ECG Biometric Recognition in Different Physiological Conditions using Robust Normalized QRS Complexes

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Abstract

This paper demonstrates subject recognition using electrocardiogram (ECG) signal in different physiological conditions. A total of 30 subjects used in this study were obtained from a non-invasive measurement called the Revitus ECG module. Each subject performed six physiological activities which are walking, going upstairs, going downstairs, natural gait, lying with position changed and resting while watching TV. Unique features were extracted in these different physiological conditions from the same subject using normalized QRS complex technique. One physiological activity acts as the enrolment template while the remaining five activities represent the recognition data. Cross correlation was used to measure the similarity between activities. Later, Multilayer Perceptron classifier was applied to evaluate the distinctiveness between subjects. The results of the experiment show that QRS complexes in different activities from the same subject were strongly correlated to each other by obtaining correlation values of more than 0.9. A classification accuracy of 96.1% when using the proposed normalized method as compared to 93.4% without using the normalized QRS complex proves to distinguish between subjects.

1. Introduction

Physiological conditions present a viable mechanism of evaluating a person's internal state under natural conditions. Carrying out different kinds of activities promotes heart rate variability. How far these changes effect the signal morphology is of our greatest concern because we are interested in investigating the consequence towards subject recognition using the ECG signal. In the past decade, ECG biometric has been studied using subjects mainly under rest condition. Little has been said about person identification in varying physiological conditions expect for recent works done in [1, 2]. However, in [1] the whole ECG morphology was used to perform subject recognition which could inherit artifacts in the ECG signal and degrade classification performance. This work also suggested of using P-QRS in exercise condition. Thus, the proposed approach lacks robustness as unique features which are extracted could not be generally used in different physiological states. Moreover, results in [2] have limited physiological movements and only determine interval length for different physiological states. This touches the issue of reliability as it needs to apply different length to perform different states. Thus, in this paper, we verify the claim that ECG biometric is a feasible method that can be used with subjects in varying physiological states implementing our robust and reliable technique. We expand the physiological state much more and prove that the proposed technique using normalized QRS complex for person identification is robust in different states. The results of the experimentation suggest that QRS complex coming from different activities of the same subject were strongly correlated but quite distinct when compared with other subjects by obtaining promising classification accuracy.

The remaining of the paper is organized as follows; the next section describes the methodology of the study. Later, Section 3 elaborates about the performance comparison of applying ECG data with and without the normalized QRS complexes. And finally in Section 4, we conclude the study based on the experimentation and results in the previous section.

2. System and method

The general architecture of our proposed system begins with signal acquisition of the ECG recordings, followed by extraction of QRS complexes as unique features, then performing normalization technique on the features and later using these extracted features to a template matching algorithm and a classifier for identification purposes between activities and different subjects. The proposed identification system is summarised as in Figure 1 and these steps are discussed in the next section.

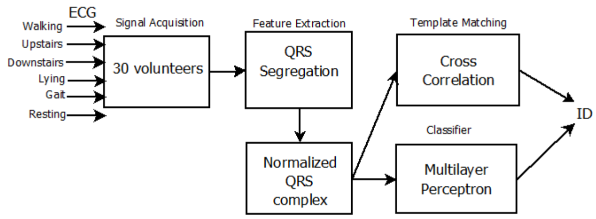

Figure 1. The Proposed Identification System

2.1. Signal acquisition

In order to obtain the general state of a subject, a non-invasive measurement device called the Revitus ECG module was used. This device enables recording of ECG signals with sampling frequency of 1000 samples per second. It has a built-in battery with 1300 mAh and is placed on the user's body. It is connected wirelessly to a notebook computer and buffers recorded data transmitted in real time or after the data collection stage into the internal memory module. Only one bipolar lead is used to measure the heart's electrical activity and corresponding surface electrodes were located as in Figure 2.

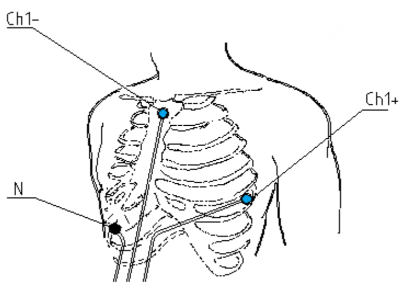

Figure 2: One bipolar leads [3]

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 midaxillary line.

A total of 30 healthy volunteers without history of cardiac abnormalities participated in the study. Each subject was asked to repeatedly perform six common daily activities which are walking, going upstairs, going downstairs, natural gait, lying with position changed and resting while watching TV. Then, these physical activities were recorded using the Revitus ECG module.

