AIRCRAFT OPERATIONS CLASSIFICATION SYSTEM

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ABSTRACT

Accurate data is important in the aviation planning process. In this project we consider systems for measuring aircraft activity at airports. This would include determining the type of aircraft such as jet, helicopter, single engine, and multiengine propeller. Some of the issues involved in deploying technologies for monitoring aircraft operations are cost, reliability, and accuracy. In addition, the system must be field portable and acceptable at airports. A comparison of technologies was conducted and it was decided that an aircraft monitoring system should be based upon acoustic technology.

A multimedia relational 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 (takeoff, landing), aircraft type, and environmental information. We extracted features from the time signal and the frequency content of the signal. A multi-layer feed-forward neural network was chosen as the classifier. Training and testing results were obtained. We were able to obtain classification results of over 90 percent for training and testing for takeoff events.

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INTRODUCTION

In this project we consider the development of a system for automatically measuring aircraft activity at airports. This would include determining the type of aircraft and the type of aircraft activity. The different types of aircraft considered in this study are helicopter, single engine, multiengine, and jet aircraft. An accurate count of aircraft operations is important to airport managers and aviation planners. These counts are difficult to obtain at non-towered airports.

BACKGROUND

A system for monitoring aircraft operations will likely include methods for directly counting the aircraft as well as the use of ancillary and statistical information to estimate total counts since it is unlikely that counters will be in constant operation at all airports (FAA, 1985). At airports without full-time tower facilities there are other indirect or ancillary indicators of aircraft operations. If this information is put in a database system, it will be useful in determining aircraft operations. The following describes some indirect sources of information on aircraft operations.

Many airports are associated with an approach control at a major airport giving the major airports information about operations at small airports. Some pilots do not use the services offered. Many airports have unicoms (local advisory service from the airport operator). This information is unreliable unless the operator is willing to log in arrivals and departures since there is no recording of the transmissions. Even then, hours of operation vary, and thus do not guarantee accurate information around the clock.

Other sources of information are flight plans filed with Flight Service Stations (FSSs). One disadvantage is that not every pilot files a flight plan when flying cross-country, and most rarely ever file a plan for a flight within the local area of their departure point. Another disadvantage is that it may be difficult to obtain this information on a regular basis from FSSs. Monitoring gas sales may also be considered, but this may be inaccurate because of the variety of sales that may occur. Another method to assist in assessment of aircraft operations would be to confirm the number and type of aircraft based at each airport and survey each aircraft owner to determine their normal aircraft use and flying patterns. Some pilots may use their aircraft purely for pleasure once or twice each month. Further, these pilots may perform touch and go maneuvers that will increase the airport usage.

Others who use their aircraft for business may only make one departure and one arrival each week. Another indicator is the category of airport. Some airports have shorter runways that are stressed for heavy loads, thus limiting the size and/or type of aircraft that operate at the facility. Additionally, airports that don't have any services or aircraft based at the airport will likely be used less and airport personnel may be able to accurately estimate the number of aircraft operations. While looking into different airports, interviews with airport managers or fixed base operators will give an indication of times that will assist the study such as "Peak Month," "Peak Week," "Busiest Day," as well as "Busiest Hour."

The above ancillary information may be useful in estimating aircraft operations and may be useful in determining where and when to monitor aircraft operations at different airports. Since the above indicators do not give direct counts, one still will need methods to directly monitor aircraft operations. The best overall approach may be to build databases with the above types of information and use statistical analysis and direct counts to increase the reliability of the analysis.

TECHNOLOGIES FOR MONITORING AIRCRAFT OPERATIONS

The following review of technical literature indicates the approaches taken for automatic aircraft detection and classification. Some of the issues involved in deploying technologies for monitoring aircraft operations include the cost of the monitoring operation, the reliability of the system, the system must be portable, the system must operate self contained in the field for two weeks, and the system must be acceptable at airports. The costs of the monitoring operation includes capital equipment costs, travel costs, labor costs, and overhead costs.

The technologies that have been considered are electromagnetic loops, radar, microwave, radiation, video, pressure counters, and acoustic technologies. Acoustic counters use a microphone located near the runway to record takeoffs that produce a strong acoustic signal (Dress & Kercel, 1994). Total operations cannot be counted directly because landings are quieter and do not register on the systems. The systems by Larson Davis are used by a number of states to count aircraft operations. The aircraft counter system has a high accuracy for counting takeoffs as reported by users. These systems have the advantage of low cost, portable, and are a demonstrated technology for operating in airport environments.

