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Biometric Identification of Cardiosynchronous Waveforms Utilizing Person Specific Continuous and Discrete Wavelet Transform Features

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***Abstract*—In this paper we explore how a Radio Frequency Impedance Interrogation (RFII) signal may be used as a biometric feature. This could allow the identification of subjects in operational and potentially hostile environments. Features extracted from the continuous and discrete wavelet decompositions of the signal are investigated for biometric identification. In the former case, the most discriminative features in the wavelet space were extracted using a Fisher ratio metric. Comparisons in the wavelet space were done using the Euclidean distance measure. In the latter case, the signal was decomposed at various levels using different wavelet bases, in order to extract both low frequency and high frequency components. Comparisons at each decomposition level were performed using the same distance measure as before. The data set used consists of four subjects, each with a 15 minute RFII recording. The various data samples for our experiments, corresponding to a single heart beat duration, were extracted from these recordings. We achieve identification rates of up to 99% using the CWT approach and rates of up to 100% using the DWT approach. While the small size of the dataset limits the interpretation of these results, further work with larger datasets is expected to develop better algorithms for subject identification.**

I. INTRODUCTION

The cardiosynchronous signal obtained through Radio Frequency Impedance Interrogation (RFII) is a non-invasive method for monitoring hemodynamics, specifically heart rate (HR) and heart rate variability, using a dipole resonant coupling method (see [1-3] for further details of the device). Biometric identification of subjects through the use of such a cardiosynchronous signal in operational environments would be highly desirable as it would enable real-time confirmation of a subject's identity prior to extraction from a potentially hostile situation [1-3]. It is a less intrusive technique compared to an ECG based biometric solution [4-5]. The use of RFII is being investigated for use as a non- invasive hemodynamic monitoring system and in the capacity of a biometric identifier. In this paper, two methods for biometric feature extraction and identification from these signals, are explored. One method is to identify the subject by extracting features found in the continuous wavelet transform (CWT) spectrogram. The second method is to extract features from the discrete wavelet transform (DWT) decomposition at various levels and identify the subject based on these features. This study is performed on data samples extracted from four different 15 minute long RFII recordings, corresponding to four different subjects. The aim in this paper is to identify subjects using a recording of as short a duration as possible. For either case, identification experiments were performed on data samples over the duration of a single heart beat.

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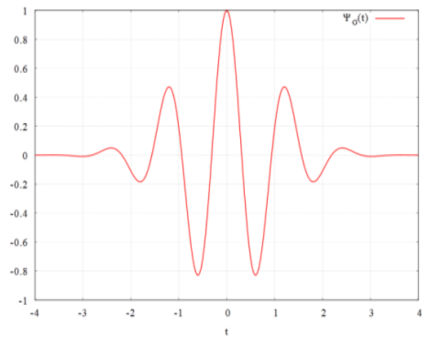

Figure 1: Morlet mother wavelet function

II. METHODS

A. Feature Extraction by Continuous Wavelet Transform

The data samples for this experiment, for each of the 500 most discriminating features for each subject were learned using 30 examples of the spectrogram from the subject. 100 spectrograms of each subject from a different portion of the

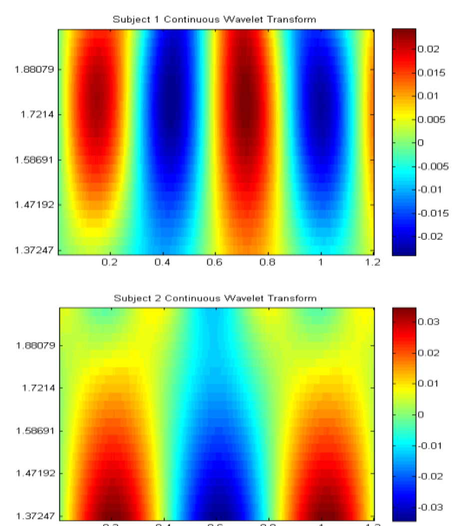

Figure 2: Example Continuous Wavelet Transforms of RFII signal from two subjects

RFII signal were then identified. The continuous wavelet transform (CWT) was used to decompose a signal into scaled and shifted functions based on a mother wavelet function ψ. The transform itself is defined as:

$$X_w(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \qquad (1)$$

This provides a time-frequency characterization (that we will call a *spectrogram*) that can be used in identifying the subject. Many types of continuous wavelets exist, however, the wavelet that has produced the best results for identification so far has been the Morlet wavelet [4,6] defined by the mother wavelet

