Identification of Cardiac Autonomic Neuropathy Patients using Cardioid Based Graph for ECG Biometric

Khairul Azami Sidek[1], Herbert F Jelinek[2], Ibrahim Khalil[3]

[1,3]School of Computer Science and Information Technology, RMIT University, Melbourne, Victoria, Australia
[2]School of Community Health, Charles Sturt University, Albury, Australia

Abstract

In this paper, the application of data mining applied on Cardioid based person identification mechanism using electrocardiogram (ECG) is presented. A total of 50 subjects with Cardiac Autonomic Neuropathy (CAN) were obtained from participants with diabetes from the Charles Sturt Diabetes Complication Screening Initiative (DiScRi). The patients can be categorized into two types of CAN which are early CAN and definite/severe CAN. Euclidean distances obtained as a result of the formation of the Cardioid based graph were used as extracted features. These distances were then applied in Multilayer Perceptron to confirm the identity of individuals. Our experimentation results suggest that person identification is possible by obtaining classification accuracies of 99.6% for patients with early CAN, 99.1% for patients with severe/definite CAN and 99.3% for all the CAN patients. These results indicate that ECG biometric is possible and QRS complex is not severely affected by CAN with the ability to identify and differentiate individuals.

1. Introduction

The global mortality of diabetes in the year 2000 was estimated to be 2.9 million deaths, equivalent to 5.2% of all deaths [1]. The total number of people with diabetes is projected to rise from 171 million in 2000 to 366 million in 2030 [2]. Globally, diabetes is likely to be the fifth leading cause of death.

Cardiovascular Autonomic Neuropathy (CAN) is a serious and common complication of diabetes which reduces the cardiac autonomic function and increases the risk of cardiac arrhythmias and sudden death, possibly related to silent myocardial ischemia and mortality. CAN strikes without the patients realizing that they suffer from it and affects up to 50% of patients with diabetes.

CAN results in the morphological change of the heart signal which indirectly affects person identification and makes the process even harder, In order to ensure the robustness of ECG biometric, it is very crucial to identify individuals even with cardiac abnormalities such as CAN.

ECG biometric has become an active field of research for human recognition since a decade ago. The fact that the geometrical and physiological deviations of the heart in different individuals portray certain uniqueness in their ECG signal [3] and the distinctiveness and stability of the ECG signal [4] validates its claim as a biometric modality.

The advancement in medical equipments, information technology and communication has the tendency to revolutionize healthcare system. The crucial development has made it feasible for the aged society to monitor and maintain their own wellbeing especially in home healthcare solutions. It is crucial to validate the identity of a person in assisting general practitioners and medical officers to obtain medical records of patients in a healthcare facility in split seconds which includes CAN patients. ECG biometric using Cardioid based graph which was introduced by Sufi et. al. in [5] represents an alternative method of recognition in a faster and easier way as compared to using ECG recordings based on the normal and lengthy Holter readings for long distance healthcare systems. Not only limited to person identification method, Cardioid based graph is capable of detecting abnormalities in the heart rhythm which may be caused by cardiac diseases and other forms of dementias as in [5,6]. The current approach of extracting features to obtain the Cardioid based graph using Euclidean distance produces reasonably good classification accuracy to differentiate between individuals. We extend the usability of Cardioid based graph on CAN patients as it has been proven to be efficient with patients in NSRDB and MITDB as in [7]. We focus on a specific form of diabetes as to show the robustness of Cardioid based graph with other types of dementias. It is reasonably enough to expand the usability of this method to CAN patients as it is the major contributors of the mortality of diabetes patients.

Based on the results of our experimentations, the classification accuracy of Cardioid based graph using

Euclidean distance gives a reasonably good classification accuracy of up to 99.6% for CAN patients. This gives an indication that ECG biometric is possible and is not severely affected by CAN with the ability to identify and differentiate individuals.

The remaining of the paper is organized as follows; the next section elaborates the method of the study which includes the data collection procedures, feature extraction method using Euclidean distance which briefly explains Cardioid based graph and Multilayer Perceptron as the classification mechanism. Later, Section 3 discusses about the performance of the proposed classification technique. Finally, in Section4, we conclude the study based on the experimentation and results in the previous section.

