# Unattended acoustic events classification at the vicinity of airports

Marco Tarabini [a,*], Giovanni Moschioni [a], Cesar Asensio [b], Davide Bianchi [a], Bortolino Saggin [a]

[a] Politecnico di Milano, Dipartimento di Meccanica, Via M. d'Oggiono 18/a, 23900 Lecco, Italy
[b] Universidad Politécnica de Madrid (I2A2), FFII – c/José Gutiérrez Abascal 2, 28006 Madrid, Spain

A R T I C L E   I N F O

*Article history:*
Received 8 March 2013
Received in revised form 10 December 2013
Accepted 22 March 2014
Available online 16 April 2014

*Keywords:*
Aircraft noise
Airport noise restrictions
Engine thrust reverse
Signal processing

A B S T R A C T

This paper describes a method for the automatic identification of acoustic events using a weighted average of sound pressure and sound intensity measured at the vicinity of airports. The classification is based on the combination of different parameters using a technique conceptually similar to the sensor fusion: the indications of different classifiers are merged using the classification uncertainty as a figure of merit. The method uses the results of a training phase for the observation of statistical distributions of sound pressure and sound intensity related parameters. The different parameters' weights are computed analyzing the overlap of probability distributions of takeoffs and landings, so that more relevance is given to the quantities presenting a low risk of misclassification. The proposed method does not require any arbitrary assumption about the parameter effectiveness, given that the indications of multiple (potentially infinite) classifiers can be merged together with weights that minimize the chance of misclassification. The method has been validated with measurements performed at the Milan Malpensa airport (Italy). Results outlined that the proposed classification criterion correctly identifies approximately 99% of events.

## 1. Introduction

The social impact of airport noise is relevant [1,2] and the public request for quieter airports lead to develop a strict legislation based on the compulsory noise monitoring which usually combine information deriving from noise level meters and radars. As underlined by the ISO 20906 [3] and in the literature [4,5], noise measurements close to the airports often involve different noise sources; complex logics are therefore needed to separate the aircraft sound events from spurious sources. In many situations, the uncertainty related to the identification of aircraft-related events is large [4], given the wide discretional margins that can be chosen in the ISO 20906 procedure. Consequently, benefits deriving from an automatic detection can be important.

The problem of automatic acoustic event recognition has already been faced in the literature: Pfeiffer et al. [6] presented algorithms aimed to recognize noise-generating events, concluding that time-frequency patterns are difficult to investigate and claiming that the more like to human hearing a method is, the more effective it turns out to be. Andringa et al. proposed the use cochleograms for the identification of aircraft-related events in residential areas [7]; results demonstrated that even in the case when the aircraft noise was 5 dB larger than the background, the detection performances were comparable to the human listeners. The recognition of ground vehicles noise (cars, trucks, etc.) was performed using Short Time Fourier Transform (STFT) [8]; results outlined that diverse events must present significant differences in order to get distinguished.

The possibility of separating the noise sources depending on their position was experimentally investigated at the vicinity of Milan Malpensa Airport [5] using a 3D sound intensity probe [9]. Results allowed discriminating the acoustic contribution of the aircraft from other sources inside the airport; the 3D probe position prevented from distinguishing between takeoffs and landings. Genescà et al. [10] separated the aircraft noise time history from that of extraneous noise sources using a microphone array, evidencing that the sound source position can be used to discriminate different aircraft-related acoustic events.

Several recent literature studies used the noise pattern recognition for the identification of aircraft takeoffs [11,12]; results evidenced that approximately 90% of events are correctly classified using a multimodal autoregressive model. A real time method for the identification of the aircraft's sounds has been proposed in Ref. [13]. A monitoring unit allowed recognizing approximately 93% of events, independently on the measurement location and on the soundscape.

* Corresponding author. Tel.: +39 (0)2 2399 8808.
*E-mail address:* marco.tarabini@polimi.it (M. Tarabini).

This paper aims to propose a novel method for the identification of aircraft-related acoustic events (takeoffs and landings) using acoustical quantities. The main idea of the proposed method is to merge the indications of existing criteria (based on the noise time history, spectrum, cepstrum and sound intensity direction) using a linear classifier with multiple thresholds computed starting from the results of a training phase. The weights of the different parameters minimize the chance of misclassification, using the measurement uncertainty as a figure of merit. The proposed method is described in Section 2. The results of measurements performed at the Milan Malpensa airport (Italy) are presented in Section 3 and the method performances is discussed in Section 4. The paper is eventually concluded in Section 5.

## 2. Method

As previously mentioned, the method is conceptually similar to the sensor fusion [14], a technique in which measurements of different sensors measuring the same phenomenon are merged together with weights that are inversely proportional to the sensors' uncertainty. In our case, the indication of different classification methods are merged together to obtain a unique (and more reliable) classifier. The uncertainty of each method is given by the chance of misclassification, that can be identified during a training phase with statistical analyses.

The proposed method for the automatic events recognition is therefore based on three steps:

1. Feature selection: identification of parameters derived from sound pressure and sound intensity that can be used to distinguish takeoffs from landings.
2. Training of a classification model that is the sum of:
   a. Statistical analysis on real measurement data for the determination of values assumed by the previously described parameters.
   b. Identification of the decision function, i.e. of a threshold for each parameter to discriminate between takeoffs and landings using statistical criteria.
   c. Combination of different parameters using the measurement uncertainty to identify the weight which minimize the risk of misclassification.
3. Testing, which involves the verification of the actual method performances: use of the automatic procedure for the (known) event recognition in conditions similar to the training ones.

There are potentially infinite criteria that can be used to discriminate takeoffs and landings using sound pressure and sound intensity measurements, but their efficiency often depends on the measurement location and on the aircraft noise characteristics. Consequently, the questions that the experimenter tries to answer are

i. Which are the (most efficient) parameters allowing to classify different acoustic events (for instance, takeoffs and landings)?
ii. Which is the thresholds for each parameter?

The proposed approach merges the indications of potentially infinite parameters and, for each of them, computes the threshold that minimizes the chance of misclassification. In the next sections, we will describe different parameters that are commonly used for the analysis of airport noise and then we will explain how to combine multiple indications using a unique classifier.

