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Experimental Training and Validation of a System for Aircraft Acoustic Signature Identification

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This paper deals with the experimental validation of an innovative system for the aircraft acoustic signature identification which has been developed by the vibration and acoustics laboratory of the Italian Aerospace Research Center. The system is composed of an algorithm for the acoustic signature identification and a dedicated neural network classifier, trained with a set of experimental aircraft noise data. The algorithm test and validation has been performed for different airplanes during takeoff and landing maneuvers. The experimental activity of ground noise measurements has been carried out at the Naples airport of Capodichino. More than 200 aircraft noise events of five aircraft types (Airbus A320, Boeing B737, McDonnel Douglas MD80, Fokker F100, Aerospatiale/Alenia ATR72), during both takeoff and landing maneuver, have been measured. This paper demonstrates the feasibility of developing a suitable artificial neural network to establish if a time signal, elaborated through a wavelet process, is or is not similar to others, having been recognized as originated from a defined type of aircraft. The artificial neural network was trained by the use of a subset of experimental data and then validated through a comparison with another subset of data from the same experimental campaign. The developed software demonstrated to give more than satisfactory results for each of the acquired spectra, with the maximum error always being under (10)%.

I. Introduction

ACOUSTIC signature identification techniques are commonly used for automatic speaker recognition, that is, the labeling of an unknown voice as one of a set of known voices. Furthermore, great interest is growing on the monitoring and prediction of ship signatures to minimize a ship's susceptibility to being detected, tracked, identified, or targeted. The acoustic signature of a naval vessel is, in fact, one of its greatest vulnerabilities.

For aeronautical applications, this branch of research possesses interesting potentiality. Identification of a noise source and the association between the cause and noise admissible levels is fundamental for airport authorities. It can be applied as support for the radar monitoring of the airports and for the verification of compliance with limitations of annoyance in the area around them. It can allow the surveillance of isolated or dangerous areas and the verification of compliance with peace agreements ("no-fly zone"). The acoustic identification of military airplanes with small radar detection (stealth) and the acoustic surveillance of strategic objectives can play a crucial role in the success of military operations.

The aim of the aircraft acoustic signature identification is to recognize the aircraft type and maneuver during different flight conditions, by processing only the emitted acoustic signal. The central task of the signal classification process is the feature extraction: the assignment of noise time histories to classes which have strictly defined properties.

The most common acoustic signature recognition techniques are derived from the speech recognition methods, founded on time-varying spectral signal representations in terms of time and frequency coordinates. Typical time-frequency distributions such as spectograms, wavelet transforms, multispectra, and Wigner distributions are used not only for the speech recognition, but also for mechanical failure detection, the analysis of seismic data processing, and biomedical engineering.

Several systems have been proposed to recognize and classify different noise sources. A common focus of these systems is represented by the capability of spectral details investigation from the acoustic signatures.

The Fourier transform, widely used for the signal analysis and processing, is not suitable to analyze time-variant spectra of nonstationary and fast transient signals. It does not provide any information regarding the time evolution of the spectral characteristics of the signal. An intuitive way to analyze a nonstationary signal is to divide it into a sequence of time segments where the signal can be reasonably treated as stationary. After that, it is reasonable to perform a Fourier transform to each of the local segments of the signal [short-time Fourier transform (STFT)]. Unfortunately, this approach depends critically on the choice of the window function. Once it is chosen, the width along time and frequency axes is fixed in the entire time-frequency plane. This causes constant time and frequency resolutions.

The wavelet transform is particularly useful for the analysis of a nonstationary and fast transient signal. Unlike the STFT analysis, the window function is a compressed or dilated version of the same function (mother wavelet) when it is shifted through the signal. It allows a time-frequency representation of the signal, contributing to overcome the resolution problems ($T = 1/df$) of the STFT. In a multiresolution wavelet analysis, the signal is decomposed with different resolutions corresponding to different scale factors (levels) of the wavelets. This procedure can be employed to represent the original acoustic noise signal with a series of detail and approximation functions. The resolution, which is a measure of the detailed information, is changed by an iterative filtering process, and a variable scale allows the upsampling or the subsampling of the signal.

Wu et al. [1] proposed the short-time Fourier transform of sampled noise signals and the principal component analysis for the feature vectors extraction. Classification has then been performed by projecting these vectors into the principal component subspace and verifying the distance from the locus of the different training sample set.

Liu [2] described a recognition system based on a biological hearing model to extract multiresolution feature vectors such as

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cochlear filter and A1-cortical wavelet transform. Different classification systems, such as the learning vector quantization (LVQ), the tree-structured vector quantization (TSVQ), and the parallel TSVQ (PTSVQ) have been implemented and compared in terms of classification error and search and training time.

Sampan [3] presented a microphone array technique to detect the presence and classify the type of the sound source. The feature vectors included the energy features extracted in a specific frequency band. A multilayer perceptron and an adaptive fuzzy logic system were used for the successive classification.

Undoubtedly, the classifier accuracy depends on the feature extraction process. The state of the art of the speech recognition techniques, like Mel-frequency cepstral coefficients, and a statistical classifier as Gaussian mixture models (GMM) or hidden Markov models (HMM) [4], seems to be inappropriate for aeronautical applications because of the poor accuracy of the spectral information.

The feature vectors obtained from the log magnitude of the STFT of acoustic signals provide, instead, good practical results. They are often followed by a principal component analysis or by a third-octave bin data partition, to compress the data into feature vectors of reasonable size [4].

As a time-frequency approach, wavelet transform for extracting distinctive information from the acoustic signatures has been investigated. It is the most promising method, used by Choe et al. [5], Maciejewski and Chang [6] and Dress and Kercel [7], that provides time-frequency multiresolution analysis useful for a compact signal representation.

