Monitoring System of Environment Noise and Pattern Recognition

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Abstract—**This paper presents an overview of the wireless monitoring system of environment noise, placed throughout Historical Centre of México City which represents an attractive technological innovation. It takes permanent measurements of noise levels and stream the data back to the main monitoring station every five minutes and the measurements of noise produced during the take-off in a location of the International Airport. The data acquisition is made at 25 KHz at 24 bits resolution. This work allows analyzing the urban noise level and its frequency range. Additionally, a computational model for aircraft recognition using take-off noise spectral features is analyzed based on other previous results. Eight aircraft categories with all signals acquired in real environments are used. The model has an identification level between 65 and 70% of success. These spectral features are used to allow comparison with other aircraft recognition methods using speech processing techniques in real environments. This system type helps to foresee potential effects to health of environment noise.**

Keywords—**noise, aircraft, pattern, recognition, monitoring.**

I. Introduction

The heavy traffic during the morning and evening rush hours creates a noise problem that is difficult to address. The noise emissions should be no more than 68 dB(A) during the day and 65 dB(A) at night. However, the noise level in most areas has been measured between 77 and 82 dB(A). The aircraft classification is based on the principle that the airline should pay a fair price that should be proportional to its noise impact, independently of the weight of the aircraft or of the transport service rendered. Committees of Aerial Transport and Environmental propose an aircraft classification based on the level of noise emission [1], [2].

This aircraft recognition, based on the preprocessed spectral features allows the comparison with other aircraft recognition methods using feature extraction with speech processing techniques, a neural model more complex and measurement segmentation in time, all in real environments [3], [4]. Some discussions have commented on the potential usefulness and feasibility of these preprocessed spectral features of take-off noise for the aircraft recognition. Their lower performance is demonstrated in this paper.

The monitoring system is presented in Fig. 1. Each node includes a half-inch prepolarized IEC 61672 Class 1 microphone [5], [6] with a windscreen, rain protection, and bird spike mounted 4 m above the road surface in a weatherproof case, a data acquisition a card of dynamic range, an industrial computer and wireless connection to Internet by means of 3G Mobile Broadband. Each node measures the noise levels every 30 seconds and streams the data back to the main monitoring station every five minutes. A portable node measures the noise produced during the take-off at International Airport. Fig. 2 shows an example of urban noise patterns of two weeks in the Historical Centre of México City. These patterns will be analyzed in a next stage.

Aircraft classification base on take-off noise becomes a complicated problem when it is done in real environments because the background noise, the weather, the speed of the take-off and even the aircraft's load can interfere with the correct detection.   Some devices with neural networks recognize the aircraft class, but they can only discriminate between jet aircrafts, propeller aircrafts, helicopters and background noise [7].

Fig. 1. Monitoring system of environment noise in México City
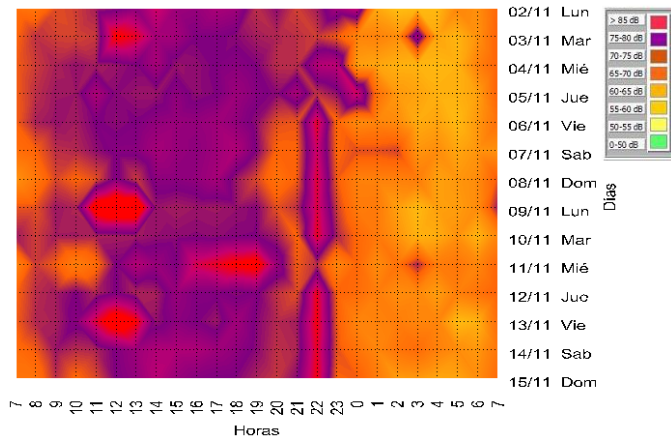
II. WIRELESS MONITORING SYSTEM

Fig. 2. Noise patterns of two weeks. Node placed at Corregidora and Pino Suárez in Historical Centre of México City

Wireless topology reduces costs and provides flexibility in setting up the monitoring systems. Each monitoring node is based on a headless industrial PC running Windows XP with a Wi-Fi adapter and a NI USB-9234 dynamic signal analyzer (DSA).

The system is designed so it can keep collecting data locally for up to 14 days. The government plans to use the acquired data to identify worst times and locations, create noise maps, and to implement regulatory actions to control and prevent the noise and promote a healthier "noise" environment and bring the city up to par with other big cities worldwide. In addition to traditional metrics used for road traffic noise such as Leq (equivalent sound level) at different averaging periods and times of day, the system is capable of recording fractional octave analysis and measuring prominent tones.

If the system analyst makes a request, the nodes are capable of transferring audio files to Central Server, for study of transient signals that may trigger alarms. This is helpful in the identification of isolated sound sources that cause annoyance.

