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Towards Improving the Characterisation of Aircraft and Background Noise

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ABSTRACT

Aircraft noise monitoring involves separately distinguishing and characterising the sound produced by aircraft from the residual (background) sound. The standard process involves the application of a threshold to divide the two classes of sound. Many authors have pointed out the various possible errors in this process and have endeavoured to find estimates for the errors. It has also been pointed out that an important element in the process is to recognise that there is always a third class - the "uncertainty class" - for which it is not possible to ascribe the sound either to aircraft or to background. Such sound must be accepted as unknown and unknowable. In this paper we investigate some of the methods that can be applied to improve the accuracy of characterisation. These include the application of neural networks for recognition of individual one- or half-second samples, dual and fuzzy thresholds in relation to the uncertainty class, spectrally derived information and dynamic loudness to distinguish aircraft from other sound. Comparisons with results based on recordings from installed noise monitoring systems under normal operating conditions will be presented.

INTRODUCTION

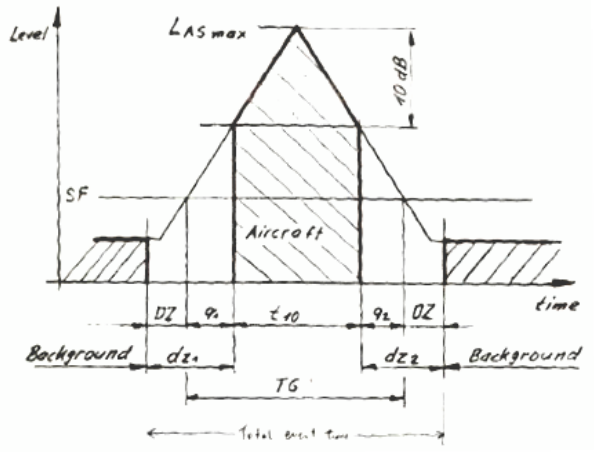
Automatic aircraft noise monitoring systems in common use involve the application of a threshold level. Its purpose is to separate noise events from non-events. A noise event has the potential of being classified as an aircraft noise event or as a non-aircraft noise event according to other available information. The other available information may be correlation with flight plans or flight trajectories derived from radar information. In this context a noise event is referred to as a potential aircraft noise event until the classification process has been completed, whereupon it becomes either an aircraft noise event (AN) or a non-aircraft noise event (NAN). To set the threshold properly, we should first determine the local noise level when no aircraft are flying. An appropriate measure for this non-aircraft noise needs to be chosen, such as an equivalent level or a percentile level over some specified time interval. Ultimately, this should be based on direct human visual observation and aural perception. In practice, because of the costs of human observations, which may have to be conducted independently at several sites and repeated at various times as conditions change, the usual approach is to take a fixed figure such as an A-weighted level between 60 and 65 dB, based on ‘experience’, and apply this to all monitoring stations around a particular airport. The issue of determining the level of the non-aircraft noise accurately is not to be taken lightly, as a recent case of litigation involving substantial financial damages shows [1].

Another approach is to apply the concept of floating threshold, whereby a threshold level is based on a percentile level, such as L90 or L95, calculated over a previous time interval such as 30 minutes. This approach works well if the pattern of the levels of aircraft noise over a period of, for example, 30 minutes is stationary, while the non-aircraft noise may be varying quite strongly. However, if the background noise is largely stationary and the aircraft noise is increasing, for example as a result of more frequent traffic, the threshold will rise and some of the aircraft noise at increasing levels will be labelled as background noise. Although there are ways of ameliorating but not entirely eliminating this effect, floating thresholds, in contrast to some widely held views, should only be used with considerable caution.

Regardless of how the threshold is determined, flight trajectories derived from radar information provide a means of ascribing a particular noise event to a particular aircraft that is shown from the trajectory pattern to be near the noise monitoring station at the time of the noise event. There are of course potential errors with radar information, just as there are with the noise detection, and analysis of these effects needs to be undertaken, as is meticulously described in [2].