Tamayo et al. (1993) developed a magnetometric sensor for detecting airport ground traffic with the goal of performing detection, discrimination and tracking of static and moving targets. The authors also reviewed other methods for solving the problem of airport traffic control such as radar, microwave gates, radiation, pressure sensors, acoustic sensors and loops (electromagnetic). Radar was determined to be too expensive and can easily be interfered with by obstacles. Radar can interfere with airport operations and may be difficult to operate in this environment. Microwave gates could not be installed flush to the ground, thus creating a potential obstacle. Microwave gates can cause electromagnetic interference, which is not acceptable in an airport environment. Radiation methods consisted of detecting infrared signatures from the target. This approach was found to be too sensitive to environmental fluctuations and weather conditions. Pressure sensors such as pneumatic tubes were likely to break and require maintenance that would be invasive to the flow of traffic and thus undesirable. Acoustic sensors were thought to be unsuitable in noisy environments. Ultrasonic sensors were dismissed due to their short range and high power consumption. Electromagnetic loops were also dismissed by the authors due to their invasive installation, maintenance and the limited information that they deliver. The authors' solution was to develop a magnetometric sensor that would detect the magnetic fields produced by ferro-metallic components in the aircraft, such as landing gear and wings. The resulting sensor systems were able to detect cars at a distance of 10 meters and aircraft up to 20 meters from their axis (due mainly to ferro-metalic components in the wings). While this range may be suitable for controlling ground flow, it would not be sufficient for detection along the runway as the distance to the aircraft to the sensor can easily exceed 20 meters if the aircraft is airborne when passing the sensor. The magnetic signatures obtained from the sensors did provide clear discrimination between vehicles and aircraft, but no information was given as to the ability to differentiate between various types of aircraft.

Hudson and Psaltis (1993) investigated ways to identify a target aircraft from one-dimensional radar range data. It was found that the quality of classification depends not only on the aspect angle to the aircraft of the radar site but also the number of range images examined for a single classification. The usability of this method on airport traffic is questionable since precise control of the aspect ratio would prove to be very difficult. As such, one must consider the classification rates when no aspect angles were taken into consideration. With rates of 57 percent, 65 percent and 86 percent for single profile, frame, and encounter classification, respectively, we see that the classification rates are low. Couple that with the cost of obtaining required permissions, installing, and maintaining radar sites at strategic locations around an airport, and this method seems unfeasible.

Adams and Esler (1995) describe a number of issues related to acoustic recognition of aircraft events. It is noted that there is a change in the sound quality as the aircraft approaches and departs from the observer. There are differences between the sound emitted from the front and rear of an aircraft. There is also the Doppler shift associated with the speed of the aircraft. It was observed that for propeller aircraft (fixed wing and helicopters) there are recognizable components in the acoustic signal that can be used for Doppler analysis. Doppler analysis for jet aircraft is more difficult because the spectrum is less coherent. Their analysis concluded that frequencies above eight kHz could be ignored. Reported problems encountered were difficult in determining corresponding features in the approaching and departing signal, and one must make allowance for the angle of flight of the aircraft relative to the observer. Some differences between speech and aircraft signals are observed. Aircraft signals are continuous without breaks as opposed to speech. However, aircraft signals have high variability due to different environmental conditions, distances, and aircraft orientations.

Adams and Esler (1996) a recognition system based on a one-third-octave filter bank and half-second L_{eq} values from acoustic signals is described. A data reduction algorithm is applied to the spectra to extract 25 features. A neural network is used to discriminate between helicopters, fixed-wing propeller aircraft, jet aircraft, and background noise of uncertain origin. The reduced data from 100 aircraft and background noise events are used to train and test the classifier. Classification accuracy was reported to be better than 80 percent.

Cabell and Fuller (1989) developed a recognition system for the identification of helicopters, propeller aircraft, jet aircraft, wind turbines, and trains from acoustic data. It is based on a decision tree. The features are extracted from the Fourier spectrum and auto-correlation function of the noise events. The best design could correctly identify 90 percent of the recordings. Scott, Fuller, Obrien and Cabells (1993) tested an associative memory and a multilayer perceptron neural network as alternatives to the decision tree. On the same data set, results show that the associative memory classifier identifies 96 percent of the sources correctly and the neural network identifies over 81 percent of the sources correctly.

