2011 International Conference on Network and Electronics Engineering
IPCSIT vol.11 (2011) © (2011) IACSIT Press, Singapore

Detection and Identification of an Aircraft by Processing its Acoustic Signature

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Abstract. The research paper is aimed on simple experimental validation of detecting and identifying an unknown aircraft by analyzing Energy Spectral Density (ESD) of its acoustic signature. To carry out the experiment, the software is developed in MATLAB environment. The feature vector space is constructed with 200 aircraft acoustic signatures which are downloaded from the Internet. The software is tested against each of the 200 acoustic signatures one by one, which yields an accuracy of 99%. The research can be extended to design a system comprising of acoustic detectors installed at suitable locations along the border of a country. Such system would be able to gather the threat information and then pass it on to the existing Air Defense of a country.

Keywords: acoustic; Energy Spectral Density (ESD); Euclidean distance; Fast Fourier transform (FFT); feature vector space.

1. Introduction

An acoustic signature (i.e. a speech signal, sound of a musical instrument or of a gun-shot etc.) has some characteristic parameters or features. These features include Fast Fourier Transform (FFT) coefficients and Energy Spectral Density (ESD) coefficients etc. For speech signals, another characteristic feature known as Mel-frequency Cepstral Coefficients (MFCC) is most widely used [1], [2]. The identification of an unknown acoustic signature can be made by first projecting its feature vector into the feature vector space of the known acoustic signatures, and then measuring the vector distance between the unknown feature vector and each of the known feature vectors in the space. The unknown signature belongs to the class of the feature vector which gives the minimum distance. A flying aircraft of a particular type/class also produces a unique acoustic signature, which hence can be used for its identification. The Air Defense System of any country is mainly based on Radar technology which employs electromagnetic waves and carries out aircraft detection, identification, and ranging. The research presented in this paper can be further extended to design a cost effective supplementary system for detection and identification of both friend and foe aircraft, and hence can enhance the conventional Air Defense System.

1.1. Literature review

Acoustic signals have been widely used for detection and identification purpose. Saad et al. introduced a method for weapon identification by capturing and analyzing its acoustic signature [3]. In this research, the captured signature is projected into a subspace of already available acoustic signatures i.e. *patterns*. The subspace is derived from a larger space by using *Backward Elimination Method*. Then the distance vector is calculated between the projected signature and each of the patterns in the subspace. The pattern which gives the minimum distance corresponds to the class of the weapon.

Nooralahiyan et al. attempted to develop a system for online vehicle classification based upon acoustic signatures [4]. The acoustic signatures are captured with the help of a microphone and a digital tape recorder.

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In this research, Linear Predictive Coding (LPC) coefficients are used as the characteristic parameter. A Time Delay Neural Network (TDNN) is trained to classify the travelling vehicles. The suggested system is mainly proposed to enhance the traffic management system.

Fargues and Duzenli developed a scheme for classification of underwater acoustic signals [5]. In this research, Mean Separator Neural Network (MSNN) is trained for classification. The proposed approach is simple as it significantly reduces the class features.

An emerging concept in acoustic technology is acoustic based sensor i.e. *acoustic missile* [6]. The first prototype *Brilliant Anti Tank* (BAT) was tested for Army Tactical Missile System (ATACMS). Generally the conventional electro-optic or electromagnetic sensors operate in narrow bandwidths. But the acoustic based sensors can acquire and process all incoming sound frequencies from any direction, and hence provide better efficiency.

