DOI Number: 10.5958/0974-1283.2019.00131.2

ECG Biometrics in Forensic Application for Crime Detection

Mihir Narayan Mohanty[1], Saumendra Kumar Mohapatra[2]

[1]Professor, Department of Electronics and Communication Engineering, [2]Research Scholar, Department of Computer Science and Engineering, ITER, Siksha 'O' Anusandhan (Deemed to be University)

ABSTRACT

The physiological property of the human being is unique for each individual. This provides the identity of specific human. Biometric features are used with the help of engineering through machines in recent years for better operation. Similar features can be used for crime detection and security purpose. The biometric features provides information and useful in forensic science. Unlike many methods, heart signal is considered in this work. In different mental condition ECG is collected experimentally in our laboratory using cardio track device. The experiment is carried with eighty subjects. The age range is between nineteen to twenty one years. The data is verified for frighten boy committed some mistakes related to academic environment. Spectral analysis using Fractional fourier transform (FFT) and Wavelet transform (WT) has been performed for R peak detection. The wavelet coefficients are considered as the weights of neural network model for detection purpose. The standard neural network structure multi layer perceptron (MLP) is utilized with wavelet coefficients. The result found excellent as compare to earlier method and exhibited in result section

Keywords: *Biometric Identification; ECG; R peaks; Wavelet; Neural Network.*

Introduction

Biometric data for identification in forensic science backs to 20*th* century. Forensic science refers to the applications of scientific principles and technical methods to an investigation in relation to criminal activities, in order to establish the existence of a crime, to determine the identity. It is thus logical that this area was a fertile ground for the use of physiological or behavioral data to sort and potentially individualize protagonists involved in offences.

Biometric identification system is one of the innovative techniques in the field of identity management system. It is an improved technology for personal data storage system and highly secured as compared to traditional security mechanism like pin and password system. This method is similar to pattern recognition technique where unique and discriminative features (biometric samples or recognition data) are extracted and then matching of these features with previously enrolled data takes place.

Biometrics is inherent behavioral or physiological properties of living beings. In other words, biometrics describes our appearance, *what* and *how* we are. Biometric traits include physiological properties like body height, face or fingerprint, as well as behavioral properties like voice, gait or signature. The main advantages of biometric authentication, including usability, availability, security and portability are directly inferred from this bond.

The complete procedure for biometric identification system is displayed in **Figure 1**. Generally in this identification technique different biological data are used for identifying someone as being him/herself. These data can be face, iris, fingerprint, ECG, and EEG as presented in **Figure 2**. While the use of biometrics for authentication purposes offers many advantages, there are also security and privacy concerns arising. Biometrics contains personal and possibly sensitive information. System, service or authentication providers shouldn't gain access to biometrics, as the information contained in biometric signals could be abused or lost.

Corresponding Author:
Mihir Narayan Mohanty
Professor, Department of Electronics and Communication Engineering,
ITER, Siksha 'O' Anusandhan
(Deemed to be University), Bhubaneswar, India
Email: mihirmohanty@soa.ac.in

- Understanding the correct processes and the legal parameters can make the difference between having a suspect's confession accepted as evidence by the court or not. With the above in mind, this chapter will focus on several salient issues, including:
- The progression from interviewing to questioning to interrogating, and how this progression relates to investigative practices
- The junctures that demonstrate the need to change from interviewing a witness to questioning a detained suspect to interrogating an arrested suspect
- The issues of physical and mental distress, and how to avoid the perception of officer-induced distress during an interrogation