Two aircraft noise event detection systems based on one-second A-weighted L_{eq} time history of the acoustic signal are described by Wallis and Snell (1995). The decision of classifying a noise event as caused by an aircraft or not is based on a series of tests performed on the shape of the time history L_{eq}. In addition, an anemometer is used to provide supplemental information on the speed and direction of the wind during the noise event. Special sensors located at the ends of the runway are used to provide timing and directional data on the takeoffs and landings of aircraft. Extensive field tests showed "excellent" performance.

Yamada, Yokota, Yamamota, and Shimizu (1985) describe an aircraft classification system that utilizes acoustic data. It composed of a one-third-octave spectral analyzer combined with a modified Gaussian classifier. Nine features are extracted empirically from the output of the one-third-octave band real-time spectral analyzer. The features consist of one-third-octave band peak levels normalized with respect to the peak A-weighted level of the noise event. Ten classes are considered in the first experiment: three types of airplanes performing takeoff or landing, helicopters, jet airplanes, propeller-driven airplanes. Sixteen classes corresponding to sixteen types of airplanes are considered in the second experiment. Eight classes corresponding to eight types of airplanes are considered in the third experiment. The classification accuracy was 86 percent, 86 percent, and 90 percent, respectively, in the three experiments.

Some systems have been proposed for the classification (Cabell, Fuller, & Obrien, 1992, 1993) of helicopter operations from acoustic data. They are based on specific properties of the helicopter signal that is impulsive and strongly periodic. They describe Gaussian classifiers and neural networks applied to the identification of the type of a helicopter. Cabell and Fuller (1991) developed a pattern recognition system to classify acoustic signals from aircraft. Five classes of vehicles were defined for the purpose of identification, namely, jet plane, propeller plane, helicopter, train, and wind turbine. All sources taken together produced a recognition rate of 90 percent. The authors indicate that with classes such as jet planes, further discrimination within the class is possible if additional features are used to create more complex decision surfaces.

From the above review and our own experiences we note a number of issues that complicate the recognition process (Harlow, Bullock & Smailius, 1997). Aircraft acoustic signals have variability due to different environmental conditions and aircraft distances. Acoustic classification systems have difficulty differentiating other events from actual takeoffs and landings. Examples are preflight throttle tests, echoes from large buildings, vehicular ground traffic, and nature. Examples of vehicular traffic are airport luggage transport, fueling trucks, and tractors for cutting grass. Different airports and different weather conditions will affect the signals. Noisy environments and natural phenomena such as thunderstorms provide problems. Multiple signals from different sources will distort the signals. Finally, aircraft of the same type will produce somewhat different signals.

At present a satisfactory system does not exist. The different technologies have different advantages and disadvantages. Electromagnetic loop technology is expensive and maintenance can interfere with operations. Magnetic field detectors have difficulty detecting aircraft at a distance. Pressure counters are likely to break and maintenance can interfere with operations. Also, they cannot determine aircraft type. Radar is expensive, is sensitive to the location of the unit, and can interfere with airport operations. Radiation (infrared) detection units are sensitive to the environment and will have difficulty classifying aircraft types. It is difficult to determine the type of aircraft from video signals. Acoustic sensors have shown success as counters of aircraft operations. The units are low cost and portable. They have difficulties with quiet aircraft landings and may be sensitive to environmental conditions. At the present time acoustic technology has proven effective in counting takeoffs and is the most promising for future development. We decided to perform an analysis of the costs factors related to developing acoustic technologies.

For these comparisons, it was assumed that one would need to monitor aircraft movements at 50 different sites during a 168 hour period (1 week). Factors considered in the comparisons were costs for development of counting procedures, capital equipment costs, travel costs for moving equipment and personnel, labor costs for operation of the equipment, and overhead costs. Certain assumptions were made about labor, development, and travel costs that influence the results. Hence the cost comparisons are approximate.

