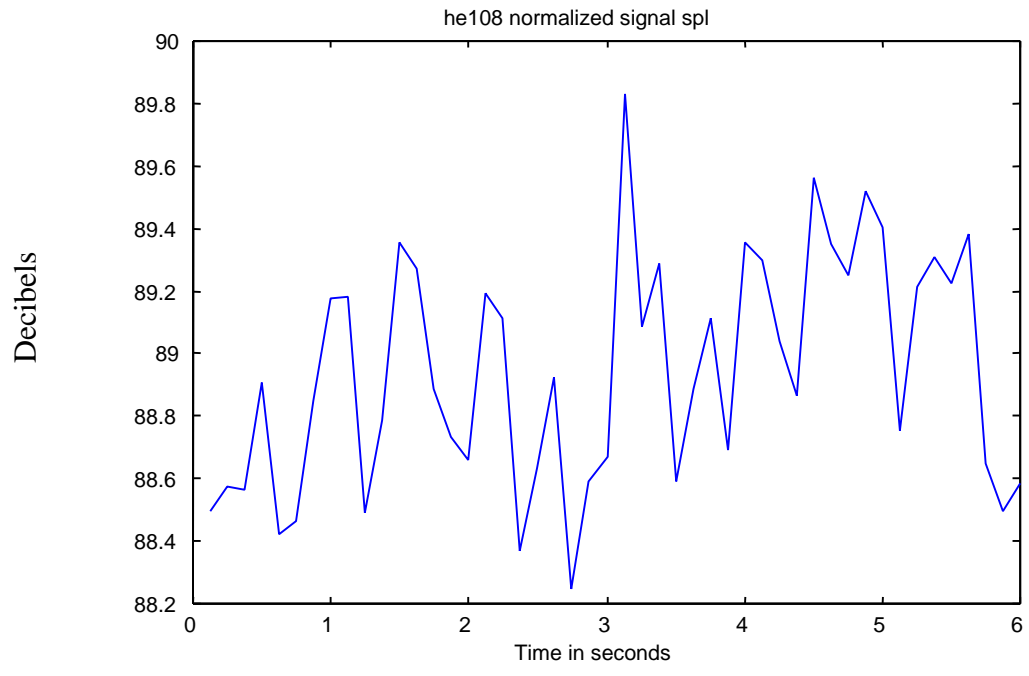
Figure 6
SPL signal from a helicopter
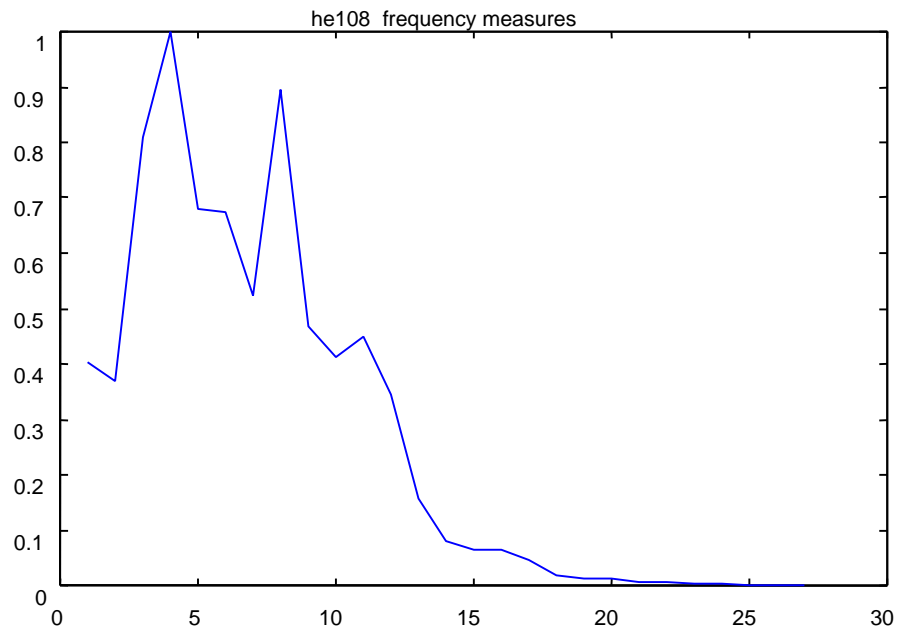
Figure 7
Frequency Response From a Helicopter

he: helicopter
spl: sound power level
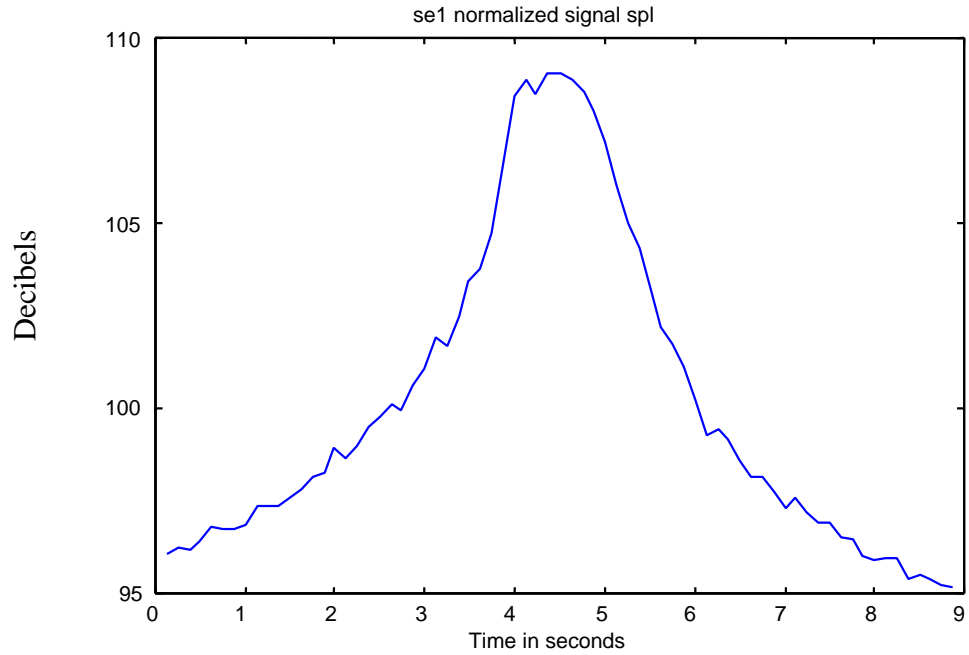
Figure 8
SPL signal from a single engine aircraft on take-off
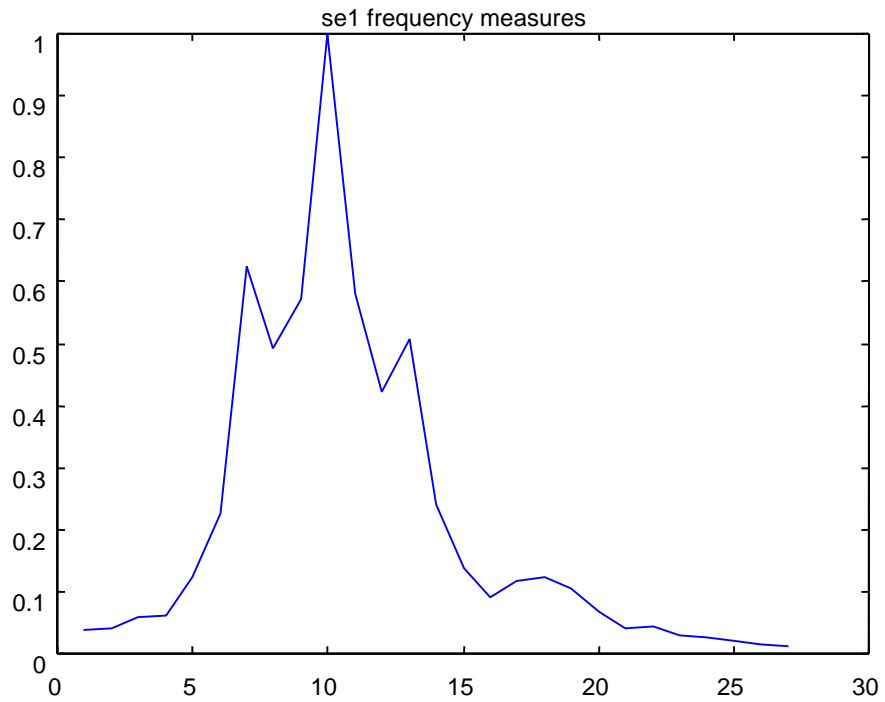
Figure 9
Frequency response from a single engine aircraft on take-off