THE UNCERTAINTY IN SPECIFYING A NOISE EVENT DERIVED FROM A THRESHOLD

One of the fundamental issues in the setting of the threshold is to recognise that there is a region of uncertainty throughout which one cannot unequivocally separate aircraft from non-aircraft noise. This fact was recognised as a feature of a noise event detection algorithm devised by Caspar Vassalli [3] of the Zürich airport authority in the early nineteen nineties. Even with human observers monitoring sound perception at one-second intervals, there is a range of levels where it is impossible to decide whether the sound is predominantly from aircraft or other sources. In the Vassalli algorithm, a dead-zone is defined to encompass those time intervals, which consist of a fixed period before the level first exceeds the threshold, a varying period immediately after the threshold is exceeded, a fixed period after the level first stays below the threshold for a fixed period (the so-called guard time), and a varying period before the level drops below the threshold and remains below it during the guard time. The varying period of the dead-zone encompasses the period when the level < LAS_max -10 dB (fig.1). There are various cases to consider when LAS_max -10 does not exceed the threshold, which were designed to overcome the defects of the DIN 45643 algorithm [4]. However, the important point in the context of this paper is to realise the existence of the uncertainty at the beginning and end of the noise event, together with the associated dead-zone. The sound exposure accumulated in the dead-zone contributes neither to the aircraft nor to the background noise. It is recognised as beyond the possibility of classification, i.e., it is ‘dead’. The algorithm was implemented in noise monitoring terminals [5] and deployed at Zürich airport during 1996 and subsequent years.



Source: (Caspar Vassalli [3])

Fig. 1. Uncertainty at the beginning and end of a noise event

FUZZY THRESHOLDS

Fuzzy set theory was designed to cope with situations where there is a non-zero probability that a particular element belongs to any one of several sets [6]. This is precisely the situation pertinent to sound pressure levels near the threshold. The sound is not obviously predominantly due to aircraft nor predominantly due to background noise, but there is some (unknown) probability that each type of source contributes. In the absence of more information, the simplest assumption is a linear distribution of level according to the following scheme [7], first described in 2004:

In fuzzy-set parlance a conventional threshold is referred to as a ‘crisp’ threshold. It is a definite predetermined value. In contrast, a fuzzy threshold is a region within which the decision as to whether the noise level is to be attributed to aircraft or not is uncertain. For a noise level within this region, there is a rule for assigning a probability, less than unity, that it is due to aircraft. For levels outside the region there is certainty (probability one or zero). Levels above the region are unambiguously assigned as due to aircraft; levels below the region are unambiguously assigned as background noise. To explain how this works, let us consider a simple concrete example. A crisp threshold T is set at 60 dB. The fuzzy threshold region ranges from 54 to 66 dB, i.e. ± 6 dB around the crisp threshold. We refer to the 6 dB figure as the ‘fuzz factor’ F. Sound levels above 66 dB are fully assigned as aircraft noise; sound levels below 54 dB are fully assigned as background noise. Levels in the region are assigned as aircraft noise and background noise according to a simple linear law as follows: the contribution ΔE_a to the normalised sound exposure due to aircraft is

$$\Delta E_a = \frac{L-(T-F)}{2F} 10^{(0.1*L)} \tag{1}$$

where L is the one-second equivalent A-weighted level of a noise sample. The corresponding contribution to the background normalized sound exposure is

$$\Delta E_b = \frac{T+F-L}{2F} 10^{(0.1*L)} \tag{2}$$

The choice of both the crisp threshold and the fuzz factor is still arbitrary, in that they are based on practical experience. However, the advantage is that the uncertainty of the deciding line between aircraft noise and background noise is reflected in the graded exposure level to be ascribed to these two categories, instead of a full acceptance or full rejection. Furthermore, the sum of the aircraft and background normalized sound exposures is equal to the total normalized sound exposure. A consequence of adopting the fuzzy instead of the crisp threshold is that more events will be recorded and in general they will be of longer duration. This is not a disadvantage if more true aircraft events are found.

As described here, the fuzzy threshold approach applies to a noise event detection algorithm in which LAS_max-10 < T+F. If LAS_max-10 >= T+F, the event sound exposure is calculated as in the Vassalli algorithm. The background sound exposure includes the contributions of the dead-zones DZ and part of q in fig.1, but appropriately scaled down to account for the uncertainty. The remaining parts of q (if any) would still be counted as unscaled contributions to the dead-zone.