Visual observations of aircraft by technicians is the simplest detection technology. However, this requires scheduling technicians to obtain complete 24-hour surveillance over a few days. During sunny and moderate weather, this is not a problem. However, this is an undesirable job during bad weather, extreme heat, and late in the evening. Furthermore, this requires paying travel costs to lodge technicians in nearby hotels. For visual observations it is assumed the crew visits 50 sites. It is assumed the travel is 100 miles to the site. The expenses are 100 miles of travel at $0.25 per mile per person, plus 7 nights lodging at $40 per night per person, and 7 days of meals at $21 per day per person. The labor costs for each crew member is 40 hours per week at $6 per hour for 52 weeks per year.

For the counter systems, we assume a one-person installation crew and two round trips to a site 100 miles away (50 weeks at 4 trips per week at 100 miles per trip at $.25 per mile). Assuming one day for installation and one day for removal of the system, the labor costs are (50 weeks at 8 hours per day at $6 per hour for 2 days plus 160 hours of trouble shooting installation sites at $6 per hour). The equipment costs for pneumatic tubes is estimated at $1,000 with a life time of five years. The equipment costs for an acoustic counter is estimated at $6,000 with a life time of five years. The next issue involves systems that require development. In this case the development costs must be considered. This might be required for acoustic or other systems that require additional development work. In this calculation, it is estimated that $60,000 is required for development costs. We assume that 10 systems are acquired with a life time to five years. The development costs are prorated and are reduced when the number of units acquired is large. The cost of the units is estimated at $10,000 with a life time of five years. The comparisons are shown in Table 1. One can observe from Table 1 that the technology based systems can be competitive on costs. Even if some development costs are involved, the costs can be mitigated if a number of units are acquired. For this reason it is advisable to have a vendor involved with any development.

Table 1. Cost of Different Technologies

	Human Observers	*Pneumatic Tubes*	*Acoustic Counter*	*Enhanced System*
Equipment Development Costs	$0	$0	$0	$600
Equipment Costs/Annual	$0	$200	$1,200	$2,000
Travel & Mobilization				
1 Person Crew	$22,600	$2,500	$2,500	$2,500
Labor Cost	$12,480	$5,760	$5,760	$5,760
Fringe (20 percent of Labor)	$2,496	$1,152	$1,152	$1,152
Sub Total	$37,576	$9,612	$10,612	$12,012
Overhead (0.4)	$15,030	$3,845	$4,245	$4,805
Total Annual Cost	$52,606	$13,457	$14,857	$16,817
Cost/Site	$1,052	$269	$297	$337

We decided to study the development of an aircraft monitoring system based upon acoustic technology. This decision was based upon our review of the technologies, a cost analysis of the different technologies, the feasibility and cost of implementation of a portable unit, and the compatibility of the technology with normal airport operations. Acoustic technology exists to operate at airports in a counting mode. This study was conducted to consider the issue of expanding the technology to include the classification capability. The study was needed in order to determine algorithms for classifying aircraft operations and to determine any problem areas in the development and deployment of a system.

AIRCRAFT OPERATIONS DATABASE FORMATION

In order to develop algorithms and evaluate the 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 (takeoff, landing) and aircraft type, and environmental information.

The equipment used in the field for recording aircraft acoustic signals, aircraft information, and the type of aircraft operation consisted of a digital camera, sound recording equipment, and a form to manually enter information related to the aircraft operation. The Kodak digital camera was used for a photographic record of the aircraft operation. 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. We processed the data at 22.05 kHz since this proved sufficient for this application.

FEATURE EXTRACTION

Sound data are often processed in the root mean square of the sound signal pressure p(t). The form is $p_{rms} = \sqrt{\frac{1}{T_2 - T_1}\int_{T_1}^{T_2} p^2(t)dt}$. 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 $L_p = 20\log_{10}\left(\frac{p}{p_o}\right)$ with units of dB or decibels. This is the sound pressure level (SPL). The quantity p_o is 20 micro Pascals, µPa, which is the perception threshold at 1000Hz (Couvreur, 1997; Crocker, (1998). The sound pressure level L_p varies too fast for interpretation and often generates too much data for storage. An averaging 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 (Couvreur, 1997). It is defined as $L_{eq} = 20\log_{10}\left(\frac{p_{rns}}{p_o}\right)$.