2.2. Feature extraction

After ECG signals have been acquired, QRS complexes are segregated using amplitude criteria of the wave. The process starts by identifying the R wave and making it the referral point since it corresponds to the most highest and prevalent peak in an ECG. From the R wave, equal numbers of data points are selected to the left and right of this reference point. We reiterate the previous step in different time instances to obtain more QRS complexes for every subject which would represent enrolment and recognition ECG dataset.

2.3. Normalized QRS complex

After QRS complexes have been segregated, our proposed normalization technique is applied. It aims to remove inherited noise caused by baseline wanders from the ECG signal by levelling it to a common scale. By doing so, it would be much easier to analyze similarities of ECG signals in a subject with varying physiological states. This technique can be defined as in Equation 1.

$$Normalization, N = \frac{x - \mu_x}{n_x} \tag{1}$$

where x is the ECG dataset, μ_x is the mean value of x and n_x is the data points in x. This process has also enabled us to avoid any pre-processing methods which normally are applied before performing feature extraction technique in order to remove baseline wander effects. Thus, the results of normalization is illustrated in Figure 3 by taking *subject 30* normalized QRS complexes.

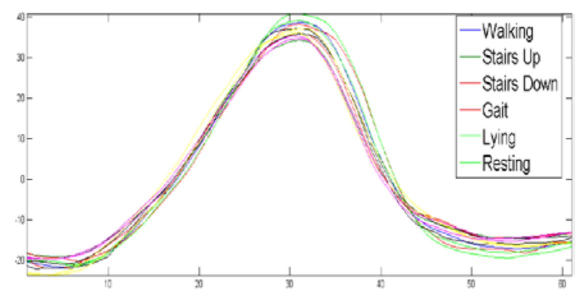

Figure 3. *Subject 30* normalized QRS complexes acquired from six physiological states where 2 QRS complexes from each condition.

As can be seen in this figure, self-similarities of QRS complexes in different physiological activities are evident which comes from the same subject. Thus, as to further verify this observation and prove the effectiveness of the proposed approach, two main aspects have to be considered and proven, i) the effect of using different physiological conditions from the same subject, and ii) using these different physiological states for a subject and comparing it with other subjects. In other words, we define these two aspects as *intra subject* and *inter subject* recognitions. Thus, this has led us to use two commonly applied methods for these types of scenarios. For intra subject recognition, a template matching mechanism is implemented which is cross correlation. While, in inter subject recognition, Multilayer Perceptron is applied. The next sections will be elaborated more on these topics.

2.4. Intra subject recognition

Cross correlation is a simple yet effective matching algorithm used to find the similarity between two unknown sources. In our case, it investigates the connection between two signals which consist of different physiological activities from the same subject and determines the dependency strength between these two variables by giving correlation values in the range of -1 to +1. A value of +1 denotes the connection between the two ECG signals as strongly connected to each other. While, a value of -1 describes that the two signals are negatively correlated. And a value of 0 indicates that the two signals have no relationship and dependency against each other. The correlation coefficient, *r*, measures the connection and can be represented as in Equation 2.

$$r = \frac{C(x,y)}{\sqrt{C(x,x)C(y,y)}} \qquad (2)$$

where *C* is the covariance between the variable that measures the strength of the signals. Successful template matching will be able to validate whether two unknown ECG signals come from the same or different sources.

2.5. Inter subject recognition

Multilayer Perceptron (MLP) is a feedforward artificial neural network model with three main components in a directed graph. The input layer is the outcome of the feature extraction technique and the output layer decides the subject's class ID. The classifier also has one or more hidden layers. Each node consists of at least one neuron with a nonlinear activation function except for the input nodes. The general architecture is depicted as in Figure 3.

Classification starts by assigning the input nodes with the extracted outcome of the features which then flows into a forward direction through the perceptron until it finally reaches the output nodes. This network is trained with the back propagation learning algorithm which adapts weights, w_n and v_n, based on lowering the error between given output and desired output.