2. Method

In healthcare infrastructure, such as hospitals and health centres, several patients are connected to the medical monitoring equipment at once. Medical officers in healthcare facilities will be flooded with ECG data coming from all directions. This may create redundant and irrelevant data that could increase resource allocated and computational complexity in the hospital server which could hinder the overall performance of the system. Cardioid based graph was proposed as a solution for security where once the identity of a patient has been validated, medical officers can take appropriate measures regarding the patient's heart condition [7]. Needless to say, CAN which could inherently change the morphological signals would significantly affect identification of individuals. Thus, in this study, we would like to investigate the possibility of using Cardioid based graph to CAN patients for ECG biometric to ease the healthcare professionals in identifying individuals with the influence of CAN. The success of this proposed system means a more easier, efficient and effective healthcare infrastructure for doctors and gives freedom from 24/7 physical monitoring for caregivers which also improves the quality of life. The healthcare scenario using Cardioid based graph for CAN patients is summarised as in Figure 1.

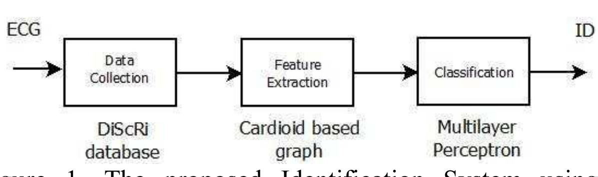

Figure 1. The proposed Identification System using Cardioid based graph.

2.1. Data collection

A total of 50 ECG datasets used in this work were taken from the Charles Sturt Diabetes Complication Screening Initiative (DiScRi). The patients can be categorized into two types of CAN which are early CAN (41 subjects) and definite/severe CAN (9 subjects). The research protocol was approved by Charles Sturt University Ethics in Human Research Committee (03/164). ECG recordings were over 20 minutes using a lead II configuration (Maclab ADInstruments Australia) and recorded on Macintosh Chart version 4 with a sampling frequency of 400 Hz and a notch at 50 Hz. ECG signals were then edited using the MLS310 HRV module (version 1.0, ADInstruments Australia) included in the Chart software package. High frequency noise was removed with a 45 Hz low-pass filter and a 3 Hz high pass filter adjusted for wandering baseline.

Once the ECG signals have been collected, an analytical method was used to obtain the QRS complex, starting from the R wave since it corresponds to the most obvious, highest and prevalent peak in ECG morphology. It then becomes the pivot where we select equal points from both directions; the right and left of the identified R wave. We repeat the process for a total of 12 times for each subject where actually each time it would cover the whole QRS complex. First Derivative based technique was used to automate this procedure [8]. The reason QRS complex was chosen in this analysis instead of P or T wave or even the whole ECG morphology were mainly because it is less affected by cardiac abnormalities, noise and artifacts as shown in [9-11]. Then, using these QRS complexes, Cardioid based graph was applied to obtain uniquely extracted features as demonstrated in [7].

2.2. Feature extraction

This next step is very crucial as it determines the persistency of the classification accuracy form Cardioid based person identification mechanism. Once the Cardioid is formed, the time series representation is lost as it is replaced by points of a closed loop as depicted in Figure 2.

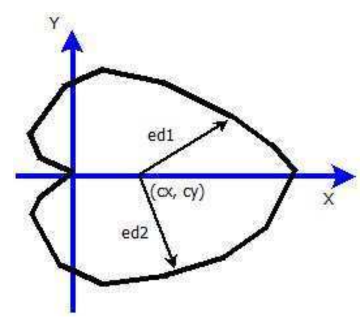

Figure 2. A Cardioid Graph.

Let's assume the ECG signal can be mathematically represented by $\mathbf{x}(t)$ as in Equation 1.

$$\mathbf{x}(t) = \{x(1), x(2), x(3), \ldots, x(N)\} \quad (1)$$

where x(t) are ECG signals consisting of QRS complexes measured in millivolts (mV) and N is the total number of QRS complexes for a given time. In order to obtain the points for the Cardioid, the QRS complexes are first differentiated as in Equation 2.

$$\mathbf{y}(t) = \mathbf{x}(t) - \mathbf{x}(t\text{-}1) \tag{2}$$

where t = 1,2,3, ..., (N-1) and $\mathbf{y}(t)$ is the differentiated ECG dataset.

