

Sound Features for Aircraft Identification

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Abstract. This paper presents a method that generates useful patterns for aircrafts' classification which bases on their sound in real environments. Having a 94.4 % of effectiveness, this method considers 13 different aircraft categories for their classification.

1. Introduction

Nowadays, noise represents an important problem for the big cities of the world; it is produced by a wide quantity of electric machines, factories, etc. In addition, one of the most annoying noises that can be found is the one generated by means of transportation. Among these, aircrafts generate the highest amount of acoustic energy. Therefore, the areas near airports are the most affected.

Some of the noise effects on humans have been detected [1]. However, these effects are not generated in the same way by all the aircrafts. Consequently, the necessity of classifying them by model or category in order to determine to which class belongs the noise of the detected airplane, emerges. Currently, there are some measurement equipments that use neural networks to identify the class of noise. Nevertheless, today, we can only distinguish between jet aircrafts, propellers aircrafts, helicopters and background noise [2].

This paper's objective is to find specific features of the aircraft-generated noise, that lead to its identification in real environments, where background noise can interfere.

The aircraft-generated noise samples used for this research were taken at 25 KHz during 24 seconds in the Mexico's City International Airport at the moments of the takeoffs.

2. Aircraft-Generated Noise Characteristics.

Aircraft-generated noise is considered a non-stationary transient signal because it starts and ends in a zero level and presents a finite duration.

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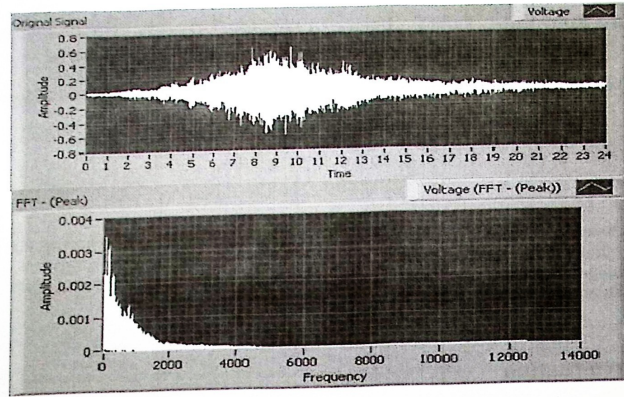


Fig 1. Signal and spectrum of frequencies of the takeoff noise of a MD87.

As Figure 1 shows, most of the energy of the signal is below 2 KHz. In this case, apart from the fact that the signal starts and ends in a zero level, we can find background noise that is more notorious in the ends of the signal because in the central part, the aircraft-generated noise covers it. This is why this signal is described by the following equation (1).

$$S(t) = \alpha_0 R_{\text{aircraft}}(t) + \alpha_1 R_{\text{source 1}}(t) + \dots + \alpha_n R_{\text{source n}}(t) \quad (1)$$

Thus, the addition of the different noise sources, which are modified by an factor which depends on the weather and the Doppler effect, among others.

3. Signal's Features Extraction

3.1. Pre-Processing

- Frequency weighting filter C. This filter, attenuates low frequencies, helping to keep stable the form of the spectrum before different samples of the aircraft because the microphone's response to low frequencies is not always adequate, especially, under 20 Hz. This filter was created to model the human ear's response to sounds of great intensity. It is used to evaluate environmental sounds and low frequency sounds in the audible frequencies band [3].

The frequency weighting filter C values can be calculated basing on the following equation (2) [4]:

$$C(f) = 20 \log \frac{1.0071 \times 12200 f^2}{(f^2 + 20.6^2)(f^2 + 12200^2)} \quad (2)$$

- Centering the signal. To center the signal, we have to look for the point with the highest intensity and see which of the ends is the nearest, taking the same number of points towards the opposite side. This is helpful for two reasons. First, it helps to eliminate the noise that is more notorious in the ends because in the centre the aircraft-generated noise covers the background noise. Second, it prepares the signal so a window can be applied to it. After this, the signal is normalized.

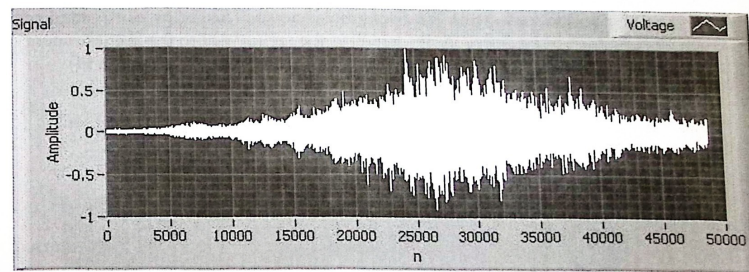


Fig 2. Centered and normalized signal.