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}}\left(e^{i\omega_0 t} - e^{-\frac{\omega_0^2}{2}}\right)e^{-\frac{t^2}{2}} \qquad (2)$$

with $\omega_0$being the central frequency of the mother wavelet (see Fig. 1). The continuous wavelet transform (CWT) cannot be performed on individual heartbeat signals as the length of the signal is too small to expose the identifying information. To overcome this, a portion of the RFII signal large enough to have the desired number of heartbeats is taken and the CWT is applied. The individual heartbeats are segmented from the signal and the corresponding portion of the transformed signal is extracted. Fig. 2 shows different subjects have differently shaped spectrograms allowing identification to be performed. Identifying spectrogram features were extracted from each query and compared to the template features from training data. Using all the features in the spectrogram is not desirable as it requires the storage of large spectrograms. Further, the use of all features in the spectrogram reduces accuracy of identification due to the fact that certain areas of the spectrograms are similar across subjects. By focusing on the most discriminative portions of the spectrogram for each subject the identification rate can be improved greatly. The Fisher ratio was used to select the most discriminative features, and is defined as:

$$F = \frac{(\mu_1-\mu_2)^2}{\sigma_1^2+\sigma_2^2} \qquad (3)$$

where μ_1 and μ_2 denote the means and σ_1 and σ_2 denote the standard deviations for the two distributions. By maximizing the Fisher ratio, the means of the distributions were separated and the variances were minimized. One subject was selected as coming from one distribution and all other subjects as coming from a different distribution. This allowed the most discriminative features in that subject to be selected by maximizing with a large Fisher ratio (Fig. 3). To identify a query spectrogram, each feature mask was applied to the spectrogram resulting in a feature vector corresponding to each subject. The query was identified as the subject whose mean feature vector was nearest to the corresponding features from the query (see Fig. 4 and Fig. 5). While any distance metric could be used but for simplicity, the L_2 norm was used for this study.

B. *Discrete Wavelet Transforms and Wavelet Packet Decomposition*

Another set of features extracted from the RFII signals uses coefficients from the discrete wavelet transform (DWT)

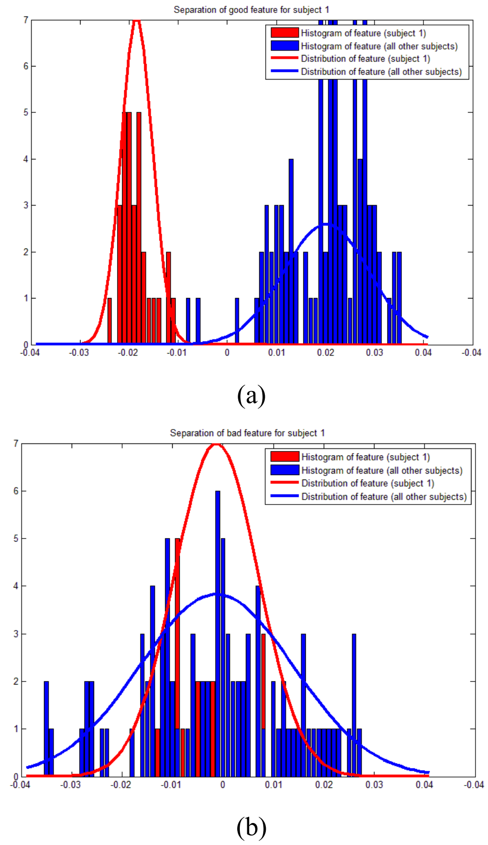

Figure 3: The two histograms give an approximation of the distribution of a feature taken from subject 1 on the left and all other subjects on the right. (a) shows the separation of the two distributions in a good feature selected while (b) shows the lack of separation for a non-optimal feature

of the signal [7]. For a given discrete signal $x[n]$, the discrete wavelet transform is given by:

