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# Cardioid graph based ECG biometric in varying physiological conditions using compressed QRS

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**Abstract.** This paper proposes a robust biometric identification system using compressed electrocardiogram (ECG) signal by varying physiological conditions. The ECG data were obtained by recording a total of 30 healthy subjects where they performed six regular daily activities repeatedly at a sampling frequency of 1000 Hz. Then, the QRS complexes are segmented by implementing Amplitude Based Technique (ABT) where it compares the amplitudes of ECG points to determine the R peak. The segmented QRS is then compressed for various levels by using Discrete Wavelet Transform (DWT) algorithms and first 3 Daubechies (db) wavelet are computed. Next, a Cardioid graph is generated. In order to verify the matching process, the classification is performed by using the Multilayer Perceptron (MLP) technique. The results show that by applying this method, the accuracy of the identification rate can be achieved as high as 96.4% even when the data file is compressed up to 73.3%. When the data file is compressed, the outcomes also demonstrate that the execution time is less compare to non-compressed data. Therefore, the biometric identification system can be implemented efficiently as there will be a lesser issue regarding the data storage, execution time and accuracy based on the outcome of the study.

## 1. Introduction

Electrocardiogram (ECG) can be used for biometric recognition because the physiological and geometrical properties of different individuals are unique, and these differences are reflected in their ECG signals as seen in the initial studies conducted [1]. Currently, available ECG based biometric systems experimented mainly with subjects under resting conditions [2]. However, it is still an under-researched area which requires further investigation to prove that ECG based biometric is robust regardless of the inclusion of the physiological condition.

There are a variety of ECG feature extraction procedures, and algorithms in practice that range from being simple to complex, in order to obtain an innovative and easy to use the method, a group of researchers have come up with Cardioid graph-based feature extraction process. This method is capable of eliminating long pre-processing time and consecutively manages to be efficient and accurate as compared to the existing methods [3]. In this era of telemedicine, transmission requiring low bandwidth would enhance better healthcare facilities [4]. Hence, it can be seen that in order to implement this



recognition system in real life, compression would become a necessity. Thus, in this research, we investigate the performance of a Cardioid graph-based biometric using compressed ECG under different physiological conditions and compare it with other compressed ECG biometric studies.

The remaining paper is organized as follows: Section 2 reviews literature on compressed ECG biometric and ECG compression algorithms, Section 3 discusses the implemented methodology, and Section 4 describes the experimental procedures, results obtained and its performance. Finally, Section 5 contains the concluding remarks.

## 2. Literature review

### 2.1. ECG compression

Data compression has become a necessity, especially when taking ECG readings. It is known that; ECG recording is lengthy, and a lot of storage capacity is needed. Thus, Padhy et al. [9] proposed a multi-lead ECG data compression using singular value decomposition (SVD) in multi-resolution for wireless body sensor network (WBSN) applications. The number of SVs is selected by applying a multi-scale energy-based thresholding method depending on the clinical importance of the wavelet sub-bands. For ECG data compression and transmission purpose, the technique is embedded with a pulse amplitude modulated direct sequence-ultra wideband technology. In order to prove the efficiency of the technique, the performance of the compression method is then evaluated using the average compression ratio (CR) and distortion measures. The study discovered that the threshold parameter could be altered in order to control CR and reduced energy consumption. Thus, the results show that the proposed method can be executed at least three times faster than the existing techniques with 19 times storage volume capacity.

A fast and efficient method is also crucial in today world where everything is running with time. Therefore, Hsieh et al. [10] proposed a rapid and efficient approach for lossless coding of wavelet-based ECG data compression by using the set partitioning in hierarchical trees (SPIHT) algorithms. Traditional SPIHT is time-consuming and has low in term of storage efficiency; therefore Hsieh et al. [10] introduced a bit plane representation of quantized wavelet coefficient that is faster and less in complexity for fast lossless coding. The bit plane is first represented by a tree data structure that consists of two types of primitive trees that are 2- and 3-primitives. The values of primitives are selected based on the number of input sampled data. An assembler is applied for simple logic coding process as a synthesis for assembling the primitive sequentially. In a comparison of traditional SPIHT, the experimental results show that the modified SPIHT technique is capable of achieving a reduction of the coding time up to 64.35% and increasing in storage efficiency at the cost of a 0.28%-bit rate.

In this study, we proposed DWT as compression method because it would be a better compression as well as an encryption algorithm for a transient signal such as ECG since DWT compression produces better reconstruction and content preservation of the original signal.