The preliminary strategy was to use the public Wi-Fi in the area which was installed in 2008, but for lack of coverage in all nodes, the communication migrated to 3G (International Mobile Telecommunications-2000 IMT-2000) system provided by a wireless carrier in areas without signal of public Wi-F. 3G allows simultaneous use of speech and data services and significantly slower data rates around 5.8 Mbps on the uplink to the data center compared to the 54 to 100 Mbps possible with 801.11X.

IEEE 802.11 divides the band from 2400 to 2483.5 GHz into channels, analogously to how radio and TV broadcast bands are carved up but with greater channel width and overlap. For example the 2.4000–2.4835 GHz band is divided into 13 channels each of width 22 MHz but spaced only 5 MHz apart, with channel 1 centered on 2.412 GHz and 13 on 2.472 GHz. By reserving certain channels for the noise monitoring system, they may be able to eliminate the slower 3G connection when they expand it.

III. COMMUNICATION PROCEDURE BASED ON TCP/IP

The nodes (measurement points) have a dynamic address assigned by a DHCP server (*Dynamic Host Configuration Protocol*). The Control Center has a IP Static address.

Control Center is comparable to a server. Nodes are similar to a Client. The nodes attempt to initiate the connection (open a Connection TCP). IF the Control Center receives this request of connection, which is validated with a key that must send each node, admits the connection.

Connections TCP/IP stay open. Each node hopes by the data request of the Control Center. The basic period of data request is 5 minutes.

Figures 3, 4 and 5 present examples of monitoring of environment noise for the Historical Centre of México City. Weighting filter A and C may be used [8], [9], [10].

IV. NOISE CHARACTERISTICS OF AIRCRAFT TAKING OFF

The Fig. 6 presents the system block diagram for the pattern generation and recognition. The take-off noise is considered a non-stationary transient signal because it starts and ends in a zero level and it has a finite duration [10].

Figure 7 presents the time-domain representation of a take-off noise typical signal. Fig. 8 shows, most of the signal energy is below 2.5 KHz. In this case, apart from the fact that the signal starts and ends in a zero level, the background noise is more notorious in the ends of the signal because in the central part, the aircraft-generated noise masks it.

For all used aircraft noises the typical form of the amplitude spectrum is observed from 0 to 5000 Hertz, for this reason, in this work was used a sampling frequency of 25000 Hz (samples per second). The amplitude spectrum has 300000 harmonics with resolution of 0.04167 Hz.