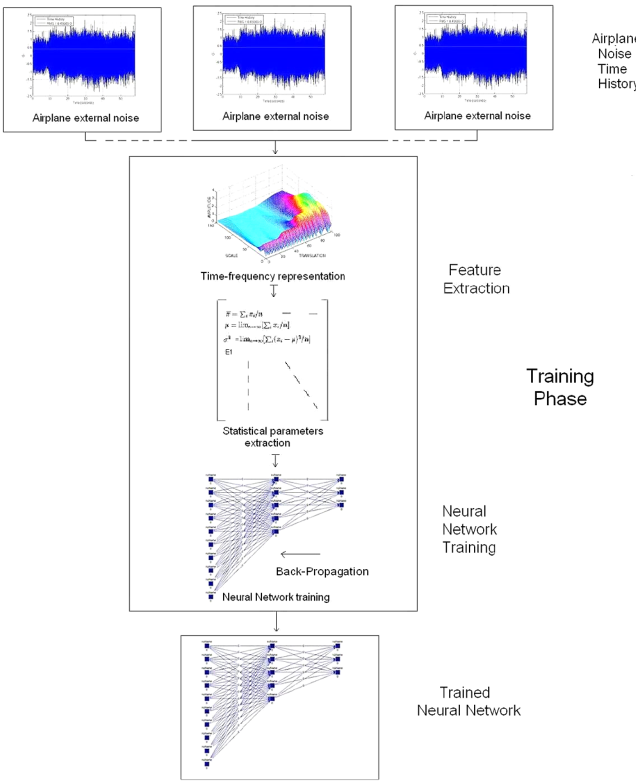

Fig. 1 Aircraft acoustic signature: training phase flowchart.

II. Aircraft Acoustic Signature identification

A. Identification Method

The method developed for the aircraft acoustic signature identification employs a wavelet multiresolution analysis of noise signals and a statistical analysis of the noise events for each aircraft class [8]. This investigation plays a crucial role in learning the system classifier, a dedicated neural network, with feature parameters of reasonable size, and condenses, at the same time, all the peculiar characteristics of each aircraft noise.

The proposed method for the aircraft acoustic signature identification can be summarized into two different phases: 1) training phase and 2) aircraft identification phase.

The *training phase* consists of the definition of the acoustic signal properties and their collection into representative feature vectors of each aircraft acoustic signature. It contributes to define an aircraft feature database on the basis of which the system classifier is designed. In the second phase, the *identification phase*, any new aircraft noise signal is processed by means of a neural network classifier that gives, as output, an estimation of the grade of similarity with the included classes.

In Fig. 1 the training phase is described. Each different airplane noise time history is time frequency analyzed on the basis of a wavelet-based decomposition. This process aims at investigating the frequency content of the original noise signals and offers, at the same time, optimum time-frequency resolution, only limited by Heisenberg's uncertainty principle [9]. The second step, the feature extraction process, is based on a statistical analysis of the wavelet coefficients and on the evaluation of the energy content of each wavelet decomposition level. This approach intends to include, in a statistical point of view, the great variability of the measured data that could affect the signature evaluation of each aircraft class. The wavelet transform coefficients for the finite impulse response (FIR) filter bank are taken from Daubechies [10]. Twelve-level wavelet transform is computed for each of the events. This phase is essential for a correct aircraft noise classification and means to carry out an optimum estimation of the acoustic information.

The classification of each aircraft noise signal employs the feature vectors obtained from the previous analysis to design a dedicated neural network. This process is a function fitting process between the feature vectors and the output vector corresponding to specific aircraft types. It is based on the classes definition and allows the identification of the degree of similarity between any unknown acoustic signal and the classes of recognition.

In the training phase, the extracted feature vectors of each aircraft noise signal, called training data set, are used to train a neural net in which the aircraft types and maneuvers constitute the output vector. This process allows one to tune the weight functions and biases between the net neuron connections.

The recognition classes, correspondent to the number of different aircraft training data, are identified with the output nodes. The back propagation training algorithm is used in the training phase.

The system is trained with the signatures obtained from different noise time histories for each aircraft and maneuver. The final result is a trained neural network which needs a sufficient number of events (patterns) to perform the correct classification of the noise signals to be identified.

The aircraft identification phase is described in Fig. 2. The process of acoustic signature extraction, described above, is again repeated on the "unknown" aircraft noise emission. The feature vector is then processed by the trained neural network classifier to recognize the airplane class with the relative percentage of successful identification. The classification process, performed by the network, consists of the evaluation of the acoustic similarity between the processed noise event and those evaluated during the training phase.

B. Wavelet-Based Feature Extraction

The feature extraction process is generally considered a data mapping procedure which determines an appropriate feature subspace of dimensionality M from the original space of dimensionality N ($M \ll N$).

Wavelet transform, particularly indicated for applications such as image compressing, data compression, and pattern recognition, is a powerful tool for acoustic signature detection purposes.

The continuous wavelet transform of a function $f(t)$ is a decomposition of $f(t)$ into a set of kernel functions $h_{s,\tau}(t)$ called the wavelets:

$$W_f(s,\tau) = \int f(t) h^*_{s,\tau}(t)\,\mathrm{d}t \tag{1}$$

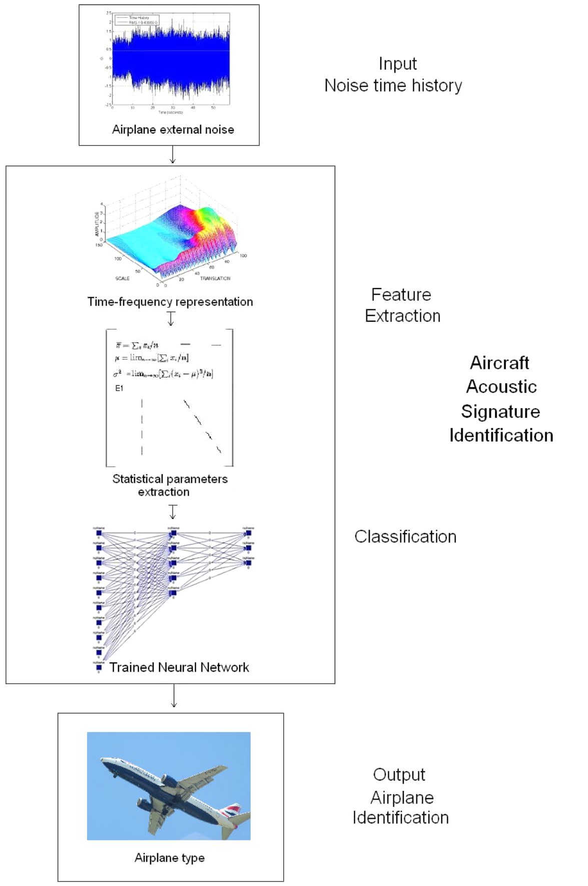

Fig. 2 Aircraft acoustic signature: aircraft identification phase flowchart.

where $*$ denotes the complex conjugate. The results of the continuous wavelet transform are many wavelet coefficients $W_f(s,\tau)$, which are a function of scale s and position τ. The wavelets are generated from a single basic wavelet (mother wavelet) $h(t)$ by scaling and translation:

$$h_{s,\tau}(t) = \frac{1}{\sqrt{s}} h\left(\frac{t-\tau}{s}\right) \tag{2}$$

where s is the scale factor and τ is the translation factor. The wavelets are dilated when the scale $s > 1$ and are contracted when $s < 1$. The wavelets generated from the same basic wavelet have different scales s and locations τ, but all have the identical shape. The constant $s^{-1/2}$ in the expression of the wavelets is for energy normalization. The wavelets are normalized as

$$\int |h_{s,\tau}(t)|^2 \, dt = \int |h(t)|^2 \, dt = 1 \tag{3}$$

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates a great amount of data. Thus, if we choose scales and positions based on powers of two (so-called dyadic scales and positions), the analysis will be much more efficient and just as accurate. We obtain such an analysis from the discrete wavelet transform (DWT). An efficient way to implement this scheme using filters was developed in 1998 by Mallat [11]. The Mallat algorithm is a classical scheme known as a two-channel subband coder.