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 is no weighting (Couvreur, 1997). 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 frequency weighting to measure the effects of noise on humans. It is widely used to measure community noise. B frequency weighting is meant to simulate the human ear at 70 phons. It is not widely used. The C frequency weighted filter is meant to simulate the human ear at 100 phons. It is flat over most of the audible frequencies. It is down 3dB at 31.6 Hz and 8000Hz. It is often used to measure the acoustic emissions of machinery.

Sound level meters equipped with filters are called spectrum analyzers. Often data are collected in octave filters or one-third octave filters. An octave band pass filter is a filter such that the upper cutoff frequency is twice the lower cutoff frequency. An octave is a doubling of frequency. This filter can be subdivided into one-third octave filters with 3 bands per octave.

In the application of aircraft counting and classification, we are interested in identifying aircraft from one-dimensional (1-D) sound signals. 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. Hence, it is important to extract features from the sound signal. An important step in object identification is to obtain information suitable for modeling the object to the automated recognition system. This process of reducing the amount of data while retaining the ability to recognize the object is called feature extraction. The features are represented as vectors. Figures 1 and 2 show the sound signals obtained from a jet and a multi-engine propeller powered aircraft, respectively.

The L_{eq} acoustic signal has a characteristic shape that is reflective of the different types of aircraft events. The L_{eq} signal can be processed to reduce the number of measurements and extract features useful for classification, see Figure 3. One measurement of relevance is the “maximum” value. Some sound events such as jet aircraft are loud. Single engine propeller aircraft landing 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 as compared to a propeller aircraft. Other measurements extracted are “skewness” which measures the skewness of the curve and “symmetry” that measures the symmetry of the curve about the maximum value, see Figure 3.