Simulations of noise events with fuzzy thresholds have been investigated [7], but fuzzy thresholds have yet to be applied in automatic aircraft-noise monitoring systems.

EVENTS NOT PURELY DUE TO AIRCRAFT NOISE OR PURELY DUE TO BACKGROUND NOISE

From time to time, when studying a record of the time history of an event, one comes across a situation where the event has been correlated (apparently correctly) to an aircraft flight trajectory, but there are sudden high values of sound pressure level, which do not seem to be consistent with aircraft noise. Providing there is no fault in the instrumentation, some other noise source that is more intense than aircraft emission is acting, apparently of short or very short duration. It becomes important to identify the nature of such a source and to eliminate its contribution to the sound exposure of the event. Another more difficult case is where, for part of the duration of the noise event, the dominant sound is due to a source other than aircraft, but there is no obvious indication in the time-history (either LAeq,1s or LAS_max,1s) of the event that such is the case. In the subsequent event processing, it is important to eliminate any such samples, which could otherwise corrupt the maximum level or sound exposure level due to aircraft.

There are three approaches that we can adopt, all of which depend on some form of spectral analysis. We consider the approaches in order of increasing complexity and effectiveness.

Comparison of A, C and Z weightings

The first simple test that one can do is to look at the time-history of the event, especially LAeq,1s, or LApeak. If there is a local spike, for example a jump of more than 4 dB/s, then examine LCpeak, LZeq, or LZI or preferably LZpeak. If there is no noticeable spike here the disturbance is almost certainly in the higher frequency range (above 1 kHz). Examination of the third-octave spectrum around this time will frequently enable one to infer that the disturbance is due to a bird perching nearby. If there are several sharp peaks close together, lasting for a short period, and the third-octave spectrum at this time shows strong harmonics above 1 kHz, then the disturbance is probably due to a siren. Regular bursts in a narrow band around 2.5 kHz are probably due to cicadas. Although this simple test is limited in its accuracy, it has proved to be quite useful in practice, particularly when there is a tendency by some operators to attribute any unusual phenomenon to instrumental failure.

Recognition based on neural networks

Several recognition schemes for noise events have been proposed, for example, based on hidden Markov processes [8], modelling of the human cochlea [9], neural networks [10,11] and pattern classification [12]. All of these processes have varying degrees of success in classifying noise events as jet, propeller aircraft, or as helicopter or background noise. When properly trained or calibrated with preliminary data, such systems have been fairly successful in classifying parts of an event as predominantly due to aircraft or predominantly due to background noise. But to classify each one-second sample accurately has so far proven difficult. Thus the neural network technique has (not yet) emerged as a means for determining if the sudden spike in an LAeq,1s or LAS_max,1s sample is due to aircraft or some other source. The main advantage in using any of these methods is if reliable radar flight-trajectory information with subsequent correlation is missing, so that only acoustic information for event identification is available. In such cases it becomes especially important to have stored audio recordings of each event, which can be used by the human listener to confirm or refute the neural network record in cases of doubt.

Perception of noise

For many years, several researchers have argued that in evaluating any noise impact, one should focus on human perception [13] rather than on a simple physical measure such as sound pressure. If aircraft noise and background noise are present at the same time, and the aircraft noise dominates the sound sensation, from the point of view of monitoring the effect on people, there is no point in trying to separate out the background noise from the total acoustic field. What counts is that the person perceives noise, is annoyed by it, and attributes it to aircraft. Then it is pertinent to employ a measure that corresponds to that perception. This aspect is already implicitly involved in the selection of threshold. Threshold should be chosen such that for levels above threshold, the sound is perceived to be predominantly due to aircraft and for levels below threshold the sound is perceived to be predominantly due to non-aircraft sources. In the work reported in [1], the researchers went to the relevant sites, listened to the sound and, based on their perception, decided whether it was due to background or to aircraft noise. At the same time they recorded the sound pressure level and thereby calculated the values of the sound exposure levels of the background and aircraft noise that were significantly more accurate than had been published by the airport authority.