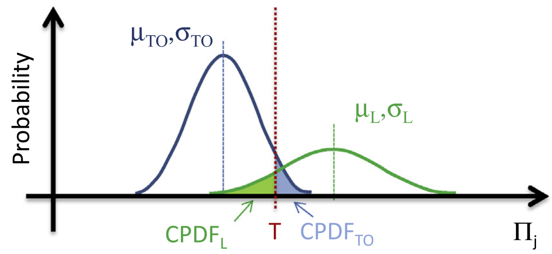


**Fig. 1.** Identification of the optimal threshold for the classification of takeoffs and landings.

### 2.1. Thresholds identification

Independently from the measurement point location and on the noise characteristics, it is always possible to derive a certain number $n$ of parameters ($\Pi$) describing the acoustic event. With the term parameter, (hereinafter $\Pi$) we refer to any numerical quantity extracted from the signal as, for instance, the maximum sound pressure level or the event duration. Each time that an aircraft passes in front of the measurement point, the parameter $\Pi_j$ assumes a value $\pi_j$. The identification of a threshold $T_j$ that allows identifying if the event is a takeoff or a landing is often problematic, but with the proposed method, $T_j$ is determined analyzing the probability distributions of the random variable $\pi_j$ during takeoffs and landings.

Let us consider a single parameter (for notation clarity the index $j$ will be omitted) and its takeoff and landing populations $\Pi_{TO}$ and $\Pi_L$. For simplicity, let us suppose that the two populations can be approximated with Gaussian distributions,[1] as shown in Fig. 1. In this case, takeoff data can be summarized by the takeoff mean $\mu_{TO}$ and by the takeoff standard deviation $\sigma_{TO}$. Similarly, landings are summarized by the landings mean $\mu_L$ and by the landings standard deviation $\sigma_L$.

The proposed criterion for the calculation of $T$ is based on the minimization of the probability of misclassification. If we consider that the *a priori* probability of the take offs is equal to the *a priori* probability of landing (and both are equal to 50%), the optimal $T$ is the one for which the cumulative probability density function (CPDF) "external" to the threshold is equal for takeoffs and landings [15]. With reference to the above figure, such a condition is given by:

$$\frac{\mu_L - T}{\sigma_L} = \frac{T - \mu_{TO}}{\sigma_{TO}} \tag{1}$$

The threshold $T$ is therefore

$$T = \frac{\mu_L \sigma_{TO} + \mu_{TO} \sigma_L}{\sigma_L + \sigma_{TO}} \tag{2}$$

The above equation indicates that

- $T$ assumes a numerical value between the mean of takeoffs and the mean of landings.
- $T$ is closer to the mean of the population with the lower relative standard deviation.

If takeoff and landing distributions are not Gaussian, the threshold $T$ has to be identified from the experimentally identified CPDF percentiles so that the probability of misclassification is equal for takeoffs and landings.

[1] Implications of such a choice will be discussed at the end of this paragraph.

### 2.2. Combination of different parameters

The number of parameters $\Pi_j$ that allows distinguishing takeoffs from landings is potentially infinite. Depending on the measurement position, on the airport characteristics and on the presence of disturbing sources, a single parameter may be more effective than the others in the event detection. Instead of choosing the parameter that, in a specific situation, provides for the best results, it is possible to combine different parameters whose thresholds have been identified according to Eq. (3).

The main idea of the proposed combination criterion is to give more relevance to those parameters for which the takeoff and landings populations are not overlapped, i.e. where the risk of misclassification is lower. Each of the $n$ parameters is associated to the cumulative probability density function (CPDF) of misclassification derived from the choice of $T_j$, hereinafter CPDF$_j$. Given that for some parameters $\mu_{L\,j} < \mu_{TO\,j}$, if data are normally distributed, CPDF$_j$ is defined as:

$$\mathrm{CPDF}_j = \begin{cases} F\left(\frac{T_j-\mu_{TO\,j}}{\sigma_{TO\,j}}\right) & \text{if } T_j < \mu_{TO\,j} \\ 1-F\left(\frac{T_j-\mu_{TO\,j}}{\sigma_{TO\,j}}\right) & \text{if } T_j > \mu_{TO\,j} \end{cases} \tag{3}$$

If data are not normally distributed, CPDF$_j$ can be identified from the experimental data, observing the percentage of events in which the parameter is larger/smaller than the threshold $T_j$. The weight of the single parameter $\pi_j$ is computed as:

$$w_j = \frac{0.5-\mathrm{CPDF}_j}{\sum_{j=1}^{N}(0.5-\mathrm{CPDF}_j)}\,\mathrm{sign}\left(\mu_{L\,j}-T_j\right) \tag{4}$$

The quantity $0.5-\mathrm{CPDF_j}$ derives from two necessities:

i. The necessity of giving more relevance to the parameters with a low risk of misclassification: therefore the weight is proportional to the complementary of CPDF$_j$, i.e. $(1-\mathrm{CPDF}_j)$.
ii. The necessity of not giving relevance to those parameters $\pi_j$ with overlapped takeoff and landing distributions. If $\mu_{L\,j} = \mu_{TO\,j}$, CPDF$_j$ is 50% and the parameter does not provide useful information for the event classification. Consequently, the quantity $(1-\mathrm{CPDF}_j)$ has been modified in $(1-\mathrm{CPDF}_j-0.5)$, i.e. $(0.5-\mathrm{CPDF}_j)$.

The expression used to assess if an event is a takeoff or a landing is given by the linear classifier $\chi$:

$$\chi = \sum_{j=1}^{N} w_j \cdot (\pi_j - T_j) \tag{5}$$

Because of the initial hypothesis of Fig. 1 (in which the landings average was larger than the takeoff average) and because of the sign of Eq. (5), if $\chi$ is positive the event is classified as a landing; if it is negative it is classified as a takeoff. Obviously, the adoption of inverse sign weights would have led to positive $\chi$ coefficients for takeoffs and viceversa.

