Determining Signal Source Integrity Using a Semisupervised Pattern Classification System

W. Satney¹, A. Carrington², T. Scantlebury-Manning² and A. Als¹

¹Computer Science, Mathematics and Physics, University of the West Indies (Cave Hill Campus), BB1100, ²Biological & Chemical Sciences, University of the West Indies (Cave Hill Campus), BB1100

Abstract - This paper focuses on a unique signal classification problem that employs digital signal processing techniques to first, separate 57 audio signals into two signal-type categories (A and B) and second, to further classify the integrity of the category A signal sources. Short-Time Fourier Transform and central tendency analyses are employed to distinguish between the signals within the categories. FFT Welch Method and Kohonen's Self-Organizing Maps are then employed to determine the integrity level of the sources associated with the signals in category A. The overall results show 91.2% accuracy in classifying the signals into categories A and B. Additionally, the system was able to achieve classification 100% when distinguishing between the poor and (somewhat) good signal source integrity. The hybrid classification system proposed in this paper has direct application to real world problems where both signal isolation and the associated integrity of the signal source need to be determined.

Keywords: Signal classification, Semisupervised learning system, FFT Welch Method, STFT, SOM.

1 Introduction

The principle concern of computer scientists and engineers when developing expert systems is the ability for these systems to apply effective pattern recognition techniques to solve classification problems. Machine learning algorithms have revolutionized how computers classify related data to decipher patterns in the data presented. Indeed, the ultimate goal of these algorithms is to mimic the learning ability of humans.

Machine learning tasks are generally broken into two main categories: supervised learning and unsupervised learning. Supervised learning algorithms are used when training data is provided as part of the problem. In this case the training data is composed of set of training targets. The algorithm analyses the training data and deduces a classifier function or a regression function. The deduced function is then able to predict the correct output classification for valid input data. Conversely, unsupervised learning algorithms are used when there is no output target(s) associated with each input data sample. Instead, unsupervised learning algorithms learn how to delineate specific input patterns based on the statistical structure of the entire set of input patterns. Another machine learning mode that may be applied to pattern recognition problems is semi-supervised learning. Semi-supervised learning techniques basically encapsulate a supervised learning algorithm and an unsupervised learning algorithm.

This research paper proposes a hybrid classification system that utilizes information made available by Short-Time Fourier Transform (STFT) analysis to distinguish between two signal categories. Feature extraction is then performed thereby simplifying the problem domain by further reducing the amount of data passed on to the pattern recognition stage. Specifically, the simplified problem is applied to the Artificial Neural Network (ANN) system for further classification. These techniques will be highlighted in the next section.

2 Background

A complete pattern recognition system typically consists of a signal gathering mechanism to record the source signals; a feature extraction mechanism to reduce dimensionality through the creation of a feature vector; and a pattern classification mechanism to distinguish between the patterns present within the source signals. Designing an effective signal classification system to solve pattern recognition problems is In particular, feature vector challenging. creation and the design of the pattern classifier prove to be the most challenging aspects. As the extraction vector is often based on spectral or entropy analyses, a brief background on some of these spectral techniques and the Self-Organized Maps pattern classification algorithm will be presented in this section.

2.1 Discrete Fourier transform (DFT)

The DFT technique is able to decompose any perpetual periodic signal into sinusoidal waves [1]. The frequency and the associated amplitude information are the key aspects of DFT required for signal analysis. The equation below represents the DFT:

$$X[k] = \frac{1}{N} \sum_{n=1}^{N-1} x[n] e^{-j2\pi k n/N}$$
(1)