$$x_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \qquad (4)$$

$$x_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \qquad (5)$$

where$g[k]$ and $h[k]$ are the low-pass and high-pass filters of the wavelet decomposition, respectively. An illustration of the typical wavelet decomposition tree is shown is Figure 6.This decomposition is similar to the CWT decomposition described in the previous section, with the difference that it uses a dyadic tree structure for decomposition. At each node of the tree, the signal is projected onto a pair of ortho-normal wavelet basis functions and down-sampled by two. One of the resultant signals contains the approximation (i.e. low frequency content) while the other contains the details (i.e. the high frequency content). Thus the number of data samples at each level of the tree is the same as the length of the original signal. In a typical DWT analysis of the signal, every node is further sub-divided into a child approximation and child detail node. Here a wavelet packet decomposition of the signal was performed [8-9]. In this case, the detail nodes are also projected onto the wavelet bases. Fig. 7 shows the approximation and detail information for a sample from class

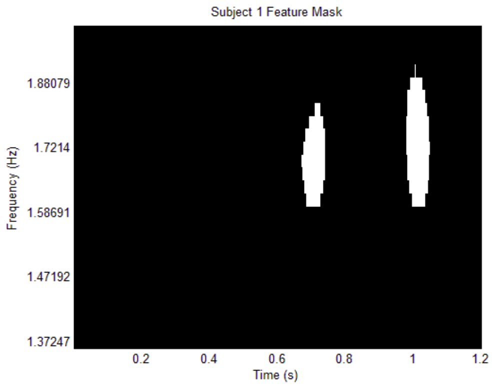

Figure 4: Feature mask for subject 1 (500 features selected)

Figure 5: Feature masks for subject 1(top left), 2 (top right), 3 (bottom left), 4 (bottom right)

one (i.e. subject 1; in this paper we use the terms class and subject interchangeably), for one level of wavelet decomposition using the Haar wavelet. The slow variations are captured in the former while the high frequency content is accentuated in the latter. Each signal undergoes 10 levels of decomposition under each of the wavelet bases. The Euclidean distance metric between decomposition levels of two samples is used as the similarity metric between them.

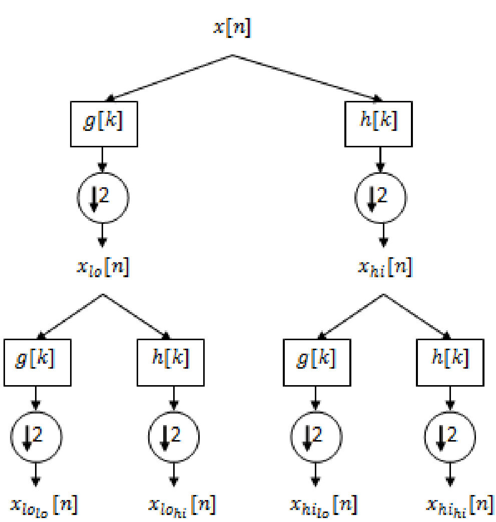

Figure 6: Two levels of DWT decomposition of a signal $x[n]$with a low pass filter $g[k]$ and a high pass filter $h[k]$. The circles represent down sampling the resulting signal by 2.

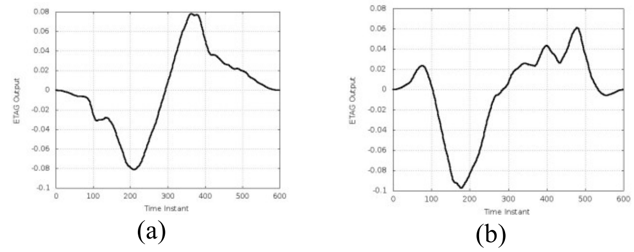

Figure. 7: Data samples from (a) class 1 and (b) class 2 in our dataset corresponding to one heart beat duration.