2. Methodology

2.1. Feature vector construction

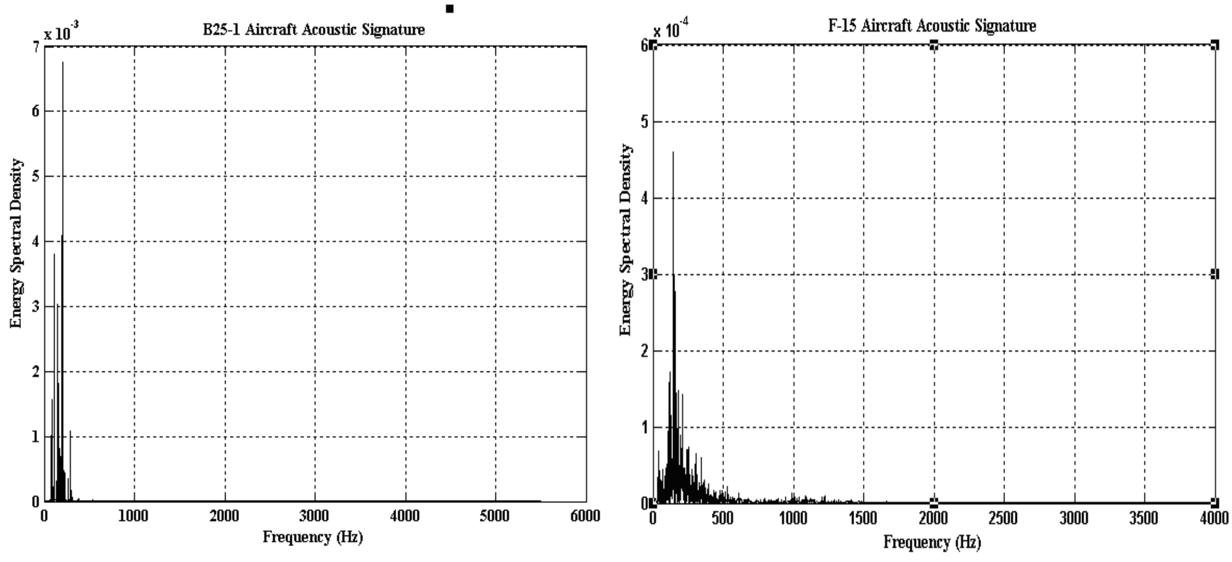
During this experimental activity, the first step is to construct the feature vectors. For this purpose, the Energy Spectral Density (ESD) of the acoustic signal is treated as the characteristic feature. For a given signal, ESD is calculated in two steps. In first step, the given signal is *normalized*, and then its Fast Fourier Transform (FFT) is calculated. FFT is an efficient algorithm of finding Discrete Fourier Transform (DFT) [7]. If the input vector $\boldsymbol{x}$ has a length N, then the FFT is also a length N vector $\boldsymbol{X}$ [8] as given by (1).

$$X(k) = \sum_{n=1}^{N} x(n) \exp(-j2\pi (k-1)(n-1)/N), \qquad 1 \le k \le N \qquad (1)$$

In second step, the (ESD) feature vector is constructed by taking squared magnitude of the FFT coefficients [9]. If $\boldsymbol{X}$ is the FFT vector of length N, then the Energy Spectral Density $\boldsymbol{\psi}$ is also a length N vector as given by (2).

$$\Psi(k) = |X(k)|^2, \qquad 1 \le k \le N \qquad (2)$$

Fig.1 shows that the Energy Spectral Density (ESD) versus frequency plots for aircraft acoustic signatures corresponding to different classes are different.



(a) (b)

Fig. 1: Energy Spectral Density as a characteristic parameter

2.2. Feature vector space

Feature vector space comprises of the feature vectors of all the known aircraft acoustic signatures. It is required as the unknown feature vector is to be projected into it, and then to be analyzed with the help of an *Identification Algorithm*. For this experiment, 200 aircraft acoustic signatures are used to construct the vector space. The PCM wave files of these signatures are downloaded from the Internet [10], [11]. These wave files are renamed using numerals for easy reference in Identification Algorithm. First 13 renamed wave files used for constructing the feature vector space are shown in Table I.