Both the frequency domain, X[k], and the time domain, x[n], are arrays of complex numbers, with k and n running from 0 to N-1. Note that k represents the k^{th} frequency component, n represents the n^{th} sample and j represents the imaginary unit. The Fast Fourier Transform (FFT) is an improved method for calculating the DFT. Although both FFT and DFT produce the same results, the FFT is exceptionally efficient at significantly reducing the computation time required [1]. Unfortunately, using Fast Fourier Transform (FFT) based methods alone have inherent problems which can greatly affect the accuracy of the analysis. This is because FFTbased methods contain a finite record of data that relate to the frequency spectrum of the signal. Consequently, these methods are susceptible to spectral leakage effects due to the windowing that is ingrained in finite-length data records. Furthermore, smearing or smoothing the estimated spectrum is the predominate effect of windowing in FFT based methods [2, 3]. Finally, FFT methods are not suitable for real world signals in which the frequency content changes often over time. Thus, periodic waves with constant frequencies are best analysed using FFT methods [4]. As pattern recognition problems usually have some real world application in which non-stationary signals are investigated [5-9], Short-Time Fourier transform (STFT) and FFT Welch Method are techniques used to overcome the challenges associated with the FFT.

2.2 Short-Time Fourier transform (STFT)

The STFT technique is able to analyse nonstationary signals in the time domain through an algorithm that is applied to various sections of the signal. The signal is processed through a moving window which breaks down the signal into a set of overlapping or non-overlapping segments in which FFT is applied on each segment. Tokmakç et. al use STFT in the classification system for stenosis from mitral valve Doppler signals yielding excellent results [10].

2.3 FFT Welch method

The application of the Welch method on the FFT algorithm is used to estimate the power spectra. This technique involves sectioning signals into overlapping segments with each data segment termed a window. The principal advantage of using this technique is that it involves less computations that other methods and it is suitable for performing analysis on nonstationary signals [5, 11]. In this study, each signal is divided into windowed sections using Hanning window. The modified the periodograms are then calculated and averaged.

2.4 Self-organizing maps (SOMs)

SOMs 'learn' to detect the inconsistencies and correlations in the input vectors to classify these vectors into a perspective grouping on a twodimensional grid [12]. The Neurons in the selforganizing map 'learn' to recognize adjacent clusters on the grid. Any four of the distance functions (i.e. dist, boxdist, linkdist and mandist) may be used to calculate the distance between the neurons from their position [12]. For instance, the dist function calculates the Euclidean distance from a home neuron to another. The neuron with the smallest Euclidean distance is selected as 'winner' and is moved towards the presented input data [13].

2.5 The Study

An assortment of fifty-seven (57) audio signals produced from two categories of sources were obtained from two independent parties¹ and stored in a signal-bank library. Each signal was labelled, A or B, based on its source category. A technical expert was instrumental in confirming the correct labelling (A or B) of the fifty-one signals supplied by the UWI. The signals in the

¹ Six (6) signals were obtained from a standardized data set and the remaining fifty-one (51) from the University of the West Indies (UWI) (Cave Hill Campus). standardized set were already pre-labelled, thus no confirmation was required.

The signals in category A represent the desired target classification for this study. Conversely, those in category B are to be discarded. Each signal in Category A contains data that may infer on the integrity of the signal's source along a continuum.

The primary objectives of this study are to employ digital signal processing (DSP) techniques to 1) separate the signals into the two categories and 2) inform on the integrity status of the sources in the desired target category. The methodology employed to accomplish these two objectives are described in the next section.

3 Methodology

3.1 Objective #1 – The signal separation process

Differentiation between the signal sources is accomplished by a two-stage filtering process as depicted in Figure 1. In stage one, a STFT analysis was employed to determine the mean (μ) spectral intensity at a predetermined reference frequency. The mean was then compared to a classification threshold value to determine the signal category. At the end of this stage the signals in category A begin to get filtered out from the entire pool of signals. The batch of signals discarded from the first stage invariably contains signals from both categories. Thus the objective of stage two is to attempt to completely separate the remaining category A signals from those in category B.



In this stage, further separation is accomplished via a central tendency analysis of the mean (μ) , standard deviation (σ) and kurtosis (β_2) of the signal intensities associated with the spectrograms. More specifically, these values are used as input to a simple algorithm which compares them to predetermined thresholds in order to separate out the remaining category B signals. The pool of signals that remain after this separation represent category A signals.