### 2.3. Aircraft noise

The noise emitted by aircrafts is the sum of:

- Aerodynamic effects, like boundary layer forming on wings, air intake turbulence and waves spreading out the tail, which generate broadband noise.
- Engines, which produce typical sound pattern related to the rotors angular speed, essentially made of low frequency harmonics and buzz saw noise proportional to the blade passing frequency.

The aircraft noise reaching the receptor is affected by the aircraft speed (Doppler effect) and by the air and ground characteristics (atmospheric absorption, reflections).

The simplest acoustic model that can be used to describe an aircraft taking off or landing (Fig. 2) is the one of a dominant point source (the airplane) that radiates broad-band non-stationary noise while moving along an approximately linear path not necessarily parallel to the ground. The receiver (i.e. the measurement instrument) is located at a fixed position at a small distance from a semi-reflective surface.

During the takeoff, propellers are the principal noise sources, given that the engines are at maximum thrust and the aircraft speed varies from (approximately) zero to the takeoff one (70–90 m/s for most of the commercial airliners). Airplane landing noise, conversely, is dominated by the aerodynamic part in the initial phase (when the aircraft approaches the runway) and may include the contribution of thrust reversal noise (hereinafter TRN) if a sudden speed reduction is required after touch down.

### 2.4. Parameters

There are different acoustical parameters $\Pi_j$ that can potentially be used to discriminate takeoffs from landings. In this section we propose different sound pressure and sound intensity based parameters that the literature review and preliminary experiments outlined as promising.

The easiest acoustic parameter to be analyzed is the sound pressure level (SPL): with a crafted choice of the measurement point position on the runway (beginning, middle or end), SPL of takeoffs may differ significantly from the one of landings. The measures that can be used for the takeoffs and landing identification are the event duration (ISO 20906 $t_{10}$), the SPL increase rate (first derivative before the pressure peak, SPL′) and the SPL curvature (the second derivative of the SPL – time graph, hereinafter SPL″). These parameters are expected to be meaningful if the microphone is close to the touching point or to the takeoff position, where there is a significant difference in the aircraft speed; a comparison between SPL of a takeoff and a landing when the measurement position (hereinafter MP) is at the beginning of the runway is shown in Fig. 3.

The index $t_{10}$ can be computed according to the indication of the ISO 20906 as the total time in which the SPL exceeds the threshold of (SPL$_{max}$ −10 dB). SPL′ is defined as the angular coefficient of the best fitting line of the SPL – $t$ plot between $t_{start}$ and $t_{max}$. Similarly, SPL″ is defined as the second-order coefficient of the best fitting parabola of the SPL – $t$ plot between $t_{start}$ and $t_{stop}$.

SPL is also useful for the identification of the use of thrust reversers. If the thrust reverse is used, the SPL curve has a first maximum when the aircraft (approximately) passes in front of the MP, and a second maximum after a few seconds, as shown in Fig. 4; the peak at time $t_{pk1}$ occurs when the aircraft passes close to the MP, the one at time $t_{pk2}$ is caused by the use of thrust reversers. Also in this case, the effect of the measurement position is

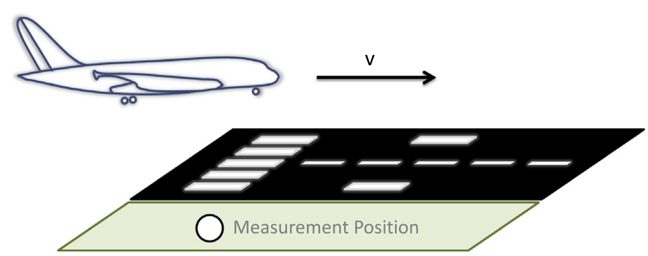


**Fig. 2.** Acoustic model.

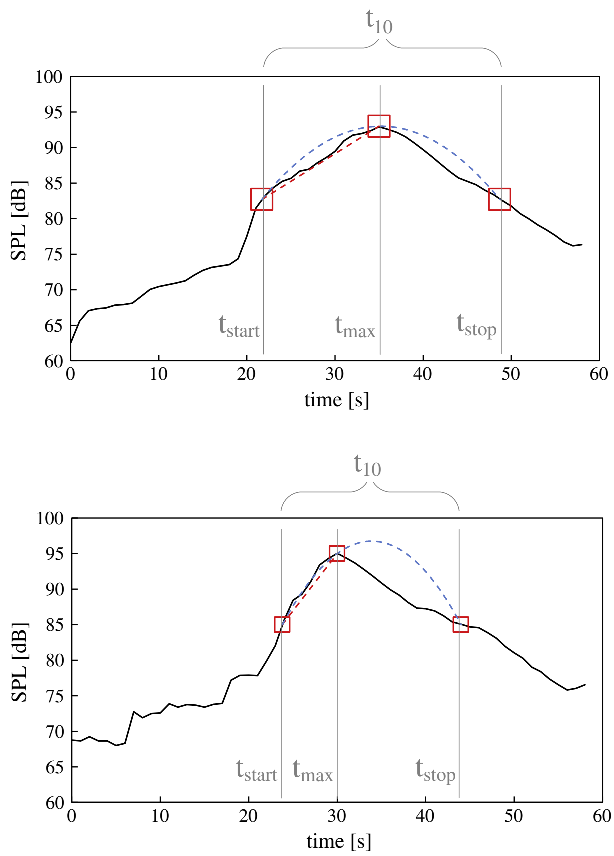


**Fig. 3.** SPL variation of takeoff (top) and landing (bottom), SPL′ (red line) and SPL″ (blue parabola). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

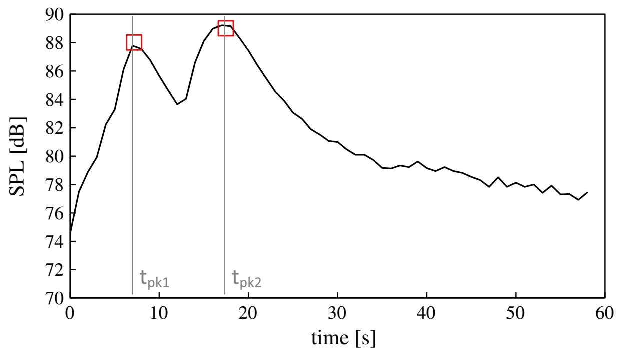


**Fig. 4.** SPL of a landing in which thrust reverser had been used.

expected to be important, given that the two peaks are visible only if the measurement position is far from the position where the thrust reversal is used.