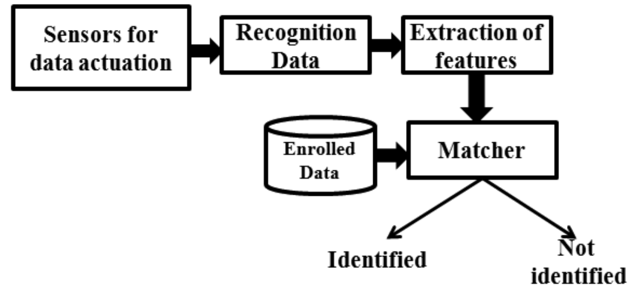

Figure 1: Biometric identification system

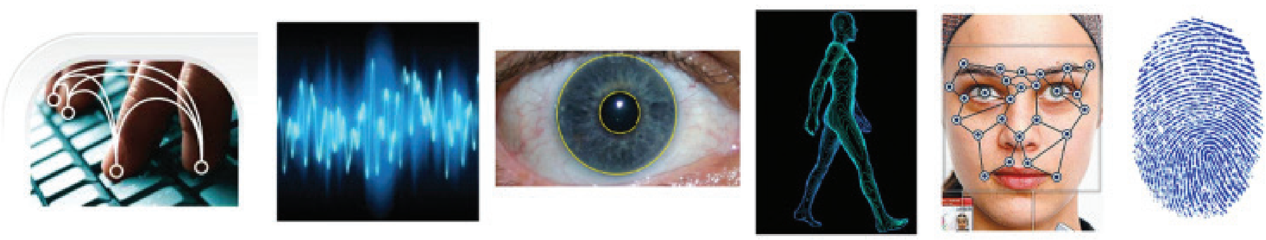

Figure 2: Different types of biometric modalities such as keystroke, voice, iris, gait, face and fingerprint.

Some of these data can be vulnerable to forgery, but our heart is constantly beating and can be used for obtaining different information based on the electrical heart characteristics[1,2,3]. There is an expanding enthusiasm for utilizing the ECG in biometric recognizable proof. Every individual has an distinctive ECG characteristics which gives robustness for falsification using fraudulent techniques[4]. Generally there are two types of ECG biometric recognition methods: fiducial and non-fiducial. Fiducial method is a preprocessing step for the detection of heartbeat. Specific points are identified in this step which is vulnerable to processing errors, due to, e.g., noise. There is no need of ECG wave detection or configuration in non-fiducial methods. These methods are generally used for reducing the preprocessing error rate. Also there are some semi-non-fiducial methods in which at least the R-peaks are detected for window alignment[5,6]. In ECG based biometric identification method the ECG data is collected every time the person arrives at the access point. There are some external factors like circadian cycle which affects the signal characteristics. For this reason the identification system should be vigorous and protected to variations in ECG. For obtaining a reasonable and perfect identification system, it is important to employ a method which can accurately deal with the usual biometric identification systems.

Keeping the level of user interaction for authentication as low as possible, adds to usability and ultimately increases user acceptance. They are available, because most biometrics don't change significantly within weeks or months and they are on hand wherever we go. From some biometrics like voice, gait or ECG, even liveliness can be derived. They are secure, because many offer high classification rates, they are not prone to shoulder surfing and counterfeit attacks at least require a certain degree of equipment and preparation. And last but not least they are portable, because most biometrics can be measured with sensors that have small form factor and would easily fit into most mobile devices[7]. A structure of different types of bioinformatics is presented in **Figure 3**.

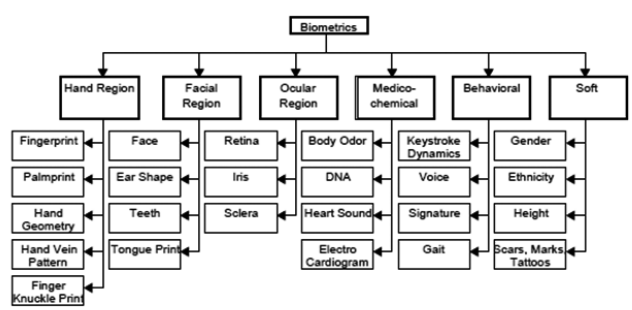

Figure 3: Structure of the different types of Bioinformatics[24]

Sate of the Art of the Work: It is one of the complicated tasks to develop an ECG based biometric identification system which can identify a person accurately. Different techniques have been applied by the researcher for getting a better identification system and some of them are cited here.

A recent study was driven by the fact that blood circulation causes periodic subtle changes to facial skin color[8]. This fact was utilized in[9,10,11,12,13] for HR estimation and [14,15,16] for applications of heartbeat signal from facial video. These facial color-based methods, however, are not effective when taking into ac-count the sensitivity to color noise and changes in illumination during tracking. Thus, Balakrishnan *et al.* proposed a system for measuring HR based on the fact that the flow of blood through the aorta causes invisible motion in the head (which can be observed by Ballistocardiography) due to pulsation of the heart muscles[17]. An improvement of this method was proposed in[12]. These motion-based methods of [17,18] extract facial feature points from forehead and cheek.

