Automobile Driver Recognition under Different Physiological Conditions using the Electrocardiogram

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Abstract

This paper presents a person identification mechanism of automobile drivers under different physiological conditions. A total of 16 subjects were used in this study from the Stress Recognition in Automobile Driver database (DRIVEDB). Discrete Wavelet Transform was applied to reveal useful hidden information in the ECG signal which is not readily available in a time domain representation. Features are extracted based on coefficients produced due to the wavelet decomposition process. These features sets were then used in Radial Basis Function (RBF) for classification purposes. Our experimentation suggests that person identification is possible by obtaining identification accuracy of 95% as compared to 91% without wavelet analysis. This also indicates the robustness of ECG biometric implemented under different physiological conditions.

1. Introduction

Physiological conditions offer a feasible method of measuring a driver's stress level. Physiological sensors determine driver's internal state under natural conditions and such metrics have been used in flight simulation for commercial and military tactical pilots [1,2], real world driving in rural roads [3] and normal daily commute in the city and highway [4]. Stress states are linked to impaired decision making capabilities, decreased situational awareness and degraded performance [4]. The advancement of on-board electronics and in-vehicle information system further improves the idea of intelligent transportation system. Results in [4] suggest that heart rate metrics are closely correlated with the driver's stress level and non critical in-vehicle information system such as radio, cell phones and on-board navigation system which can assist the driver to ease up the stress level.

Heart rate metrics such as heart rate variability has also been used for the detection of abnormal heart activity which portrays certain irregular cardiac conditions. Besides that, in the past decade, the electrocardiogram (ECG) signal itself has been used for person identification [5-8]. These studies have been supported by research in [9,10] which takes into account the uniqueness of the physiological and geometrical differences of the heart in different individuals, the distinctiveness and stability of ECG as a biometric modality. Taking another step forward in intelligent transportation system, the ECG can also be used as a mechanism for automotive driver recognition which could further enhance the security of a vehicle. The earlier studies of ECG as a form of biometric were commonly focused on normal ECG conditions without any severe changes in the ECG morphology due to the effect of different physiological conditions [5,7,8]. In this recent years, initial studies have been made to prove the robustness of ECG as a biometric system in different physiological states as in [6,11]. These reviews shows that the ECG morphology would be affected by the physiological conditions but it has not been tested on normal daily commuters especially automotive drivers.

In this paper, we validate the claim that ECG biometric is a viable method to be used in a real world driving environment. The conventional approach of obtaining information from the raw ECG signal might hide important credentials which may be significant in person recognition. Thus, transforming the raw ECG signal based on the time-amplitude representation to a wavelet representation would highlight important characteristics which are not prevalent in the time domain. Wavelet analysis which proved to be useful in detecting cardiac abnormalities since a decade ago would be the main approach of identifying and extracting unique features in different physiological states. Based on the transformation, important characteristics such as the wavelet coefficients would be analyzed to differentiate amongst individuals. These coefficients are further applied in Radial Basis Function (RBF) for identification purposes. Our experimentation results on 16 subjects from the Automobile Driver Stress Recognition database (DRIVEDB) suggest classification accuracy of up to 95%.

The remaining of the paper is organized as follows; the next section describes the methodology which includes

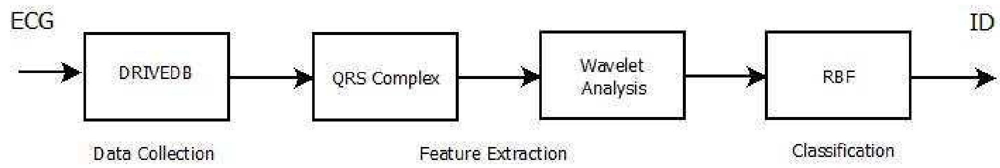

Figure 1. The Proposed Identification System.

the data acquisition process, feature extraction mechanism, applying the extracted ECG features to wavelet analysis which results in wavelet decomposition coefficients and later using RBF as the classification mechanism. Later, Section 3 discusses about the performance comparison of applying ECG data with and without wavelet analysis to the classification technique. Finally in Section 4, we conclude the study based on the experimentation and results in the previous section.