TABLE I. RENAMIED WAVE FILES

Aircraft class/type	Wave file name	Renamed as
B25-1	b25-1.wav	1.wav
B-131	b131.wav	2.wav
CH-146 Griffon	griffon.wav	3.wav

2.3. Unknown feature vector

Ideally, the unknown aircraft signature is to be captured in run time with the help of a recording device attached with the computer which is running *detection and identification* software; and subsequently its feature vector is to be calculated. During this experimental activity, for proof of concept, the software is tested against each of the 200 vectors in the feature vector space. Thus each vector in the space is one by one treated as *unknown*.

2.4. Identification algorithm

The three arguments to the Identification Algorithm are *unknown feature vector*, *feature vector space*, and *size of feature vector space*. The algorithm calculates the Euclidean Distance of the unknown feature vector with each member in the feature vector space starting from the first vector i.e. corresponding to wave file *1.wav*. The respective distances are stored in the *EuclideanDistanceArray*. As all the wave files are renamed using numerals in ascending order e.g. *1.wav*, *2.wav* etc., the index of the minimum Euclidean Distance in *EuclideanDistanceArray* indicates the class of the aircraft to which the unknown signature actually belongs to. For example, if index of minimum distance in the array is 2, then as per Table I the unknown signature belongs to B-131 aircraft because the respective wave file is renamed as *2.wav*.

2.5. Reason for using Euclidean distance

Euclidean distance is chosen to calculate the vector distances. This choice is made as the Euclidean distance and its variants are widely used for vector distance measures for applications in science, economics, and image recognition etc [12]. Moreover, it is the most widely used method in spectral distance measures [13]. In simplistic way, if $\boldsymbol{X} = (x_1,x_2,x_3,....x_n)$ and $\boldsymbol{Y} = (y_1,y_2,y_3,.....,y_n)$ are two vectors, each of size n, then the Euclidean Distance [14] between these two vectors is given by (3).

$$d(X,Y) = \sqrt{(y_1 - x_1)^2 + (y_2 - x_2)^2 + ...+ (y_n - x_n)^2}$$
$$= \sum_{i=1}^{n} (y_i - x_i)^2 \qquad (3)$$

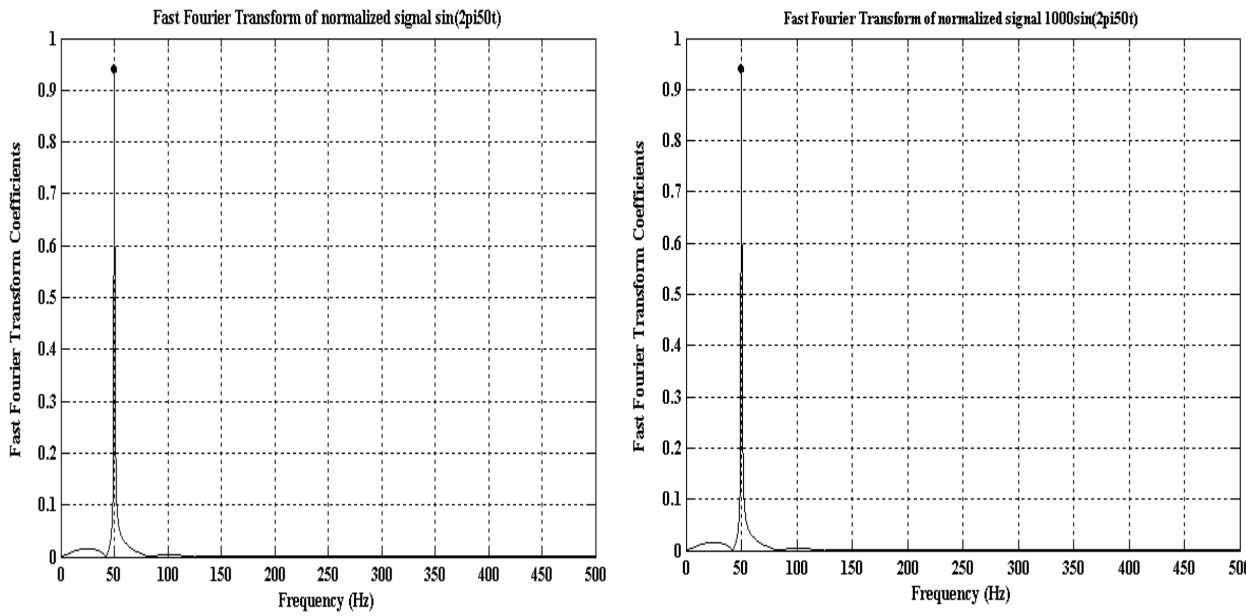
An important variant of Euclidean Distance is Weighted Euclidean Distance which is used when variables in a given vector are on different measuring scales. For example consider a two dimensional vector of order *1x2*, which gives temperature and pressure at a given height above sea level. In this example effect of one unit addition in temperature is different from the effect of one unit addition in pressure. The different measuring scales are compensated by assigning weights to each contributed term in the vector [15]. In this paper, absolute Energy Spectral Density coefficients are used as characteristic feature. As all the variables are on the same scale so simple form of Euclidean Distance is used instead of the *weighted* one.