ECG based human verification system was proposed in [19] for both healthy and cardiac irregular condition. They have used heart beat level and segment level information fusion methods. principal component analysis (PCA), linear discriminant analysis (LDA) and within-class covariance normalization (WCCN) for beat variability compensation followed by cosine similarity and S-norm as scoring were used in their work. Their proposed PCA algorithms perform 25% realisable on PTB data base. Same PCA was applied in[20] for identification purpose and 92.9% classification accuracy was obtained in their work. Authors in[21] extracted 19 features from each heart beat for the identification purpose. Template matching and adaptive thresholding was applied in their work for matching purpose. The matching was calculated by using correlation between features and 99% accuracy was obtained from their proposed system. ECG can be employed as a continuous authentication system. When the human heart pumps blood, subtle chromatic changes in the facial skin and slight head motion occur periodically. These changes and motion are associated with the periodic heartbeat signal and can be detected in a facial video[22]. Takano et al. first utilized the subtle color changes as heartbeat signals from facial video acquired by a camera to estimate HR[23].

Biometrics Method for Human Identification Using Electrocardiogram: This work exploits the feasibility of physiological signal electrocardiogram (ECG) to aid in human identification. Signal processing methods for analysis of ECG are discussed. Using ECG signal as biometrics, a total of 19 features based on time interval, amplitudes and angles between clinically dominant fiducials are extracted from each heartbeat. A test set of 250 ECG recordings prepared from 50 subjects ECG from Physionet are evaluated on proposed identification system, designed on template matching and adaptive thresholding. The matching decisions are evaluated on the basis of correlation between features.

The advantages of using the ECG for biometric recognition can be summarized as universality, permanence, uniqueness, robustness to attacks, liveness detection, continuous authentication and data minimization.

With time-varying biosignals there is high risk of instantaneous changes which may endanger biometric security. Recordings of the cardiac potential at the surface of the body are very prone to noise due to movements. However, even in the absence of noise, the ECG signal may destabilize with respect to a biometric template that was constructed some time earlier. The reason for this is the direct effect that the body's physiology and psychology have on the cardiac function. Therefore, a central aspect of the ECG biometrics research is the investigation of the sources of intra-subject variability. ECG of two different persons is presented in **Figure 4**.

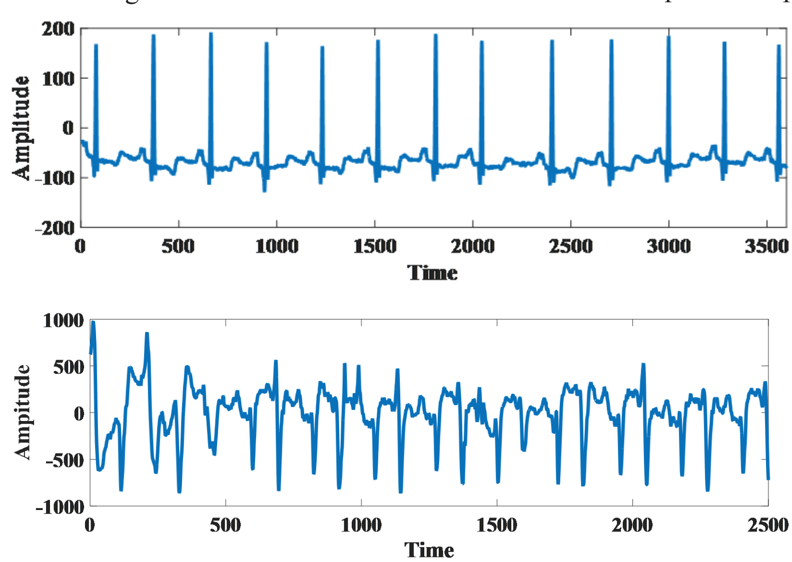

Figure 4: Different ECG patterns for different persons

Wavelet Transform: Basically wavelet transform decomposes the signal in different scales. This will represent to the resolution of the signal. The corresponding frequency can be found according to time localization. Because of its scaling property, it holds a unique position for time-frequency analysis of the non-stationary signals. Since ECG is a category of non-stationary as well as noisy signal, wavelet transform is chosen for such analysis[25]. In this case, noise is removed and simultaneously the specific peaks are located clearly.

DWT provides a cosy relationship of a signal in time and frequency domain and can be defined as:

$$D(c_1, c_2) = \sum_{c_1}\sum_{c_2} S[c_2]2^{-\frac{1}{2}}\left(\grave{E}2^{-\frac{1}{2}}j - c_2\right) \quad \ldots(1)$$

Here $D(C_1,C_2)$ is the DWT coefficients $S[C_2]$ is the discrete signal.