se: single engine
spl: sound pressure level
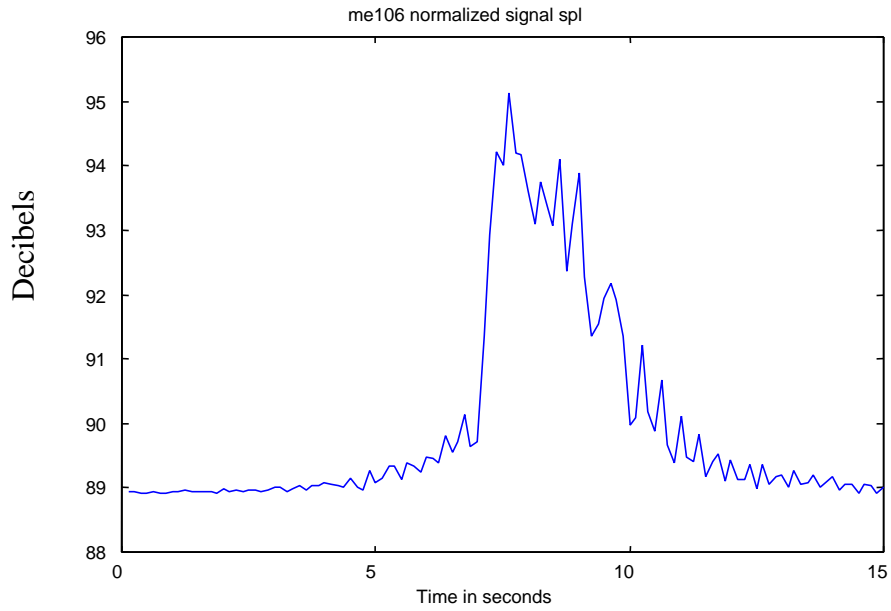
Figure 10
SPL signal from a multi engine aircraft on take-off
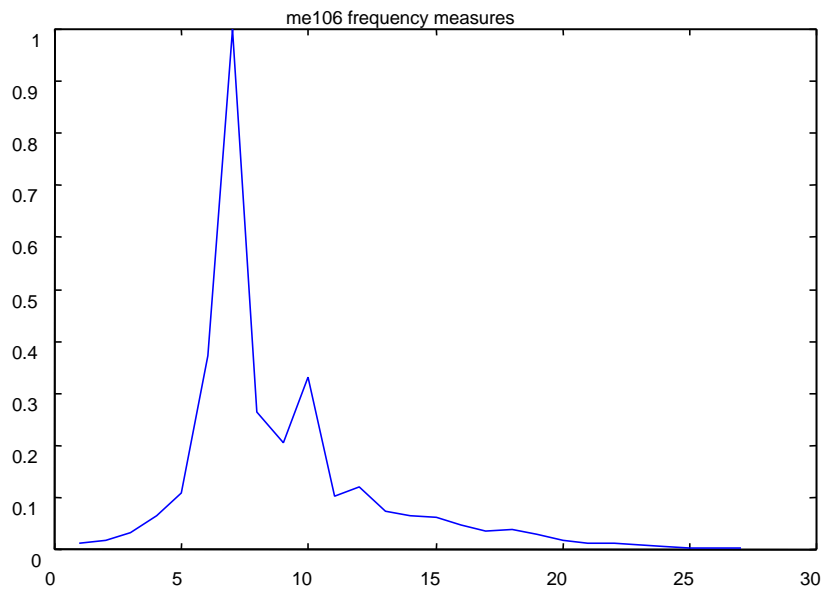
Figure 11
Frequency response of a multi engine aircraft on take-off

me: multi engine
spl: sound pressure levl
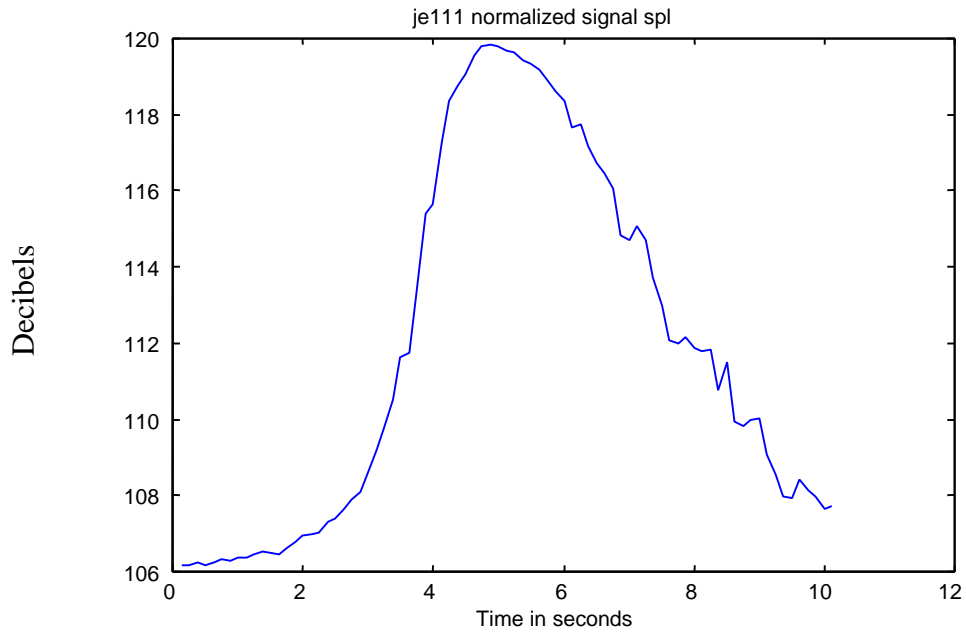
Figure 12
SPL signal from a jet aircraft on take-off
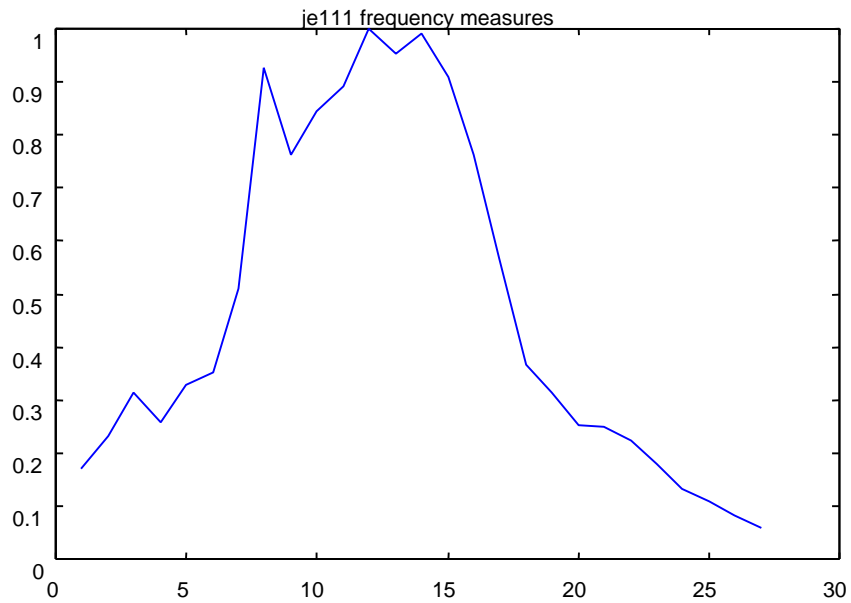
Figure 13
Frequency response of a jet aircraft on take-off

je: jet
spl: sound pressure level

Feature Extraction Methods

There are a number of useful methods for extracting features. Variations on the data pyramid are useful data representation methods. A data pyramid is a hierarchical structure where data are represented at different resolutions at various levels in the pyramid. The pyramid gives successive approximations of the input data in decreasing detail as the levels descend in the pyramid. The Gaussian and Laplacian pyramids are often used. More recently, wavelet transforms (WT) have been used to construct these pyramids [5]. The wavelet transform represents the original signal at any level in the pyramid by a coarse resolution signal and a detail signal. Like other transforms, the wavelet transform allows for reconstruction of the input data. Important components of the wavelet transform are the wavelet filter G and the mirror filter H. The wavelet transforms have the advantages of 1) being a multi resolution representation of the signal, 2) supporting zooming and providing a highly compact representation for high resolution data, 3) being close to the human discrimination system as compared to other transforms, and 4) providing a high compression ratio. Wavelet structures can be constructed with an arbitrary amount of smoothness [6]. The WT is a generalization of the short time Fourier transform (STFT) and has shown itself to be valuable in determining features for the discrimination of objects.