Other parameters can be derived from the sound pressure spectrum. The noise produced by turbofan engines' blades propagates as pressure waves with buzz saw shape (referred to as buzz saw noise, hereinafter BSN). Such a condition, because of the high peripheral fan speed, is mostly evident during the takeoffs and can be therefore used to distinguish takeoffs and landings. The BSN is typically embedded in a slow varying wideband noise (e.g. atmospheric agents, wakes, turbulence, etc.) and its spectrum is characterized by equally spaced harmonic components. Aircraft-related events can be classified on the basis of the frequency difference between the harmonics: if the engine noise is dominant the frequencies of the spectral peaks are equally spaced. Conversely, during landings, the aerodynamic noise is prevalent and the spectral peaks' frequencies are randomly distributed. A possible criterion for the event classification is based on the frequency difference between adjacent spectral peaks and on the ratio between the differences standard deviation and mean.

In our experience, best results are obtained if spectra are computed between the times $t_{start}$ and $t_{stop}$ and afterwards de-trended to ease the triggering operation. Each spectrum is approximated (in a least square sense) with a quadratic function and the result are subtracted from the original spectrum. Peaks can be identified using the interpolation approach described in Ref. [16]. A comparison of de-trended spectra between a takeoff and a landing is shown in Fig. 5.

The parameter used for the statistical analyses is related with the variability of the frequency difference between adjacent spectral peaks. Said $f_i$ the frequency of each of the $i$ peaks, the frequency difference array is computed as $\delta_i = (f_{i+1} - f_i)$ The variability of the frequency differences $\delta_i$ is summarized with the standard deviation $\sigma(\delta_1, \delta_2, \delta_3, \ldots, \delta_n)$, hereinafter $\sigma(\delta_i)$. A comparison between values of $\delta_i$ for data presented in Fig. 5 is shown in Fig. 6.

An additional frequency domain criterion that can be used to distinguish takeoffs and landings is the presence of a dominant tonal component with increasing frequency during takeoffs. In the common takeoff procedure, the thrust level is slowly increased and stabilized for a few seconds, then increased to the takeoff thrust. Let us call $p_{max}(f)$ the largest spectral peak at a certain time: if such a peak is generated by the engines during the takeoff, the frequency $f$ of $p_{max}$, hereinafter $f^*(t)$, will slowly increase, remain constant and then increase again. This typical frequency pattern will be absent in landings, where the random noise characteristics are dominating.

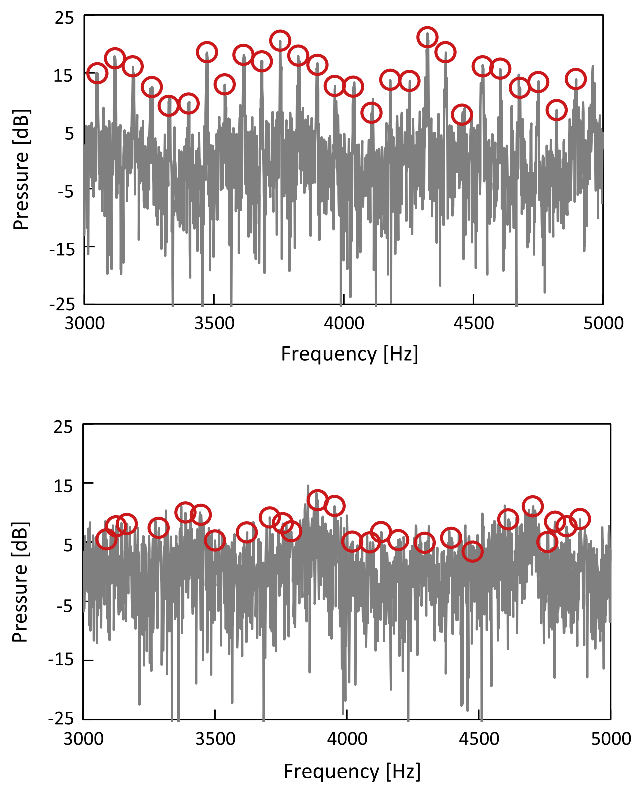


**Fig. 5.** Detrended spectra extracted by a waveform recording a takeoff (top) and a landing (bottom).

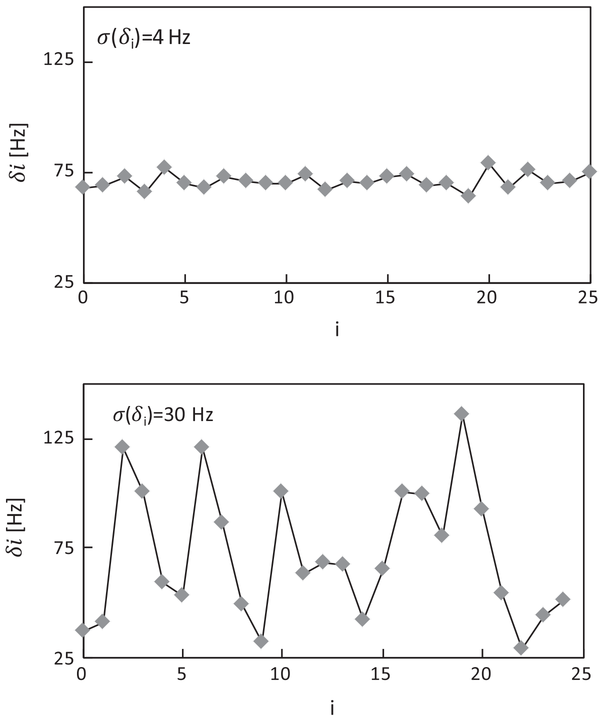


**Fig. 6.** Comparison of takeoff (top) and landing (bottom) harmonic spacing.

A comparison between $f^*(t)$ (evidenced by the dotted line on the STFT) of a takeoff and of a landing is shown in Fig. 7. The takeoff $f^*(t)$ plot exhibits a well-defined pattern: from 25 to 30 s $f^*$ increases from 900 to 2400 Hz, then remains constant for approximately 3 s and eventually increases. Once that a stable rotation speed is achieved, the airplane speed increases and the BPF drifts