In wavelet analysis any signal space of a multi-resolution approximation can be decomposed into lower frequency (lower-resolution) approximation and high frequency (higher-resolution) approximation. The noise is eliminated by discarding the detail coefficients D1, D2. Secondly, in our method, using filtering approach before wavelet and FT analysis we have removed most of the unwanted noise of the signal. The probability of error in R peak detection is minimized in spite of the presence of drastic irregularity in the baseline[26,27].

Haar wavelet is the simplest and first of wavelet family that resembles to a step function. Daubechies is the mostly discussed wavelet family in signal processing approach. It is generally represented as dbN where, N signifies order of the wavelet. An order of 2, 4 and 6 has been used for comparison of the unhealthy person from a normal person. In this case the 'R' peaks are detected successfully by selecting the optimum coefficients. Different mother wavelets like Coiflet, Symlet and Daubechies have been tested for this problem. The best result with Daubechies has been reported. In case of high pass filtering Db 6 and for low pass filtering Db 2 have shown the best result and is shown in result section.

For 'R' peak detection the following processor has been proposed.

- Consider the filter ECG signal as the input and calculate the wavelet co-efficient.
- Initialize the window time the total time can be evaluated as total number of samples/sampling frequency.
- Find the maximum and minimum for each window from all possible QRS segment.
- Now locate the R peaks of QRS complexes from different segment.

Neural Network: An artificial neural network (ANN) is a generalized mathematical model which is based on biological nervous systems. The fundamental elements of neural networks are artificial neurons. Input, output, and hidden are three basic layers of a simple neural network as presented in **Figure 5**. In feed-forward networks, the signal flow is from input to output units, strictly in a feed-forward direction. Both linear and non-linear classification problems can be solved by applying ANN with various type of network structure and learning algorithm.

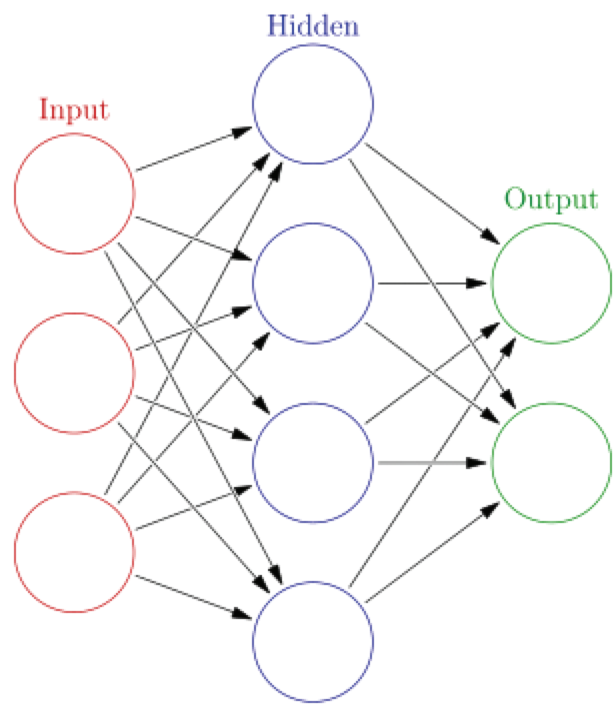

Figure 5: Standard neural network structure

In neural network the output of the hidden layer h and output layer y can be calculated as:

$$h = \sigma(W_1 x + b_1) \quad \ldots(1)$$

$$y = \sigma(W_2 h + b_2) \quad \ldots(2)$$

where W_1 and W_2 are the weights of neuron and x is the input. b_1 and b_2 are the bias. σ is the activation function. The weights are considered with the wavelet coefficients.

Results

In different mental condition ECG is collected experimentally in our laboratory using cardio track device. The experiment is carried with eighty subjects. The age range is between nineteen to twenty one years. The data is verified for frighten boy committed some mistakes related to academic environment. ECG signal with high pulse rate (above 100) is considered for the proposed work. A sample signal is presented in Figure 2. For extracting the QRS complex from the signal, it is decomposed by applying wavelet decomposition method. A decomposed ECG is shown is **Figure 6**.