This very practical filtering algorithm yields a fast wavelet transform—a box into which a signal passes and out of which wavelet coefficients quickly emerge [12]. The original signal S passes through two complementary filters and emerges as two signals: the low-frequency component that represents the approximation coefficients, and the high-frequency component that represents the detail coefficients, Fig. 3. It performs, at the same time, a dyadic decimation (downsampling) of the signal.

In the proposed approach, the wavelet transform coefficients for the FIR filter bank were taken from Daubechies, Fig. 4. However the choice of the wavelet family has been demonstrated as not very relevant when using both a long time signal and a statistical analysis on the signal wavelet decomposition.

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance.

In a wavelet multiresolution analysis, a signal of length $N = 2L$ can be expanded in α different ways, where α is the number of binary subtrees of a complete binary tree of depth L, Fig. 5. As a result, $\alpha \geq 2^{N/2}$.

As this number may be very large, and because explicit enumeration is generally unmanageable, it is interesting to find an optimal decomposition with respect to a convenient criterion, computable by an efficient algorithm. The number of scale decompositions is typically determined by looking for a minimum of the criterion. Because the analysis process is iterative, in theory it can be continued indefinitely. In reality, the decomposition can proceed only until the individual details consist of a single sample or pixel. In practice, it is necessary to select a suitable number of levels, based on the nature of the signal, or on a suitable criterion such as entropy [13]. The use of entropy allows one to determine whether a new splitting is of interest to obtain minimum-entropy decomposition.

The left unilateral binary subtree of depth $D = 12$ has been chosen to detect the major frequency components of the signals, Fig. 6.

Twelve-level wavelet transform was computed for each of the events. The feature extraction process was based on the estimation of first-order statistical parameters and energy content of the wavelet coefficients of each resolution level.

The proposed wavelet-based feature extraction process consisted of the following:

1) 12-level Daubechies $D4$ wavelet transform for each of the events;
2) statistical and energy analysis of the wavelet transform coefficients of the FIR filter bank;
3) feature vectors calculation and normalization;
4) neural network training and classification.

The approximations of the signal at each level were discarded and the detail functions of each level were analyzed. By processing the

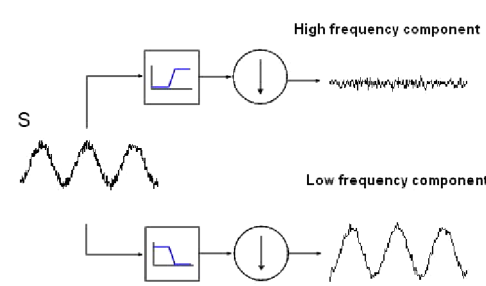

Fig. 3 Schematic diagram of discrete wavelet transform.

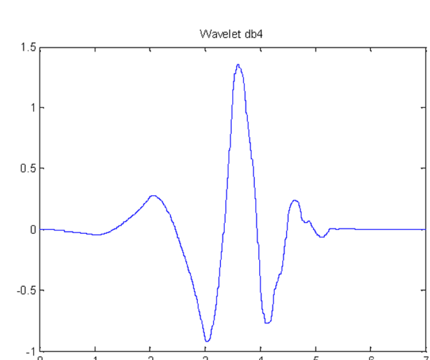

Fig. 4 Wavelet db4 mother.

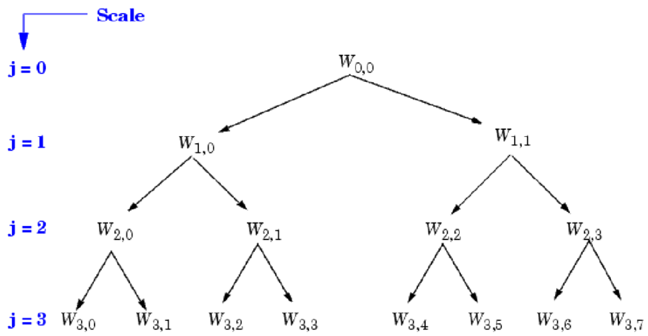

Fig. 5 Wavelet binary subtrees.

signal on wavelet subspaces, the temporal character was not lost; it was compressed by a factor of 2 for each transform level. This algorithm allowed one to condense the acoustic signal information and to extract relevant features from the acoustic events to design a neural network classifier.

The aircraft acoustic signature features made use of the first-order statistical parameters and the energy content of the wavelet coefficients to extract the signal features from the acoustic emission of each aircraft noise data. The feature vectors, consisting of the global statistical parameters (average, standard deviation and variance) and the energy concentration of the wavelet coefficients, calculated for each resolution level, have been used to design the neural network classifier.

In Fig. 7, the noise time history (bottom and right) of an Airbus A320, during a landing maneuver on Naples airport of Capodichino, is reported. The related Daubechies-4 wavelet coefficients of each resolution level are presented.

III. Experimental Training and Validation

As described in the previous paragraph, the system, developed for the aircraft acoustic signature identification, processes noise time histories of airplanes and gives, as output, the identified airplane and maneuver, together with an index of the percentage of successful identification. On the whole, the system performs online processing of the noise events but requires a previous collection of aircraft noise measurements to learn the system classifier. The algorithm input is the noise time history of the airplane to be identified; the identification task is possible only for airplane types and maneuvers for which the classifier has been trained.

A preliminary evaluation of the developed algorithm for acoustic signature recognition has been numerically performed by simulating different airplane noise sources [5]. Subsequently, the algorithm test and validation have been experimentally carried out for different airplanes. An experimental campaign, focused on the collection of noise measurements produced by several airplanes during takeoff and landing maneuvers, has been performed to refine and validate the system. In this paper, the experimental results, in terms of airplane classes analyzed and then recognized, are presented.

