**Scientific Journal of Faculty of Science, Menoufia University**

https://sjfsmu.journals.ekb.eg/

# Analysis Techniques and Feature Extraction on ECG: A Review

**Mariana Barsoum*, Ibrahim Omara and Mohamed S. Khalaf**

*Department of Mathematics and Computer Science, Faculty of Science, Menoufia University, Egypt*

*Correspondence
Email: marianabarsoum0@gmail.com

**ARTICLE INFO.**

Received: 03/01/2024
Accepted: 10/02/2024

**ABSTRACT**

Electrocardiogram (ECG) is an inconsistent signal that is used to measure the heart rate. Electrocardiogram is used recently to identify people and protect data as an optimal solution. It can also be used in unimodal and multimodal systems. One of the advantages of using an electrocardiogram is that the person is still alive. This makes plagiarism more difficult compared to any other biometric feature. Doctors can diagnose diseases by comparing the shape and pattern of signals. To diagnose a patient by recording an ECG. Noise is removed in order to obtain a better evaluation. We find that extract ECG is of great importance in diagnosing heart diseases and human recognition. One of the ECG cardiac sessions is made up of P-QRS-T waves. To determine the time and amplitude periods in the ECG by extracting the features or other features are analyzed at a later time. In this verse we will list the ECG techniques and their analysis.

Keywords: Electrocardiogram; biometrics; P-QRS-T waves

## 1. Introduction

The goal of the biometrics system is to uniquely identify or validate between people based on behavioral and physiological characteristics, including walking, fingerprint, and retina ( Fratini, Antonio, et al. (2015); Jain, A. K., Ross , et al. (2004)). Recognition is important and is used in many modern applications, which represent a large part of our daily life such as financial transactions, smartphones, cars and data protection. To illustrate the comparison between the different biometric systems is listed in the table1. The security system is the primary component of the schedule that is used for identification. It is easy to re peat the biometrics of the same person. We find the DNA system difficult to duplicate. Security becomes weak in both face and sound, and in contrast, we find it safer in DNA, retina, and palm print (Nawal, M et al. (2014); Vaidya, M. (2015).).

Cost and complexity are also discussed in the table1. In the palm and fingerprint system, we find complexity moderate, we find it more complicated in DNA and retina, and complexity is less in voice recognition. Identity uniqueness is mentioned as a third element in a table1. Iris recognition is a unique biometric. People find that they have different iris and unique properties, such as in the DNA biometric and palm fingerprint system. We find that in the case of sound and face exclusivity becomes less. In the table1 also, the environmental impact was also discussed, so biometrics were changed as well. An environmental impact occurs when an accident occurs, such as hand injury, and then affects the biometrics. Therefore, we find DNA and ECG environmental impact less than facial and voice recognition (Bolle, R. M et al. (2013)). ECG We can define it in a simple way that it records the electrical activity produced by the heart. Sample ECG signals associated with a common cardiac cycle are illustrated in Figure 1. ECG is an effective non-surgical tool that is used in many vital applications, for example, heartbeat examination, diagnosis of heart disorders, and biometric identification. To discover the ECG signal had a prominent role in the discovery of arrhythmias. So, it played a major role in the study of biomedicine (Vaidya, M. (2015)).

**Table 1. The difference between some vital systems.**

| Biometric system | Environmental Impact | Cost & Complexity | Unique Identity | Security |
|---|---|---|---|---|
| Voice Recognition | More | Less | Less | Less |
| Face Recognition | More | Moderate | Less | Less |
| Electrocardiogram | Less | Less | Moderate | Moderate |
| Fingerprint | Moderate | Moderate | More | Moderate |
| Iris | Less | More | More | Moderate |
| Palm print | Moderate | Moderate | More | Moderate |
| DNA | Less | More | More | More |