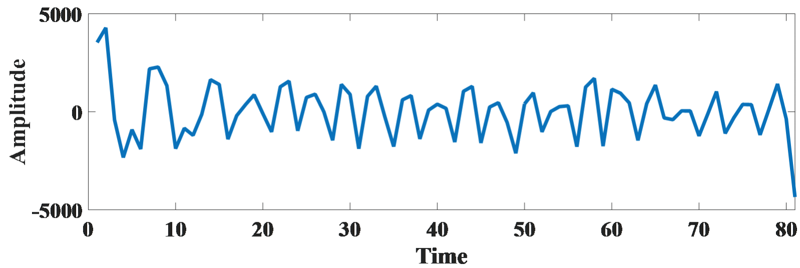

Figure 6: Decomposed ECG

As shown in **Figure 7**, the heartbeat rate is highest. Since, the normal heart beat rate of an average healthy person lies in between 72 to 120. Thus, a value of 132 as heartbeat indicates the degree of illness the person is affected with. Hence it requires immediate attention. The R-peaks are also of highest amplitude. Similar results could be observed from the wavelet features in **Figure 8**.

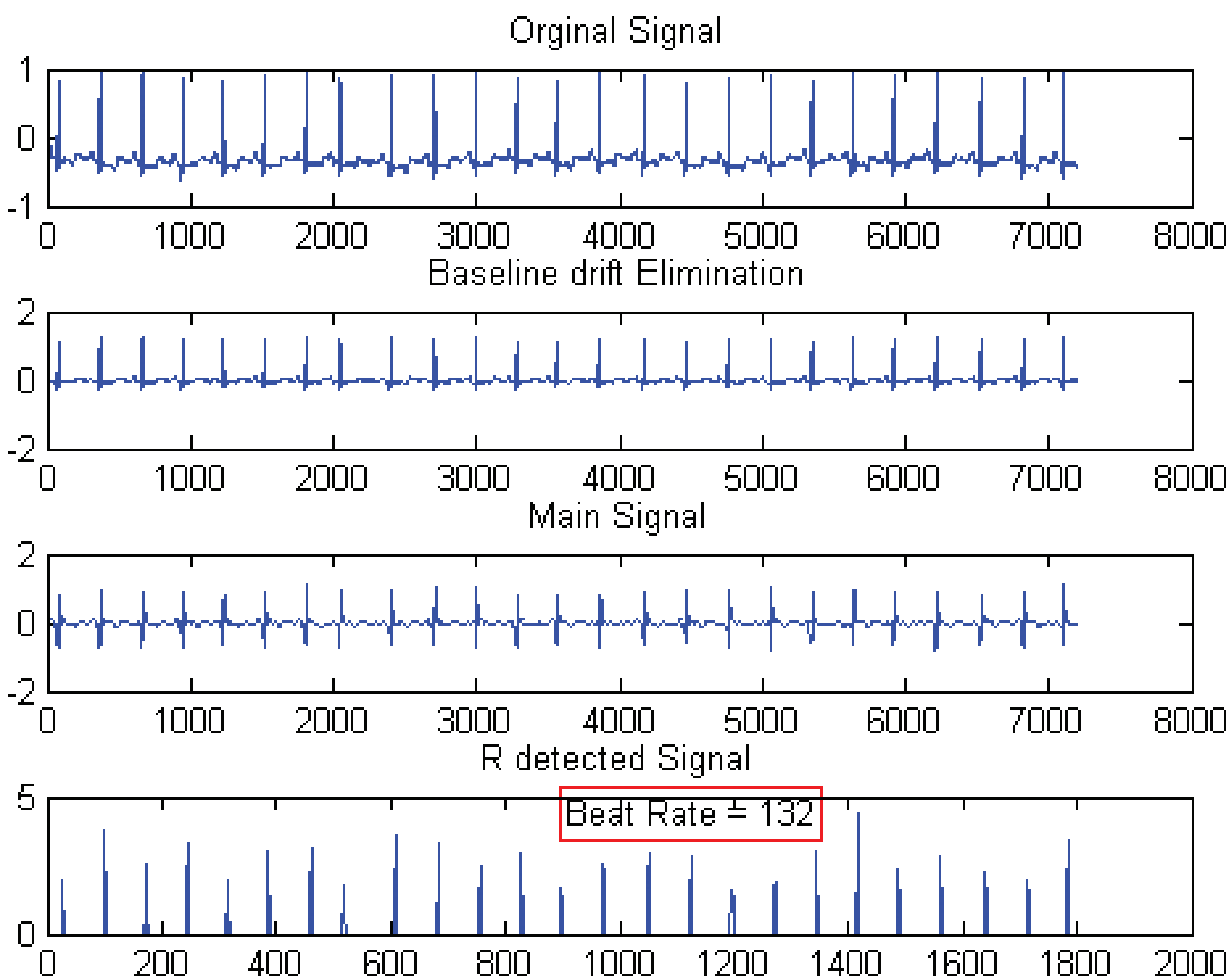

Figure 7: Identification of a terminal ill person from R-peak using db2 wavelet features