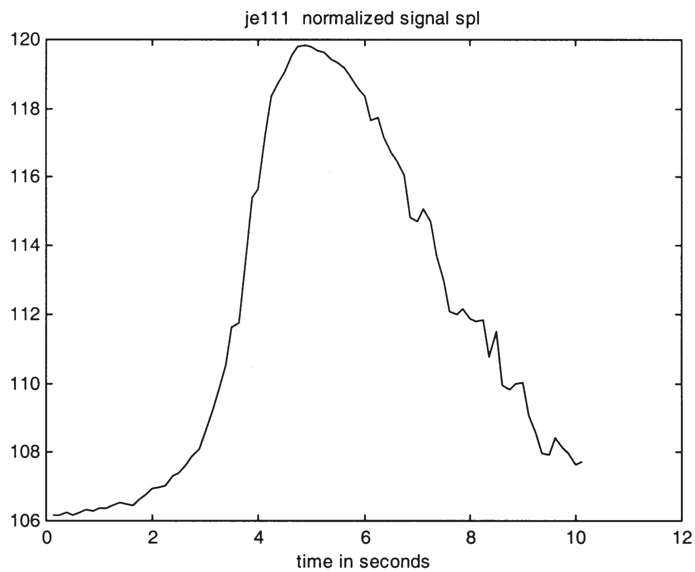

Figure 1. Sound Signal for Jet Aircraft Takeoff

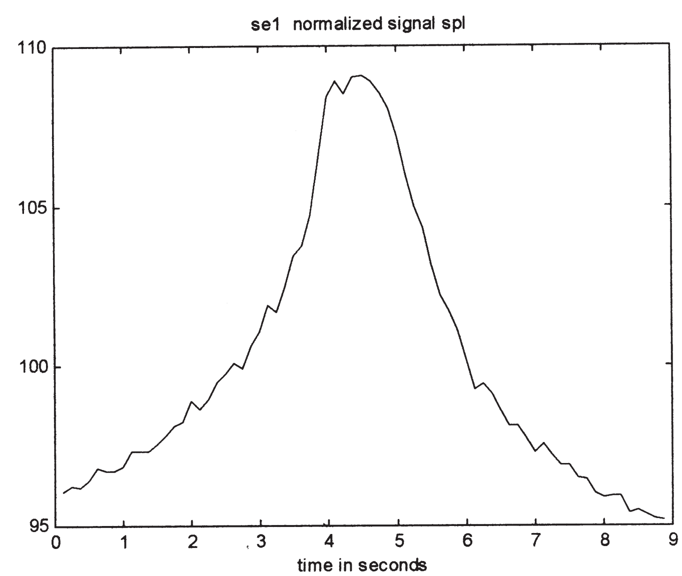

Figure 2. Sound Signal for Single Engine Aircraft Takeoff

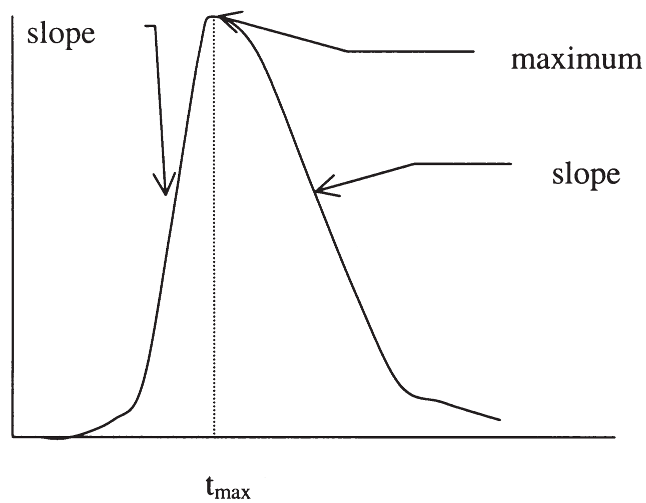

Figure 3. Measurements form Time Domain

One would expect frequency measures to reflect differences in the aircraft. These are readily obtained from portable spectral analyzers that can operate in the field for several weeks. The measures we considered are one-third-octave frequency measures since they are readily collected with spectral analyzers. We used sound data at a sampling rate of 22,050 Hz. This implies that we can estimate frequencies up to 22,050/2 Hz without aliasing. For this reason, we limited our frequencies to 8,000 Hz. Therefore, 27 frequency measures are taken up to 8,000 Hz. We extracted these measures for the aircraft as it approached and departed the acoustic sensor. The speed of the aircraft is reflected in the shift of the frequencies. It should be noted that the frequency discrimination of the one-third-octave filters is not sufficient to obtain an accurate measure of the Doppler shift.

CLASSIFICATION

Let us now consider signal classification which 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, we will have an *n*-dimensional feature vector that is the input to a classifier. Neural networks were selected for the classifier.

Artificial neural networks (ANN) can be grouped into simple-layer and multiple-layer nets (Fausett, 1994). There are two types of training—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. Backpropagation nets require supervised training. ANNs are "trained," meaning they used previous examples to establish the relationships between the input variables and the output variables. Once an ANN is trained, the neural network can be presented with new input variables and it will generate the output classification.

A multi-layer feed-forward neural network was chosen as the classifier. It is very important to define the network's structure properly. In our case, there are three layers in the neural network—an input layer, a hidden layer, and an output layer. It is sufficient to have one hidden layer because it reduces 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) are needed to be distinguished. Each output neuron represent 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 a network's performance. If more hidden neurons are used, one gets a higher training accuracy, but a lower testing accuracy. After several repeated training and testing, we found that the performance is best for a network with a hidden layer with 8 neurons (Harlow, 1999). This configuration was used with the time domain and frequency measures of the approaching aircraft.

We had a total of 105 takeoff events for jets, multi-engine, and single engine planes and helicopters. We used all of the available helicopter data even though they were not all takeoff events. Helicopters will 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 takeoff or landing signal. We used 12 of the samples for testing and the rest for training. The training results were 99 percent correct classification. The accuracy of testing was 100 percent classification accuracy. These results are given in Tables 2 and 3.

We conducted one final study. 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. We collected 48 sound events of vehicles such as cars and trucks

Table 2. Training Results

	Helicopter	*Jet*	*Multi-engine*	*Single engine*
Helicopter	13	0	0	0
Jet	0	11	0	0
Multi-engine	0	1	21	0
Single engine	0	0	0	47

Table 3. Testing Results

	Helicopter	*Jet*	*Multi-engine*	*Single engine*
Helicopter	2	0	0	0
Jet	0	2	0	0
Multi-engine	0	0	3	0
Single engine	0	0	0	5

for this study. We also implemented a binary tree classification method with a neural network classifier at each node of the tree. The tree classification system is shown in Figure 4. 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 training results of correct classification were 100 percent. The testing results were also 100 percent. The results are given in Tables 4 and 5.