## 2. Related work:

Diagnosing heart disease has a major problem through ECGs is the difference in the ECG signal from one person to another (Banerjee, S et al. (2013)). Such problems can cause some difficulties in the process of diagnosing heart diseases, and therefore an electrical signal must be analyzed for each pulse. Therefore, the analysis of ECG records can have a long range. It is possible that some errors occur during the analysis of the ECG caused by fatigue, (Luz, E. J. D et al. (2016)). and to interpret this indication requires a great knowledge. There are two types of properties, which are physiological and behavioral, such as physiological properties, DNA, iris, face and fingerprints. Examples of behavioral characteristics are sound, gait, and signature to identify people. Security and restricted access to areas that are protected by people is a biometrics feature. (Pal, S., Mitra et al. (2012); Wahabi, S et al. (2014) ). ECG is widely used among researchers because it provides great and unique advantages to individuals, as the ECG signal is analyzed and used in various applications and purposes.

Depending on the applications provided through ECG technology, the analysis contains some steps, such as preprocessing, feature extraction, feature selection, feature transformation and classification. We find that the first to use ECGs planning in biometrics uses is Biel et al.'s, taking into account the peculiarities of biometric measurements as an example (ease of obtaining the diurnal characteristic), and permanence (not changing over time), universality (possession of the characteristic by the individual), and uniqueness (no two individuals share the same characteristic) (Sahoo, S. K et al.(2012)).

This remainder of this research is organized as follows: The literature survey of ECG mechanism is given in section 3, while section 4 is devoted to ECG preprocessing. In section 5, we summarized the ECG feature extraction methods, while feature selection and feature transformation schemes are provided in section 6 and section 7, respectively. Section 8 is introduced the classification methods of ECG. Finally, conclusions are presented in section 8.

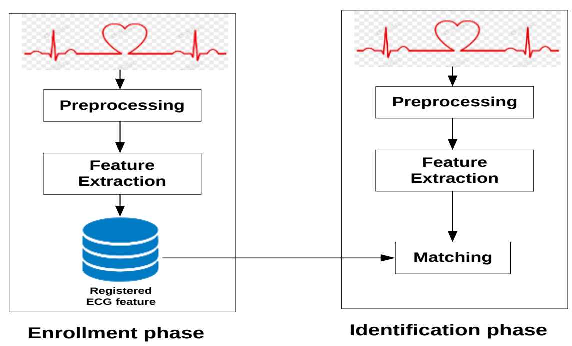


**Figure 1. The general phases of ECG.**

## 3. ECG Preprocessing Approaches

The goal of the preprocessing approach is to eliminate noise and artifacts, ECG recordings are usually polluted and therefore these noise must be reduced (P, Q, R, S, T (T (P-onset, P-peaks, P-offset, QRS-onset, QRS-offset, T-onset, T-peaks and T-offset)) as shown in Figure 2.

### 3.1 Filtering

The pre-processing stage uses filtering to remove noise from an ECG signal. Usually, Initially the ECG signal is filtered before it is analyzed. Band pass filtering is also largely used to delete muscle noise (De Chazal, P et al (2004)).