After obtaining vectors **x** and **y**, a closed loop graph is generated based on a scattered XY graph called the Cardioid. The x-axis represents the ECG amplitudes of the QRS complexes, in this case, vector **x** and the y-axis are differentiated ECG of vector **x** represented by vector **y**. After this process is completed, the time series of the ECG signals is converted to a two dimensional loop. From this closed loop graph, the centre coordinate called centroid and the distance of the centroid to a given point on the Cardioid called extrema points are extracted.

Centroid is obtained by Equation 3 and it can be represented as *cx* and *cy*.

$$(cx,cy) = \left[\frac{\sum_{i=1}^{N} x(i)}{N}, \frac{\sum_{i=1}^{N} y(i)}{N} \right] \tag{3}$$

where *cx* and *cy* are the coordinate position of the centroid in the Cardioid graph. Making the centroid as the reference point, te Euclidean distances, *ed(i)* are then computed using Equation 4.

$$ed(i) = \sqrt{(cy - y(i))^2 + (cx - x(i))^2} \tag{4}$$

where *ed(i) = ed1, ed2, ed3, ..., ed(n).*

These features extracted from the Cardioid based graph are then applied to MLP for classification procedures which will be elaborated in the next section.

2.3. Classification

Multilayer Perceptron (MLP) has several layers and a feedforward structure with an error based training mechanism. MLP is derived by an input layer which consist of the extracted features (in our case, the Euclidean distances), 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. An input vector is applied to the input layer which then passes the network in a forward direction through all layers. Figure 3 depicts the general architecture of an MLP.

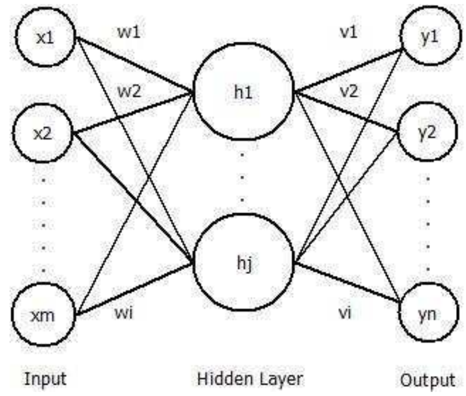

Figure 3. A Multilayer Perceptron Network.

A neuron in a hidden layer is linked to each neuron in the layer before and after it, In Figure 3, weight w_i connects input node x_m to hidden node h_j, and weight v_k connects h_j to output mode y_n. Classification starts by assigning the input nodes x_m, $1 \le m \le l$ equal to the corresponding data vector component. Then data propagates in a forward direction through the perceptron until the output nodes y_n, $1 \le n \le n$, are reached [12]. The MLP acts as a classifier, estimates the necessary discriminant functions, and assigns each input vector to a given class. The learning algorithm adapts the weights based on minimizing the error between given output and desired output.

3. Experimentation and discussion

We tested the Cardioid based graph using 50 subjects obtained from DiSciRi database. The ECG dataset for each subject consists of 12 QRS complexes where each QRS contains 12 different instances. Half of the QRS complexes are used as training data and the remaining QRS complexes acts as the testing data. Figures 4 and 5 shows the QRS complexes of patients with early and definite CAN.

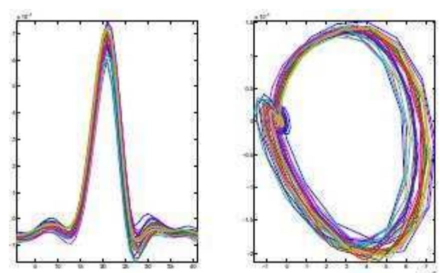
Figure 4. QRS complex and Cardiod of an early CAN patient.

After obtaining the relevant number of QRS complexes, we calculated the centroid of the closed loop and Euclidean distances using Equation 3 and 4. Again figures 4 and 5 illustrate the Cardioid based graph formed from early and definite/severe CAN patients. Based on both figures, self-similarity is shown between instances for the same patients but different QRS and Cardioid shapes between patients.