- Separating the background noise. In order to separate the background noise, we have to calculate the standard deviation of the signal and we get the values minor to the standard deviation; the highest values are taken to zero. This is done under the premise that the information held in the values minor to the standard deviation is background noise. The standard deviation is calculated by means of the following equation (3).

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2} \quad (3)$$

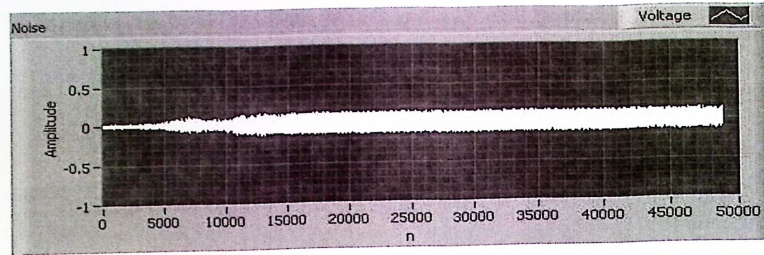


Fig 3. Background noise of the signal.

- Applying Gauss window. Now, we have to apply a Gauss window to the two signals we have: the signal of the aircraft-generated noise and the resulting signal of the separation from the background noise. This helps us to stand out the spectrum characteristics in the center of the signal, where the highest energy of the signal is. The Gauss window is calculated basing on the equation (4).

$$W_g(x) = e^{-\frac{f(x)^2}{2\sigma^2}} \quad (4)$$

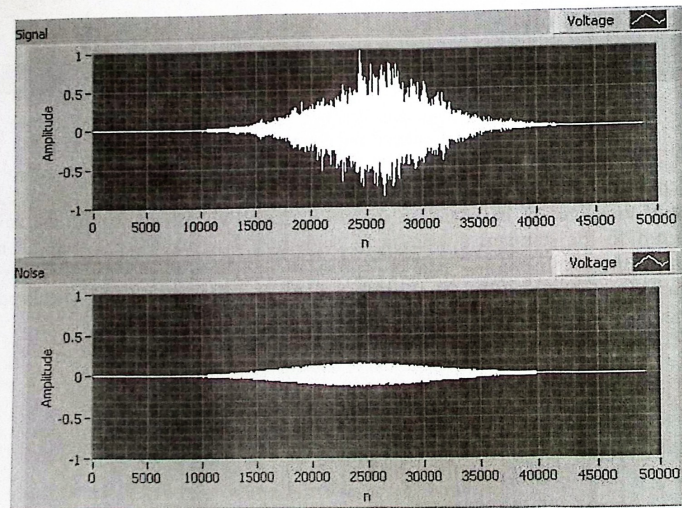


Fig 4. Signal and background noise after application of the Gauss window.

3.2. Processing

For the pre-processed signal we use the autoregressive model, in order to model the aircraft-generated noise behavior. This model is used by the LPC (Linear Prediction Code) to describe the vocal tract as an IIR (Impulse Infinite Response) filter. This model considers that a sound can be described as an IIR filter with a white noise entrance, which, when passing through it, generates sound [5], [6]. This filter is described by the following equation (5).

$$R_z(z) = \frac{1}{\sum_{l=0}^p a_l z^{-l}} = \frac{1}{A(z)} \quad (5)$$

Therefore, the first thing to do is to calculate $A(z)$ which are the filter quotients. The $A(z)$ vector is calculated by solving the following equation (6) using the *Levinson – Durbin* [6] method.

$$\begin{bmatrix} R_{ss}(0) & R_{ss}(-1) & \Lambda & R_{ss}(-(p-1)) \\ R_{ss}(1) & R_{ss}(0) & \Lambda & R_{ss}(-(p-2)) \\ M & M & \Lambda & M \\ R_{ss}(p-1) & R_{ss}(p-1) & \Lambda & R_{ss}(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ M \\ a_p \end{bmatrix} = - \begin{bmatrix} R_{ss}(1) \\ R_{ss}(2) \\ M \\ R_{ss}(p) \end{bmatrix} \quad (6)$$

$R_{ss}(k) = R_{ss}(-k)$ therefore $R_{ss}(-1) = R_{ss}(1)$ and so on.

To get the $R_{ss}(k)$ values, we use equation (7). The $1/N$ factor is the factor of the partial autocorrelation scale, which guarantees the coefficients stability [6].

$$R_{ss}(k) = \frac{1}{N} \sum_{l=0}^{N-1-k} S(l+k)S(l) \quad \text{for } |k| < p+1 \quad (7)$$

We have to choose a “p” number. The bigger this value is, the filter’s frequency response will be more approximated to the FFT. In this case, the number used was $p=310$ (it was obtained by means of experimentation); it was chosen because if p were a lower value, some characteristics would be lost, and if it were a higher value, it would be more susceptible to the variations between patterns of the same class, which can be produced by the wind, humidity, the speed of the takeoff, or just the differences existent between engines; at the same time, it lets us differentiate between the different classes of aircrafts.