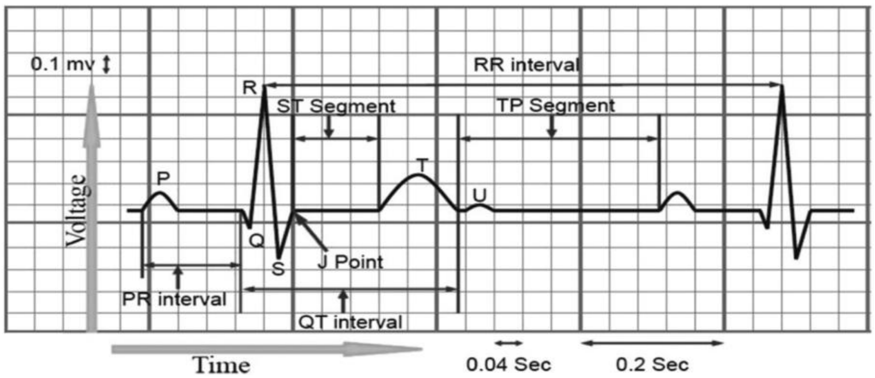


**Figure 2. ECG Standard fiducially points (P, Q, R, S, T, and U).**

**Table 2. Types of noise.**

| Type of noise | Definition |
|---|---|
| Hardware noise | Noise produced by equipment that was used in ECG measurements. |
| Noise from electricity | It is a noise produced by medical devices in the case of patient care with a frequency ranging between 100 kHz and 1 MHz. |
| Muscle contraction | It is a noise resulting from contraction in other muscles except the heart. |
| Electrode motion artifacts | It occurs due to differences in skin resistance to electrode movement. |
| Noise from electrical contact | This noise is caused by a lack of adhesion between the skin and the electrode, which causes the measurement system to be cut off. |
| Baseline wander | This noise occurs through the patient's inhalation, which makes changing the baseline mandatory for ECG signals. |
| Power line interference | a signal in the frequency of 50 or 60 Hz, and its bandwidth is below 1 Hz. |

* Types of noise are described and categorized into categories, so that we can compare signs between different patients as shown in table 2 (Elhaj, F. A et al. (2016)).

A comparison of general notch filter, comb notch filter and equiripple notch filter was made by (Bai, Y. W et al (2004)). By measuring the average squared error, performance is measured. Equiripple notch filter is more effective because it retrieves signal details, in contrast, the comb and general notch filters weaken ECG signal features. (Khan, M et al (2011)) reducing the ECG signal a noise signal residual algorithm has been proposed. Raw ECG signal was assumed to be a linear combination of ECG signal and noise.

A comparison of FIR and IIR filters was made by (Rani, S et al (2011)) in order to remove the noise in the ECG signal. The mean signal strength and spectral density are the evaluation factors for the interference noise elimination. (Ling, B et al (2011)) In order to remove the power line interference from the ECG signal the FIR Equiripple digital filter was designed and implemented. Note that the signal strength is reduced more in the Equiripple method compared to the window method. We find that the number of required elements is less in the Equiripple method than the window method, and there is also a need for mathematical elements.

A method based on experimental mode for removing high frequency noise and baseline wander was suggested by Manuel B.V. et. al. in (Blanco-Velasco et al (2008)). Intrinsic Mode Functions (IMF), we find that noise falls as the first IMF function. Different IMFs are processed to remove noise.

In the field of experimental situation analysis, the window method is suggested by (Kabir, M. A et al (2011)). Unlike traditional methods that completely ignore the initial (IMF). This approach preserves complex QRS information. In Empirical Mode Decomposition domain the signal is optimized from noise and then converted into a wave field, to preserve the QRS information the adaptive threshold system is applied. In the field of separate wavelet transformation, an adaptive fine threshold is implemented to reduce the noise that remains after the Empirical Mode Decomposition operation.

**3.2 Resampling**

In order to maintain database consistency and arithmetic cost, artifact removal and digitization are used. After filtering an ECG signal, it was resampled and digitized at the frequency of 125 Hz, 200 Hz, 250 Hz, 257 Hz, 360 Hz and 1 kHz (Gupta, R et al; Odinaka et al (2010)). To eliminate the noise, we find that Wavelet transform (WT) -based down sampling was used for this purpose. The discrete WT (DWT) is one of the important methods that allows a rapid calculation of Wavelet transforms. To analyze the noise of the ECG signal, we find that the DWT does this. Hence, to remove the noise, the neural network is applied, which is used as a filtering stage.

**3.3 Normalization**

In the pre-treatment stage, amplitude normalization is used, which is optional. Its purpose is to visually compare the signals between individuals. The ECG signal is normalized by dividing the features for each pulse by taking the mean of the last eight regular pulses (Vaidya, M. (2015)). Pre-processing stages are performed, such as estimating a linear predictive model (LP) and calculating the remaining error signal, and this occurs before determining the ECG signal (Martis, R et al.( 2009)). LP analyzes an ECG signal as a previous set of linear signals. Using LP coefficients, an ECG signal can be expected from a linear predictor.