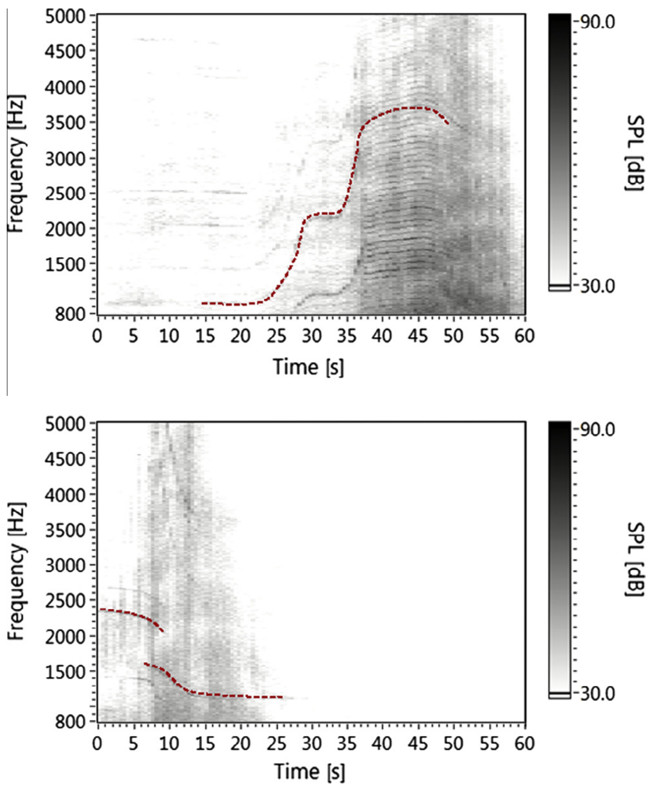


**Fig. 7.** Result of $f^*$ detection for a takeoff (top) and a landing (bottom).

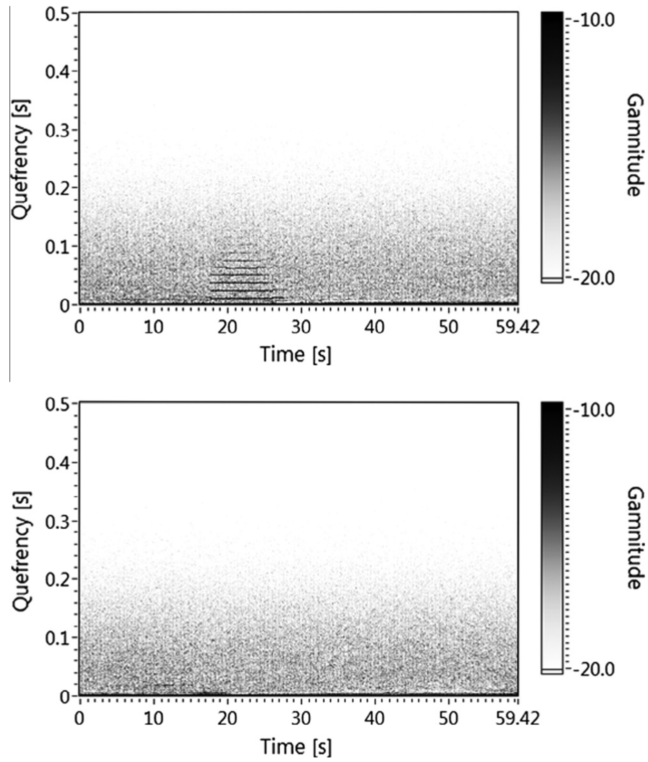


**Fig. 8.** Comparison between a takeoff (top) and a landing (bottom) cepstrogram in which BSN consistence has been checked.

because of Doppler effect. On the contrary $f^*(t)$ plot of the landing is almost constant from 0 to 5 s and then rapidly decreases. Also in this case, analyses are usually more efficient if performed between $t_{start}$ and $t_{stop}$ and should be limited to frequencies larger than 800 Hz, where the BSN is dominant.

The necessity of summarizing the plots with a single value leads to the definition of the index $t(f^*)$, defined as the maximum time span in which $f^*$ is increasing.

The presence of equally spaced harmonics suggests the possibility of using Cepstrum algorithm [17], which is the result of taking the Fourier transform of a spectrum logarithm. Cepstrum can be used to outline the presence of periodic components in the signal spectrum, and seems therefore useful for the takeoffs identification. The cepstrograms (also known as short-time cepstrum) of a takeoff and a landing is shown in Fig. 8: the presence of multiple lines with a quefrencies[2] lower than 0.1 s indicates the presence of periodic harmonic components. The main pattern disappears after approximately 28 s: owing to the directional characteristics of the noise emitted by the propellers, BSN mainly propagates from the engines towards the nose of the airplane, as also shown in Fig. 7. When the aircraft passes in front of the measurement position there is a rapid passage from BSN to wide band noise, and no dominant quefrencies are observed. The lower plot in Fig. 8 shows that no dominant quefrencies are present during the landing.

Also in this case it is necessary to summarize data with a numerical index; a convenient choice can be the number of BSN patterns in the short-time spectrogram. In the case presented in Fig. 8, this number is equal to 6 for the takeoff and to 0 for the landing. Obviously, other parameters can be defined, such as the time in which the dominant quefrency is constant; being the landing quefrencies randomly distributed, this parameter is expected to be large in takeoffs and small in landings.

[2] The independent variable of Cepstrum analysis, measured in seconds.