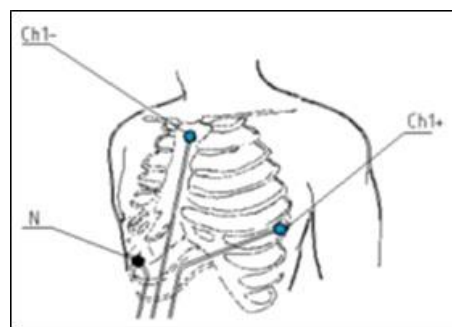
### 2.2. Compressed ECG biometric

Person identification has been improving day by day where now it is a trend to apply bio-signal such as ECG for biometric recognition purposes. Carvalho et al. [11] in their study purposed a compression-based ECG biometric identification using a non-fiducial approach. A total of 25 participants were involved in this study where they were exposed to three different emotions condition, which are disgust, fear and neutral for three days. The fifth order of Butterworth low pass filter with a cut off frequency of 30 Hz is applied for filtering. Then, an algorithmic entropy is known as Kolmogorov notion, and Lloyd-Max quantization are used as a lossy-compression scheme. By using this method, the results are able to achieve high accuracy of up to 89.3% for person identification.

### 3. Methodology

#### 3.1. Signal acquisition

The ECG signals are recorded at a sampling frequency of 1000 Hz. with a non-invasive measurement device called Revitus ECG module. These ECG data were obtained from Magda Smolen of AGH University of Science and Technology, Krakow, Poland. It is placed on the user's body, and transfers recorded data in real-time to a notebook computer via a wireless connection. Figure 1 shows the bipolar lead and corresponding surface electrodes that are used to measure the ECG where Channel 1 (+) is located in the fifth intercostal of the anterior line, Channel 1 (-) in the manubrium of sternum on the right side and Ground is in the fifth intercostal of the mid axillary line. A total of 30 healthy volunteers were asked to repeatedly perform six regular daily activities such as working, going upstairs, going downstairs, natural gait, lying with position changed and resting while watching TV.

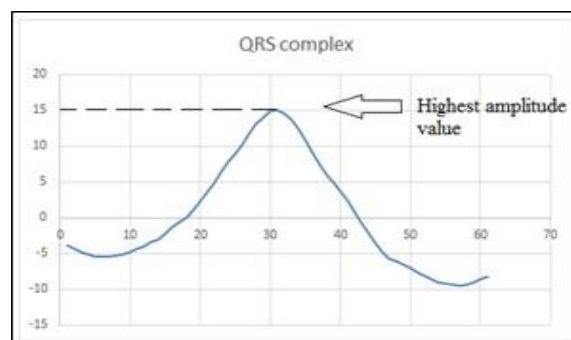


**Figure 1.** One bipolar lead (User Manual for Revitus ECG module)

#### 3.2. Feature extraction

In this paper, the feature extraction process involves QRS segmentation, DWT compression and Cardioid graph-based feature retrieval step. All the procedures are elaborated in the following subsections.

**3.2.1. QRS segmentation.** From the ECG samples obtained, the QRS complex is segregated using the Amplitude Based technique (ABT). ABT compares the amplitude of the ECG points, and the ranges of points that rise higher to an amplitude threshold are considered as a tentative QRS complex. As an example, for Figure 2, the amplitude threshold is 15.



**Figure 2.** QRS complex

After determining the QRS complex that could be the QRS candidate, the highest peak of this amplitude range is deemed to be the R peak.

**3.2.2. DWT algorithm.** In this section, the Discrete Wavelet Transform algorithm is explained in detail. A signal is decomposed into a set of basis functions, called wavelets. These wavelets are obtained from a single prototype wavelet  $\psi(t)$  called the mother wavelet by scaling and translations. According to [7], the orthonormal or wavelet basis can be defined as in Equation 1.

$$\Psi_{(j,k)}(x) = 2^{j/2} \Psi(2^j x - k) \quad (1)$$

The scaling function is given by Equation 2.

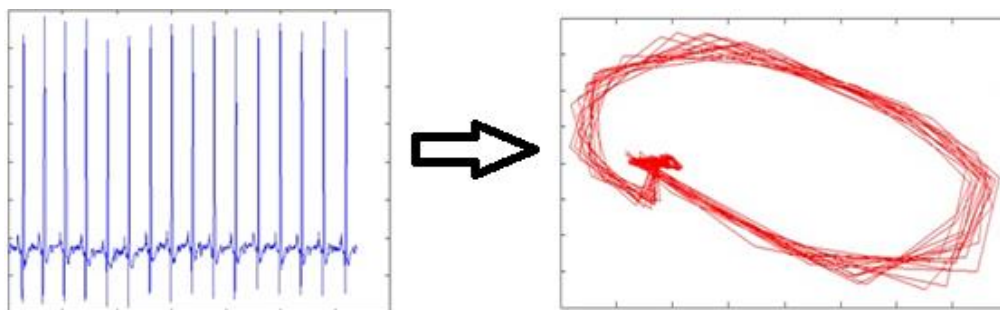
$$\varphi_{(j,k)}(x) = 2^{j/2} \varphi(2^j x - k) \quad (2)$$

where  $\Psi$  is called the wavelet function and  $j$  and  $k$  are integers that scale and translate the wavelet function. The factor ' $j$ ' in Equations 4 and 5 is known as the scale index, which indicates the wavelet's width. The location index  $k$  provides the position.