The experimental activity of ground noise measurements has been carried out at the Naples airport of Capodichino. Test activities have been executed in 2 weeks (16–27 May 2005). More than 200 aircraft noise events of five aircraft types (Airbus A320, Boeing B737, McDonnel Douglas MD80, Fokker F100, Aerospatiale/Alenia ATR72), during both takeoff and landing maneuvers, have been measured.

A. Noise Data Collection

The experimental activity has been performed at one of the four GESAC (Naples Airport Management Company) noise monitoring

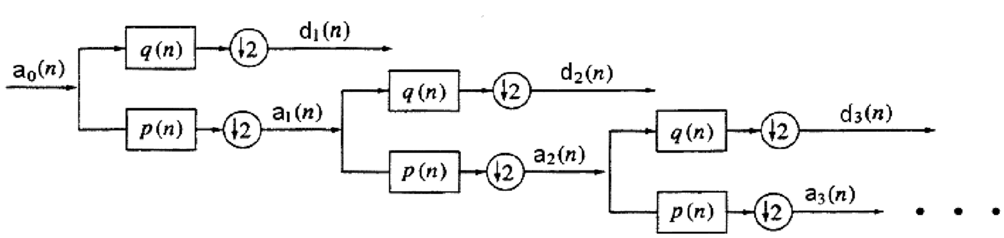

Fig. 6 Left unilateral binary subtree.

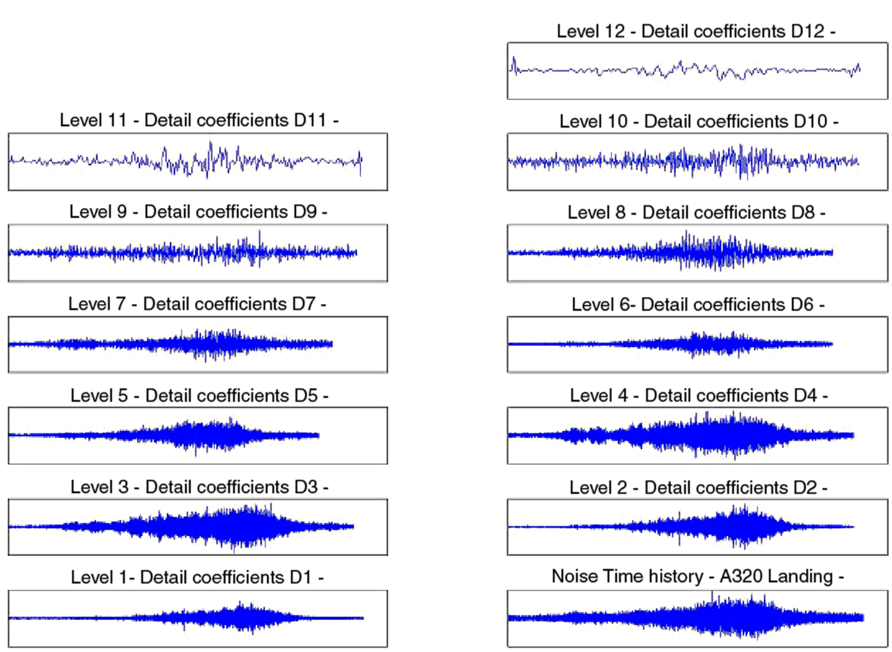

Fig. 7 Twelve-level wavelet transform using D-4 discrete wavelet transform. From the bottom, A320 landing noise time histories at different levels are presented.

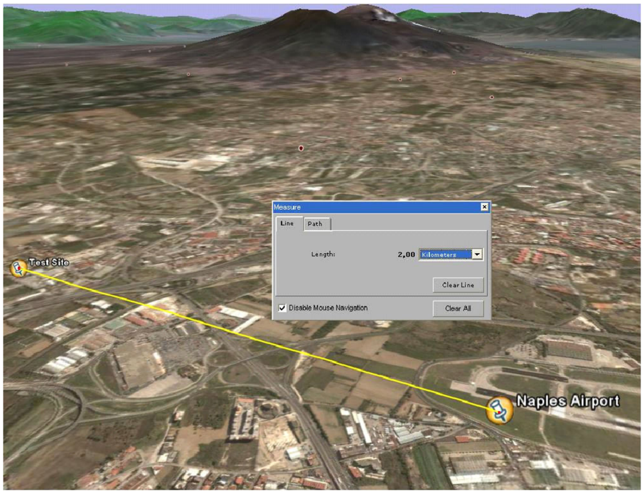

Fig. 8 Test site distance from the Capodichino airport.

stations. The test site was located near the Naples airport (about 2 km), positioned along the clear-way zone, Fig. 8. The final landing phase or initial takeoff phase of several airplanes has been evaluated.

Omnidirectional microphones have been placed, with a dedicated tripod, at about 1 m from the paved edge, and pointed upward. The acoustic events have been recorded with a digital tape recorder. Recorder configuration and operation have been performed with a laptop PC through a SCSI connection, Fig. 9.

Noise signals have been measured with a sample frequency of 40 kHz. In Table 1, the number of total measurements for each class (aircraft and maneuvers) is reported. Data sets were divided into training and identification data. The first have been used to train the neural network, whereas the second have been employed to test the classifier performance. Noise data measurements were grouped into nine airplane classes as follows: 1) Airbus A320 takeoff, 2) Airbus A320 landing, 3) Boeing B737 takeoff, 4) Boeing B737 landing, 5) Fokker F100 takeoff, 6) Fokker F100 landing, 7) MD82 takeoff, 8) MD82 landing, and 9) ATR72 landing.

They correspond to three engine configurations: 1) two turbofans with engine on wing (A320, B737), 2) two turbofans with engine on fuselage (MD82, F100), and 3) one turboprop (ATR72).

Meaningful differences in the measured noise data for each airplane class have been observed. They were attributed to the following reasons: 1) different airplanes, airlines, weight, trust, number of passengers, airplane aging; 2) very different flight altitude; 3) very different weather conditions (temperature, humidity, wind, etc.) and consequently different sound wave propagation and attenuation; 4) no stationary background noise (industrial activity, birds, airport traffic, etc.); and 5) no dead acoustic environment (terrace floor and building reflection).

The nonuniformity of the different noise data for each class (airplane and maneuver) has represented the key problem for the identification task. Despite the nonuniformity of the events included in a class, a lot of efforts have been addressed toward the extraction of a set of independent features. In other words, data variability of each class has been verified small enough to make the features as representative of such a class of acoustic signature.