The defects in using A-weighted sound pressure levels in relation to noise perception are now well understood, but there is still a major reluctance to employ the significant improvements offered by psychoacoustic metrics [14] in aircraft noise monitoring, especially loudness [15], in spite of the clear evidence for its efficacy [16]. In particular, the choice of the most suitable metric to use in setting the threshold is especially important. Even if the primary aim is to establish the LAS_max and LAE values of aircraft noise events, we should be using a metric that is much more closely related to perception in order to decide the separation between aircraft and background noise. A much better parameter to use for this purpose is stationary loudness [15]. In the case of jet aircraft, for a given loudness level, the A-weighted level can vary in excess of 5 dB; in the case of helicopters the variation can exceed 10 dB; in the case of general community noise the variation can exceed 20 dB [17]. Once one takes this step in basing the threshold on loudness, the next step should be to base the whole of event evaluation (maximum and impact values) on loudness. In view of the deeply entrenched practices and standards based on A-weighting this would be too drastic a step for many noise-management operators. But modern noise monitoring systems are certainly capable of handling various event algorithms simultaneously and thus providing more sensible data to be recorded and studied for comparison with the conventional data until the community can be become accustomed to a more rational approach .

Dynamic loudness

Advantageous as the stationary loudness algorithm is in comparison to A, B, C or D-weighting, it does not cover all of the acoustic situations that we need to deal with. More than thirty years ago Zwicker [18] published a method to deal with the perception of time-varying sound, but only recently has an authoritative standard emerged [19], which now enables the dynamic loudness procedure to be implemented in standard aircraft noise monitoring terminals [20]. The dynamic loudness standard involves computation of specific loudness samples at intervals of 2 ms. It has also been established that an appropriate measure of loudness perception is the five-percentile loudness N5 over an appropriate time interval [14]. In our implementation, because of certain architectural features in the noise-monitoring terminal, it was more convenient to work with samples at 0.5 ms intervals – at the same time satisfying all requirements of the standard at 2 ms intervals. Also, because it is customary to work externally with one-second samples such as LAeq,1s, LAS_max,1s, we have adopted the five-percentile loudness level LN5 over one-second intervals as the working parameter in studying noise event characterisation. This means that each LN5 value is based on 100 samples of the 0.5 ms stream. Investigations with this approach and comparisons with conventional event characterisations are under way [20]. Some trials have been undertaken with LN5 as threshold, using recorded data from field-operating noise-monitoring terminals, so far with encouraging results.

A new tool

The application of the dynamic loudness algorithm has led to the emergence of a new tool for investigating the problems caused by short-duration extraneous sounds during an aircraft noise event. The algorithm involves a final step called time integration where a form of nonlinear low-pass filtering occurs. The input signal to this process (at 0.5 ms sample rate) is readily available, and its maximum value can be readily determined during each one-second interval. Comparison of this value with the N5 value reveals whether or not there has been a loud short-duration sound during this one-second period. Since both the N5 and maximising processes are synchronous, the one-second sample during which the disturbance occurs is correctly designated. As such, the corresponding Leq,1s or LCpeak,1s value can be excluded from any of the further aircraft event processing. In the case of LS_max,1s values, some care is needed because of the SLOW time constant. The anomalous value may first occur at a later one-second interval; in addition the subsequent 3 or more samples are likely to be corrupted following the impulse. As a result of these considerations, it is easy to incorporate this process in any automatic event detection and processing algorithm, in contrast to the common practice of either ignoring any such circumstance or searching through the time history of an event to find the suspect samples, and re-calculating the relevant characteristics of the noise event.

CONCLUSION

We have discussed various factors that influence the choice of separation of community noise from aircraft events. There are now several tools that one can utilise to reduce the number of noise events wrongly classified as background or wrongly classified as aircraft. But it is important to realise that even with optimally chosen thresholds, events are not necessarily entirely due to aircraft or entirely due to background throughout the duration of the event. Then it is necessary to have a means of classifying each one-second sample as predominantly aircraft or predominantly background, such as with neural network recognition and the application of dynamic loudness. Rather than limiting monitoring to the measurement of simple physical parameters, we have emphasised the importance of human perception as the basis in determining thresholds and in isolating extraneous samples from aircraft noise events. At the same time there is plenty of space for imaginative new approaches in what many would see as a rather boring prosaic field.

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