The wavelet transform is a multi-resolution transform, which uses different resolutions for analyzing signals at varying frequency. The transformation is performed individually, on separate segments of the time-domain signal, which are at different frequencies. Both the high pass and low pass filters can be obtained from a single Quadrature Mirror Filter (QMF) function that defines the wavelet. In our work, we select Daubechies (*db*) wavelet due to its resemblance of an ECG signal.

**3.2.3 Cardioid graph from compressed QRS complexes.** In order to generate a Cardioid graph, two sets of points are required. The QRS amplitudes are considered as vector  $x$ , and their differentiated values as vector  $y$  and two-dimensional closed-loop plot are generated, which resembles a Cardioid shape.

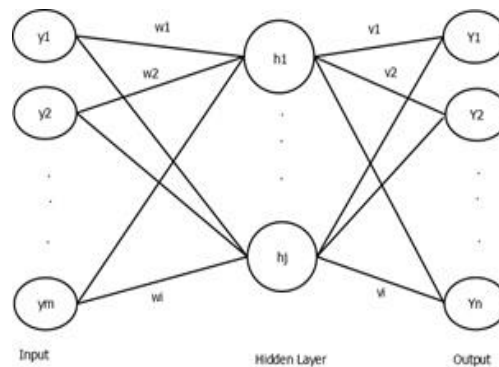
Figure 3 shows an ECG sample taken from NSRDB of Subject 16265 and the corresponding Cardioid graph.



**Figure 3.** Sample ECG from NSRDB and corresponding Cardioid graph

### 3.3. Classification

A neural network is used as the classifier so that it can be trained to understand the differences between features belonging to different physiological conditions. Multilayer Perceptron (MLP) consists of several layers and a feed-forward structure with an error-based training mechanism. The backpropagation, the input data is continually presented to the neural network. Through the help of each presentation, an error is calculated by comparing the obtained output of the neural network to the preferred outcome. This error is then fed back to the neural network and is used to modify the weights in such a way that the error decreases repetitively with each iteration, and the neural model output approaches the desired outcome. This process is known as "training" [8]. From the input layer, an applied input passes the network in a forward direction through all layers. Figure 4 depicts the general architecture of an MLP classifier applied to features of Iqbal et al. [5].



**Figure 4.** Multilayer Perceptron Classifier with input and output parameters

## 4. Experimental and Results

### 4.1. Experimental procedures

After the QRS complexes are acquired, wavelet toolbox of MATLAB is utilized to compress them. MATLAB implements the decomposing DWT based on Mallat's pyramidal algorithm. In Mallat's pyramid algorithm; from the wavelet coefficients, two smoothing and non-smoothing filters are constructed and used in all stages continually. For a signal of length  $L$ , and a total number of data  $D=2^N$ , initially  $D/2$  data at a scale of  $L/2^{(N-1)}$  are computed. In the next step,  $(D/2)/2$  data at a scale of  $L/2^{(N-2)}$  ... are calculated until 2 data at a scale of  $L/2$  is obtained. The goal is to reconstruct the signal based on a lesser number of coefficients while accounting for all the energy that was present in the original signal.

For each subject, six physiological states were considered. Two ECG samples from each physiological conditions of every subject were taken. Thus, we had 12 inputs for each subject and a total of 360 inputs that the classifier was trained with. From the compressed QRS complexes, we obtained the Cardioid graph using differentiation technique. Finally, MLP with a ten-fold cross-validation technique was applied to classify the individuals and was used to evaluate the generalization accuracy of the algorithm. The compression is performed at three decomposition levels and the first three *db* wavelets. For each decomposition level and *db* wavelet, the classification accuracy is acquired.