Table 1 Number of measured runs for each class (aircraft types and maneuvers)

Aircraft	Maneuver	No. of runs	Training data set	Identification data set
MD82	Takeoff	25	13	11
MD82	Landing	31	13	17
A320	Takeoff	20	13	7
A320	Landing	28	13	15
B737	Takeoff	20	13	7
B737	Landing	24	13	11
F100	Takeoff	17	11	3
F100	Landing	23	13	9
ATR72	Landing	4	3	1

B. Aircraft Noise Analysis

The aircraft noise analysis demonstrated the possibility of extraction of homogeneous parameters from aircraft noise measurements, Fig. 10. This activity allowed the evaluation of the feature vector terms and their reliability for the characterization of aircraft classes. The feature vectors have been evaluated in terms of their aptitude of collecting all of the acoustic information useful for the aircraft recognition. Following, some terms of the feature vectors obtained for the different class of airplanes are presented. The analysis has been extended to all the noise signals measured during the experimental campaign and distinguished for the different aircraft types. Figure 11 represents the energy distribution of the

Fig. 10 A320 landing noise measurement.

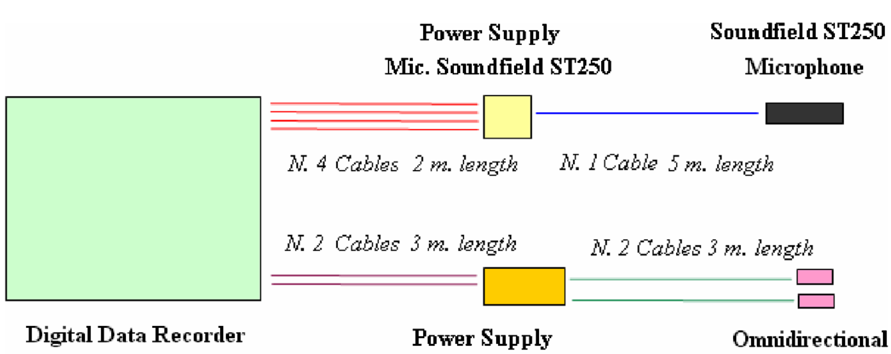

Fig. 9 Test setup: noise measurement stations.

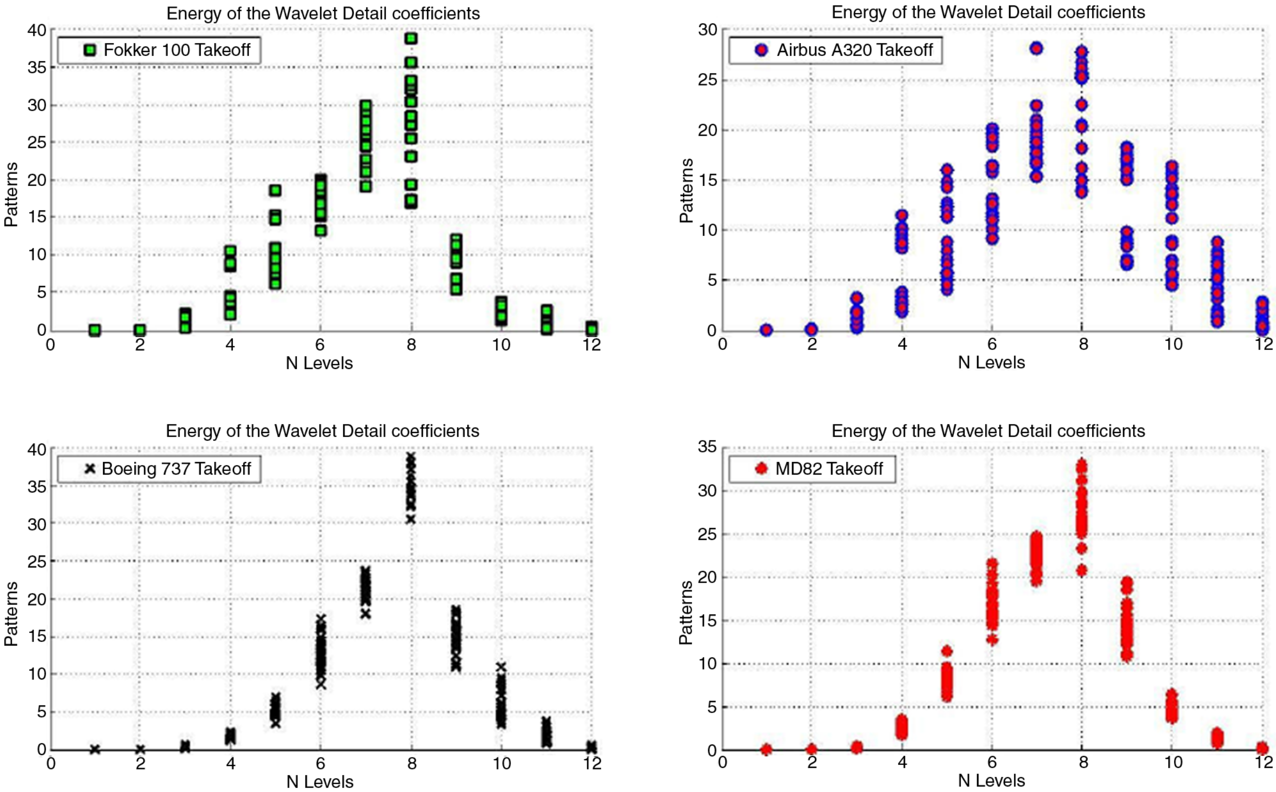

Fig. 11 Energy of the wavelet detail coefficients for the different classes.

wavelet detail coefficients, calculated for each resolution level. The standard deviation distribution of the values extracted from each aircraft noise signal is described in Fig. 12. These data are representative of the different distributions of the feature parameters obtained for each aircraft class. To characterize the variability of the parameters employed for the aircraft classification, the analysis has been also addressed toward the identification of the domain and range of the given events (see Figs. 13 and 14). The differences observed are indicative of the homogeneity of the noise signals emitted from specific airplanes and the possibility of designing a classifier to recognize the different classes. Such results confirmed the reliability of the strategy proposed.