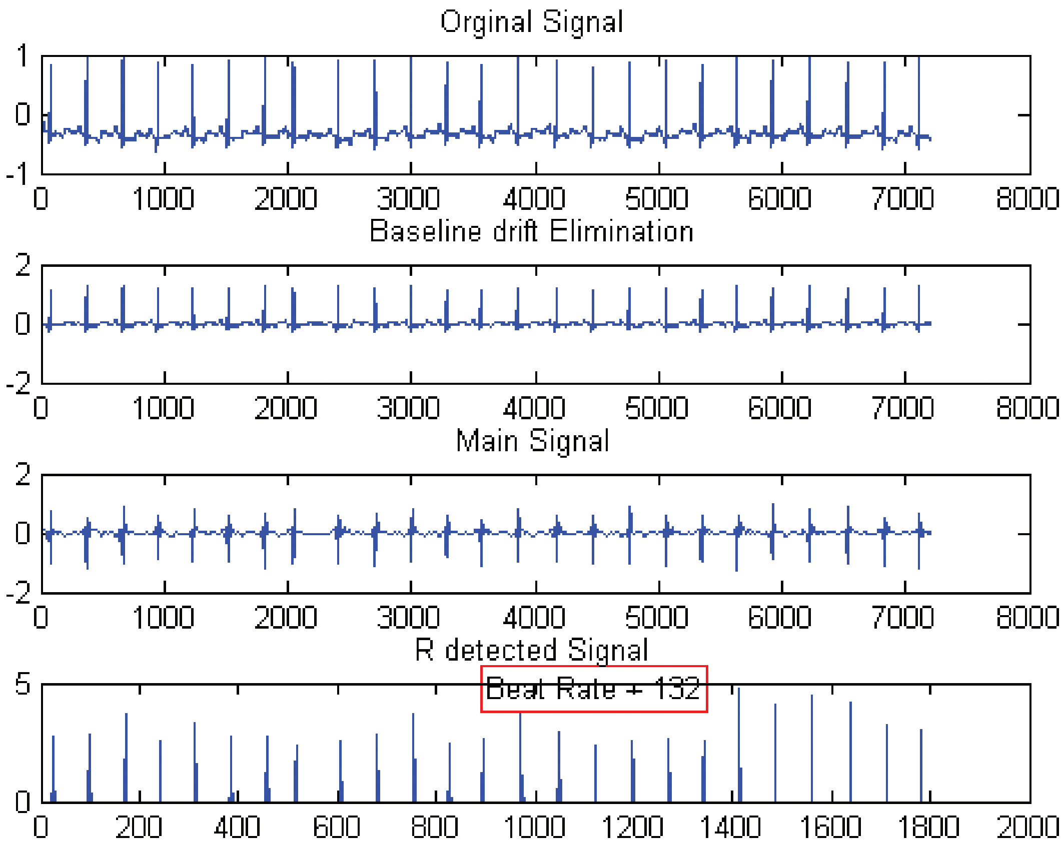

Figure 8: Identification of a terminal ill person from R-peak using Haar wavelet features

The R-peaks are also large although less than that in Figure 7 and Figure 8. Both db and Haar family of wavelet has been used to rate the normal person based on his/her heartbeat. Analysis of these coefficients indicates corresponding R-peaks point towards a normal human being.

After getting the required QRS feature a neural network model is designed for the classification purpose. It classifies the normal ECG and the ECG with high pulse rate. The performance of the neural network classifier is presented in **Figure 9**.