2.6. Normalizing acoustic signature

The Identification Algorithm is based on calculating the Euclidean Distances which in turn depends on the magnitude of the data samples as shown in (3). Two signals of the same aircraft class but with different strength may lead to false results. The signal strength of the unknown signal would vary with varying capture conditions. The signal capturing conditions for the known signals in Feature Vector Space and those of unknown signal would differ most of the time. To overcome this problem, all the known and unknown signatures are first normalized and then their FFTs and ESDs are calculated. For a given time domain vector ***y***, the normalized vector $\boldsymbol{y}_{Norm}$ is given by (4).

$$y_{Norm} = y / max(abs(y)) \qquad (4)$$

Fig. 2 shows the effect of normalization. The FFT coefficients calculated after normalizing a weaker time domain signal i.e. *sin(2π50t)* are exactly same to the coefficients calculated after normalizing the much stronger time domain signal of the same class i.e. *1000sin(2π50t).*



(a) (b)

Fig. 2: Effect of normalization

3. Main Results

3.1. False alarm rate

MATLAB environment is used to develop the software. The unknown signature, that is to be identified, is not actually captured; rather already available known vectors in the vector space are treated *unknown* one by one for testing of the software. During this experimental activity, 1% false alarm rate is calculated which is quite low. However, if the unknown acoustic signature is captured with the recording device in run time then, owing to varying capture conditions, false alarm rate is going to be little higher. The false alarm rate would also increase with an increase in size of the feature vector spaces.

3.2. Improving execution speed

The calculation of FFT, ESD, and Euclidean Distance involves many multiplication operations, which consumes a lot of CPU resources. For smaller vector space size, the software execution speed is fine; however it slows down with an increase in size. The problem can be overcome by writing software for *parallel computing environment* [16].

4. Conclusion

The research can be extended to design an *aircraft acoustic detection system*. This will be a cost-effective system, and can be used to supplement the conventional Air Defense of a country. The system will be able to detect low flying aircraft which the conventional radars may skip. The conventional radars emit electromagnetic radiations, so they can be detected and hit by anti-radiation missiles. However, the suggested system, being passive in nature, cannot be detected. While designing the suggested system, the feature vector space shall comprise of acoustic signatures of all the friend, foe, and commercial aircraft which may use the airspace of a given country. The proposed methodology is not only effective for aircraft identification but it can also be utilized for identification of other ground and aerial vehicles.

5. Acknowledgment

The author would like to thank Sana, Bilal, and brother Tahir for their help and encouragement in making this effort. The author is also grateful to his instructors Mr. Sikander Hayat, Mr. Shakeel Alvi, and Mr. Fraooq-e-Azam, for their valuable guidance throughout the project phase.

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