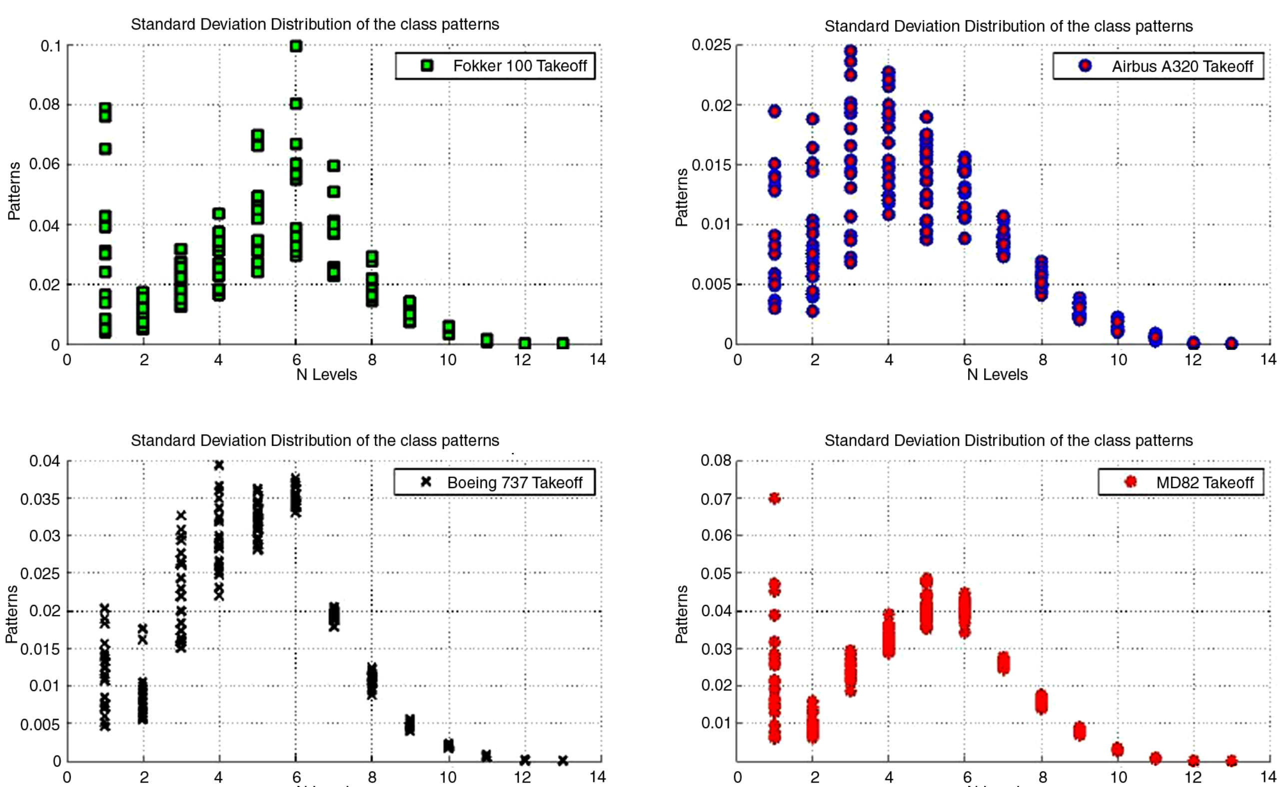

Fig. 12 Standard deviation distribution for the different classes.

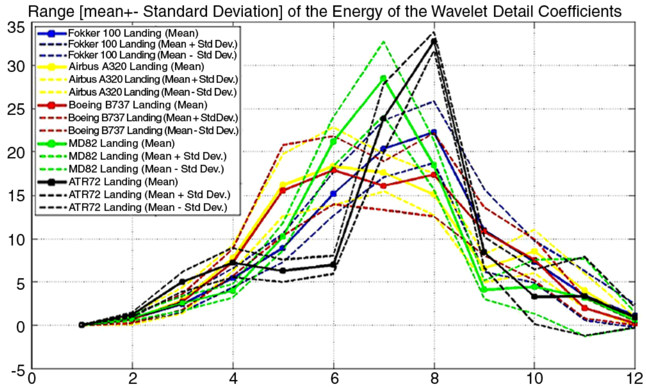

Fig. 13 Range of the energy of the wavelet detail coefficients for the different classes.

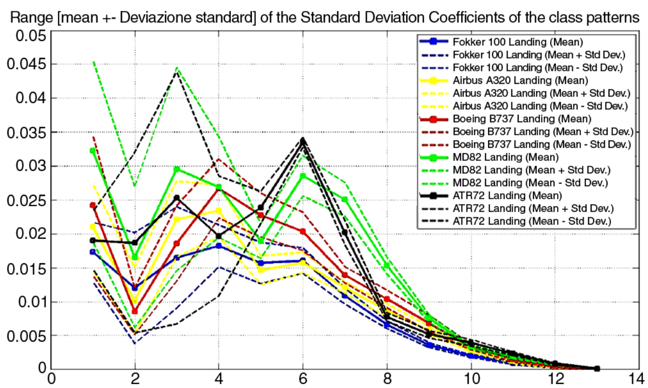

Fig. 14 Range of the standard deviation coefficients of the class patterns.

Meaningful differences in the statistical parameters, extracted from the measured noise data of each class, have been observed. In spite of the environmental influence (background noise, weather conditions) on the aircraft acoustic signatures, the regions of similarity, obtained for the nine classes of aircrafts, resulted in being peculiar and recognizable. For each aircraft class, the noise signatures measured during the landing and takeoff maneuvers have been compared. Figures 15–22 show the range of the signature values calculated for the different types of aircraft. This confirms the possibility of aircraft recognition by acoustic signature identification.

C. Results

The proposed system for aircraft acoustic signature identification has been developed by combining the wavelet multiresolution analysis (WMRA) with an artificial neural network (ANN). After a thorough analysis of the aircraft noise signals, the feature values

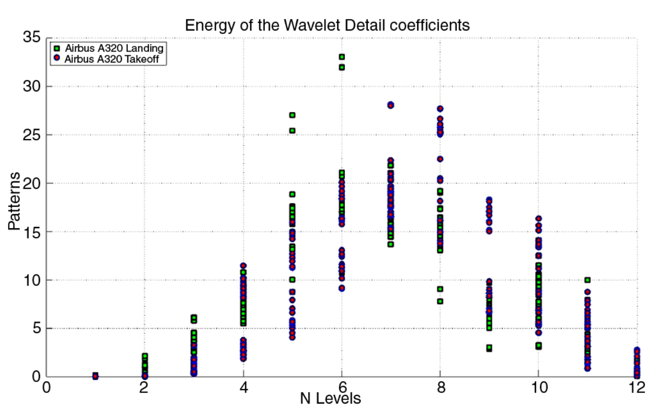

Fig. 15 Airbus A320: comparison of landing and takeoff wavelet detail coefficients.