NODO 3 — NIVEL SONORO CONTINUO EQUIVALENTE CADA UNA HORA

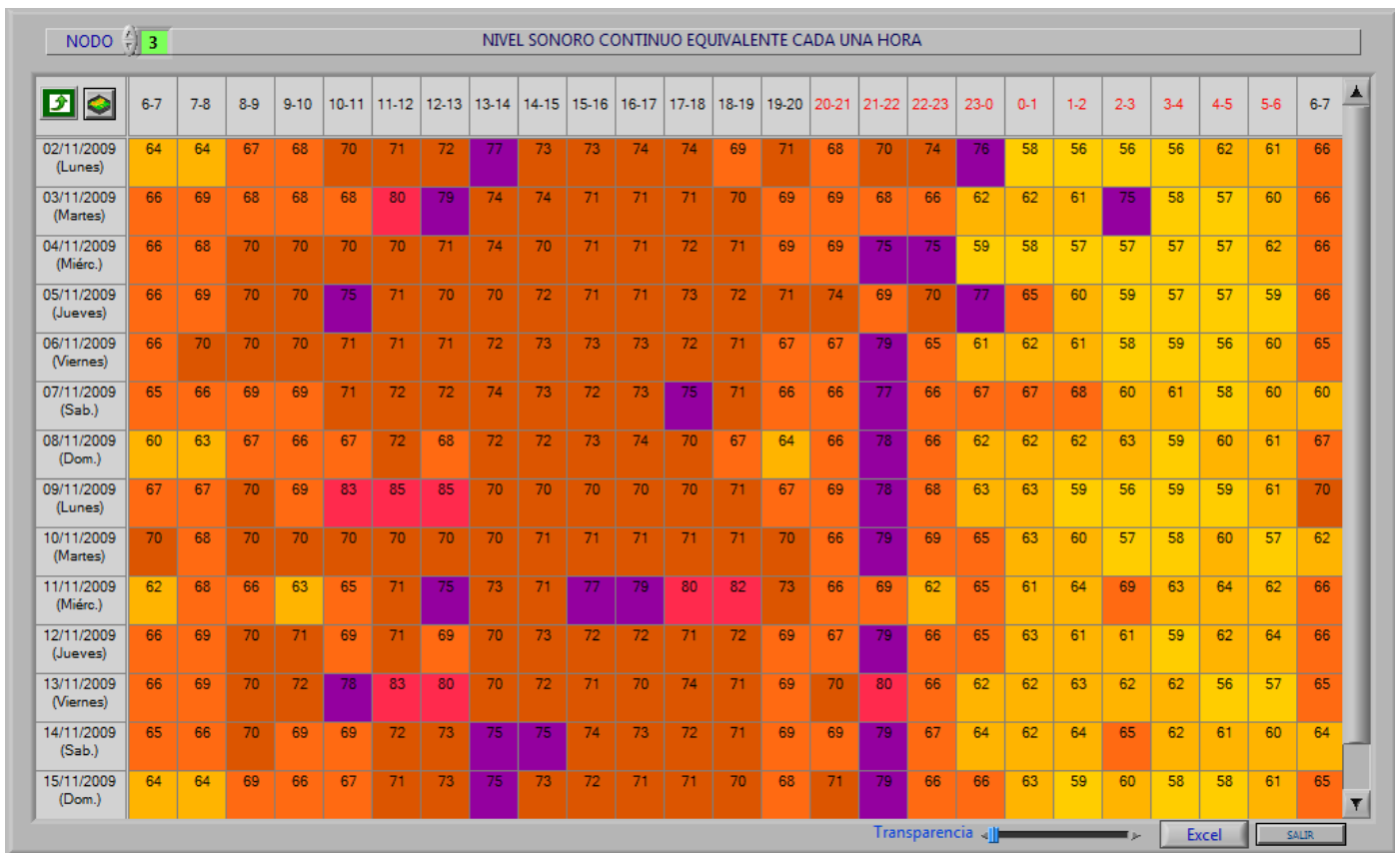|	6-7	7-8	8-9	9-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-23	23-0	0-1	1-2	2-3	3-4	4-5	5-6	6-7
02/11/2009 (Lunes)	64	64	67	68	70	71	72	77	73	73	74	74	69	71	68	70	74	76	58	56	56	56	62	61	66
03/11/2009 (Martes)	66	69	68	68	68	80	79	74	74	71	71	71	70	69	69	68	66	62	62	61	75	58	57	60	66
04/11/2009 (Miérc.)	66	68	70	70	70	70	71	74	70	71	71	72	71	69	69	75	75	59	58	57	57	57	57	62	66
05/11/2009 (Jueves)	66	69	70	70	75	71	70	70	72	71	71	73	72	71	74	69	70	77	65	60	59	57	57	59	66
06/11/2009 (Viernes)	66	70	70	70	71	71	71	72	73	73	73	72	71	67	67	79	65	61	62	61	58	59	56	60	65
07/11/2009 (Sab.)	65	66	69	69	71	72	72	74	73	72	73	75	71	66	66	77	66	67	67	68	60	61	58	60	60
08/11/2009 (Dom.)	60	63	67	66	67	72	68	72	72	73	74	70	67	64	66	78	66	62	62	62	63	59	60	61	67
09/11/2009 (Lunes)	67	67	70	69	83	85	85	70	70	70	70	70	71	67	69	78	68	63	63	59	56	59	59	61	70
10/11/2009 (Martes)	70	68	70	70	70	70	70	70	71	71	71	71	71	70	66	79	69	65	63	60	57	58	60	57	62
11/11/2009 (Miérc.)	62	68	66	63	65	71	75	73	71	77	79	80	82	73	66	69	62	65	61	64	69	63	64	62	66
12/11/2009 (Jueves)	66	69	70	71	69	71	69	70	73	72	72	71	72	69	67	79	66	65	63	61	61	59	62	64	66
13/11/2009 (Viernes)	66	69	70	72	78	83	80	70	72	71	70	74	71	69	70	80	66	62	62	63	62	62	56	57	65
14/11/2009 (Sab.)	65	66	70	69	69	72	73	75	75	74	73	72	71	69	69	79	67	64	62	64	65	62	61	60	64
15/11/2009 (Dom.)	64	64	69	66	67	71	73	75	73	72	71	71	70	68	71	79	66	66	63	59	60	58	58	61	65