The frequency response $H(w)$ of the IIR filter is obtained basing on the following equation (8). The coefficients obtained after applying the FFT are divided term by term.

$$H(w) = \frac{FFT(1)}{FFT(A(z))} \quad (8)$$

A FFT of 4096 was used because it allows us good precision with few values. Now, we calculate the magnitude of each term of the vector given by equation (9).

$$|H(w)| = \sqrt{Re^2 + Im^2} \quad (9)$$

When we apply the FFT of 4096 to a signal sampled at 25,000Hz we get 2048 coefficients that are equivalent to 12,500 HZ. Of all the 2048 values, a great part is mostly zeros, and many others are values that do not allow us to distinguish between classes; this is why only the first 140 points were taken, because there is where we can find the biggest differences between classes.

After this, the autoregressive model is applied to the two signals obtained from the pre-process that are shown in Figure 4.

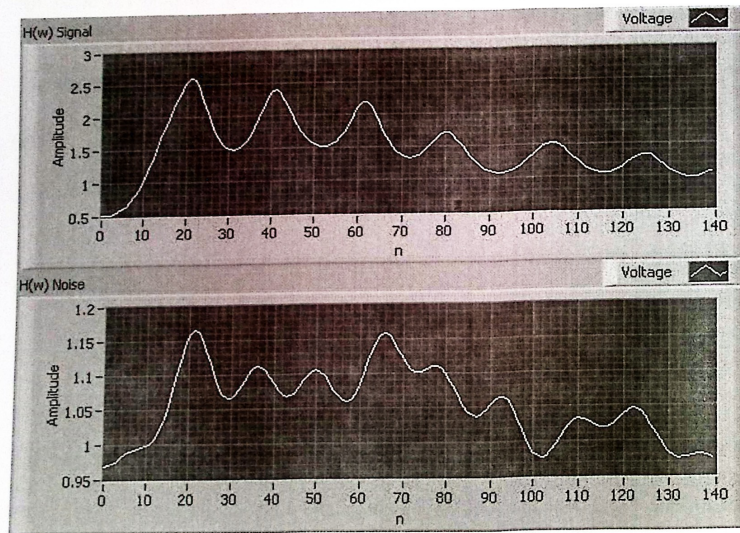


Fig 5. Signal and background noise frequency response.

Now, we subtract the $H(w)$ coefficients of the background noise from the $H(w)$ coefficients of the signal.

Due to the subtraction some of the coefficients might be negative, in which case, they are taken as a 0. This subtraction attenuates the frequencies introduced by the background noise in the aircraft-generated noise.

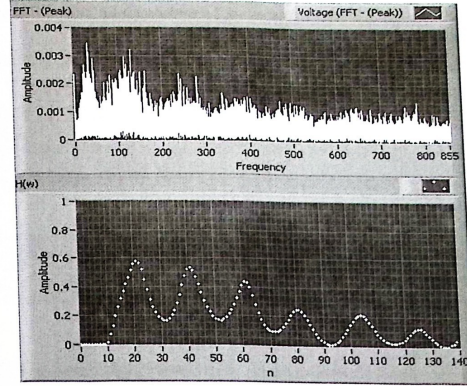


Fig 6. FFT and $H(w)$ of a MD.

As Fig. 6 shows, the $H(w)$ with few points approximates to the envelope of the FFT but with some differences. The main difference is that the first peak shown in the FFT does not appear because of the weighting filter C which keeps stable the $H(w)$ of the different aircrafts of the same class.

Finally, we have to normalize the $H(w)$ by means of the following:

- We take the maximum value of the $H(w)$ and we divide it by all the points, as shown in equation (10).

$$H_{\text{norm}}(w) = \frac{H(w)}{\text{MAX}(H(w))} \quad (10)$$

- We calculate the mean and the Standard deviation of $H_{\text{norm}}(w)$; next, we apply equation (11).

$$H_{\text{norm}2}(w) = \frac{H_{\text{norm}}(w)}{(w + \sigma) \text{ME}} \quad (11)$$

In this case, ME is the mean, σ is the Standard deviation of H_{norm} and $\alpha =$ is a factor to make that most of the $H_{\text{norm}2}(w)$ values are minor to 1.

When we do the normalization this way, we make that in case any value of $H(w)$ gets out of the range, the others remain stable. See Figure 7.