**4 ECG Feature Extraction**

Feature extraction helps us to obtain a set of features through which good classification can be achieved. First, the classification and training system must be tested in order to allow the developer to assess the performance of a set of features (Bai, Y. W et al. (2004)). In order to achieve acceptable classification performance, a different set of features must be trained to choose the feature.

The P-QRS-T complex features for an ECG signal basically correspond to the locations, durations, amplitudes, and shapes of particular waves or deflections inside the signal. Typically, an ECG signal has a total of five major deflections, including P, Q, R, S, and T waves, plus a minor deflection, namely, the U wave as shown in Figure 2 (Lin, H. Y et al. (2014) ).
(Viknesh, V et al (2013)) process the ECG signal of the heart was carried out by the MTLAB. By transforming a wavelet, they process the QRS complex and filter out the noise. The goal was to compress the data and reduce the noise of the ECG signals. But they were not able to find other features of ECG signals.

Through an algorithm the feature extraction system was proposed by (Soorma et al. (2014)). This algorithm is used to analyze any non-linear signal because the feature of any signal is extracted by this algorithm. In order to extract the ECG signals, a wavelet transform and Huang Hilbert Transform were used.

In order to extract the features in the electrocardiogram, a discrete wavelet transform was used by (Srivastava et al. (2013)). They also used a neuro-fuzzy approach, which was combined with artificial neural networks and fuzzy logic. Through this approach, the data was analyzed and classified, and its accuracy exceeded 90%, but the sensitivity ranged between 60% and 70%.

(Coast, Douglas A., et al. (1990) ) a method for checking for arrhythmias is described by Hidden Markov Models. This method collects both the statistical and structural information of the ECG signal in a single model. This method has been useful in detecting complex QRS as well as R-R intervals to identify arrhythmias. The accuracy of this proposed system ranged from 50% to 80%.

**5 Feature Selection**

One of the most important concerns of analyzing ECG signals is the high dimensions of feature space, such as computational time and classification accuracy. The feature selection can be defined as a set of techniques that we can use to define subsets of features that are related to each other in order to build strong learning models and to achieve this the non-related and increased features are removed. We find that the goal of choosing a feature is to provide an understanding of the basic process by which data is generated, and also to provide a faster and more cost-effective learning process. Methods of feature identification are grouped into three categories, called wrapper, filter, and embedded methods (Srivastava et al. (2013); Berkayaet al. (2018)).

**5.1 Filter-based selection**

As previously mentioned, the selection methods dependent on the filter are general procedures for selecting the feature, through which the features are classified according to criteria that were previously determined. We find that some studies on the selection of filter-dependent features for ECG signals include choice based on information acquisition, hazy agglomeration, correlation criteria and Fisher's degree. Correlation criteria are a feature selection algorithm that takes into account criteria such as a feature’s affinity for a particular category and the feature’s association with other features. When mutual information is used as a feature selection method, these two variables will be a feature and a particular class. A fuzzy c-means algorithm is used for fuzzy clustering-based feature selection. The relative distance among the patterns and cluster prototypes are calculated for the computation of fuzzy memberships in the fuzzy c-means algorithm (Ceylan, Ret al.( 2009) ). The information obtained measures the amount of information that is absent and present in order for the feature to contribute to the grading of the classification around the selection of a particular feature. In the fuzzy c-means algorithm the relative distance between cluster models and patterns is calculated in order to calculate fuzzy membership (Ceylan, Ret al.( 2009) ).

**5.2 Deterministic Wrappers**

The most frequently used wrappers methods are the sequential selection methods, which measure the contribution of each feature to the classification, by removing different numbers of features from and to the original feature set until a better standard value is reached (Gunal, S et al. (2009)).