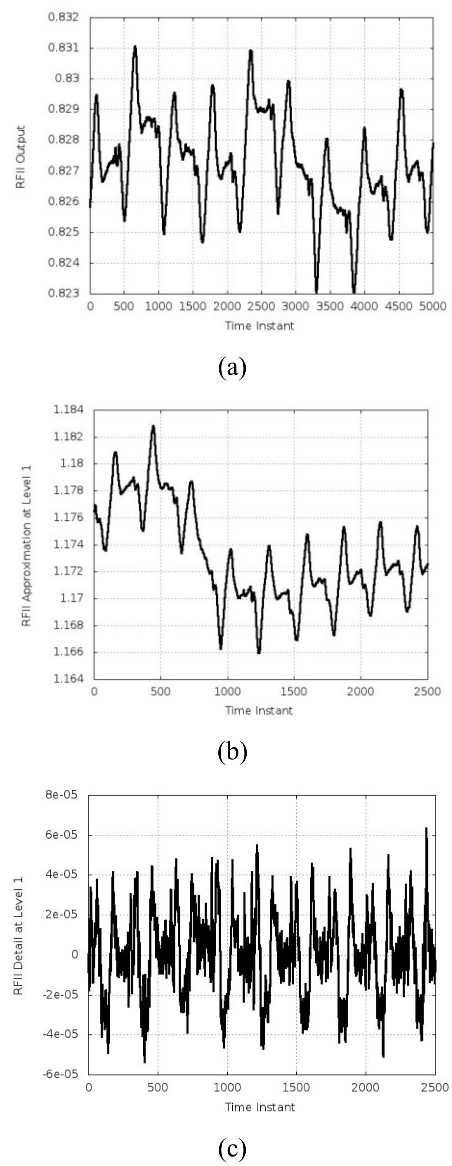

Figure 8: (a) shows the signal that is decomposed into (b) and (c), (b) shows the approximation coefficients for one of the user RFII signals, where the slow variations in (a) are captured and (c) shows the detail coefficients which captures the high frequency variations of the signals. These coefficients are for one level of DWT decomposition using haar wavelet bases.

User identification may be performed by determining the Euclidean distance between two data samples and searching for the pair with minimum distance. As mentioned earlier, the data samples we use for our experiments correspond to one heart beat duration in the RFII signal. This, for example, corresponds to 600 sample points in Fig. 8(a). These sample points were extracted between the low to high transitions in the signal. Examples of data samples from class 1 and from class 2 in our dataset are shown in Fig. 7.

III. RESULTS

A. CWT Identification

The 500 most discriminating features for each subject are learned using 30 examples of the spectrogram from the subject. One hundred spectrograms of each subject from a different portion of the RFII signal are then identified. Different wavelets were used to identify the spectrogram. The Morlet wavelet performed best, identifying 99% of the spectrograms correctly. The 4 spectrograms that were misidentified look to be a result of bad segmentation of the data as they are not registered correctly like the rest of the spectrograms are. This can be overcome in the future with better segmentation algorithms. Nine types of wavelets with varying parameters were examined for a total of 45 different wavelet configurations. All wavelets were generated using MATLAB's cwt function. For brevity, only the best performing wavelet in each type is shown in Table I.

TABLE I. RESULTS OF CWT IDENTIFICATION

Wavelet (MATLAB cwt parameter)	**Accuracy**
Morlet (morl)	99%
Daubechies (db7)	95.75%
Biorthogonal (bior2.8)	95.5%
Meyer (meyr)	88.5%
Mexican Hat (mexh)	66%
Discrete Meyer	95.25%
Reverse Biorthogonal (rbio1.5)	98.5%
Symlet (sym7)	95%
Coiflet (coif4)	88.75%

B. DWT Identification

Various levels of DWT decomposition of the signals are used in order to differentiate between data samples of the four classes, as was described in section II.B. The data samples used here correspond to one heart beat duration of an individual as mentioned earlier. We have 188 such samples for each of the four classes in our database.

Using the Haar, Daubechies 2, 5, and 10, the biorthogoanl 2.8, 3.5, and 5.5 wavelets all resulted in a 100% identification rate at 2, 5, and 10 levels of wavelet decomposition.

IV. CONCLUSION

Both the CWT and the DWT methods show high accuracy in identifying a subject from a single heartbeat. In particular, DWT demonstrated remarkably robust subject identification in this small dataset. These results suggest that there are identifying features in the temporal-frequency domain that are exposed once a wavelet transform is applied. While this shows promise for identification of a subject using wavelet decomposition, the small size of the dataset limits the interpretation of the results. Further work with larger datasets will allow us to test the proposed algorithms and show more statistically significant results.

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