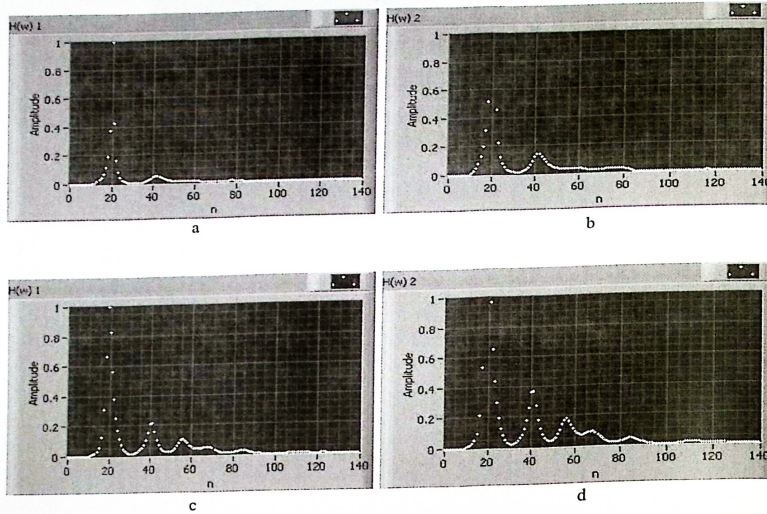


Fig 7. a) ATR-42 (1) with classic normalization, b) ATR-42 (1) with the proposed normalization, c) ATR-42 (2) with classic normalization, d) ATR-42 (2) with the proposed normalization.

Figure 7 shows two aircraft ATR-42, with big variations between them. We can observe that in the classic normalization a) and c), the second peak is multiplied by 4, it changes from 0.05 to a little over 0.2. On the other hand, if we use the proposed normalization b) and d), the variation is from 0.15 to a little over 0.35, so, it is multiplied by a factor of 2.33. The differences between the two ATR-42 owe only to component $n = 20$. As shown in a), this component is very big, thus attenuates the other points. However, when using the proposed normalization, although component $n = 20$ is out of range, it has a value of 1.78 and the other points are less affected, so, they remain stable and recognizing is made easier.

4. Results

By using this methodology, a backpropagation neural network was created. It counts with 140 input neurons, 27 middle neurons and 13 output neurons; 55 patterns were used for training, 6 per class, causing repeated patterns in certain classes.

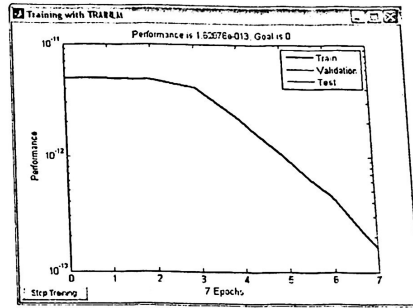


Fig 8. Neural network training.

It was obtained a 94.4% of effectiveness with 90 patterns. It is important to remark that these patterns are contaminated with voices, barks, bird's sounds, background music, etc. and they were obtained under different weather conditions during 3 different measurements (June 25th, 2007; July 6th, 2007 and December 21st, 2007).

Table 1. Mistakes per category.

Category	Total number of patterns (training patterns)	Number of mistakes
Airbus 1	5 (4)	0
Airbus 2	4 (3)	0
Airbus 3	13 (6)	1
Airbus, Boeing 737-800	10 (6)	2
Atr-42	2 (2)	0
Boeing 737-100, 737-200	2 (2)	0
Boeing 737-600, 737-700	13 (6)	0
Boeing 747-400	1 (1)	0
Fokker F100	8 (5)	0
Fokker F100 2	2 (2)	0
Fokker F100, Boeing 737-200	9 (6)	0
Fokker F100, Boeing 737-200 2	11 (6)	1
MD87, MD88	10 (6)	1

Figure 9 shows one of the sample patterns used, which lacking a considerable part of the signal, was correctly classified as a MD87.

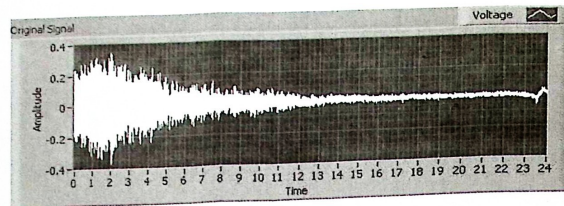


Fig 9. Noise example of a MD87.

5. Conclusions and Future Work

In spite of having complicated circumstances due to the noise, which can be generated by a great number of different sources, with this technique we can get good results without these circumstances interfering with the identification.

In addition, a test was made, changing the sample frequency to 12500 Hz, the AR model with $p = 155$ and a FFT of 2048, in order to keep the same Δf . In this case similar results were obtained, with a diminution of 75% of the processing time.

For later work, the differences of the yield when applying this technique after segmenting the original signal must be analyzed. Also, new parameters to create the neural network should be tested; for example, the area under the curves found in the response of frequency $H(w)$ of IIR filter that modelates the noise; another parameter that can be considered are the slopes found in the highest points of each peak existent in the $H(w)$ response.

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