### 4.2. Results

**Table 1.** Classification accuracy rates and corresponding compression ratios of the system

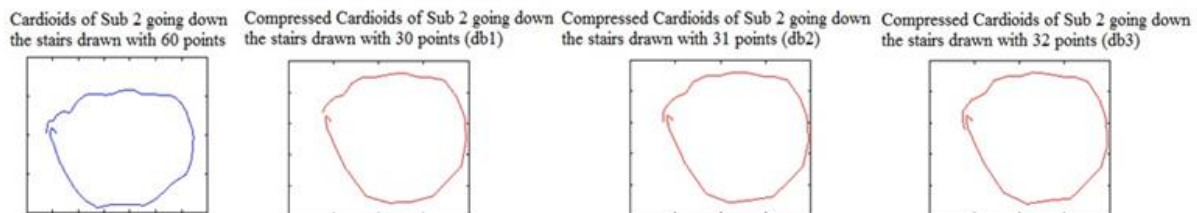
Level of Decomposition	Daubechies Wavelet	Compression Ratio (%)	Identification rate (%)
N = 1	<i>db1</i>	50.0	96.10
	<i>db2</i>	48.3	96.40
	<i>db3</i>	46.7	96.40
N = 2	<i>db1</i>	75.0	95.30
	<i>db2</i>	73.3	96.40
	<i>db3</i>	70.0	96.11
N = 3	<i>db1</i>	88.3	93.06
	<i>db2</i>	85.0	95.30
	<i>db3</i>	81.7	93.06

From Table 1, it can be noticed that the best identification rate of 96.4% is obtained when the level of decomposition is 1 and 2 in the filter bank, with *db2* and *db3* wavelets implemented. For our data, at each decomposition level, the maximum compression always occurs at *db2*.

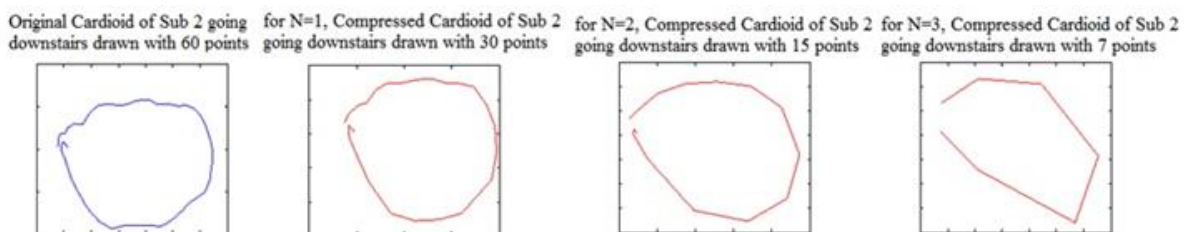
Table 1 produces three inferences, which are:

- i. If a moderate compression, for e.g. 50% is desired, only one level of decomposition with db1 wavelet is sufficient to produce quite accurate rates.
- ii. If the situation demands a highly compressed database, 3 levels of decomposition can be implemented, and as high as 88% of compression can be achieved, but it does not affect the identification rate drastically. With 88% of compressed data, the classification accuracy rate is 93.06%, while with 85% compressed data, the rate is 95.3%.
- iii. For a compression rate greater than 70% and less than 75%, the identification rate reaches as high as 96.4%, which is the same as the result discussed in Iqbal et al. [5] (that uses non-compressed QRS complexes to draw the Cardioid graph).

Figure 5 shows the original Cardioid graph of Subject 2 going down the stairs together with the other figures that are drawn from compressed QRS complexes. This figure specifically concentrates on the compression that occurs when the level of decomposition  $N = 1$ . The compression rate also varies with the Daubechies (db) wavelet applied. As the Daubechies wavelet progresses from 1 to 3, the compression ratio decreases and the Cardioid becomes more detailed.



**Figure 5.** Cardioid graphs of Subject 2 drawn from compressed QRS complexes at Level of Decomposition = 1; for *db1*, *db2* & *db3*



**Figure 6.** Compressed Cardioid graphs belonging to Subject 2 going down the stairs for Level of Decomposition = 1, 2 & 3; at *db*

Figure 6 demonstrates the Cardioid graphs drawn for different compression ratios. The least number of points used to reconstruct the original Cardioid is 7. As the compression ratio increases, the resemblances between the graph's shape also reduces. However, as seen from Table 1 above, even with a compression ratio of 88.3%, the identification rate obtained is 93.06%.

## 5. Conclusion

This paper is based on the concept of compressed ECG biometric system. The Cardioid graph-based approach is also implemented; however, compressed QRS complexes are used instead of regular QRS sample. The compression rates for various levels of DWT decompositions and first 3 Daubechies wavelets are computed. Similar accuracy rates as that of Iqbal et al. [5] and Iqbal & Sidek [6] are obtained for two instances when db2 and db3 wavelets are used with decomposition level of  $N = 1$  and  $N = 2$ . According to the results, once compared to the experiment with non-compressed ECG as input, same identification rates of 96.4% can be achieved, when the data file size is compressed up to 73.3% and execution time is reduced by 63%. Furthermore, compression ratios up to 85% and as low as 50%



are achieved. The later results with other decomposition levels and db wavelets are also reasonable, the lowest classification accuracy rate being above 93%. The highest execution time is 8.53s for the compressed method and 13.37s for the non-compressed method. Depending on the application requirement, the compression rates provide good balance with the identification rates and execution times.

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