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Fig. 3. Noise level, time, date, and amplitude (dBA). Node placed at Corregidora and Pino Suárez in Historical Centre of México City
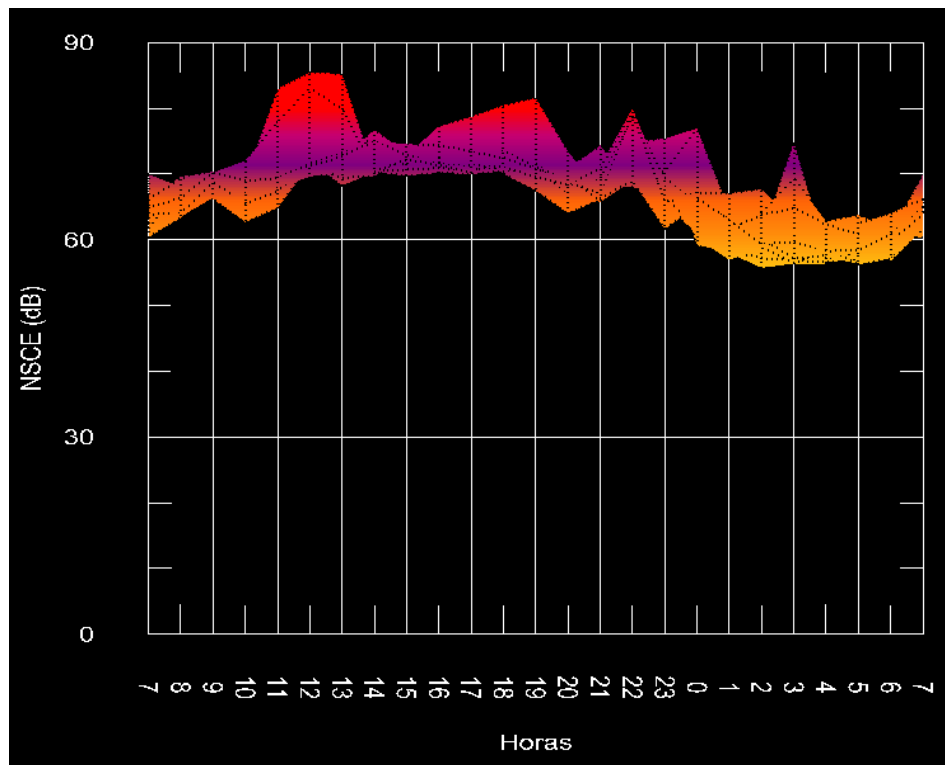
Fig. 4. Noise map displaying noise level in dBA (NSCE), time: hours (Horas). Node placed at Corregidora and Pino Suárez in Historical Centre of México City
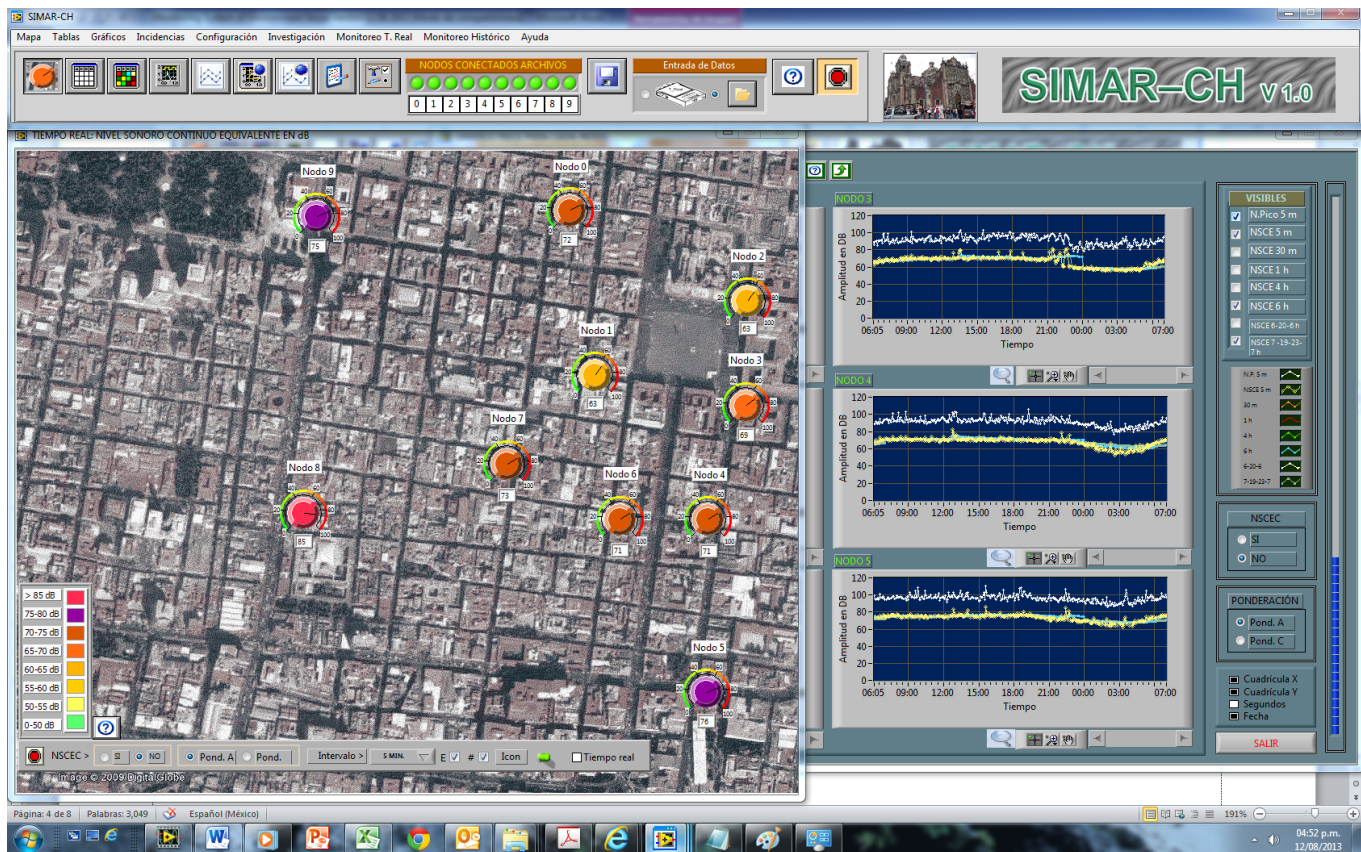
Fig. 5. Central server interface in the Control Centre