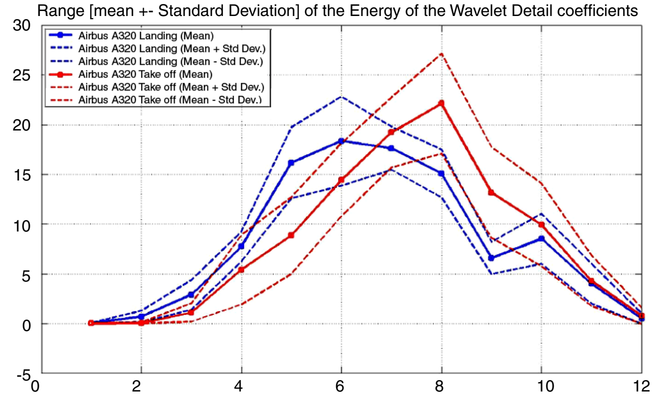

Fig. 16 Airbus A320: wavelet detail coefficient range comparison of landing and takeoff.

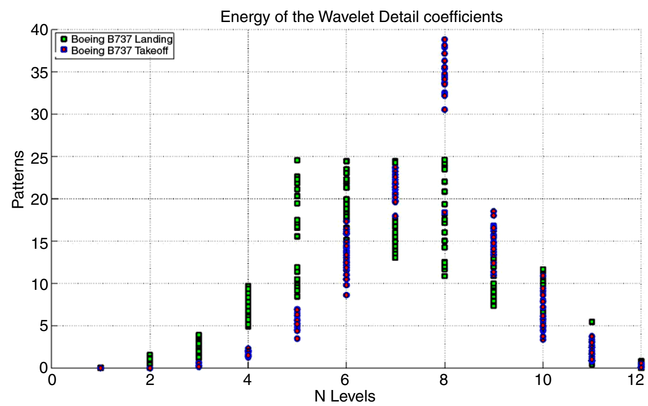

Fig. 17 Boeing B737: comparison of landing and takeoff wavelet detail coefficients.

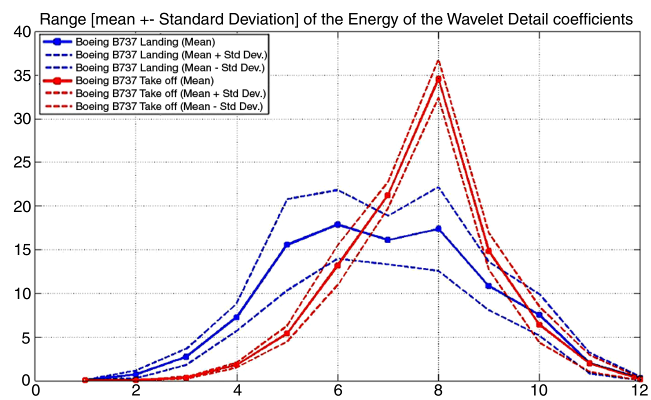

Fig. 18 Boeing B737: wavelet detail coefficient range comparison of landing and takeoff.

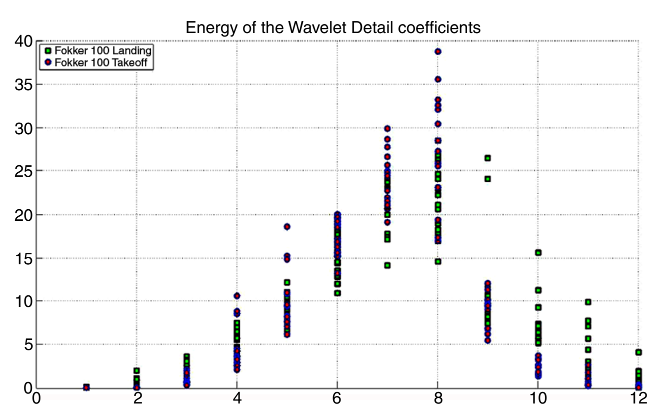

Fig. 19 Fokker 100: comparison of landing and takeoff wavelet detail coefficients.

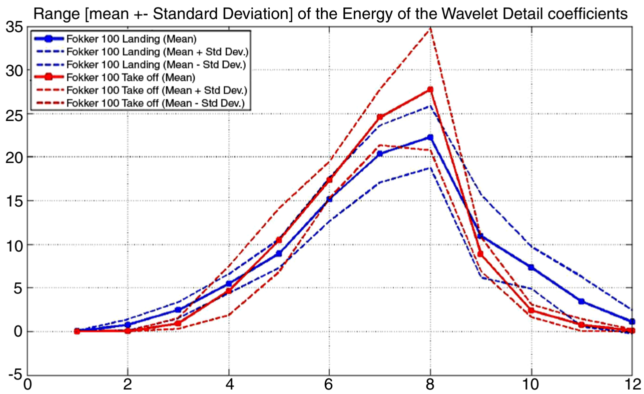

Fig. 20 Fokker 100: wavelet detail coefficient range comparison of landing and takeoff.

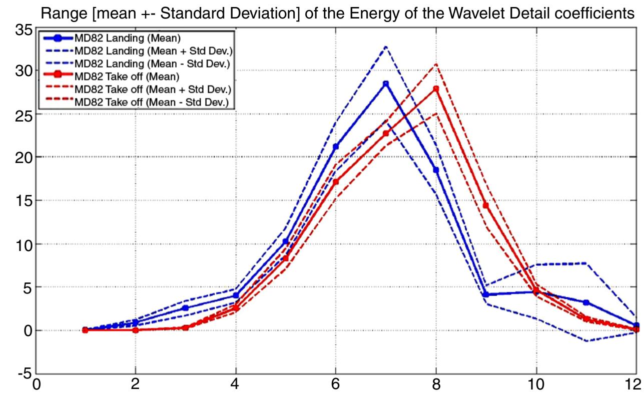

Fig. 22 MD82: wavelet detail coefficient range comparison of landing and takeoff.