**5.3 Randomized Wrappers**

Another way we can choose the preferred feature of the ECG signal analysis algorithm is the genetic algorithm-based selection approach (GA). Genetic algorithm is a research method and is inspired by the biological development process. The principle of the genetic algorithm is to keep the most beneficial solutions among a group of possible solutions to a specific problem. Therefore, it is expected to find new solutions and be closer to the optimal solution Berkayaet al.( 2018)).

**6 Feature Transformation**

Reducing the dimension of features is the primary goal of both feature selection and feature transformation, and therefore we find most researchers use these terms. However, shifting the feature accomplishes this goal by converting the original area into a less distant subspace, we find that selecting the feature reduces the dimension by choosing a more distinct subset among a set of primary features. Transformation of features and selection of features We find that they are equivalent approaches. In this section, we will list the known methods for transformation features (Hyvärinen, A et al. (2000)).

**6.1 Principal component analysis (PCA)**

PCA is one of the well-known methods of extraction of features, and it helps to reduce the dimensions of the signal classification. It also acquires unique solutions through a orthogonal structure that is defined on the matrix of maps. PCA also computes the base components as a percentage of the total data change.

**6.2 Linear discriminant analysis (LDA)**

Linear discriminant analysis is used to convert a set of features into smaller groups. New features It is possible to apply the main idea: the distance between the degree is large and the distance within the category is reduced.

**6.3 Independent component analysis (ICA)**

ICA is a statistical approach that, in turn, transforms random data that are multidimensional and converts it into a set of statistically independent features from each other as possible. The goal of ICA technology is to solve problems related to the problem of cocktail parties, and it is also intended to separate mixed signals into components. Independent component analysis It is assumed that the measurement of the given signal is produced due to the linear combination of the source of the elements (Hyvärinen, A et al. (2000)).

7. **Classification**

For ECG classification and analysis there are many classifiers that have been used, which can be classified into multiple categories such as artificial neural network (ANNs), LDA, neighbor (kNN), decision tree (DT), support vector machine (SVM), and Bayesian classifiers.

**7.1 Artificial neural networks (ANN)**

Artificial neural networks are a model of biological neural networks. And that there are also neurons linked together, consisting of hidden layers or as inputs and outputs, and this approach is one of the most used patterns. Artificial neural networks its goal is to solve the problems that result from linear and nonlinear classification with the learning algorithm and network structure.

**7.2 Linear discriminant analysis (LDA)**

Linear discriminant analysis was developed by Fisher in 1936, through which more accurate models were produced than sophisticated and modern classification methods. Its purpose is to increase the contrast between the various class to the variation within the class, and also provides the highest possible distinction between the layers, and is also used in some of the recent classifications of the ECG (Liu, Qet al. (2014)).

**7.3 K-nearest neighbor (KNN)**

K-nearest neighbor classifies vector features based on the description of the closest training sample in the feature area. For unknown features, the distance between this unknown vector and the training set vector is measured using the Euclidean distance. Then, an unknown feature vector is assigned to the class in which the closest k samples mostly belong to. Thus, a kind of majority voting approach is applied. As we know that the value of k is a positive integer and it is considered as a strong influence factor used for classification accuracy. K-nearest neighbor It has been widely used in problem solving process, pattern recognition and also it is used in ECG classification.

**7.4 Support vector machine (SVM)**

Support vector machine It is used as a tool through which to solve the problems of binary classification and that this technology has a great generalization performance. The main idea of the Support vector machine is to find the maximum boundary between boundary Support vectors and training data, which is used to increase the maximum margin. Support vector machine can be classified as either linear or non-linear. Whereas, the linear kernel makes the support vector machine a linear classifier, while other kernel functions, such as Gaussian radial basis, polynomial, and sigmoid make the support vector machine a nonlinear classifier. A support vector machine is widely used in most ECG studies.

