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COMPRESSED ECG BIOMETRIC USING CARDIOID GRAPH BASED FEATURE EXTRACTION

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ABSTRACT

In this paper, a Cardioid graph based feature extraction technique is applied to perform compressed Electrocardiogram (ECG) biometric. To the best of our knowledge, Cardioid graph based method has not been implemented on compressed ECG before. Another merit of this methodology is that no decompression of the compressed ECG signal is necessary before the recognition step. The QRS complexes obtained from the ECG signal is compressed using Discrete Wavelet Transform (DWT), followed by the Cardioid graph retrieval procedure. Compression is performed in three decomposition levels and with the first two Daubechies wavelets. Classification is conducted on all the three levels using Multilayer Perceptron (MLP) Neural Network. Maximum compression of 87.5% is achieved with an accuracy rate of 93.75%. For compression rate of 85%, the identification rate obtained is 98.75%. The same highest recognition rate of 98.75% is attained both with non-compressed and compressed data. The classification accuracy rates suggest that compressed ECG biometric with Cardioid graph based feature extraction is feasible and is capable of producing a robust biometric system.

Keywords: compressed ECG biometric, cardioid graph, discrete wavelet transform.

INTRODUCTION

An ECG signal describes the electrical activity of the heart. It provides information about the heart rate, rhythm and morphology [1]. Compression technology is a practical solution while considering remote person identification and patient monitoring, due to the vast ECG signal size and limited transmission bandwidth. Regular ECG biometric implementation is restricted by the huge data storage requirement. Management of system execution time and ECG archive size is an issue for remote telecardiology scenarios, where the ECG signal of a patient needs to be sent to a hospital that is remotely monitoring his/her health. Therefore, it can be clearly noticed that compressing the ECG signal is far more efficient when transmission and storage is contemplated. Moreover, in the above mentioned scenarios, the compressed signals need to be decompressed before performing authentication. This added step introduces unavoidable delay in the processing stages. However, among the existing compressed ECG biometric studies, very few perform recognition directly on the compressed data. This paper aims to achieve better classification accuracy, while at the same time minimize the database storage so that the verdict is produced faster, with compressed ECG.

There exist literatures that have investigated compressed ECG such as [4-7]. These studies have experimented to find out different approaches to compress ECG data. Signal compression can be performed using various transformation techniques, such as, Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) [4], [5]. In [5], performance metrics based on percentage root-mean-square difference (PRD), Compression Ratio (CR), Mean Square Error (MSE), Signal to Noise ratio (SNR) were used to determine the better compression method among all the transformation methods mentioned above. Among the three transformation methods, DCT and FFT yielded better CR, but DWT provided a good balance between CR and signal content, thus making DWT decomposition more suitable for content preservation. Furthermore, another study in [6] addressed the issue of using compressed ECG that were not decompressed before performing human identification. Symbol substitution data mining algorithm was used to compress 18 ECG entries from Normal Sinus Rhythm Database (NSRDB). A total of 157 characters were used to generate the compressed ECG signal. The template size of ECG was compared to face template size of another study, and achieved 8302 times faster processing duration. However, the average classification rate was not mentioned. In a similar study by Sufi and Khalil [7], 9 ECG entries from the NSRDB were compressed using 148 characters and (0-9) numeric sub groups. Expectation Maximization clustering technique was performed to classify the compressed ECG signals. Higher compression was achieved, and processing time was 8533 times faster, as compared to the face template size. ECG data compression is expected to reduce storage requirement, conserve bandwidth, lower transmission and processing time. Compressed ECG biometric is an under-researched area, and investigation should be conducted to fill this gap.

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In this study, the outcomes are compared with two other studies that also perform compressed ECG biometric [6] and [7]. However, they have used symbol substitution as the compression method whereas we have used DWT to compress the QRS complexes. Another difference between [6] and [7] and this research is that, although data from NSRDB is used in all these three studies, our data is resampled to 360 Hz. Once the QRS complexes are compressed at three decomposition levels, Cardioid graph based feature extraction method is applied. Classification with MLP is performed on the acquired features and as a result, identification rate of as high as 98.75% is achieved when the data is compressed by 85%.