2. System and method

ECG signals can be continuously obtained to provide feedback without interfering with the driver's task. This information will be vital in order to assist the driver to cope with different physiological conditions. For example, in a situation where there exist cardiac abnormalities, the on board navigation system can send a message to related authorities such as hospital or ambulance service to assist the driver in critical life threatening situations. Similar to this case, the engine of a car can be immobilised by the in-vehicle information system if it does not recognise the identity of the driver. In order to authorize this action, the system should be able to use an efficient algorithm to detect the identity of an individual. In this stage, feature extraction technique plays a significant role in the identification process.

In this paper, when ECG are collected, QRS complex are used instead of the whole ECG morphology because it is proven to be stable and not heavily affected by abnormal cardiac conditions [12,13]. Discrete Wavelet Transform was applied to reveal useful hidden information in the QRS complex which is not readily available in a time domain representation. Features are extracted based on coefficients produced due to the wavelet decomposition process, these features sets were then used in RBF for classification purposes. The proposed identification system is summarised as depicted in Figure 1.

2.1. Data acquisition

ECG data from 16 different individuals used in this work were taken from an online public database available in PhysioBank [14] called the Stress Recognition in Automobile Driver database (DRIVEDB) with sampling rate of 496 Hz. Recordings were obtained from healthy volunteers driving on predefined route including city streets and highways in and around Boston, Massachusetts. These datasets were collected by electrodes placed on a modified lead II configuration to minimize motion artifacts and to maximize the amplitude of the R waves. Since the R wave indicates the most visible, highest and sharpest peak of the ECG morphology this analytical based method acts as the referral point in capturing the QRS complex. From the R wave, equal points are selected from both sides of the identified R wave and the process is repeated which actually covers the QRS complex. First Derivate based technique [15] was applied to automate this procedure.

2.2. Feature extraction

Extracting information or features from ECG signal has been found vital in identifying and explaining various pathological conditions. The process can be done by analysing the ECG data using various signal processing techniques. Thus, these methods become an essential and persuasive tool for extracting vital information from ECG signals.

In this work, Discrete Wavelet Transform (DWT) was applied to obtain further information which is not readily available in its original ECG time-amplitude representation. This analysis suite transient signal like ECG which contains high degree of non-periodic components and a higher magnitude of high frequencies than its harmonic contents.

2.2.1. Discrete wavelet transform

Mathematical transformation is applied to a signal to reveal hidden information which is not evident in time domain form. DWT, a multiresolution signal approach represented as $x(t)$ at scale j_0, is defined as a wavelet series expansion in terms of the scaling coefficients, $c_{j(k)}$ and the wavelet coefficients, $d_{j(k)}$ as in Equation 1.

$$\mathbf{x}(t) = \sum_{n=-\infty}^{\infty} c_{j_0}(n)\varphi_{j_0,n}(t) + \sum_{j=j_0}^{\infty}\sum_{n=-\infty}^{\infty} d_j(n)\psi_{j,n}(t) \quad (1)$$

Thus, $\mathbf{x}(t)$ can be decomposed into a signal $x_{j0}(t)$, being a low pass approximation of $\mathbf{x}(t)$ and a set of signals $y_j(t)$ which gives varying degree of high resolution details of $x(t)$. The scaling function, φ, is introduced to efficiently represent the approximation signal, $x_j(t)$ at different resolution. While on the other hand, introducing the wavelet function, ψ, accounts for the details of the signal which relates to the mother wavelet. Choosing the appropriate mother wavelet is important as it determines the characteristics of the resulting wavelet transformation through translation and scaling. In this paper, *coiflet* was chosen as the mother wavelet based on their shape that resembles the QRS complex and its capability of prefect reconstruction. Figure 2 compares the shape of *coiflet* with the QRS complex.

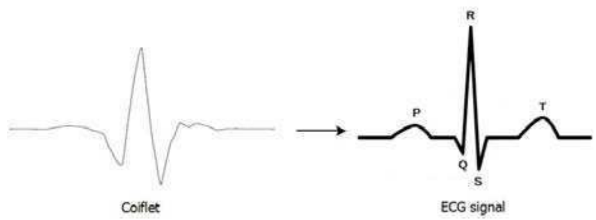

Figure 2. Coiflet as compared to QRS complex.

The reconstruction of the original signal uses the summation of the discrete wavelet coefficients which consist of approximation and detail coefficients rather than continuous integrals which can be represented as in Equation 2.

$$\mathbf{x}_n = a_{n-1} + d_0 + d_1 + \ldots + d_{n-1} \qquad (2)$$

where a is the current approximation value of $n - 1$, and d are the detail coefficients from 0 to $n - 1$.

