inter•noise 96
25th Anniversary Congress – Liverpool

INCE: 74

RECOGNITION OF ACOUSTIC SIGNATURES OF AIRCRAFT NOISE EVENTS

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1. INTRODUCTION

Airport noise monitoring systems in current operation detect aircraft noise events by time correlation of measured sound pressure level and radar tracking information. While this method generally works well, there are limitations and a need for more powerful approaches is being increasingly felt. Time-frequency analysis has the potential not only to distinguish aircraft noise from other noise sources but also to discriminate between broad classes of different types of aircraft. In addition, new methods developed during the last decade in signal processing, pattern recognition, neural networks and fuzzy logic, which have been successfully employed in areas such as speech recognition, medical diagnosis and image interpretation, are available for application to noise source identification.

In this paper we show some of the results obtained on different classes of noise events, using well-known methods of time-frequency analysis [1], enhanced by some lesser known methods derived from physiological considerations [2]. We limit the discussion to methods that can be practically implemented in noise monitoring terminals in current use and show that significant enhancement of aircraft noise detection in commercially available outdoor monitoring equipment can be achieved. In particular, automatic real-time discrimination between jet aircraft, fixed wing propeller aircraft and helicopters under varying atmospheric conditions is now becoming a practical possibility.

2. THIRD OCTAVE CHARACTERISATION

One of the most readily available methods of time frequency analysis of noise events is based on third-octave filter banks. For example, if the outputs of the filters are converted to half-second Leq values, the resulting time signals exhibit distinct patterns that are far more detailed than occur in the commonly employed one-second A-weighted Leq time history of noise. There is clearly much information that can be determined about the noise source from these signals, however, two questions immediately arise:

(i) Is there sufficient information present in such signals to characterise the nature of the acoustic source?

(ii) Is a substantial part of the information in the signals redundant for the purposes of characterisation?

We believe that both questions can be answered with "yes".

Figure 1 shows third octave noise patterns recorded during a typical take-off of a single-engined propeller aircraft. Figure 2 shows corresponding patterns for a twin-engined jet during landing. The patterns show a considerable richness of texture in contrast to the unweighted Leqs of the events shown in the lowest traces.

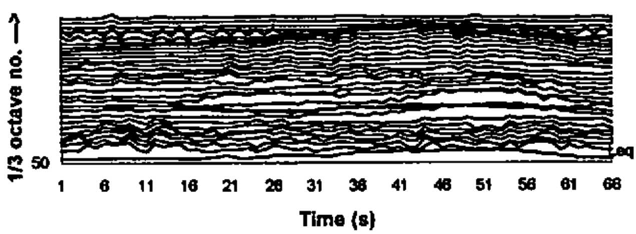

Fig.1. Third octave record of a single-engined propeller aircraft at take-off.

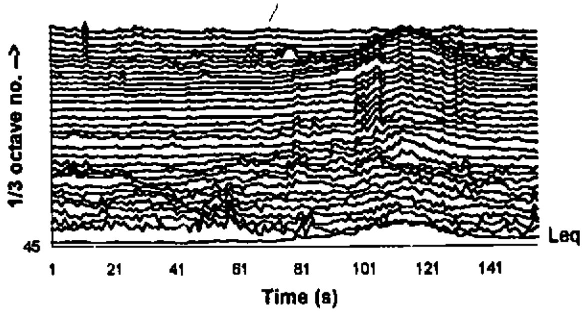

Fig. 2. Third octave record of a twin-engined jet aircraft during landing.

The time variation in the responses of the different filters can be ascribed to a number of causes arising from the motion of the aircraft. One important effect is due to the spatial variation in acoustic radiation from the aircraft. As the aircraft approaches and recedes, these spatial variations show up as time variations in the individual third octaves, but are barely noticeable in the time history of the half-second Leq of the event.

3. DATA SET REDUCTION

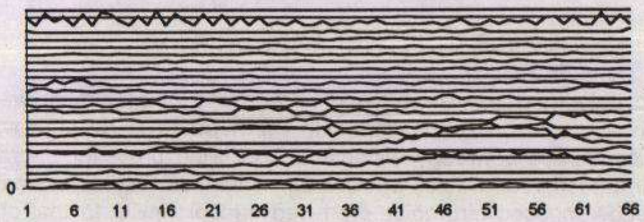

Fig.3. DLS data reduction applied to Fig. 1.

Any automatic recognition process will have to cope with a large variation in angle of observation and weather conditions and consequent large variations in the recorded patterns. As such there will be much redundant information which is not specific to the aircraft or background noise source. Where there is much redundant information, the recognition process will have difficulty in coming to a correct decision, or it may require an inordinate amount of computing power to achieve a satisfactory result. Therefore some form of data reduction is required which will preserve the essential characteristics of the acoustic source. The group of DLS algorithms developed by Reuter [2] (*Differenzleistungsspektrum*) provides one approach to achieving this.

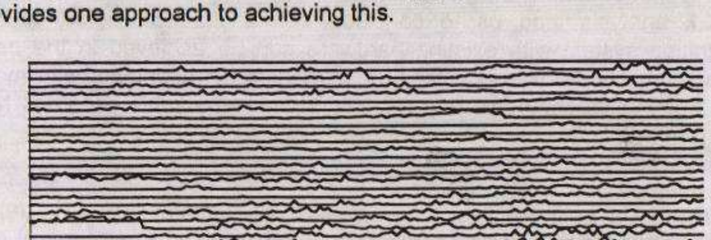

Fig. 4. DLS data reduction applied to Fig. 2.

These algorithms depend on determining a moving average of the spectrum for each time interval. The deviation of the spectrum above this moving average provides the useful data. Reuter developed his methods from considerations of physiology, human perception and the fuzzy logic

processes that are inherent in decision making. We have applied the DLS algorithms differently from Reuter, but find that they work very well with time-varying third-octave spectra.
Figure 3 shows the patterns of DLS reduced data obtained from fig.1 (single-engined propeller aircraft).
Figure 4 shows the corresponding data obtained from Fig.2 (twin-engined jet aircraft).

4. NEURAL NETWORK ANALYSIS

The reduced data from 100 aircraft and background noise events were used to train a simple neural network with 25 inputs. The network was trained to discriminate between helicopters, fixed-wing propeller aircraft, jet aircraft and background noise of uncertain origin. An interesting case was where superimposed bird noise produced a level similar to that of a single engined aircraft. In all these cases, after training, the network was able to correctly discriminate between the four classes with a success rate better than 80%. This was achieved without any special tuning of the DLS parameters or optimisation of the neural network architecture. All of the required algorithms were implemented in a Lochard environmental monitoring unit (EMU) with standard hardware and customised firmware. After off line training of the network, the EMU was able to run in real time with raw microphone input signals and achieve the identification success rate quoted.

5. CONCLUSION

The results obtained with appropriate data set reduction and neural network analysis lead us to conclude that a practical noise source recognition system with existing hardware can be achieved in the near future. There is much scope for further refining of algorithms with more rapid training procedures. Very recently some remarkable progress has been reported in this area [3].

References

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