Table I presents some examples about noise pollution and its effects on health. The harmful effects are related with the exposure time, sound pressure level and its frequency range.

TABLE I. NOISE POLLUTION AND ITS EFFECTS ON HEALTH (SOME EXAMPLES)

Effect	Exposure time	Sound pressure level	Frequency range
Vibration on visual acuity [14]-[19]	Seconds	110 dB	4 a 800 Hz
Human body vibration [19]	Seconds	105 dB	4 a 100 Hz
Breathing frequency variation [14]-[17]	Seconds	70 dB	0.5 - 100 Hz
Ear pain or discomfort [14]-[17]	Seconds	110 dB	50 - 8000 Hz
Abdominal discomfort [16]	Seconds	80 dB	800 Hz
Speech interference [14], [15]	Minutes	50 dB	100 - 4000 Hz
Stress [20]	Minutes	105 dB	Whole range
Endocrine disturbance [14]-[17]	Days	80 dB	3000 - 4000 Hz
Sleep disturbance [21], [22]	10 - 15 events per night	45 dB	Associated to aircraft noise
Hearing threshold shift and loss [14]-[16]	Months	80 dB	3000 - 6000 Hz
Vibro-acoustic disease [18]	Years	90 dB	< 500 Hz
Cardiovascular disease [15]	Years	90 dB	< 500 Hz
Hypertension [20]-[22]	Years	50 dB	Associated to aircraft noise
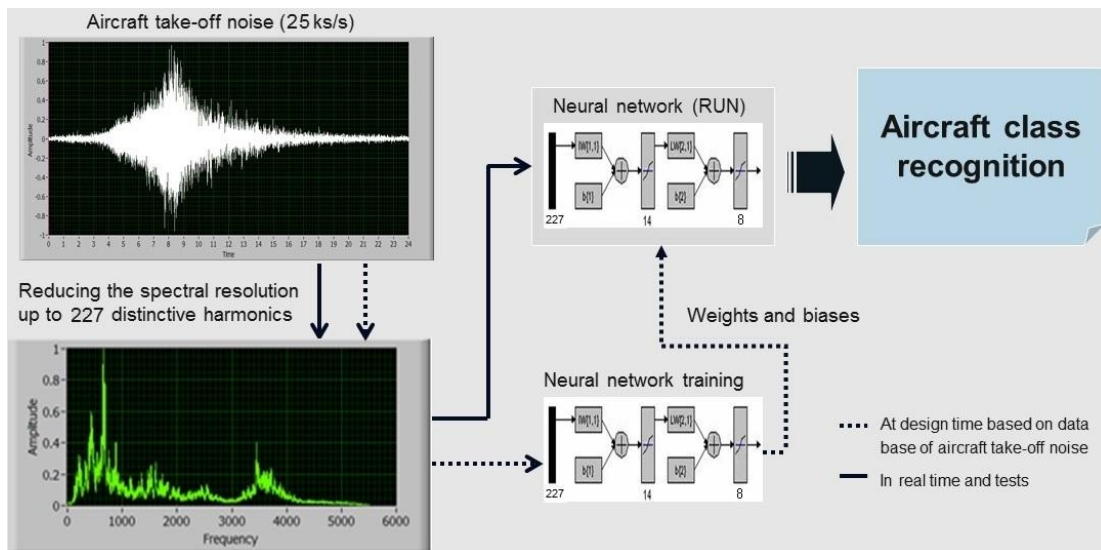
Fig. 6. System block diagram for the pattern generation and recognition

The spectral resolution (number of harmonics) must be reduced because of the following reasons:

1. The amplitude spectrum has 300000 harmonics and its processing will be very complex.
2. It is only of interest the spectral form.