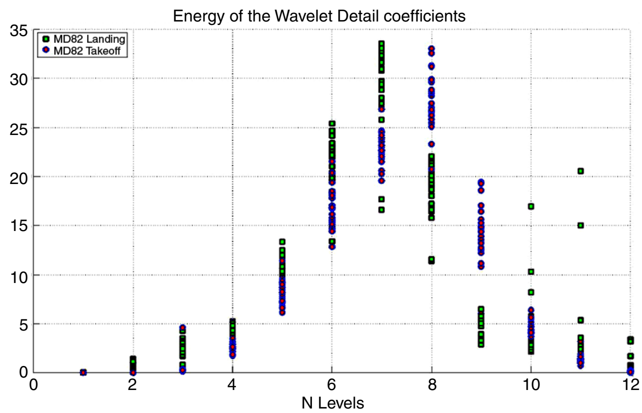

Fig. 21 MD82: comparison of landing and takeoff wavelet detail coefficients.

extracted have been employed to train a neural network. By means of the artificial classifier (ANN) an evaluation of the degree of similarity between the input (the unknown airplane sound pressure time history) and the classes (airplane and maneuver), for which it has been trained, has been performed. The identification of the noise signals has been carried out through an index giving the estimation of the grade of correct recognition.

The results of an identification phase are reported in Fig. 23. It provides different types of information: the identified aircraft and maneuver, the index of relative percentage of successful identification, the file to be identified (input), and a plot of the noise time history (sound pressure versus time) of the processed file.

The degree of similarity, between the current file (input) and those employed for the database training, is expressed in a percentage scale. The 0% value means no similarity with any class; the 100% value means full similarity with one specific class. Thus, a rank of 100% identifies the class having the highest similarity with the input.

In Table 2 the experimental results of the classification test are reported. The analysis of the system performance has been carried out in terms of correct and false identifications. This process was feasible because for each sound pressure time history to be identified, the relative airplane and the maneuver were already known.

In the case of correct identification, the third column of Table 2 describes, for each airplane and maneuver, the number of correct identifications for which the second highest classification rank is <80%; whereas, the fourth column describes the number of correct

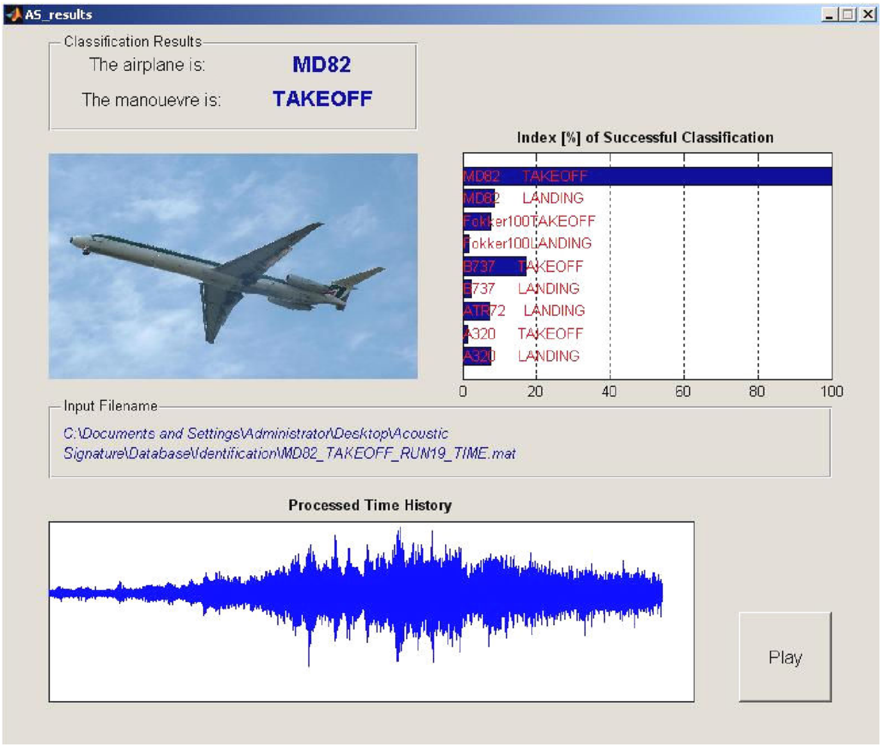

Fig. 23 Aircraft Identification: MD82 takeoff.

Table 2 Classification results

Aircraft	Maneuver	Correct identification 2nd < 80%	Correct identification 2nd > 80%	Wrong identification True > 80%	Wrong identification True < 80%
A320	Takeoff	5	1	0	1 (75%)
A320	Landing	8	5	1 (88%)	1 (70%)
B737	Takeoff	7	0	0	0
B737	Landing	8	2	1 (99%)	0
ATR72	Landing	1	0	0	0
F100	Takeoff	3	0	0	0
F100	Landing	6	1	1 (88%)	1 (<50%)
MD82	Takeoff	10	1	0	0
MD82	Landing	14	3	0	0

identifications for which the second highest classification rank is >80%.

The number of wrong identifications is reported in the fifth and sixth columns of Table 2. In this case, the true airplane and maneuver have not obtained the maximum rank (100%) in the classification process. Thus, for each class, the number of occurrences for which the true airplane has been classified with a rank >80% ($\neq$ 100%) is reported in the fifth column; whereas the number of occurrences for which the correct airplane and maneuver have been classified with a rank <80% is reported in the sixth column.

IV. Conclusions

Noise emissions are a critical problem for aircraft. Identification of the noise source and the association between the aircraft and the emitted sound pressure level is fundamental for airport authorities. Each aircraft presents its own signature by the point of view of noise emitted spectrum. Several algorithms based on the recognition of this kind of information have been developed in literature. Classical fast Fourier transform (FFT) extracts a limited amount of information from the time signal. By using the wavelet transform, this work demonstrates the necessity of collecting information about time variations of the frequency content of the signal to detect moving sources. The wavelet multiresolution analysis of the aircraft noise signals has allowed the definition of a reliable approach. Besides, the procedure developed for aircraft identification (ID) employs a neural network as a classifying algorithm, to define the belonging or not of a vector to a class of elements with some defined properties.

The developed system, unlike electromagnetic radar or ultrasonic sonar, has been thought of as a passive (only listening) modus operandi to allow the identification of airplane types and maneuvers by processing only the sound emissions. The developed artificial neural network has been demonstrated as able to establish if a time signal, elaborated through a wavelet process, is or is not similar to another, having been recognized as originated by a defined type of aircraft.

The artificial neural network was trained by the use of a subset of experimental data, in this same frame of activity, acquired and then validated through the comparison with another subset of elements, and somehow originated by the same experimental campaign.

Experimental data were obtained at the Napoli Capodichino Airport and were relative to (five) different kinds of aircraft.

The developed system was demonstrated as able to give more than satisfactory results for each of the acquired spectra, with the maximum error always under (10)%. Though the tests showed a good success rate in aircraft ID, the tests were done at the same location. The robustness of the ID technique has to be investigated by extending the experimental analysis to a greater noise database comprising several types of aircraft.

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