An audio signal can be characterized by the short-time Fourier spectrum of a signal [7], [8]. The question then becomes one of extracting feature vectors from the short-time Fourier transform (STFT). A common method used is the mel-warped cepstra transform. Let FFT be the fast Fourier transform and FFT^{-1} be its inverse. Let s be the signal over a frame, then $cep(s) = FFT^{-1}\left(\log|FFT(s)|\right)$. Since $\left(\log|FFT(s)|\right)$ is real and symmetric, the FFT and FFT^{-1} are equal up to a multiplicative constant. The cepstrum is, therefore, the spectrum of the log of the spectrum. The mel-warped spectrum is obtained by attenuating high frequencies in $\left(\log|FFT(s)|\right)$ before taking the inverse transform. The mel-scale is based on the non-linear human perception of sound frequencies [7], [9]. Generally, about 14 of the low cepstral coefficients are required for recognition. The use of the cepstra is justified if the sound signal can be modeled as a product where S=VH. Here S is the FFT of s and V is a periodic signal imposed on a nonperiodic signal H. This has often proven an effective approach in audio object recognition tasks [4]. For this situation, log(S) = log(V) + log(H), and the periodic component is separated from the nonperiodic part. Each of these components may be important in characterizing the object, and they can be separately modeled. Often the periodic component is more important. The Fourier transform of a real and symmetric function contains only real terms or the cosine terms of the transform. Since

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$\left(\log|FFT(s)|\right)$ is a real function and discrete for our sample data, the Fourier transform of the extended discrete function that is symmetric is a cosine function. Hence, the cosine transformation is an appropriate way to compute the cepstral coefficients.

The Karhunen-Loeve transform (KLT) is a transformation where the input data are decomposed into orthogonal eigenvectors. The eigenvectors are a function of the signal with a direct correspondence to the signal. This transformation is the optimal transformation and gives the largest energy for the fewest possible number of basis vectors. This method has a disadvantage, however, in that it is computationally expensive compared to other methods where the basis vectors are fixed. There has been renewed interest in the KLT in recent years. Sirovich has used the method to extract physical features from turbulence data [10]. The KLT is known as an optimal approach for data reduction and feature determination.

Features from the Time Domain Signal

The L_{eq} signal has a characteristic shape that is reflective of the different types of aircraft events as the previous figures indicate. The L_{eq} signal can be processed to reduce the number of measurements and extract features useful for classification. One measurement of relevance is the maximum value. Some sound events such as jet aircraft are louder than others. Contrastingly, single engine propeller aircraft landings are very quiet. Other measures can be related to the shape of the curves. A fast aircraft such as a jet will have a curve that is steeper as the plane approaches when compared to a propeller aircraft, see Figure 6,
Figure **8**, Figure 10, and Figure 12. One measure is called alpha. A second order polynomial is fit to L_{eq} from the beginning of the sound event to t_{max}, which is the time of the maximum sound level. If a2 is the coefficient of the second order term, then $a = \dfrac{1}{a2}$. This measurement should reflect the manner that the sound builds up to the microphone. Two other measurements are b1 and c1 that are the slopes of the curve from the beginning of the event to t_{max} and from tmax to the end of the event respectively. These measurements again reflect the rate at which sound builds up to the microphone. Another measurement extracted is skewness, which is the obliqueness of the curve about t_{max}. Here, skewness is defined as $\text{skewness} = \dfrac{\overline{m}^3}{s^3}$, where $\overline{m}^3$ is the third central moment. This term reflects the difference in the function to the left and right of tmax. Another measure involves the symmetry of the function about t_{max}. The measure is a ratio of the area to the right of t_{max} to the area to the left

of tmax. The following figure indicates these measures.
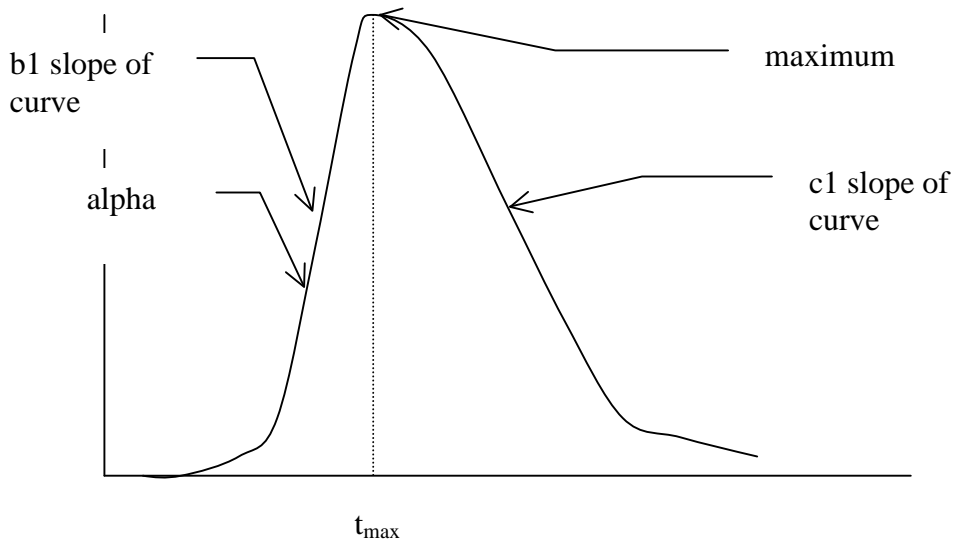
Figure 14
Measurements from time domain

Frequency Measures

While many expect frequency measures to reflect differences in the aircraft, they do not always adhere to this pattern. Frequency measures reflect differences in the aircraft. For instance, examinations of Figure 7, Figure 8, and Figure 11 reveals that the frequency content of the helicopter is concentrated in frequency measures of 3-10. The single engine propeller aircraft frequency content is concentrated in frequency measures of 6-13, whereas, the multi engine propeller aircraft frequency content is concentrated in frequency measures of 5-10. The jet aircraft frequency content is concentrated in frequency measures of 7-18. Table 1 gives the frequencies corresponding to the frequency measures a reason to consider frequency measures is that they are readily obtained from portable spectral analyzers that can operate in the field for several weeks.

Classification

Signal classification is the process of identifying the object associated with a given input signal. Once the features have been extracted as described in the last section, an n-dimensional feature vector will input a classifier. Neural networks were selected for the classifier.

Artificial neural networks (ANNs) attempt to solve complex problems with an architecture that mimics the nervous system. ANNs are mathematical systems comprised of a number of processing units that are linked via weighted interconnections [11]. A processing unit is a mathematics equation often referred to as a transfer function. A processing unit takes weighted signals from other neurons, combines them, transforms them, and outputs a numeric result. An individual computational element sums input values, which produces a nonlinear output. Large assemblies of these simple elements can solve problems requiring massive constraint satisfaction. ANNs have the additional advantage of learning the optimal connection weights between processing elements. This learning process eliminates the tedious programming that often accompanies complex problems.

Artificial neural networks have been developed as generalizations of mathematical models of human cognition or brain biology. They consist of neurons, links between neurons, weight associated with each link, and the activation function with each neuron [11]. Figure 15 illustrates a simple neural network. The first layer containing *X1, X2, X3* is called the input layer; x_1, x_2, and x_3 are output of these input nodes. The weights for connection links between input nodes to hidden neuron *Y* are w_1, w_2, and w_3, respectively. The net input, y_i, to neuron Y is the sum of weighted signals from neuron X1, X2, and X3:

$$y_i = w_1\, x_1 + w_2\, x_2 + w_3\, x_3 \qquad (4)$$

The activation *y* of neuron *Y* is given by a function of its net input, $y = f(y_i)$, e.g., the logistic sigmoid function (see Figure 16) [12].

Neuron *Y* is connected to neurons Z_1 and Z_2 with weight v_1 and v_2, respectively. Neuron *Y* sends its signal *y* to each of these neurons. In general, the values received by Z_1 and Z_2 will be different because these signals are scaled by weights, *v1* and *v2*. In a typical network, the activation Z_1 and Z_2 of neuron Z_1 and Z_2 depends on inputs from multiple neurons instead of just one as shown in this example.

$$f(y) = \frac{1}{1 + e^{-y_i}} \qquad (5)$$

In general, the calculations of a neural network use matrix multiplication methods. If the connection weights for a neural network are stored in a matrix $W = (w_{ij})$, the net input to

neuron *Yj* (with bias on neuron *j*) is simply the dot product of the vectors $X = (x_1, ..., x_i, ...x_n)$ and W_j (the jth column of the weight matrix) [11]:

$$Y_{ij} = b_j + \sum_i^n X_i W_{ij}$$ (6)

The bias (b_j) acts like a weight on a connection from a unit whose activation is always one. Increasing the bias increases the network input to the unit. It is adjustable and equivalent to a threshold to the activation of a neuron.