The following suppositions are presented:

1. A reduction method of spectral resolution (with average spectrum) improves the processing results at initial and final times within the measurement interval of aircraft noise. In other words, a feedforward neural network was trained with one noise pattern which was acquired from zero seconds from the aircraft take-off until 24 seconds later; in run time, if the aircraft take-off noise is acquired from 5 seconds until 24 seconds, this time displacement of 5 seconds will affect little the spectral form if its spectral resolution has been reduced.
2. A moving average filter creates a typical form of the aircraft take-off noise spectrums.
3. Decimated average spectrums, with a rate X, conserve the typical spectral form.
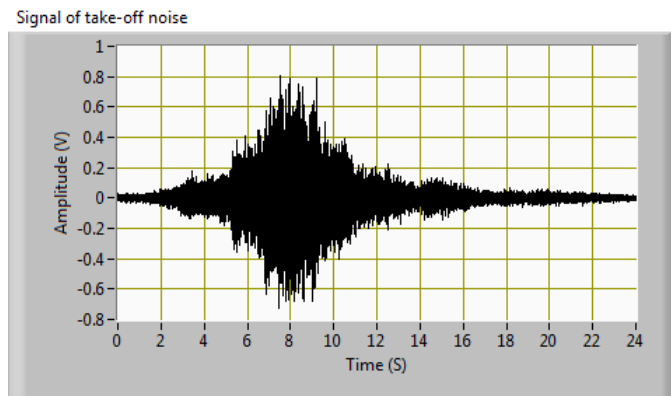
Fig. 7. Time-domain representation of typical signal of take-off noise with sampling frequency of 25 kHz (25 ks/s) for a Boeing 737-200
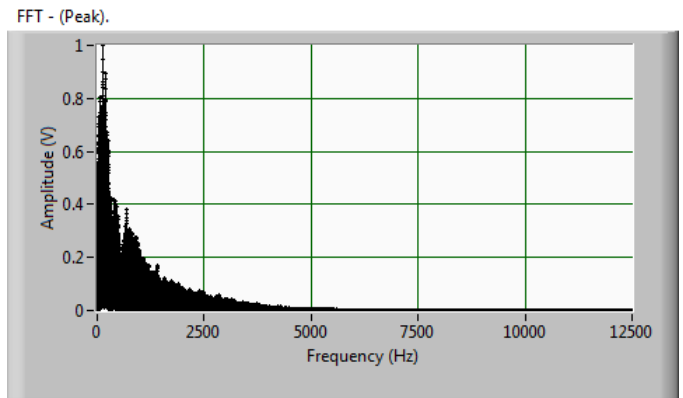
Fig. 8. Frequency-domain representation of the signal of Fig. 7

In this work was used the *Bartlett-Welch* method [11], [12], [13] for spectral estimation. The Bartlett method consists on dividing the received data sequence into a number K, of non-overlapping segments and averaging the calculated Fast Fourier Transform. It consists of three steps:

1. The sequence of N points is subdivided in K non overlapping segments, where each segment has length M.

$$x_i(n) = x_i(n+iM), \quad i = 0,1,...,K\text{-}1, \quad n = 0,1,...,M-1 \quad (1)$$

2. For each segment, periodogram is calculated $\hat{P}_{xx}(f)$

$$\hat{P}_{xx}(f) = \frac{1}{M}\left|\sum_{n=0}^{M-1} x_i(n)e^{-j2\pi fn}\right|^2, \quad i = 0,1,...,K-1 \quad (2)$$

3. The periodograms are averaged for the K segments and the estimation of the Bartlett spectral power can be obtained with (3).

$$\hat{P}^{B}_{xx}(f) = \frac{1}{K}\left|\sum_{i=0}^{K-1}\hat{P}^{(i)}_{xx}(f)\right|^{2} \qquad (3)$$

Welch Method [13] unlike in the Bartlett method, the different data segments are allowed to overlap and each data segment is windowed.

$$x_{i}(n) = x(n+iD),\ n = 0,1,...,M-1,\ i = 0,1,...,L-1 \qquad (4)$$

Where iD is the point of beginning of the sequence i-th. If D=M, the segments are not overlapped. If D=M/2, the successive segments have 50% of overlapping and the obtained data segments are L=2K.

Why Welch method is introduced?
- Overlapping allows more periodograms to be added, in hope of reduced variance.
- Windowing allows control between resolution and leakage.
The Welch method is hard to analyze, but empirical results show that it can offer lower variance than the Bartlett method, but the difference is not dramatic.
• Suggestion is that 50 % overlapping is used.

The data segment of 600000 samples, acquired in 24 seconds, is divided in 24 segments: K=24, with 50% of overlapping, therefore, L=2K=48 overlapped data segments, later is applied the FFT (periodogram) to each segment and they are averaged. In this paper, 8 aircrafts types were tested. The rate of training/validation patterns per plane was 8/3. The trained neural network was tested with 75 patterns in data base and several real time measurements performed in five days.

The Figs. 9, 10, 11 and 12 present an example of aircraft noise signals processed with this method.

The diminution of the spectral resolution allowed maintaining the spectral form with smaller amount of information for the neuronal network training.