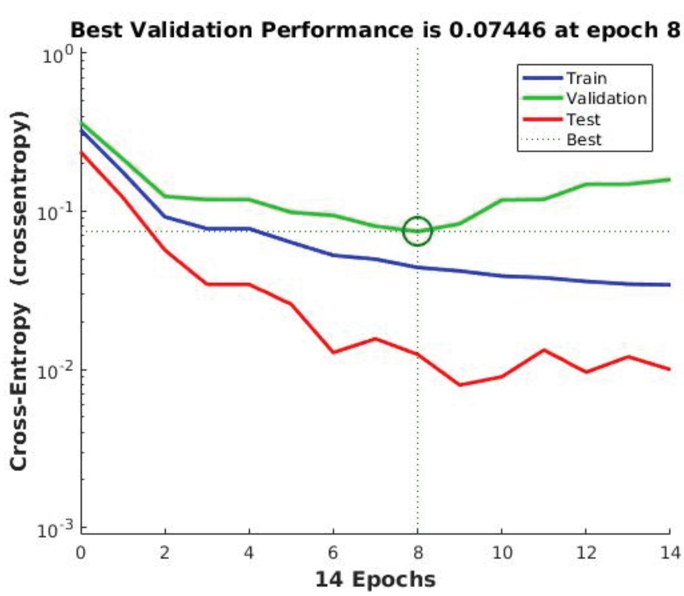

Figure 9: Performance of the Neural Network classifier

Accuracy of a classifier is measured from the confusion matrix. In Figure 10 confusion matrix of the proposed classifier is presented and 96% accuracy is obtained. ROC curve of the neural network in training, testing and validation is presented in **Figure 11**. Result obtained from the proposed system is compared with earlier method and is presented in **Table 1**.

Figure 10: Confusion matrix of the classifier

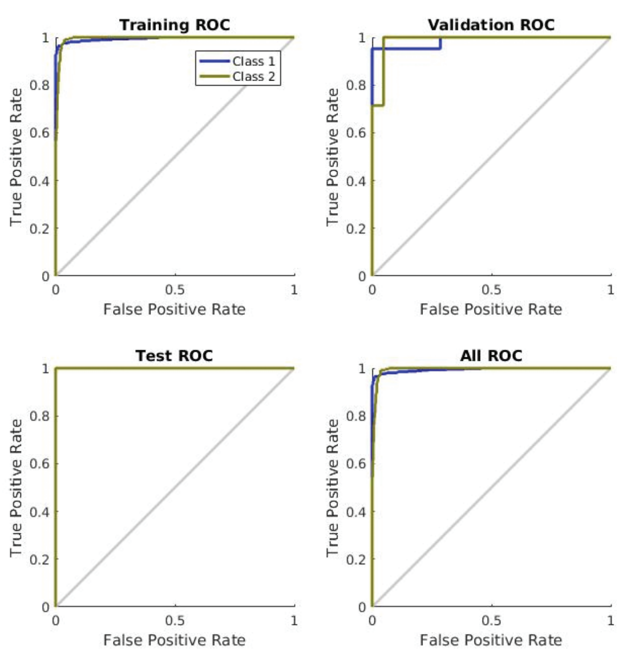

Figure 11: ROC of the neural network classifier

Table 1: Comparison of result with earlier method

Method	Accuracy
EMD [2]	76.19%
SVM [4]	93%
PCA [20]	92.9%
Proposed System	96%

Conclusion

ECG based biometric recognition system is proposed for human authentication purpose. Wavelet features are classified using neural network classifier and the result shows that the neural network classifier for identification is performing well. This system can be implemented in forensic science for biometric identification purpose. Further different feature extraction and classification methods can be taken for better result.

Ethical Clearance: Not required

Source of Funding: Self

Conflict of Interest: Nil

REFERENCES

1. Sidek KA, Mai V, Khalil I. Data mining in mobile ECG based biometric identification. Journal of Network and Computer Applications. 2014 Sep 1;44:83-91.
2. Agrafioti F, Hatzinakos D, Anderson AK. ECG pattern analysis for emotion detection. IEEE Transactions on Affective Computing. 2012 Jan;3(1):102-15.
3. Agrafioti F, Hatzinakos D. ECG biometric analysis in cardiac irregularity conditions. Signal, Image and Video Processing. 2009 Dec 1;3(4):329.
4. Hejazi M, Al-Haddad SA, Singh YP, Hashim SJ, Aziz AF. ECG biometric authentication based on non-fiducial approach using kernel methods. Digital Signal Processing. 2016 May 1;52:72-86.
5. Odinaka I, Lai PH, Kaplan AD, O'Sullivan JA, Sirevaag EJ, Rohrbaugh JW. ECG biometric recognition: A comparative analysis. IEEE Transactions on Information Forensics and Security. 2012 Dec;7(6):1812-24.
6. Israel SA, Irvine JM, Cheng A, Wiederhold MD, Wiederhold BK. ECG to identify individuals. Pattern recognition. 2005 Jan 1;38(1):133-42.