Artificial neural networks can be grouped into simple-layer and multiple-layer nets. There are two types of training, namely, supervised and unsupervised training for a network. Supervised training is accomplished by presenting a sequence of training vectors or patterns, with associated target output vectors. Then, the weights are adjusted according to its learning algorithm. Back propagation nets require supervised training. Typically, an architecture or structure of a neural network is established and one of a variety of mathematical algorithms is used to determine the weights of interconnections to maximize the accuracy of the outputs produced. ANNs are trained, meaning they use previous examples to establish the relationships between the input variables and the classification variables in setting these weights. Once ANNs is trained, the neural network can be presented with new input variables to generate a classification.
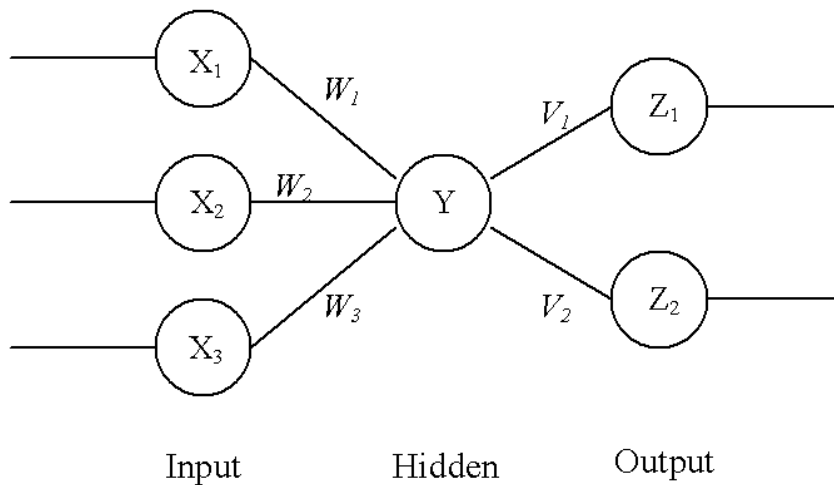
Figure 15
Simple neural network
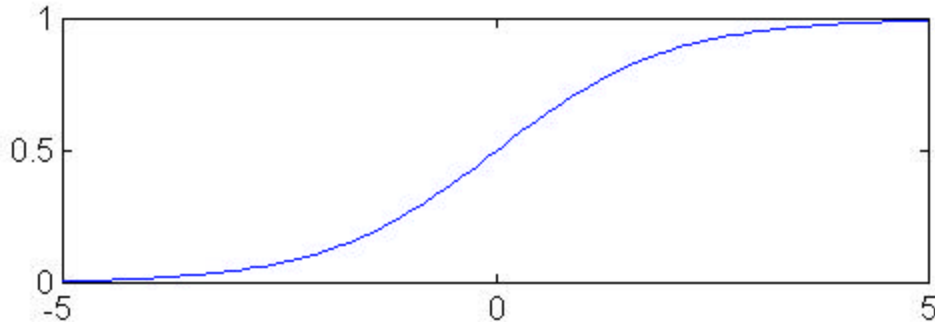
Figure 16
Logistic sigmoid function

Classification applications of ANNs involve developing systems that will classify the category into which an item falls. The neural network learns to distinguish between two or more categories provided based on the features of the input data [13]. Given a simple classification example, an ANN is used to classify two classes (class 1 and class 2) with five features. The design of the ANN includes an input layer of five neurons x_1, x_2, x_3, x_4, and x_5 and an output layer of two neurons c_1 and c_2 with a value of 1 or 0. When these five features belong to class 1, c_1 will be 1. Otherwise, c_1 is equal to 0. When these five features belong to class 2, c_2 will be 1. Otherwise, c_2 is equal to 0. C1 and c2 can not have the same value simultaneously. The structure of the neural network containing two hidden layers (layer 1 and layer 2) that have four and three neurons, respectively, is given in Figure 17.

Back propagation neural networks (BP) are probably the most common neural architecture implemented today. BP ANNs are "Multilayer Feed Forward Networks," meaning they have a layered architecture where data flows into one layer, through one or more hidden (internal layers) and out an output layer. Data flows in one direction known as "Feed Forward," and has multiple layers known as "MultiLayer." BP is actually an iterative gradient decent learning algorithm used to set the weights. The error between the neural network outputs and desired outputs are propagated backwards through the network to aid in the determination of the new values of the weights. This is done for each training data record repeatedly until the error reaches a stable minimum.
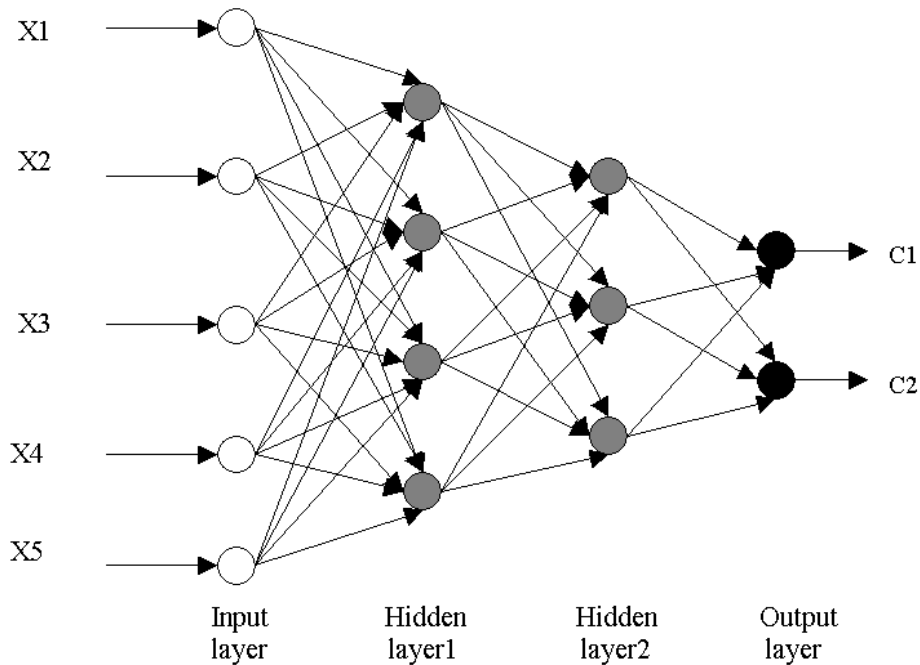
Figure 17
Example neural network

One reason BP neural networks are so common is because they perform relatively well on a wide variety of applications [11]. They can also be used for functional modeling, classification, and time series types of applications. Probabilistic Neural Networks (PNN) also can be used as classifier, but they require a lot of data. Due to a limitation of data, BP was chosen as the out classifier.

There are three steps in the process of training a back propagation neural network. These steps are the feed-forward of the input patterns, the back propagation of the associated error, and the adjustment of the weights. Untrained networks have randomly initialized weight values [12]. When an initialization is performed, a network state will be created that is completely unique. This leads to the possibility that identical training runs with newly initialized networks may exhibit different learning characteristics. However, the converged states of two such training runs will be nearly identical in the vast majority of cases.

Whatever type of model is used, it is necessary to determine the input and output. In this case, the input is the set of normalized feature vectors. The output from the program is class numbers corresponding to helicopter, jet, single-engine, and multiple-engine. BP nets require the output to be binary numbers.

To generate a successful neural network model, one must:

Step 1. Data Preparation

After generating the conceptual model, the data must be gathered. This is often the most tedious task in model development. All the data must be separated into two groups: training data and testing data. The training data includes as many numbers as possible in order to train a best network. The amount of testing data, however, must be at least 10 percent of amount of training data in order to verify the quality of the created network. The testing data is not included in the training data.

Step 2. Design the neural network model

With the training data available, one can set up the model with the neural network program. It is usually best to start with a simple network/hidden layer construction so that one can quickly validate the model's ability to train and learn relationships. One then specifies the network, the training data files, and the initial parameters. The default training parameters work for many problems and all parameters are adjustable during training.

Step 3. Train the network generated.

The training parameters may need to be tuned so that the specified values match the training characteristics for the model.