Spectral representation up 2.5 KHz

Fig. 10. Average spectral representation of Fig. 9, up 2.5 KHz. 2500 harmonics. White curve is filtered with moving average filter

Spectral representation up 2.5 KHz

Fig. 11. The filtered curve is normalized

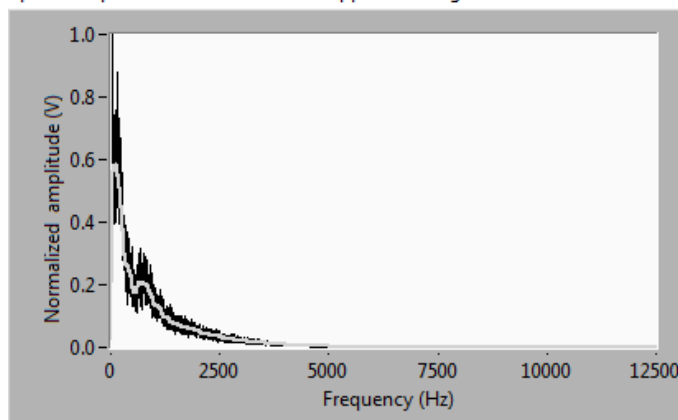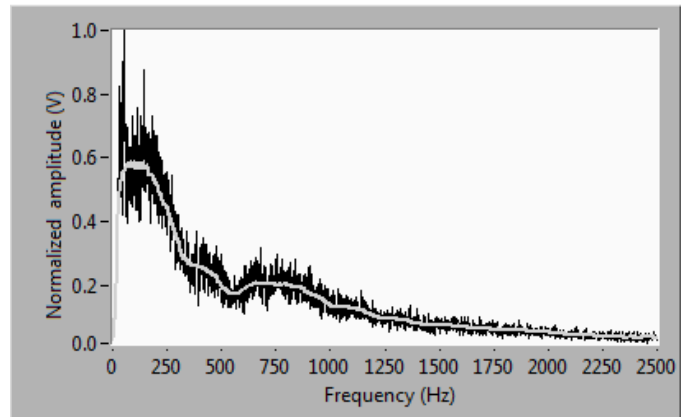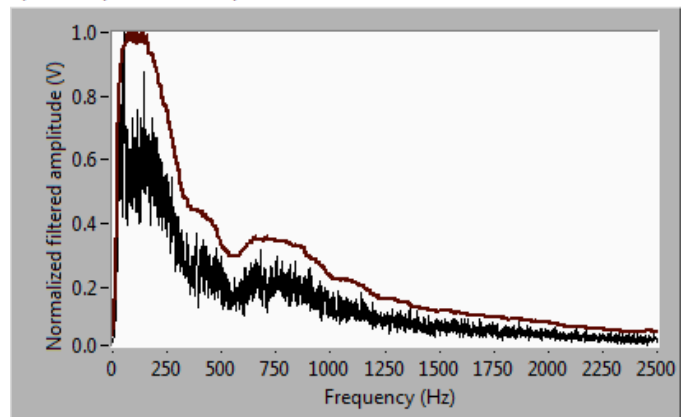Spectral representation with 48 overlapped data segments.

Fig. 9. Average spectral representation of 48 overlapped data segments, for a Boeing 737-200. Each segment has 25000 samples (one second). Filter rank = 50, 12500 harmonics. White curve is filtered with moving average filter

Spectrum decimation up 2.5 KHz. Decimation factor = 11
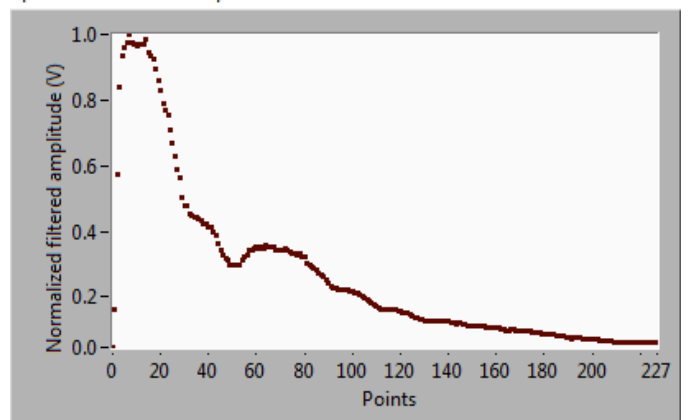

Fig.12. Normalized filtered curve with decimation. The 227 points (processed harmonics) are the neural network inputs