The last group of parameters can be derived from the sound intensity vector that, behind assumption of single active component and spherical propagation, can be used to identify the source position and power. Even if airport noise is often due to the superposition of multiple sources, in the close vicinity of runways, takeoff and landing aircraft noise is dominant [5] and the single point-source approximation is reasonable. Sound intensity vector is commonly measured starting from its Cartesian components: in the following, we will refer to $I_x$ as the component perpendicular to the runway, $I_y$ for the component parallel to the runway and $I_z$ for the vertical intensity component. The knowledge of the intensity vector allows computing different quantities related with the position of the aircraft such as the aircraft altitude or its speed over the runway.

One of the most obvious differences between takeoffs and landings is that in the first case the aircraft altitude increases, in the latter the altitude decreases. It seems therefore obvious to use $I_z$ to discriminate between the events. Nevertheless, taking off aircrafts run on the ground for most of the runway, with takeoff distances ranging from approximately 1 km for the commercial airliners to more than 2 km for the heaviest ones. During landings, airplanes fly over the ground for at least 300 m from the head of runway and descent following a path with about 3° slope; the limited acoustic radiation angles of incidence may limit the validity of this parameter. In our experience, better results are obtained if the MP is located near the runway head and if $I_z$ is averaged between the runway head and the MP. Since the MP location is known, the averaging period can be identified using the angle of the sound intensity vector in the horizontal plane.

Airplanes, before taking off, enter the runway from the head and begins to run from a null or negligible speed. Conversely, landing airplanes fly over the entrance of the track pointing to the so-called aiming mark. The speed difference between the two conditions is significant, especially if the MP is close to the aiming point. Different parameters related to the aircraft speed can be used: the easiest one to derive from intensity measurement is the angular velocity of the sound intensity vector in the horizontal plane. The angular velocity can be conveniently computed in conditions similar to the ones described in the previous paragraph, i.e. between the instant in which the aircraft is located on the head of the runway and the MP. Fig. 9 shows a comparison between measured angle span for a takeoff (top) and a landing (bottom) when the head of the runway is located at an angle of approximately 230° (and MP is located at an angle of 180°, since $I_y$ is null). The plots show that the takeoff (top) is characterized by an intensity vector angular velocity lower than 10°/s and the velocity during the landing is larger than 20°/s.

Another difference between takeoffs and landings is the aircraft acceleration (i.e. position second derivative), that is positive for takeoffs and negative for the landings. The position of the aircraft on the runway can be computed as the intersection between the sound intensity vector and the runway. The position can be approximated with a second-order curve in a least square sense: if the second order coefficient is positive, the event can be classified as a takeoff and vice-versa. Further indication can be derived from the uncertainty of such a coefficient, which provide information on the reliability of the derived data. The selection of the time interval for the regression is also critical; best results in our experience were obtained considering a time interval of 6 s centered on the MP.

The sound pressure measured at the receiver depends on both the source strength and on the spherical attenuation. The actual source power can be estimated according to the ISO 9613. Similarly to what was previously done for the pressure level, different parameters can be derived from the sound power level (maximum, first and second derivatives, RMS). The reference power parameter

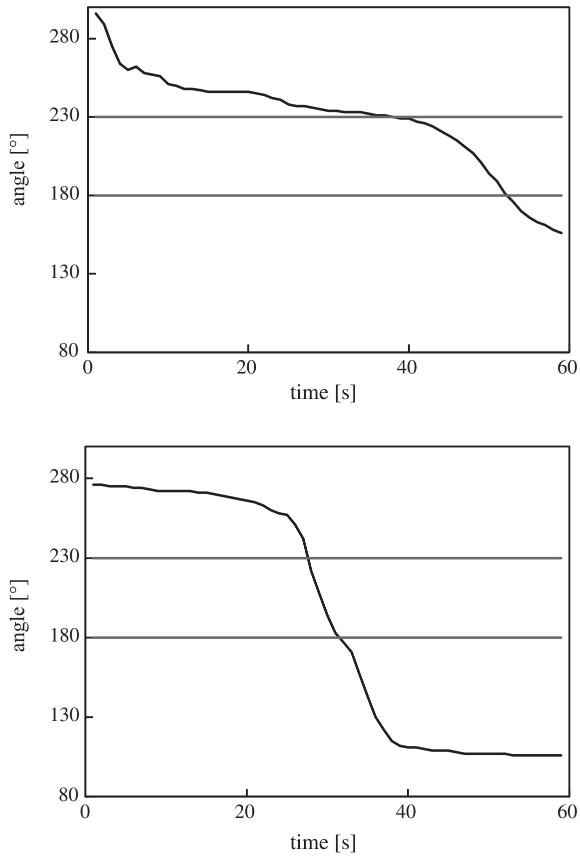


**Fig. 9.** Intensity vector rotation for a takeoff (top) and a landing (bottom).

can be the $LP_{\mathrm{RMS}}$ value between $t_{start}$ and $t_{stop}$ (hereinafter $LP_{\mathrm{RMS}}$), but other parameters as the maximum power level or the $t_{10}$ computed on the power instead of the pressure can be used.

## 3. Case study

The proposed method has been validated with tests performed at Milan Malpensa airport for civil aviation. This is one of the largest airfield in Italy; located in the north of the country in a mostly green area it consists of two terminals with relative parks for the aircrafts, two runways and a heliport. The tracks are parallel, 3.9 km long, 60 m wide, oriented towards North West direction. The airplanes can run both direction during takeoffs and landings according to handling rules and atmospheric agents (mainly wind). The environment outside the airport area presents access roads, a highway, a railway and vegetation. Finally, atmospheric conditions normally varies during the year from snowy and icy to sunny and warm.

### 3.1. Experimental setup

Sound pressure and sound intensity were measured with a setup similar to that adopted in previous studies [5,18]. A 3D sound intensity probe was arranged with six half-inch microphones manufactured by BSWA, with nominal sensitivity of 50 mV/Pa. Microphones spacing was 40 mm; such a distance, thanks to the compensation algorithms described in Ref. [9], allowed reliable measurements (±1 dB) between 20 and 4500 Hz. Data were sampled by two 24 bits NI 9234 data acquisition boards (stored in a cDAQ chassis) with a pass-band of 5 kHz. A fit-to-purpose virtual instrument was developed in LabVIEW to acquire and store the six sound pressure time histories. Data were offline processed to derive some of the parameters described in Section 2. Measurements were performed in two weeks: the first week of acquisition was used for the system training, the second for the system verification.