Neural Network Implementation

The detailed information of the neuron network is explained in this section. The system is implemented in the Matlab neural network toolbox.

The structure of the Neural Network

A multi-layer feed-forward neural network was chosen as the classifier. It is very important to define the network's structure properly. A general structure of the classification network is shown in Figure 17. In this case, there are three layers in the neural network: an input layer, a hidden layer, and an output layer. It is enough to have one hidden layer for practical applications, because it can reduce the complexity of the network.

The number of input neurons depends on the number of features used in classification. Because 35 features have been extracted from the aircraft sound record, 35 input neurons are needed. The number of output neurons depends on the number of classes of the aircraft being separated. Four output neurons will be needed because four kinds of aircraft (helicopter, jet, multi-engine and single engine) need to be distinguished. Each output neuron represents two states : 0 or 1. When it is active, the value is 1, so the aircraft belongs to that class. The number of hidden neurons is crucial for the network's performance. If more hidden neurons are used, a higher training accuracy but a lower testing accuracy is obtained. This is called overtraining. The final network structure for aircraft classification is given in Figure 18.
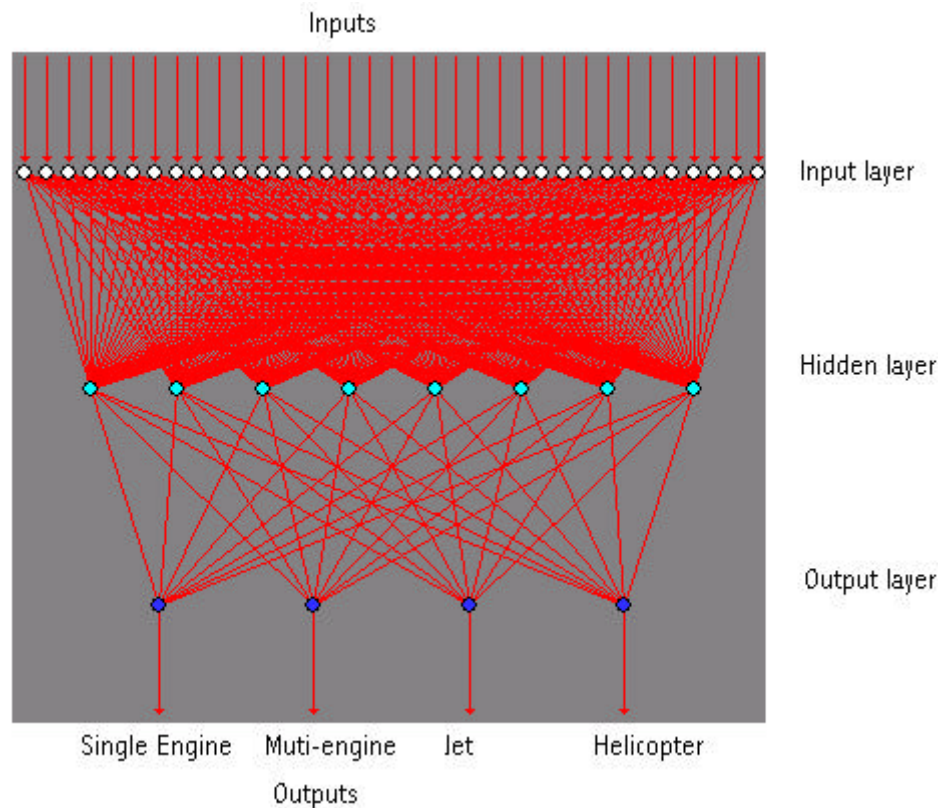
Figure 18
Neural network for aircraft sound classification

Data Preparation

The helicopter class was represented as 1, jet was 4, multi-engine was 3, and single-engine was 2. A Matlab program was programmed to change them to 0001, 1000, 0100 and 0010 instead of 1, 4, 3 and 2, respectively, as required by the neural network.

There are three neuron models in the Matlab Neural Network toolbox. They include: Tan-Sigmoid, Log-Sigmoid, and Linear transfer function. In this case, the Log-Sigmoid transfer

function was used because the value of classification is 0 or 1. There are many training methods in Matlab Neural Network Toolbox. Comparing the speed and the training and testing result, The Automated Regulation (TRAINBR) was fast in training and gave the best classification accuracy.

Different training and testing samples were used to train and test the network. After several repetitions of training and testing, the performance was found to be best for a network with a hidden layer with 8 neurons.

Case 1 Study

In this study, 83 samples of aircraft operations were used as described in the following table.

Table 2
Representations of Aircraft Types

	Helicopter	Jet	Multi-engine	Single engine	Total number
Representation in number	1	4	3	2	x
Representation in binary	0001	1000	0100	0010	x
Number of data	5	8	24	46	83

Classification Results with 77 Training and 6 Testing Samples

Table 3
Testing data set

	Helicopter	Jets	Multi-engines	Single engines
Number	1 (#2)	1 (#8)	2 (#15, #16)	2 (#39, #40)

The training results had an 87 percent accuracy rate.

Table 4
Training results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	4	0	0	0
Jets	0	6	0	1
Multi-engines	0	0	17	5
Single engines	0	0	0	44

The testing results had a 100 percent accuracy rate.

Table 5
Testing results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	1	0	0	0
Jets	0	1	0	0
Multi-engines	0	0	2	0
Single engines	0	0	0	2

Classification Results with 75 Training and 8 Testing Samples

Table 6
Testing data set

	Helicopter	Jets	Multi-engines	Single engines
Number	1 (#5)	1 (#9)	3 (#33, #34, #35)	3 (#81, #82, #83)

The training results had an accuracy of 94.6 percent.

Table 7
Training results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	3	0	1	0
Jets	0	7	0	0
Multi-engines	0	1	18	3
Single engines	0	0	0	43

The testing results gave a 100 percent rate.

Table 8
Testing results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	1	0	0	0
Jets	0	1	0	0
Multi-engines	0	0	3	0
Single engines	0	0	0	3

Classification with 72 Training and 11 Testing Samples

Table 9
Testing data

	Helicopter	Jets	Multi-engines	Single engines
Number	2 (#2, #4)	2 (#8.#9)	3 (#24, #25, #26)	4 (#71, #72 #73, #74)

The training results gave 97.2 percent accuracy.

Table 10
Training results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	3	0	0	0
Jets	0	6	0	0
Multi-engines	0	1	19	1
Single engines	0	0	0	42

The testing results gave a 91.67 percent rate.

Table 11
Testing results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	1	0	1	0
Jets	0	2	0	0
Multi-engines	0	0	3	0
Single engines	0	0	0	4

Case 2 Study

This case study used all of the available data. There were 96 take-off events for jets, multi-engine, and single engine planes. A few of the samples data files were bad and could not be used. All of the available helicopter data was used even though they did not take off. Helicopters fly in different paths to their landing area depending upon the traffic. They do not follow runways and will, in general, take a path that keeps them near the runway a short amount of time. One must be located near their landing area to obtain a good take-off or landing signal. Otherwise, it is a fly by to the recording instrument. The data is given in the following table.

Table 12
Case 2 data set

	Helicopter	Jet	Multi-engine	Single engine	Total number
Representation in number	1	4	3	2	x
Representation in binary	0001	1000	0100	0010	x
Number Of data	15	13	25	52	105

Classification Study with 98 Training and 7 Testing Samples

Table 13
Testing data

	Helicopter	Jets	Multi-engines	Single engines
Number	2 (#1,#9)	1 (#23)	2 (#30, #31)	2 (#104, #105)

The training results were 98 percent correct classification.

Table 14
Training results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	13	0	0	0
Jets	0	12	0	0
Multi-engines	0	0	21	2
Single engines	0	0	0	50

The accuracy of testing was 100 percent correct classification.

Table 15
Testing results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	2	0	0	0
Jets	0	1	0	0
Multi-engines	0	0	2	0
Single engines	0	0	0	2

Classification Study with 94 Training Samples and 11 Test Samples

Table 16
Testing data

	Helicopter	Jets	Multi-engines	Single engines
Number	2 (#7,#8)	2 (#24,#25)	3 (#32,#33, #34)	4 (#96,#97, #98,#99)

The training results were 100 percent correct classification.

Table 17
Training results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	13	0	0	0
Jets	0	11	0	0
Multi-engines	0	0	22	0
Single engines	0	0	0	48

The testing results were 91 percent correct classification accuracy.

Table 18
Testing results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	2	0	0	0
Jets	0	2	0	0
Multi-engines	0	0	3	0
Single engines	0	0	1	3

Classification with 93 Training and 12 Testing Samples

The samples used for testing are given in the following table.