The remaining of the paper is organized as follows; Section 2 describes the methodology

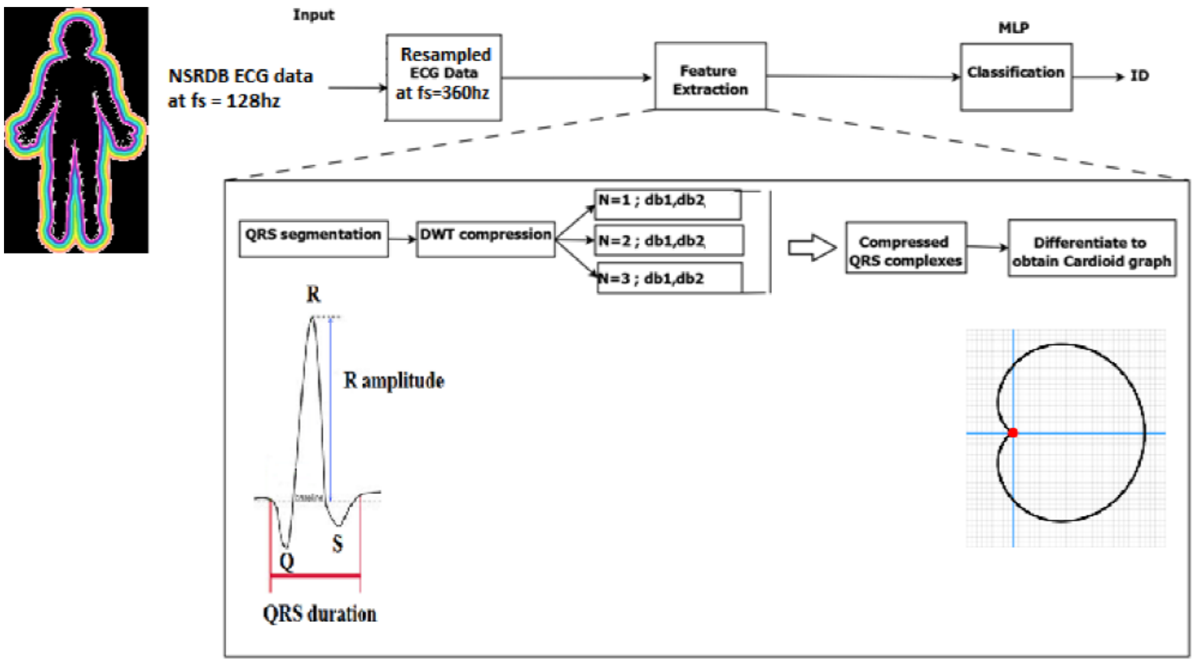

Figure-1. The proposed system model for compressed ECG biometric.

implemented, Section 3 elaborates the experimental procedures and results obtained, Section 4 provides the comparison with existing studies and Section 5 delivers the concluding remarks on the study based on the results.

METHODOLOGY

In this paper, a compressed ECG biometric system is proposed and implemented, that is based on the Cardioid graph based method.

The proposed model is shown in Figure 1. ECG data are acquired from the MIT-BIH Normal Sinus Rhythm Database (NSRDB), which is available on Physionet website [8]. Once the QRS complexes are separated, they are compressed using DWT. Compressed QRS for three decomposition levels and two Daubechies wavelet are obtained. From these compressed QRS complexes, the Cardioid graph is attained. Later, classification is performed on the features to achieve the classification accuracy. In order to realize the difference in identification accuracy between using compressed and non-compressed data, classification is also performed on the non-compressed data, for better comparison. These steps are further elaborated in the later subsections.

ECG data acquisition

ECG signals of all the subjects were acquired from an online physiological signal archive for biomedical research. The database of MIT-BIH Normal Sinus Rhythm Database (NSRDB) includes 18 ECG recordings of healthy subjects referred to the BIH Arrhythmia Laboratory. The database has sampling frequency of 128 Hz and each subject has 30 seconds of ECG recordings. These ECG entries are obtained from the publicly available online website called PhysioNet. For our study, we considered 10 subjects and the ECG signal were resampled to 360 Hz.

Feature extraction

Feature extraction is a procedure that determines specific properties of an ECG signal. These properties are always distinct to the particular ECG signal and can be used to represent it. This step is crucial in determining the accuracy of the resultant system output. In this paper, the feature extraction process involves QRS segmentation, DWT compression and Cardioid graph based feature retrieval step.

QRS segmentation

After resampling the obtained ECG signal, QRS complexes are separated using their amplitude requirements as in [8].

DWT compression

The QRS complexes are transformed into a set of wavelet coefficients. Through a few number of coefficients, the original QRS complexes can be represented. The number of coefficients varies with the decomposition level and Daubechies wavelet used.