7. Unar JA, Seng WC, Abbasi A. A review of biometric technology along with trends and prospects. Pattern recognition. 2014 Aug 1;47(8):2673-88.
8. Wu HY, Rubinstein M, Shih E, Guttag J, Durand F, Freeman W. Eulerian video magnification for revealing subtle changes in the world.
9. Poh MZ, McDuff DJ, Picard RW. Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. Optics express. 2010 May 10;18(10):10762-74.
10. Monkaresi H, Calvo RA, Yan H. A machine learning approach to improve contactless heart rate monitoring using a webcam. IEEE journal of biomedical and health informatics. 2014 Jul;18(4):1153-60.
11. Li X, Chen J, Zhao G, Pietikainen M. Remote heart rate measurement from face videos under realistic situations. InProceedings of the IEEE conference on computer vision and pattern recognition 2014 (pp. 4264-4271).
12. Poh MZ, McDuff DJ, Picard RW. Advancements in noncontact, multiparameter physiological measurements using a webcam. IEEE transactions on biomedical engineering. 2011 Jan;58(1):7-11.
13. Kwon S, Kim H, Park KS. Validation of heart rate extraction using video imaging on a built-in camera system of a smartphone. In2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2012 Aug 28 (pp. 2174-2177). IEEE.
14. Haque MA, Nasrollahi K, Moeslund TB. Heartbeat signal from facial video for biometric recognition. InScandinavian Conference on Image Analysis 2015 Jun 15 (pp. 165-174). Springer, Cham.
15. Haque MA, Nasrollah K, Moeslund TB. Can contact-free measurement of heartbeat signal be used in forensics?. In2015 23rd European Signal Processing Conference (EUSIPCO) 2015 Aug 31 (pp. 769-773). IEEE.
16. Haque MA, Nasrollahi K, Moeslund TB. Efficient contactless heartbeat rate measurement for health monitoring. International Journal of Integrated Care. 2015 Oct 20;15(7).
17. Balakrishnan G, Durand F, Guttag J. Detecting pulse from head motions in video. InProceedings of the IEEE Conference on Computer Vision and Pattern Recognition 2013 (pp. 3430-3437).
18. Irani R, Nasrollahi K, Moeslund TB. Improved pulse detection from head motions using DCT. In2014 international conference on computer vision theory and applications (VISAPP) 2014 Jan 5 (Vol. 3, pp. 118-124). IEEE.
19. Li M, Li X. Verification based ECG biometrics with cardiac irregular conditions using heartbeat level and segment level information fusion. In2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2014 May 4 (pp. 3769-3773). IEEE.
20. Jekova I, Bortolan G. Personal verification/identification via analysis of the peripheral ECG leads: Influence of the personal health status on the accuracy. BioMed research international. 2015;2015.
21. Singh YN, Gupta P. Biometrics method for human identification using electrocardiogram. InInternational Conference on Biometrics 2009 Jun 2 (pp. 1270-1279). Springer, Berlin, Heidelberg.
22. Haque MA, Nasrollahi K, Moeslund TB. Heartbeat signal from facial video for biometric recognition. InScandinavian Conference on Image Analysis 2015 Jun 15 (pp. 165-174). Springer, Cham.
23. Takano C, Ohta Y. Heart rate measurement based on a time-lapse image. Medical engineering & physics. 2007 Oct 1;29(8):853-7.
24. Unar JA, Seng WC, Abbasi A. A review of biometric technology along with trends and prospects. Pattern recognition. 2014 Aug 1;47(8):2673-88.
25. Mohapatra SK, Mohanty MN. RBFN based automatic ECG Classification in healthcare System. Indian Journal of Public Health Research & Development. 2018;9(11):2287-92.
26. Palo HK, Mohanty MN. Wavelet based feature combination for recognition of emotions. Ain Shams Engineering Journal. 2017 Jan 28.
27. Mohapatra I, Pattnaik P, Mohanty MN. Cardiac Failure Detection Using Neural Network Model with Dual-Tree Complex Wavelet Transform. InInternational Conference on Intelligent Computing and Applications 2019 (pp. 87-95). Springer, Singapore.