Table 19
Testing data

	Helicopter	Jets	Multi-engines	Single engines
Number	2 (#8, #9)	2 (#22,#23)	3 (#39, #40, #41)	5 (#91, #92, #93, #94, #95)

The training results were 99 percent correct classification.

Table 20
Training results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	13	0	0	0
Jets	0	11	0	0
Multi-engines	0	1	21	0
Single engines	0	0	0	47

The accuracy of testing was 100 percent classification accuracy.

Table 21
Testing results

	Helicopter	Jets	Multi-engines	Single engines
Helicopter	2	0	0	0
Jets	0	2	0	0
Multi-engines	0	0	3	0
Single engines	0	0	0	5

Case 3 Study

A final study was conducted. This study included 48 sound events that were not aircraft events. Various background sound events such as tractors, car, trucks, construction sounds, or natural sounds like thunder may occur at airports. Forty-eight sound events of vehicles such as cars and trucks were collected for this study. Also, a binary tree classification method with neural network classifier at each node of the tree was implemented. The tree classification system is shown in the following figure.
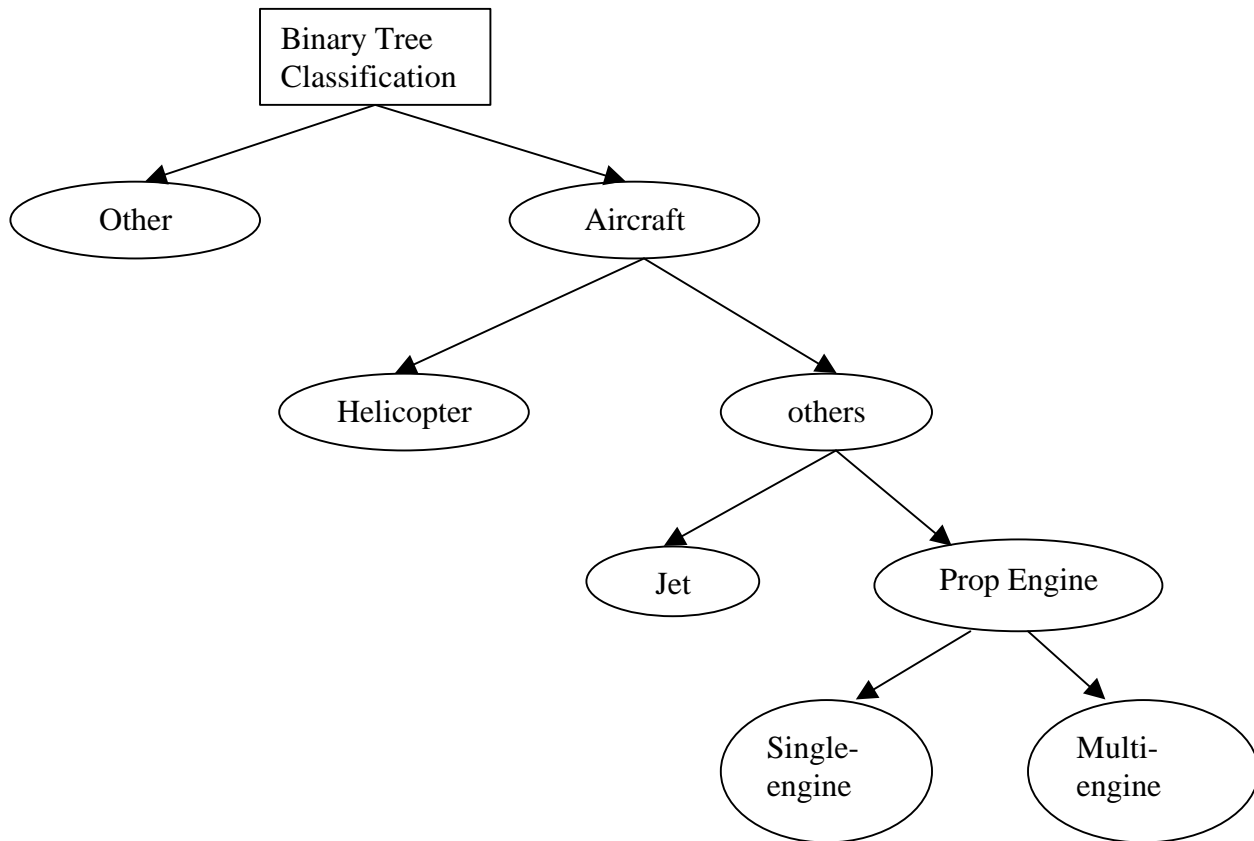
Figure 19
Binary tree classification

We used 153 sound samples consisting of 105 aircraft data and 48 vehicle events. Of these, 133 samples were used for training and 20 samples were used for testing. The following two tables give the training and testing data

Table 22
Training data

	Non aircraft Traffic	Aircraft Helicopter	Aircraft Jets	Aircraft Multi-engines	Aircraft Single engines
Number	41	13	11	22	46

Table 23
Testing data

	Non aircraft traffic	Aircraft Helicopter	Aircraft Jets	Aircraft Multi-engines	Aircraft Single engines
Number	7	2	2	3	6

The training results were 100 percent correct classification. They are given in the following table, (Table 24).

Table 24
Training results

	Non aircraft	Aircraft
Traffic	41	0
Helicopter	0	13
Jets	0	11
Multi engines	0	22
Single engines	0	46

The testing results were also 100 percent correct. They are given in the following table.

Table 25
Testing results

	Non aircraft	Aircraft
Traffic	7	0
Helicopter	0	2
Jets	0	2
Multi engines	0	3
Single engines	0	6

Classification Software

A flexible software system was developed to perform the classification. It allows processing and displaying of the raw data, perform classifications, and training of the classification network on new data if it becomes available. The software is programmed in Matlab. The following figure (Figure 20) shows the interface to the system. Before the other buttons are pressed, the Data button needs to be pressed to indicate the drive letter that contains the data. The Draw & Play button can be used to plot and play the sound of an aircraft event. The Preprocessing, Extraction Feature and Classification buttons are necessary steps of classification on a new sound sample. The Info button is used to explain the software. The Close button is used to exit the software.

Figure 20
Interface to software system

The Data button operates as follows. After clicking this button, type the disc that contains that data. The following Matlab window will then be shown, (Figure 21).

MATLAB Command Window

File Edit Window Help

```
aircraft.m     channel.wav    process_class

» aircraft
»
***************************************************************************
*                            DEMO                                        *
*                           Part 1                                       *
*                      Data Preprocessing                                *
*        This program is used to extract the sound pressure level and    *
*      One-third Octave frequency reponse for aircraft approaching and   *
*      leaving parts from the raw aircraft data.                         *
***************************************************************************


Enter the path and choose the raw data in the next steps...
Please give the disk which contains data: e

.          je213     me151     me85     sel68     se223     se43     se76
..         je232     me156     me91     sel70     se224     se49     se8
he103      je239     me158     me92     sel71     se229     se50     se88
he108      je252     me209     sel      sel72     se233     se52     se90
he194      je87      me216     sel04    sel78     se240     se55     se93
he198      me106     me227     sel13    sel83     se243     se58     se98
he262      me126     me230     sel14    sel85     se244     se59     test.wav
he266      me128     me234     sel2     sel91     se29      se6
jel11      me132     me238     sel30    sel_t     se3       se61
jel18      me134     me241     sel37    se204     se30      se63
jel43      me139     me242     sel5     se208     se37      se65
jel45      me140     me32      sel64    se217     se40      se69
jel48      me150     me74      sel67    se220     se42      se72

Please choose the data from above:
```