Given that one of the possible outcomes of the analyses was the automatic identification of the thrust reversal noise, the 3D probe was located close to the touching point, at 130 m from the centerline of the closest runway (960 m from the other). The actual position was chosen to accomplish with the airport safety rules and on the basis of the experience of experiments performed in Madrid Barajas airport [19]. A picture of the intensity probe with the airport on the background is shown in Fig. 10.

### 3.2. Method training

The first step of the proposed method is the analysis of the parameters $\pi_j$ CPDF in order to identify the weights $w_j$ for the computation of the index $\chi$. In this phase the type of event (takeoff–landing) was derived from the airport flight-plan and from audio recordings. Parameters were computed on a set of 50 takeoffs and 50 landings. The parameters included in the analysis were:

a. The SPL increase rate (SPL′).
b. Number of BSN patterns in short time Cepstral analysis.
c. The standard deviation of frequency differences between spectral peaks $\sigma(\delta_i)$.
d. The time in which the dominating spectral component increased its frequency $t(f^*)$.
e. The magnitude of the vertical intensity component $I_z$.
f. The RMS power level $LP_{RMS}$.
g. The aircraft acceleration.
h. The average speed before the MP.

The weight of the single parameters $w_j$ was computed according to the procedure described in Section 2 under the assumption of normally distributed data (verified with Anderson–Darling normality tests). The results of the training phase are summarized in Table 1. Results show that the more reliable indicators are:

- The time in which the dominating spectral component increased its frequency $t(f^*)$, in which the probability of misclassification $CPDF_j$ is 5%.
- The average speed before the MP and the average aircraft acceleration are also reliable indicators, with $CPDF_j$ of 6 and 7% respectively.
- $I_z$, BSN, $\sigma(\delta_i)$ and $p_{max}$ have comparable weights (close to 10%), endorsable to a misclassification rate between 20% and 30%.

**Fig. 10.** Picture of the 3D probe, with the airport and the runway visible on the background.

**Table 1**
Results of the training phase.

| Parameter $\pi_j$ | $\mu_{TO}$ | $\sigma_{TO}$ | $\mu_L$ | $\sigma_L$ | $T_j$ | $CPDF_j$ | $w_j$ |
|---|---|---|---|---|---|---|---|
| SPL′ | −10.5 | 2.7 | −10 | 5.2 | −10.5 | 50% | 0% |
| BSN | 2.5 | 1.5 | 1.0 | 0.6 | 1.4 | 24% | 11% |
| $\sigma(\delta_i)$ | 11.5 | 5.2 | 17 | 2.4 | 15.2 | 23% | 11% |
| $t(f^*)$ | 4.9 | 1.9 | 0.9 | 0.5 | 1.7 | 5% | 19% |
| $I_z$ | −56 | 9.7 | −39 | 18 | −50.0 | 27% | 10% |
| $LP_{RMS}$ | 73 | 8.2 | 50 | 18 | 66.2 | 19% | 13% |
| Avg. acceleration | −0.3 | 0.8 | −10 | 5.9 | −1.4 | 7% | 18% |
| Avg. speed before MP | 20.5 | 5.8 | 61 | 21 | 29.3 | 6% | 18% |

- The weight of SPL′ are very low, given that the risk of misclassification is close to 50%.

Numerical values indicate that the most reliable parameters have larger weights, while the unreliable ones are marginally considered in $\chi$. The advantage of the proposed method is that the weight are computed on the basis of experimental results, without any arbitrary assumption of the experimenter.

### 3.3. Method verification

The method verification was performed on 94 events (47 takeoffs and 47 landings acquired in the second week of measurements). Also in this case, the type of event was known and the method validity was assessed by comparing the actual event with the one predicted by our model. Results (Fig. 11) evidenced that 93 over 94 events were correctly identified; the index $\chi$ during takeoffs had a mean value of −4.7 and a standard deviation of 1.9. The index $\chi$ during landings had a mean value of 11.7 and a standard deviation of 4.1. The only event not correctly identified (a landing classified as a takeoff) was characterized by an index $\chi$ of 0.3. As later discussed, in case of $\chi$ values close to zero it is possible to request the operator action to classify correctly the event.

## 4. Discussion

Results evidenced that the use of an index computed merging the indications of different parameters derived from sound pressure and sound intensity measurements is more reliable than each

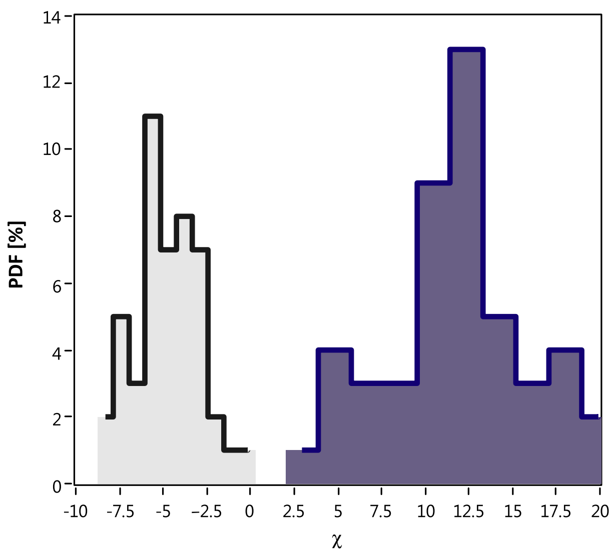


**Fig. 11.** PDF of the population of $\chi$ during the method verification campaign. The left histogram (negative values) summarizes the takeoffs, the right histogram summarizes the landings.

single parameter from which it derives. The relative weight of different parameters has been computed so as to minimize the probability of event misclassification.

Although there are several parameters (features) that have not been included in our analyses, experimental results evidenced the advantages of giving more relevance to the quantities with low probability of misclassification. In our case, the most reliable classifiers were derived from the sound spectral characteristics and from the sound intensity vector. As already outlined in Section 2, the parameter weights $w_j$ cannot be used for tests performed in other airports (or even different locations in the same airport), given that the numerical values depend on the position of the MP on the runway, on the airport characteristics and on the presence of other noise sources. Nevertheless, the $w_j$ computation is based on the training phase results and, in any condition, more relevance is given to those parameters that, in the specific location, allowed distinguishing takeoffs from landings in the training phase.