DWT was chosen because of its low degree of redundancy as far as data reconstruction is concerned. Due to this factor, DWT is much faster in terms of the computational complexity when compared to other wavelet transform methods such as Continuous Wavelet Transform and Dyadic Wavelet Transform.

2.3. Radial basis function

A Radial Basis Function (RBF) network has an input layer (in this case, **x**), a hidden layer with a non-linear RBF activation function and a linear output layer as shown in Figure 3.

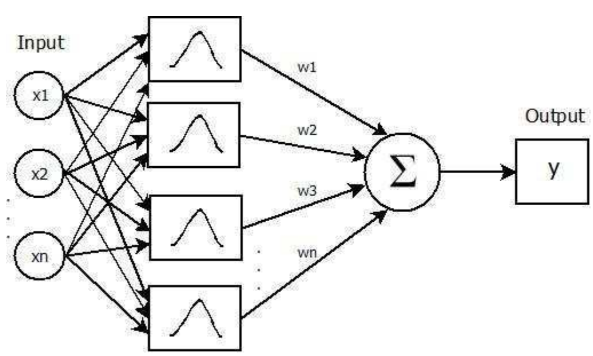

Figure 3. Radial Basis Function Network.

The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the centre of the neuron. An RBF network positions one or more RBF neurons in the space described by the predictor variables. The Euclidean distances is computed from the point being evaluated to the centre of each neuron, c_i, and RBF is applied to the distance to computer the weight (influence), w_i, for each neuron. The further a neuron is from the point being evaluated, the less influence it has. The best predicted value for the new point is found by summing the output values of the RBF functions multiplied by weights computed for each neuron which calculates the classification accuracy of the signal as shown in Equation 3.

$$\mathbf{y}_n = \sum_{i=1}^{N} w_i \phi \left(\| \mathbf{x} - c_i \| \right) \qquad (3)$$

where N is the number of neurons in the hidden layer, c_i is the centre vector of neuron i, and w_i are the weights of the linear output neuron.

3. Experimentation and results

A total of 8 QRS complexes were collected from each driver. This gives a total of 128 instances for all the drivers in the database. Based on the QRS complexes, an experiment was conducted where these QRS complexes were applied to the DWT function which extracts wavelet coefficients. These features were then substituted to the RBF network for classification purposes.

In order to justify that identification procedure using DWT would give a better result, we repeated the same steps as the proposed system, only this time the QRS complexes does not go through wavelet analysis but instead it goes directly to RBF network for classification. The results of the comparison with and without wavelet analysis are summarised in Table 1.

Table 1. Classification with and without wavelet analysis.

Classification	Accuracy (%)
RBF with DWT	95
RBF without DWT	91

Based on the result in Table 1, applying the classification technique directly to the QRS complexes gives a reasonably good accuracy rate. This is related to the healthy conditions of all the drivers which experience temporary physiological driving conditions. However, if the QRS complexes were applied to wavelet analysis, the classification accuracy was much higher with a classification accuracy of 95% which shows an increase of 4% as compared to the previous results. This shows that significant features are obtained from the time-frequency domain which is not prevalent in the time-amplitude representation. In both conditions, the results suggest that the QRS complex are dominant regardless of the physiological condition and it supports recent studies in [12,13] which states that the QRS alone can become a biometric feature.

Thus, it is suggested that the proposed identification mechanism should be located on the in-vehicle information system which connects the physiological sensors and the on-board electronics to further improve the concept of intelligent transportation system. Automotive driver recognition is just one applied area which this proposed identification mechanism can be included. It could be also integrated in security systems such as airport and border security, financial institution or even the distribution of benefit scheme.

4. Conclusion

In this paper, we have demonstrated the idea of automated driver recognition under different physiological conditions using ECG. The objective of the study is twofold; i) to provide better security for automotive drivers in order to avoid car thefts and ii) to recognize and identify the automotive drivers in different physiological driving conditions. Our experimentation results suggest that ECG based identification is possible for automotive drivers with different physiological driving conditions. In order to enhance the identification mechanism, applying wavelet analysis to ECG signal further improves the classification accuracy to 95% from 91% without DWT. Moreover, both situations suggest that QRS complex are dominant regardless of the physiological driving conditions experienced by the automotive drivers and can be used as a biometric feature without using the whole ECG morphology.

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