Figure 21

Display after preprocessing

By clicking the Preprocessing button, the following Matlab window will be displayed. If option 1 is chosen, then the data will be displayed as shown in Figure 22. Plots of the SPL signal and frequency data will be obtained.

```
MATLAB Command Window                                              _ □ ×
File   Edit   Window   Help

*********************************************************************
*                          DEMO
*                          Part 1
*                       Data Preprocessing
*       This program is used to extract the sound pressure level and
*     One-third Octave frequency reponse for aircraft approaching and
*     leaving parts from the raw aircraft data.
*********************************************************************


Enter the path and choose the raw data in the next steps...


*****************************************************************
*                                                               *
*                    MENU                                       *
*                                                               *
*    Select 1: to preprocess the raw data.                      *
*            (When you want to interrupt the process, press ctl+c)*
*          0  and enter: to exit.                               *
*                                                               *
*                                                               *
*****************************************************************


Please input your choice: 1

.         je213     mel51     me85      sel68     se223     se43      se76
..        je232     mel56     me91      sel70     se224     se49      se8
hel03     je239     mel58     me92      sel71     se229     se50      se88
hel08     je252     me209     sel       sel72     se233     se52      se90
hel94     je87      me216     sel04     sel78     se240     se55      se93
hel98     mel06     me227     sell3     sel83     se243     se58      se98
he262     mel26     me230     sell4     sel85     se244     se59      test.wav
he266     mel28     me234     sel2      sel91     se29      se6
jelll     mel32     me238     sel30     sel_t     se3       se61
jell8     mel34     me241     sel37     se204     se30      se63
jel43     mel39     me242     sel5      se208     se37      se65
jel45     mel40     me32      sel64     se217     se40      se69
jel48     mel50     me74      sel67     se220     se42      se72

Please choose the data from above:mel26
```
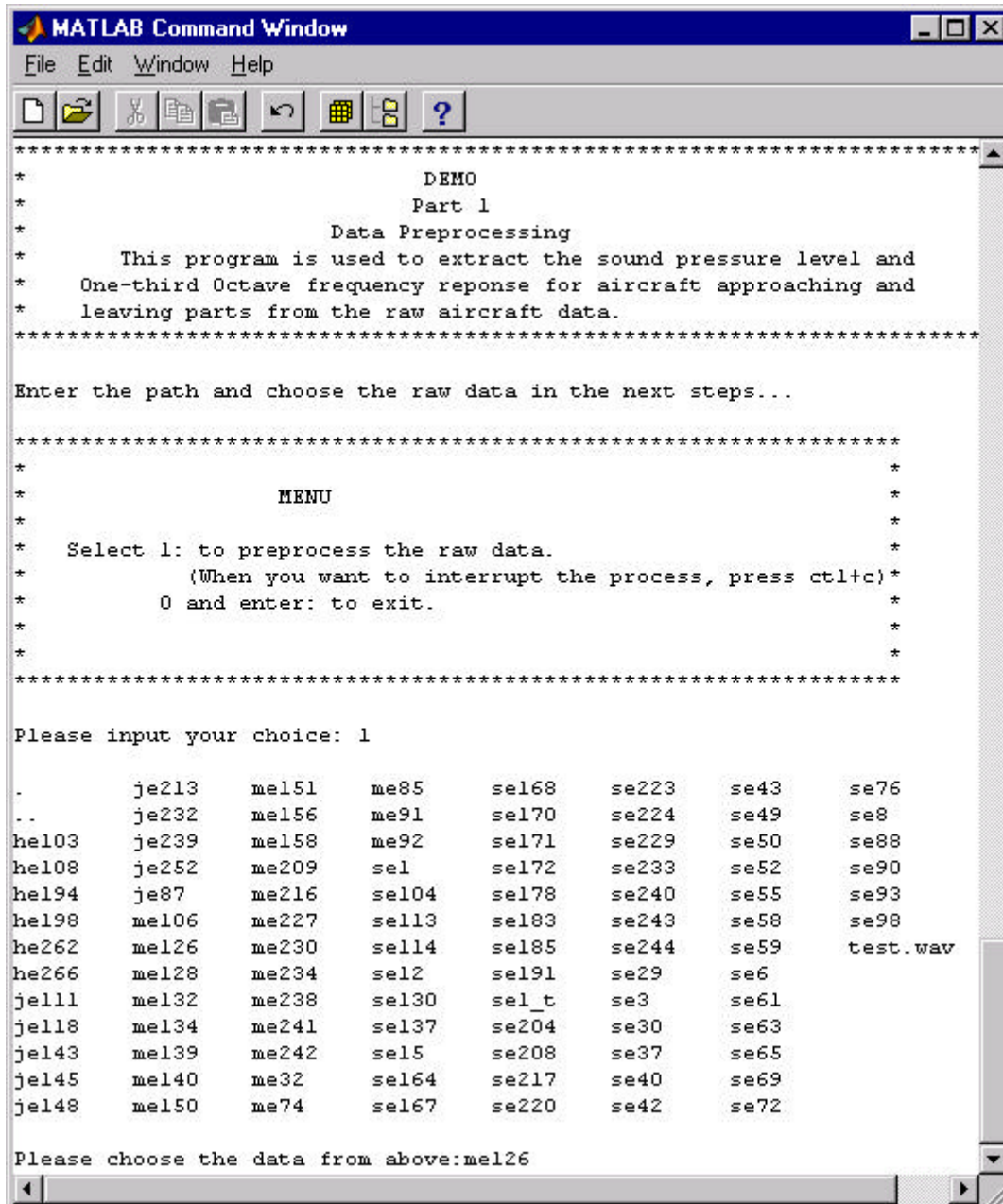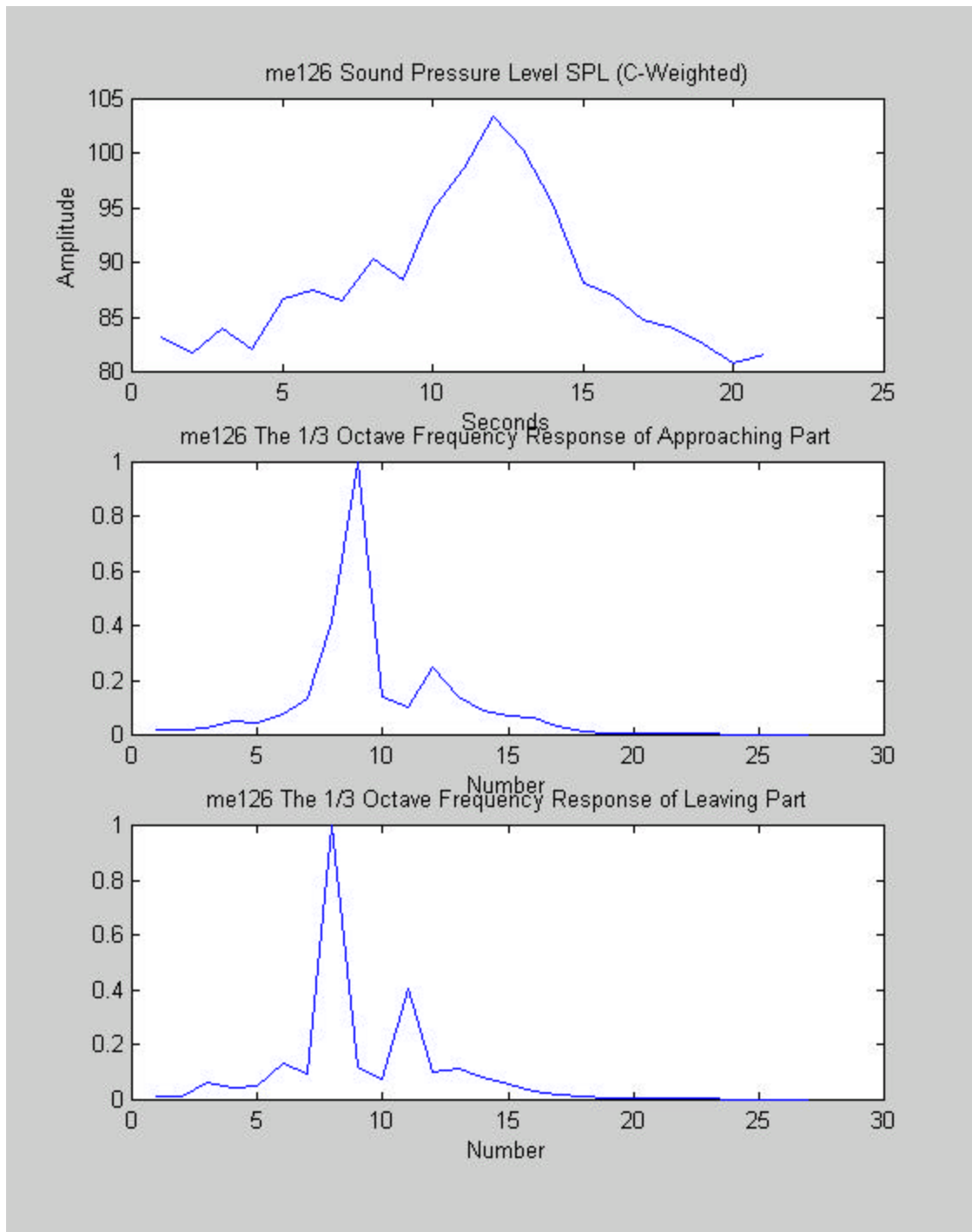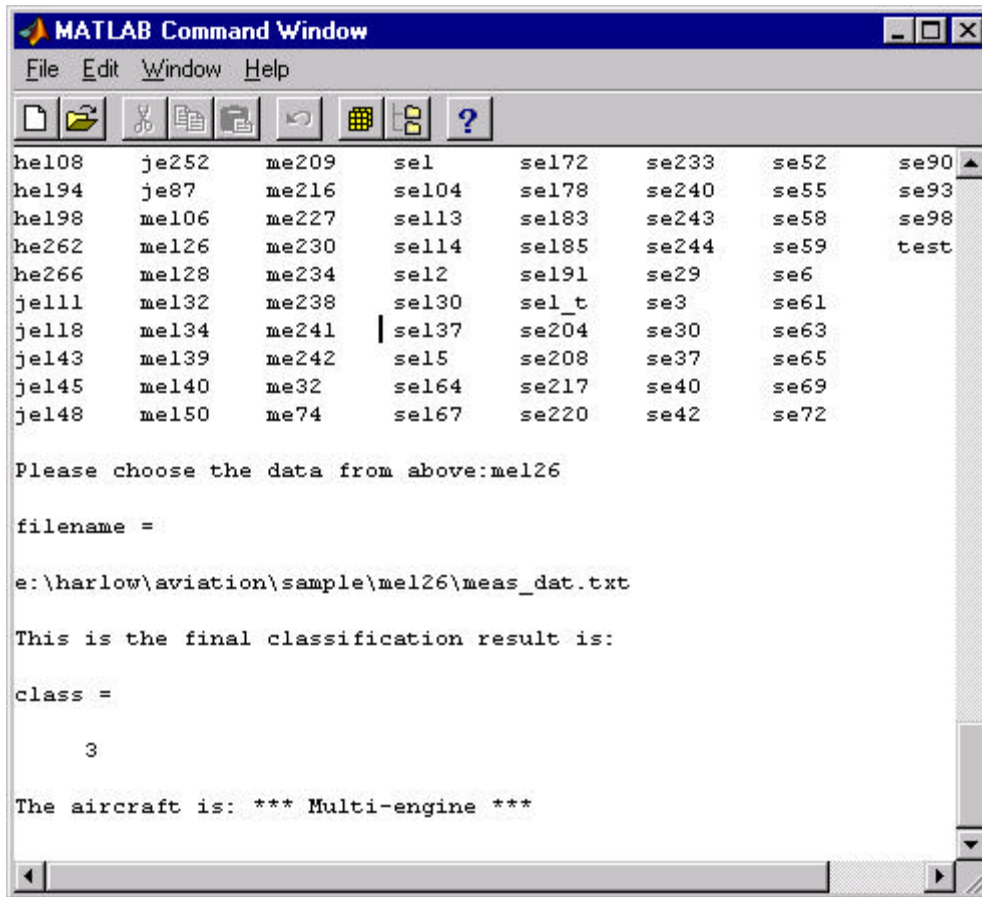
Figure 22
Preprocessing window