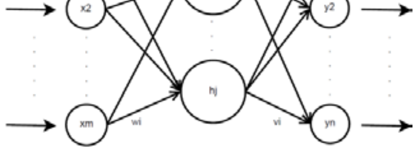

Figure 3: Multilayer Perceptron

3. Experimentation and results

A total of 12 normalized QRS complexes were collected from each subject for the self-similarity analysis between activities (intra subject) where 2 QRS complexes were acquired from each state. Walking acts as the enrolment data and the remaining five physiological states are described as recognition data. Similar procedures are applied to inter subject recognition. The difference is that the enrolment and recognition comes from different subjects. Let's assume Walking is A, Stairs up is B, Stairs down is C, Gait is D, Lying is E and Resting is F. So, using correlation coefficient, we compare (E_x,E_{15}), (E_x,R_1), (E_x,R_2), (E_x,R_3), (E_x,R_4) and (E_x,R_5) where E_x is the 2nd QRS complex from A of subject *x*, E_{15} is the 16th QRS complex from A of subject *x*, R_1 means the 16th QRS complex from B of subject *x*, R_2 means the 16th QRS complex from C of subject *x*, R_3 means the 16th QRS complex from D of subject *x*, R_4 means the 16th QRS complex from E of subject *x* and R_5 means the 16th QRS complex from F of subject *x*. Why the 16th value? This time instance is assumed to be in the intense period of physiological condition. We could choose the 2nd QRS complex from each activity but it would be unfair and would not represent the whole result as the 2nd QRS complex is in the initial stage where the subject is about to perform an activity. So, the results from all 30 subjects were very encouraging where not a single value was below 0.9 which indicated A, B, C, D, E and F from the same person was strongly correlated as shown in Table 1.

Furthermore, inter subject results gave significantly good classification performance by obtaining 96.1% accuracy using the normalized QRS complex to MLP classifiers and 93.4% without our proposed method as described in Table 2. This result indicates that ECG biometric is possible and QRS complex is not severely affected by varying physiological states.

4. Conclusion

In this paper, we have successfully demonstrated a simple yet efficient method of person identification with subjects in different physiological conditions. The results of the experiment suggest that the proposed technique gives significantly good subject recognition output for intra and inter subject recognitions. This outcome also suggests that QRS complex can act as a biometric modality in different physiological conditions with the ability to identify and differentiate individuals.

Table 1. R Values in Different Physiological Conditions from the Same Subject

State/ Subject	**A (E_X,E_{15})**	**B (E_X,R_1)**	**C (E_X,R_2)**	**D (E_X,R_3)**	**E (E_X,R_4)**	**F (E_X,R_5)**
E_1	0.9852	0.9904	0.9804	0.9839	0.9337	0.9841
E_2	0.9954	0.9964	0.9956	0.9916	0.9986	0.9983
E_3	0.9832	0.9980	0.9906	0.9960	0.9958	0.9994
E_4	0.9967	0.9933	0.9989	0.9984	0.9943	0.9952
E_5	0.9925	0.9944	0.9877	0.9749	0.9951	0.9916
E_6	0.9890	0.9733	0.9721	0.9901	0.9936	0.9929
E_7	0.9936	0.9948	0.9962	0.9983	0.9967	0.9969
E_8	0.9845	0.9653	0.9789	0.9882	0.9198	0.9744
E_9	0.9942	0.9987	0.9991	0.9995	0.9958	0.9986
E_{10}	0.9953	0.9987	0.9944	0.9953	0.9931	0.9908
E_{11}	0.9975	0.9916	0.9964	0.9930	0.9984	0.9981
E_{12}	0.9890	0.9907	0.9488	0.9907	0.9949	0.9773
E_{13}	0.9919	0.9677	0.9697	0.9845	0.9869	0.9815
E_{14}	0.9800	0.9795	0.9888	0.9976	0.9820	0.9939
E_{15}	1.0000	0.9226	0.9755	0.9756	0.9371	0.9840
E_{16}	0.9711	0.9894	0.9976	0.9950	0.9978	0.9980
E_{17}	0.9944	0.9964	0.9985	0.9956	0.9961	0.9958
E_{18}	0.9960	0.9970	0.9908	0.9931	0.9949	0.9973
E_{19}	0.9994	0.9976	0.9953	0.9918	0.9497	0.9967
E_{20}	0.9976	0.9963	0.9864	0.9897	0.9884	0.9990
E_{21}	0.9978	0.9983	0.9861	0.9989	0.9987	0.9955
E_{22}	0.9985	0.9995	0.9930	0.9983	0.9979	0.9994
E_{23}	0.9977	0.9981	0.9938	0.9972	0.9986	0.9972
E_{24}	0.9876	0.9365	0.9672	0.9941	0.9948	0.9893
E_{25}	0.9887	0.9645	0.9748	0.9488	0.9854	0.9897
E_{26}	0.9981	0.9528	0.9892	0.9770	0.9851	0.9792
E_{27}	0.9901	0.9916	0.9874	0.9966	0.9175	0.9763
E_{28}	0.9987	0.9888	0.9992	0.9911	0.9895	0.9993
E_{29}	0.9872	0.9887	0.9880	0.9991	0.9983	0.9976
E_{30}	0.9746	0.9772	0.9838	0.9934	0.9891	0.9985

Table 2. Classification Using Multilayer Perceptron

Classification	Type
With Normalized QRS Complex	96.1%
Without Normalized QRS Complex	93.4%

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