Discrete Wavelet Transform (DWT) consists of a series of filtering and subsampling. At each level, a set of 2j−1 coefficients are calculated, where j < J is the scale and N = 2J is the number of samples in the input signal. Two sets of coefficients are calculated simultaneously. Both high-pass and low-pass filter are applied to the signal followed by downsampling with a factor of 2. The two types of filtering occur at the same time. This step produces the input signal for the next level. Both the high pass and low pass filters can be obtained from a single Quadrature Mirror Filter (QMF) function that defines the wavelet. This decomposition is repeated in a recursive cascade structure of binary tree with nodes known as a filter bank. Figure-2 graphically represents this process, where x(n) is the original signal, h(n) and g(n) are the high pass and low pass filter impulse response respectively. Reconstruction occurs with filtering and upsampling of the resultant coefficients. DWT produces different wavelet families like Daubechies (db), Haar, coiflets, etc. Among each family of wavelets there are wavelet subclasses defined by the number of coefficients and the level of iterations [9]. In our work, we select Daubechies wavelet due to its resemblance of an ECG signal. This means that wavelet transform can concentrate most of the signal in a small portion of the coefficients and provide efficient compression [10-12].

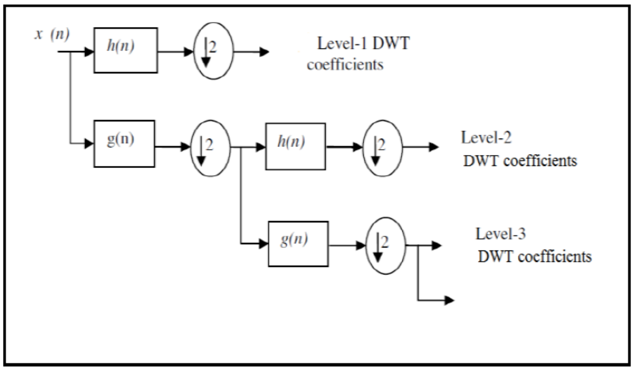

Figure-2. DWT filter bank representation.

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. With these vectors x and y, a two dimensional closed loop plot is generated which resembles a Cardioid shape.

Mathematically, ECG signal can be denoted by x(m) as in Equation (1).

$$x(\mathrm{m}) = \{ x(1), x(2), x(3), \ldots, x(\mathrm{n})\} \quad (1)$$

where x(m) are ECG signals composed of QRS complexes measured in millivolts (mV) and M is the total number of QRS complexes for an ECG wave for a given time. After obtaining the vector x(m), it is then differentiated to obtain y(m) as shown in Equation (2).

$$y(\mathrm{m}) = \{x(2)-x(1), x(3)-x(2), ..., x(M)-x(M-1) \quad (2)$$

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 MLP and many other neural networks uses a learning algorithm called back propagation. By means of back propagation, 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 (back propagated) 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". The input layer in MLP consists of the extracted features (in our case, the differentiated QRS complexes), one or more hidden layers, and an output layer (which determines the class of ID). Each layer in MLP consists of at least one neuron. From the input layer, an applied input passes the network in a forward direction through all layers [13] [14]. Figure-3 depicts the general architecture of an MLP classifier.

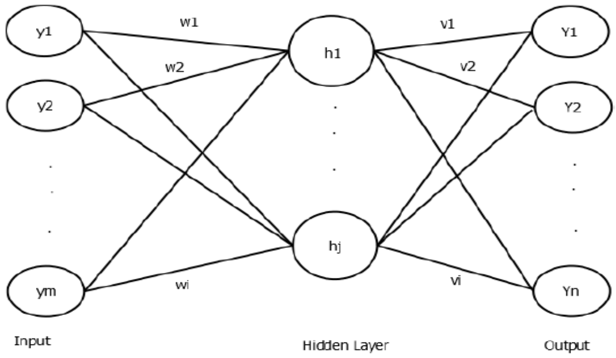

Figure-3. Multilayer perceptron flowchart.

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EXPERIMENTATION AND RESULTS

A total of 10 subjects from NSRDB was considered. From the ECG signal of each subject, eight QRS complexes were taken. Thus, we had 8 inputs for each subject and a combined total of 80 (8x10 = 80) QRS complexes. From the compressed QRS complexes, we obtained the Cardioid graph using equations 1 and 2. Finally, MLP with 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 two db wavelets. For each decomposition level and db wavelet the classification accuracy is acquired. From Table 1, it can be noticed that, identification rate as high as 98.75% is obtained at all three decomposition levels in the filter bank. Based on the DWT compression theory, the maximum compression always occurs when the signal is most compatible with the scaling and wavelet function of the Daubechies wavelet.