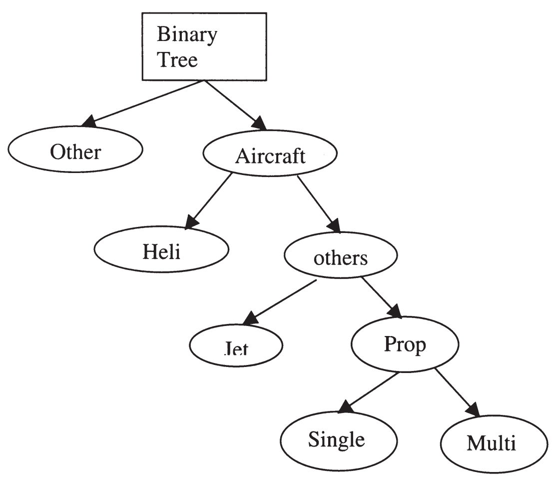

Figure 4. Binary Tree Classification

Table 4. Training Results

	Non aircraft	*Aircraft*
Traffic	41	0
Helicopter	0	13
Jets	0	11
Multi-engine	0	22
Single engine	0	46

Table 5. Testing Results

	Non aircraft	*Aircraft*
Traffic	7	0
Helicopter	0	2
Jets	0	2
Multi-engine	0	3
Single engine	0	6

The choice of features is an important problem in the development of a classification system (Fukunaga, 1990). More features may allow one to perform better classification, but the feature set often contains redundant features. It is best to keep only the most effective features and remove the redundant features. A reduction in the number of features results in reduced complexity and computation time for the classifier. With a limited number of training samples one may also get better classification rates with a smaller number of features (Fukunaga, 1990).

We did some experiments to determine the most effective measures. We extracted the time domain measures and also frequency measures as the object approached and departed the acoustic sensor. For the aircraft vs. non-aircraft experiment nine measures were found to be significant. Five of these measures were frequency measures of the approaching object and four were frequency measures of the departing aircraft. In the aircraft category of helicopter vs. other aircraft, four measures were found to be significant. These were a time domain measure (the slope of the curve), two frequency measures of the approaching aircraft, and one frequency measure of the departing aircraft. For jet vs. propeller aircraft, the most significant measure was a frequency measure of the approaching aircraft. For multiengine vs. single engine propeller the most significant measures were a time domain measure of slope and two frequency measures of the approaching aircraft. These results indicate that a reasonable subset of the features can be extracted for classification. These results are not conclusive, since additional data would need to be collected under a wide variety of environmental conditions in order to determine the best measures.

In order to provide for updating the system, a flexible software system has been developed. The system allows one to process, display the raw data, and perform classifications. The software also provides for retraining the classification network as one experiments with the system and new data becomes available. The software is programmed in Matlab (MathWorks, 1998).

DISCUSSION

Our discussion in the “Technologies for Monitoring Aircraft Operations” section indicates that there are issues related to the deployment of the different technologies for monitoring aircraft operations. Acoustic technology was determined to be the best developed and the most feasible technology upon which to develop an aircraft operations monitoring system. This study considered the development of a classification system to determine the type of aircraft involved in aircraft operations.

The results of the classification studies indicate that automatic classification of aircraft takeoffs can be accomplished at acceptable rates. Operations such as landings that are quiet events may not be detected. Also, the monitors will have to be located near runways with aircraft operations. If there are several runways or operations are occurring on the runway far from the sensor, then the acoustic signal may be very weak at the sensor. Several sensors may be needed to cover all the areas of operation. For smaller airports, this should not be a problem. Since the automatic classification of aircraft operations will not cover the operations at every airport all the time, the automatic counts will need to augmented with statistical models as discussed in the “Background” section.

These results demonstrate the feasibility of developing an automated aircraft operations monitor. Current hardware exists for portable operation that will record the time and spectral information required for classification. The system needs further testing with data collected under varying environment conditions. It is difficult to obtain data under adverse weather conditions due to the risk to personnel near runways under adverse conditions. The next stage in the work would be to place an automated data collection system in the field to collect data under adverse conditions. In addition, studies need to be conducted on the best manner to incorporate automatic aircraft operations counters with statistical and ancillary information in order to obtain the best estimate of aircraft operations.

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