3.2 Objective #2 – The determining integrity status

The use of statistical analysis (mean, standard deviation, min, max, kurtosis and skewness) derived from the FFT Welch method is input into the SOM network to classify each of the Category A signals obtained from stage one of the signal separation process. This classification may then be used to infer certain qualities about the signals' source. The description of the six qualities that can be determined based on the SOM classifications are provided in Table 1.

Classification Category	Description
1	Noisy Signal
2	Below average
3	Somewhat average
4	Average
5	Good
6	Very good

SOM categories two (2) through six (6) infer on the relative integrity of the signal source along a continuum. Those signals classified in category 1 are deemed to be too noisy and should be discarded.

It should be noted that all work was undertaken using MATLAB and the key parameters employed are provided in Table 2.

Signal Characteristics		
Recording sample frequency	44100 Hz	
STFT Analysis		
Hamming window size	2 ¹⁰ data points	
Overlap	50%	
FFT Welch Method		
Number of samples	ns = max(size(sig))	
Number of windows	nw = 16	
Hanning windows size	hanning(floor(ns/nw))	
SOM Analysis		
Num. of Neurons	6 (2 x3 hexagonal network)	
Num. of epochs	7000	

4 Results

Figures 2 and 3 show two examples of spectrograms associated with signals from Category A and B, respectively. The proposed two-stage separation method proved to be 91.2% accurate in correctly distinguishing between the signals in these categories. Only three (3) signals from category A and two (2) signals from category B were miscategorised.

The technical experts are acute when distinguishing between sources that are either (very) good or poor. Example spectrograms associated with these signals classifications are provided in Figures 2 and 4, respectively. Indeed, even to the untrained ear, the audio signals associated with these two sounds are distinct. However, classification categories 2, 3 and 4 as described in Table 1 often prove difficult to distinguish even to trained experts. Therefore the value of the proposed system lies in its ability to determine the integrity of the signal's source along the entire continuum from 2 to 4.



Figure 2 – Spectrogram of signal from Category A



Figure 4 – Spectrogram of signal from Category A with poor structural integrity

A cluster analysis was done on all the signals obtained from stage 1 of the signal separation process using a fully connected self-organizing map. Figure 5 shows the location of the six (6) neurons in relation to the data and therefore, by extension, it also highlights the six associated clusters.

Cluster 6 represents the only signal whose source was considered to be very good. Cluster 5, which represents those sources considered to have good integrity, contained seven (7) signals. Cluster 2, 3 and 4 contained eighteen 18 signals in total and represent sources with integrity levels from average to below average along the continuum. Finally, noise dominated the signals in cluster 1. Thus this cluster represents the case where the signal samples that are unusable.



Analysis of the pool of category A signals obtained from stage two of the separation process revealed that they were all from sources with poor integrity.

The two-stage separation process correctly identified all five (5) of the poor signal sources and the single good signal source within the standard data set. A UWI technical expert was used to classify the other fifty-one (51) signals which they supplied. This expert confirmed that the system correctly identified 18 poor cases.

5 Discussion

In this study, we investigated a total of 57 signals from two signal categories (A and B) obtained from two independent sources. The proposed STFT and FFT Welch method combined Kohonen's Self-Organizing Maps proved successful in both separating the signal categories and further classifying the integrity of each signal source in the target category. Specifically, the system is 91.2% accurate when distinguishing signal source categories. Furthermore, the system is 100% accurate in

determining both the poor integrity category A source signals, the good integrity category A source signal and those recorded poor quality signals that are unusable due to background noise.

In the field technical experts have the ability to distinguish between signals within categories A and B. Moreover they are also capable of distinguishing between the good and the poor category A signal sources. The potential benefit of this work lies in the ability of the system to one step further and infer on the integrity of the signal's source along a continuum. This is seen in the 27 cases which proved difficult to place on the continuum using only the expert's auditory senses.

6 Conclusion

The proposed hybrid system was 91.2% successful in separating the two signal categories. Noise within the recorded signal is believed to be a major contributor to the categorisation errors. The system also shows great promise with its ability to determine the integrity of the signal's source along a continuum. Future work will examine DSP techniques that will serve to reduce the presence of this noise and raise the categorization success percentage and improve the signal source integrity analysis.

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