V. NEURAL MODEL AND PERFORMANCE EVALUATION

The neural network has 227 inputs. Every input is a harmonic normalized and processed, an example was presented in Figs. 9 to 12. The output layer has 8 neurons, corresponding to the 8 recognized aircraft. After several tests, the neural network was successful with a hidden layer of 14 neurons. The activation functions are tan-sigmoid. The Fig 13 presents the topological diagram and training performance. The training performance was successful with an error of $1.12851e^{-10}$ in 300 epochs.
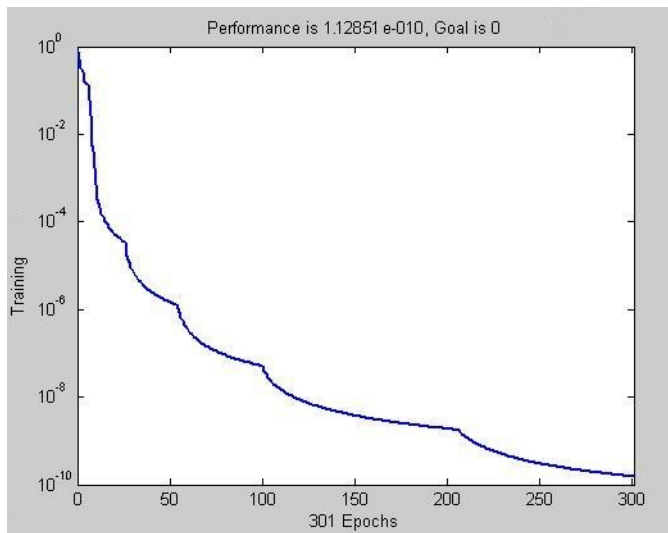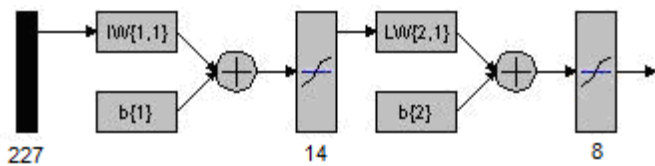

Fig. 13. Neural network topology and training performance. Input: 227 neurons (processed harmonics of aircraft noise). Output layer: 8 neurons (aircrafts type)

A test of aircraft recognition is presented in Table II. The average identification level is 65%. Table III shows a performance evaluation, in percent of success, compared with the referenced method in [3]. The aircraft recognition methods using feature extraction with speech processing techniques [3], [4], [23], a neural model more complex and measurement segmentation in time [4], all in real environments, have higher performance than an aircraft recognition method whose signals were acquired in controlled environments and with preprocessed spectral features [24]. In this paper the methods are evaluated under similar conditions.

TABLE II. AIRCRAFT RECOGNITION RESULTS WITH PATTERNS IN DATA BASE

AIRCRAFT CLASS	PATTERNS FOR TEST	RECOGNIZED	PERCENT OF SUCCESS
Airbus 1	8	5	62
Airbus 2	9	6	67
Airbus 3	9	5	55
Airbus, Boeing 737-800	10	7	70
Atr-42	6	4	67
Boeing 737-100, 737-200	14	9	64
Boeing 737-600, 737-700	12	8	67
Boeing 747-400	7	5	71
TOTAL	**75**	**49**	**65**

TABLE III. PERFORMANCE EVALUATION COMPARED TO THE PUBLISHEDED METHOD [3] IN PERCENT OF SUCCESS.

AIRCRAFT CLASS	PUBLICATED METHOD [3]. (USING ONLY LINEAR PREDICTION CODE)	METHOD ANALYZED IN THIS PAPER
Airbus 1	80	62
Airbus 2	83	67
Airbus 3	66	55
Airbus, Boeing 737-800	71	70
Atr-42	100	67
Boeing 737-100, 737-200	72	64
Boeing 737-600, 737-700	77	67
Boeing 747-400	75	71
TOTAL	**80**	**65**

VI. CONCLUSIONS AND FUTURE WORK.

The system makes various types of spectral analyses and allows to obtain the main used statistical indicators for environment noise which can be expressed in dB(A) or dB(C) depending of the used weighting filter. Possible potential affectations to health can be determined, to different exposition times, which can give an idea of what can happen if the sonorous levels stay during a certain time.

The system allows making measurements of noise produced by airplanes at airport during take-offs. The

measurement of the events is during 24 seconds, with sampling frequency of 25 KHz. The most representative frequencies of signal are below the 2.5 KHz.

Different analyses are developed, as well as the aircraft identification as much in real time, as in sounds stored previously, which have been stored without any class of processing. This allows that during a measurement simply the information of the take-offs is captured and later a deep analysis is made of the stored information.

The aircraft recognition based on their take-off acoustic impact improves to an environment noise monitoring system. The cited methods are robust to disturbances such as sounds of birds which they are near the microphone, barks, sounds of trucks, sounds of other airships which they are maneuvering within the airport, sounds generated in the houses near the point of measurement like music, works, even voices of the operators; in addition to the variations generated by the climate, the speed and the load of the airplane at the moment of the take-off.

The aircraft recognition methods using feature extraction with speech processing techniques, parallel or combined neural models and measurement segmentation in time [3], [4] or spatially are the appropriate technical-scientific recommendations for a best performance.

For future work, we will used spatial information to extract patterns related with aircraft position. This will improve the recognition performance and the acoustic impact estimation.

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