42

Figure 23
Results of preprocessing

If the Classification button is chosen, the window shown in the following figure will be obtained. The classification results for the selected data are given in the figure.

```
MATLAB Command Window                                    _ □ ×
File  Edit  Window  Help

 □ 🖿  🗙 🖺 🖺  ⟳  ▦ 🖺  ❓

hel08    je252    me209    sel      sel72    se233    se52     se90 ▲
hel94    je87     me216    sel04    sel78    se240    se55     se93
hel98    mel06    me227    sel13    sel83    se243    se58     se98
he262    mel26    me230    sel14    sel85    se244    se59     test
he266    mel28    me234    sel2     sel91    se29     se6
jelll    mel32    me238    sel30    sel_t    se3      se61
jel18    mel34    me241  | sel37    se204    se30     se63
jel43    mel39    me242    sel5     se208    se37     se65
jel45    mel40    me32     sel64    se217    se40     se69
jel48    mel50    me74     sel67    se220    se42     se72


Please choose the data from above:mel26


filename =


e:\harlow\aviation\sample\mel26\meas_dat.txt


This is the final classification result is:


class =


     3


The aircraft is: *** Multi-engine ***
```
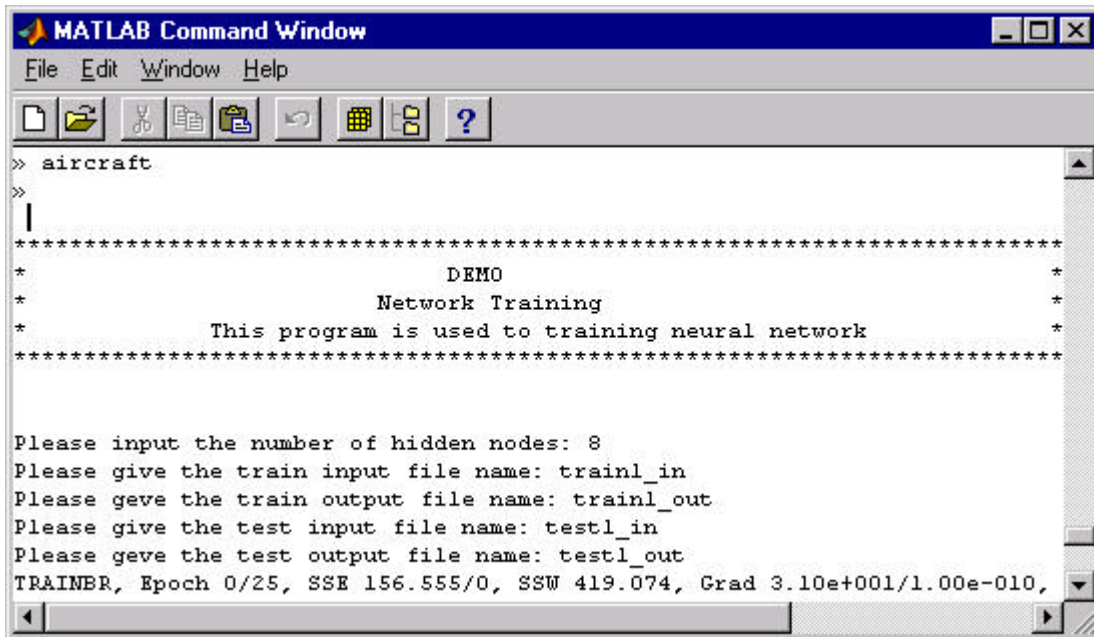
Figure 24
Display from classification

If additional data is obtained and it is necessary to refine the classification method, then the network can be retained. In this case, use the Network Training button. This display is shown in the following figure, (Figure 25).

Figure 25
Training network

DISCUSSION OF RESULTS

This project focused on developing a prototype aircraft operations monitoring system. The results show that an automatic acoustic monitoring system suitable for field development can be developed. The results of the classification studies indicate that automatic classification of aircraft operations can be accomplished at acceptable rates. A software system for classifying aircraft operations that is flexible and adaptable has been designed. As additional data is collected, the system can be easily retrained and tested on new data. Caution in working with companies that can supply the data collection equipment is advised. These companies are small and can change their focus and products quickly. This may affect any software that depends on their products. For this reason, a flexible software system has been designed here.

CONCLUSIONS

We have shown the feasibility of developing an aircraft operations monitoring system. The software developed is flexible and compatible with any acoustic data collection platform. A prototype system has been developed with a vendor that has exhibited stability. The primary limitation of the study is a limited data set of aircraft operations.

RECOMMENDATIONS

The results indicate that the development of a production system is feasible. A key point is that a vendor having a stable commitment to their products is imperative. Our most recent discussions with Larson Davis indicate their desire to develop and market a system. They seem to have stability in their management personnel and their approach to markets. It is recommended that the development be pursued with Larson Davis. They have two products for data collection. One is the 820 unit that can be used for aircraft counting. The other is the 824 unit that collects 1/3 octave frequency information four times per second. This unit will operate in the field on batteries and should be the basis for future development.

ACRONYMS, ABBREVIATIONS, & SYMBOLS

ANN	Artificial neural network
BP	Back propagation neural network
FFT	Fast Fourier transform
IFFT	Inverse Fourier transform
L_p	Sound pressure level
L_{eq}	The equivalent continuous sound level over a specified time interval
MFCC	The Mel Frequency Cepstral coefficients
p(t)	Sound signal pressure
p_{rms}	RMS value of sound signal
SLM	Sound level meter
SPL	Sound pressure level
WT	Wavelet transform

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