Although different criteria for the computation of the weights $w_j$ are possible, the one proposed in this paper is the one that minimizes the chance of misclassification. In our test case, the best criterion was $t(f^*)$, which granted a probability of misclassification of 5%. The common choice in many of the existing literature studies is to use only the parameter that, during the training phase, performed better. The simultaneous use all the parameters (giving more relevance to $t(f^*)$ and no relevance at all to SPL′) allowed a probability of misclassification of 1%, i.e. much lower than the probability of misclassification of the best parameter. The choice of using the best parameter does not account for possible mismatches between training and testing conditions and is less robust than the one based on the computation of the index $\chi$.

Different parameters have been proposed upon considering the acoustic characteristics of aircrafts' noise; some of them are widely used in airport noise monitoring, others (such as the frequency difference between adjacent spectral peaks or the cepstrum-derived features) have never been used for aircrafts event classification, and have been proven to be effective. The use of other parameters derived, for instance, from camera measurements or from other sensors is expected to increase the method reliability and can be included in future researches.

A positive aspect deriving from the use of the index $\chi$ is that when the latter is close to 0 (or when it is outside a certain confidence interval, that can be identified during the training campaign) the chances of misclassification are large; it is therefore reasonable to request the evaluation of an operator for further analyses.

## 5. Conclusions

This work described a method that can be used to identify the aircraft takeoffs and landings with the combination of several different parameters derived from sound pressure and sound intensity measurements. The analysis of the noise time history and spectral characteristic allowed identifying a group of parameters that assume different values in takeoffs and landings. Events are classified using a threshold for each parameter. The parameters thresholds and the relative weights of the different parameters are computed minimizing the risk of misclassification. The proposed method has been validated with measurements performed at Milan Malpensa airport. Experimental results outlined that the method correctly identify takeoffs and landings, with a misclassification rate close to 1%. Although other tests could be useful for a deeper method validation (different airports, different measurement positions), the proposed method always gives more relevance to the parameters granting a lower misclassification rate and is therefore robust and does not require any subjective evaluation about the parameters' efficiency.

## Acknowledgement

Authors gratefully acknowledge Società Aeroporti Milano for the support in the testing activity.

## References

[1] Schaffer B, Thomann G, Huber P, Brink M, Pluss S, Hofmann R. Zurich aircraft noise index: an index for the assessment and analysis of the effects of aircraft noise on the population. Acta Acustica United Acustica 2012;98:505–19.
[2] Schreurs E, Jabben J, Bergmans D, Koeman T. Background Noise: An Increasing Environmental Problem? Acta Acustica United Acustica 2010;96:1125–33.
[3] ISO 20906. Acoustic-unattended monitoring of aircraft sound in the vicinity of airports; 2009.
[4] Asensio C, Recuero M, Ruiz M. Aircraft noise-monitoring according to ISO 20906, evaluation of uncertainty derived from the classification and identification of aircraft noise events. Appl Acoust 2011.
[5] Moschioni G, Saggin B, Tarabini M. Contribution of airports to noise in surrounding environment; identification and measurement of noise sources. In: Proceedings of internoise, Istanbul; 2007.
[6] Pfeiffer S, Fischer S, Effelsberg W. Automatic audio content analysis. In; Proceedings of the fourth ACM international conference on multimedia; 1997. p. 21–30.
[7] Andringa T, van Hengel P, Muchall R, Nillesen M. Aircraft sound level measurements in residential areas using sound source separation. In: Proceedings of the 33rd international congress and exposition on noise control engineering, Prague, Czech Republic; 2004.
[8] Wu H, Siegel M, Khosla P. Vehicle sound signature recognition by frequency vector principal component analysis. In: Instrumentation and measurement technology conference, IMTC/98. Conference proceedings IEEE; 1998, p. 429–34.
[9] Moschioni G, Saggin B, Tarabini M. 3-D sound intensity measurements: accuracy enhancements with virtual-instrument-based technology. IEEE Trans Instrum Meas 2008;57:1820–9.
[10] Genescà M, Romeu J, Pàmies T, Sánchez A. Real time aircraft fly-over noise discrimination. J Sound Vib 2009;323:112–29.
[11] Fernández L, Pogrebnyak O, Rodríguez J, Guerra S. Noise pattern recognition of airplanes taking off: task for a monitoring system. Progr Pattern Recogn Image Anal Appl 2007:831–40.
[12] Rojo Ruiz A, Sánchez Fernandez L, Felipe-Riverón E, Suárez Guerra S. Computational model for aircraft's takeoffs pattern recognition. Progr Pattern Recogn Image Anal Appl 2008:14–21.
[13] Asensio C, Ruiz M, Recuero M. Real-time aircraft noise likeness detector. Appl Acoust 2010;71:539–45.
[14] Brooks RR, Iyengar SS. Multi-sensor fusion: fundamentals and applications with software. Prentice-Hall Inc.; 1998.
[15] De Sa JM. Pattern recognition: concepts, methods, and applications. Springer Verlag; 2001.
[16] Renders H, Schoukens J, Vilain G. High-accuracy spectrum analysis of sampled discrete frequency signals by analytical leakage compensation. IEEE Trans Instrum Meas 1984;33:287–92.
[17] Childers DG, Skinner DP, Kemerait RC. The cepstrum: a guide to processing. Proc IEEE 1977;65:1428–43.
[18] Moschioni G, Saggin B, Tarabini M. The use of sound intensity for the determination of the acoustic trajectory of aircrafts. Madrid: International Congress on Acoustics; 2007. p. 2–7.
[19] Asensio C, Moschioni G, Ruiz M, Tarabini M, Recuero M. Implementation of a thrust reverse noise detection system for airports. Transport Res Part D: Transport Environ 2013;19:42–7. http://dx.doi.org/10.1016/j.trd.2012.12.003.