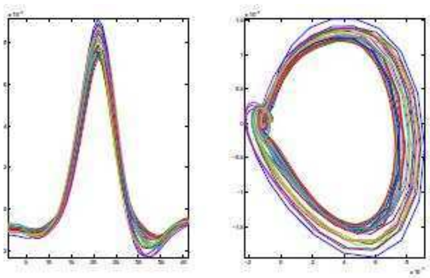

Figure 5. QRS complex and Cardioid of a definite/severe CAN patient.

Finally, MLP was applied to classify the individuals and a tenfold cross validation technique was used to evaluate the generalization accuracy of the induction algorithm. The results of the experimentation are summarized as in Table 1.

Table 1. Classification accuracies of CAN patients

Classification	Accuracy (%)
Early	99.6
Definite/Severe	99.1
All (Early + Definite/Severe)	99.3

Based on the results, we can point out two main deductions: (1) the process of person identification is not severely affected by CAN and identifying individual is possible and (2) the QRS complexes from CAN patients are stable and uniform neglecting the effects of cardiac abnormalities.

4. Conclusion

In this paper, we have demonstrated an efficient and accurate method of person identification for CAN patients using MLP classifier on Cardioid based graph. The results of the experiments suggest that the proposed method give significant person identification with classification accuracies of 99.6% for patients with early CAN, 99.1% for patients with definite/severe CAN and 99.3% for all CAN patients. This result indicates that ECG biometric is possible and QRS complex is not severely affected by CAN with the ability to identify and differentiate individuals.

References

[1] Roglic G, et al. The burden of mortality attributable to diabetes: Realistic estimates for the year 2000. Diabetes Care 2005;8:2130-2135.

[2] Wild S, et al. Global prevalence of diabetes: Estimates for the year 2000 and projection for 2030. Diabetes Care 2004;27:1047-1053.

[3] Hoekema R, Uijen G, van Oosterom A. Geometrical aspects of the interindividual variability of multilead ECG recordings. IEEE Trans Biomed Eng 2001;48:551-559.ISSN 0018-9294.

[4] Wubbeler G, Stavridis M, Kreiseler D, Bousseljot R, Elester C. Verification of humans using the electrocardiogram. Pattern Recogn Lett 2007;28:1172-1175. ISSN 0167-8655.

[5] Sufi F, Khalil, Tari Z, A Cardioid based technique to identify cardiovascular diseases using mobile phones and body sensors. In Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. ISSN 1557-170X, 2020; 5500-5503.

[6] Sufi F, Khalil I, Habib I. Cardioid-based faster authentication and diagnosis of remote cardiovascular patients. Security and Communication Networks 2011;4:1351-1368.ISSN 1939-0122.

[7] Sidek K, Sufi F, Khalil I. Data mining technique on Cardioid graph based ECG biometric authentication. In Biomedical Engineering, Proceedings of the IASTED International Conference on, volume 35. ACTA Press, 2011; 53-57.

[8] Sufi F, Fang Q, Cosic I. ECG R-R peak detection on mobile phones. In Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE. ISSN 1557-170X, 2007; 3697-3700.

[9] Tawfik M, Selim H, Kamal T. Human identification using time normalized QT signal and the QRS complex of the ECG. In Communication Systems Networks and Digital Signal Processing, 2010 7th International Symposium on. 2010; 755-759.

[10] Sidek K, Khalil I. Application of data mining on polynomial based approach fro ECG biometric. In Biomedical Engineering, IFBME Proceedings: The 5th Kuala Lumpur International Conference on, volume 35. Springer-Verlag Heidelberg. ISBN 978-3-642-21728-9,2011;476-479.

[11] Sidek K, Khalil I. Person identification in irregular cardiac condition using electrocardiogram signals. In Engineering in Medicine and Biology Society, 2011. 33rd Annual International Conference of the IEEE. ISBN 978-1-4244-4122-8/11, 2011;3772-3775.

[12] Theis FJ, Meyer-Base A. Biomedical Signal Analysis: Contemporary Methods and Applications. The MIT Press, 2010.

Address for correspondence.

Khairul Azami Sidek
School of Computer Science and Information Technology, RMIT University, 3001, Victoria, Australia
khairul.sidek@student.rmit.edu.au