Tables are to be formatted as shown in Table-1. Table captions should be placed at the top. Tables should be cited in the text as Table-1. Columns should not run to a different page. Wide tables can cut across the two columns, but the text that follows it must be of two columns once again. Allow sufficient gap (at least 5pt) between the Table and the text above/below.

From Table-1, we can conclude:

- High classification accuracy of 98.75% can be obtained for both non-compressed and compressed data.
- If a moderate compression, for e.g. 50% is desired, only one level of decomposition with db1 wavelet is sufficient to produce the same high identification rate of 98.75% as obtained with non-compressed data.
- If the situation demands for a highly compressed database, 3 levels of decomposition can be implemented, and as high as 85% of compression ratio can be achieved, without compromising the identification rate of 98.75%.

Table-1. Classification accuracies and corresponding compression ratios of the system.

Level of decomposition	Daubechies Wavelet	Compression Ratio (%)	Identification rate (%)
None (non-compressed)	None	0	98.75
N = 1	*db1*	50	98.75
	db2	47.5	97.5
N = 2	*db1*	75	98.75
	db2	72.5	96.25
N = 3	*db1*	87.5	93.75
	db2	85	98.75

Therefore, depending on the identification rate requirement or storage availability, the implementer has quite many options at hand, none of which jeopardize the classification accuracy rate excessively.

Figure-4 shows the original Cardioid graph of Subject 4 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 wavelet applied. As the Daubechies wavelet progresses from 1 to 2, the compression ratio decreases, and the Cardioid becomes more detailed. Although the Cardioid graphs are plotted using less points, they retain their distinct pattern.

Figure-5 demonstrates Cardioid graphs drawn for different compression ratios. The least number of points used to reconstruct the original Cardioid graph is 5. 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 87.5%, the identification rate obtained is 93.75%.

COMPARISON OF RESULTS

The similarity between our investigation and both the studies conducted in [6] and [7] lies in the ECG data used. However, our compression methodology is different and we have resampled the data from NSRDB. Also, in [6] and [7], the compression ratios are not mentioned. In our study we have provided alternative compression ratio and identification rate which can be considered depending on the implementation scenario. Table 2 summarizes the comparison. As can be seen from this table that we have managed to obtain 98.75% of identification rate with 10 subjects at compression rate of 85%.

The results suggest that compressed ECG biometric using Cardioid graph based method is feasible, and it can act as a gateway to wide range of applications.

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CONCLUSIONS

In this paper, a new method is applied to perform compressed ECG biometric. Unlike the existing studies, the proposed system conducts classification directly on the compressed ECG signal, eliminating the requirement of decompression before performing recognition. Since the file size is compressed, the overall system execution time will also be reduced and faster subject identification can be performed. From the results, it can be seen that even with a high compression ratio of 85%; reliable identification rate of 98.75% can be produced. Moreover, the proposed compressed ECG biometric system can be performed using an easily implementable Cardioid graph based feature extraction technique leading to a robust system that produces high outcomes.

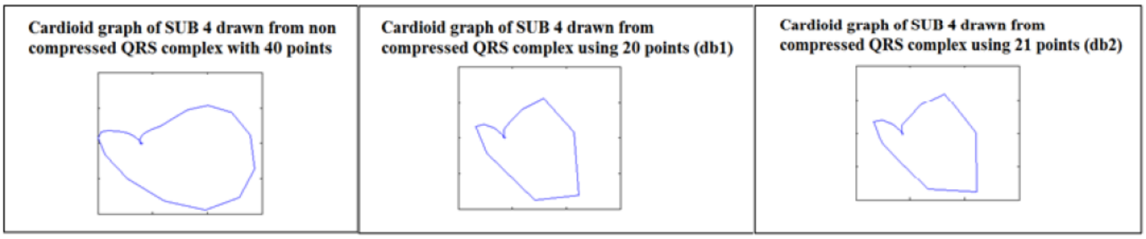

Figure 4 Cardioid graphs of Subject 4 drawn from compressed QRS complexes at Level of Decomposition = 1; for *db*1 & *db*2

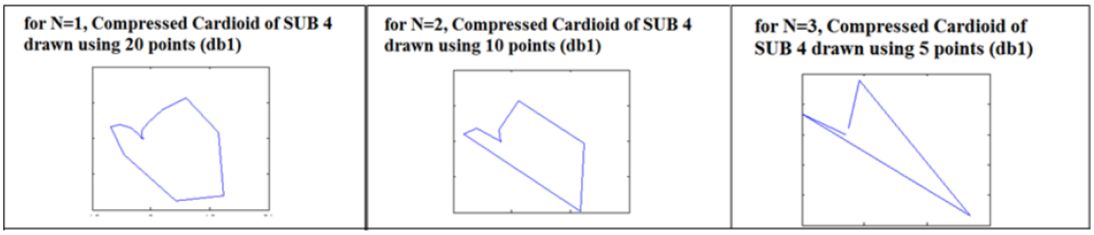

Figure-5. Compressed cardioid graphs belonging to subject 4 for level of decomposition = 1, 2 & 3; at *db*1.

Table-2. Result comparison with other studies.

Study	Number of subjects	Database	Compression method	Classification Accuracy (%)
Sufi & Khalil [7]	9	NSRDB	Symbol Substitution	100%
Sufi, Khalil & Mahmood [6]	18	NSRDB	Symbol Substitution	N/A
Proposed method	10	NSRDB	DWT	98.75%

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REFERENCES

[1] F. Agrafioti and D. Hatzinakos, 2009. ECG biometric analysis in cardiac irregularity conditions. Signal, Image and Video Processing. 3(4): 329-343.

[2] S. C. Fang and H. L. Chan. 2013. QRS detection-free electrocardiogram biometrics in the reconstructed phase space. Pattern Recognition Letters, 34(5): 595-602.

[3] J. D. S. Luz, D. Menotti, and W. R. Schwartz. 2014. Evaluating the use of ECG signal in low frequencies as a biometry. Expert Systems with Applications. 41(5): 2309-2315.

[4] A. Shinde and P. Kanjalkar.2011. The comparison of different transform based methods for ECG data compression. 2011 International Conference on Signal Processing, Communication, Computing and Networking Technologies (ICSCCN). July 2011. 332-335.

[5] K. Ranjeet, A. Kumar and R. K. Pandey. 2011. ECG Signal Compression Using Different Techniques.

Advances in Computing, Communication and Control: Proc. of the International Conference, ICAC3 2011, January 2011. 125: 231-241.

[6] Sufi, I. Khalil and A. Mahmood. 2011. Compressed ECG biometric: a fast, secured and efficient method for identification of CVD patient. Journal of Medical Systems. 35(6): 1349-1358.

[7] Sufi and I. Khalil. 2011. Faster person identification using compressed ECG in time critical wireless telecardiology applications. Journal of Network and Computer Applications. 34(1): 282-293.

[8] K. A. Sidek, I. Khalil, and M. Smolen. 2012. ECG biometric recognition in different physiological conditions using robust normalized QRS complexes. Computing in Cardiology (CinC): Proc. of the 39th Computing in Cardiology Conference. September 2012. 97-100.

[9] M. Misiti, Y. Misiti, G. Oppenheim and J. M. Poggi. Wavelet Toolbox™ 4 User's Guide. 2010. [Online]. From: www.di.univr.it/documenti/OccorrenzaIns/matdid/matdid844164.pdf. [Accessed on 20 May 2015].

[10] S. Dangeti. 2003. Denoising techniques-a comparison. M.S. thesis, Dept. Elect. and Comp. Eng., Andhra Univ. College Eng., Visakhapatnam. 2003. [Online]. From: http://etd.lsu.edu/docs/available/etd-1219102-152426/. [Accessed on 19 May 2015].

[11] Discrete Wavelet Transform. 2002. [Online]. From: http://klapetek.cz/wdwt.html. [Accessed on 14 May 2015].

[12] J. Olkkonen, (Eds.). 2011. Discrete Wavelet Transforms-Theory and Applications. Croatia: In Tech.

[13] R. Kruse, C. Borgelt, F. Klawonn, C. Moewes, M. Steinbrecher and P. Held. 2013. Computational Intelligence: A Methodological Introduction. London: Springer.

[14] V. Mai, I. Khalil and C. Meli. 2011. ECG biometric using multilayer perceptron and radial basis function neural networks. 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). August 2011. 2745-2748.