**7.5 Decision tree (DT)**

Decision tree its purpose is to set observations about a particular element to a conclusion. We find that this conclusion is either a target value or a possible target value. Based on the difference in this conclusion, we find that the Decision tree's structure is a regression or classification of trees. While the leaves of regression trees represent continuous values, the leaves of classification trees represent class labels. Multiple DT training is done with a subset of the training data. Types of majority voting are used in this approach so that the output class label is set according to the number of votes from all individual trees. In ECG classification studies this approach is often used frequently (Liu, Qet al. (2014)).

**8. Conclusion**

This paper presented a survey on various methods of ECG signals. The main goal of this paper is to consolidate the fundamental information on all the aspects of ECG analysis and to present this information for the benefit of the research community to enable researchers to obtain the answers to the possible questions on any stage of ECG analysis via a single resource.

**References**

Bai, Y.W., Chu, W.Y., Chen, C.Y., Lee, YT., Tsai, Y. C., & Tsai, C.H. (2004). Adjustable 60Hz noise reduction by a notch filter for ECG signals. In Proceedings of the 21st IEEE Instrumentation and Measurement Technology Conference (IEEE Cat. No. 04CH37510), 3, 1706-1711). doi: 10.1109/IMTC.2004.1351410

Banerjee, S., & Mitra, M. (2013). Application of cross wavelet transform for ECG pattern analysis and classification. IEEE transactions on instrumentation and measurement 63(2), 326-333. doi: 10.1109/TIM.2013.2279001

Berkaya, S. K., Uysal, A. K., Gunal, E.S., Ergin, S., Gunal, S., & Gulmezoglu, M.B. (2018): A survey on ECG analysis. Biomedical Signal Processing and Control 43, 216-235.

Blanco-Velasco, M., Weng, B., & Barner, K. E. (2008): signal denoising and baseline wander correction based on the empirical mode decomposition. Computers in biology and medicine,38(1),113. doi.org/10.1016/j.compbiomed.2007.06.003

Bolle, R. M., Connell, J. H., Pankanti, S., Ratha, N. K., & Senior, A.W., (2013). Guide to biometrics. Springer Science & Business Media. doi: .10.1007/978-1-4757-4036-3

Ceylan, R., Özbay, Y., & Karlik, B.(2009): A novel approach for classification of ECG arrhythmias: Type-2 fuzzy clustering neural network. Expert Systems with Applications 36(3), 6721-6726. doi.org/10.1016/j.eswa.2008.08.028

Coast, Douglas A., & et al. (1990). An approach to cardiac arrhythmia analysis using hidden Markov models. IEEE Transactions on biomedical Engineering 37(9), 826-836. DOI: 10.1109/10.58593

De Chazal, P., O'Dwyer, M., & Reilly, R.B .(2004): Automatic classification of heartbeats using ECG morphology and heartbeat interval features. IEEE transactions on biomedical engineering 51(7), 1196-1206. doi: 10.1109/TBME.2004.827359

Elhaj, F. A., Salim, N., Harris, A. R., Swee, T. T., & Ahmed, T. (2016). Arrhythmia recognition and classification using combined linear and nonlinear features of ECG signals. Computer methods and programs in biomedicine 127, 52-63. doi.org/10.1016/j.cmpb.2015.12.024

Fratini, Antonio, & et al. (2015). Individual identification via electrocardiogram analysis." Biomedical engineering online, 14(1), 1-23. doi.org/10.1026/j.cmpb.2015.12.024

Gunal, S., Gerek, O. N., Ece, D. G., Edizkan, & R. (2009). The search for optimal feature set in power quality event classification. Expert Systems with Applications 36(7), 10266-10273. doi.org/10.1016/j.eswa.2009.01.051

Gupta, R., Bera, J. N., & Mitra, M. (2010) Development of an embedded system and MATLAB-based GUI for online acquisition and analysis of ECG signal. Measurement, 43(9),1119-1126. doi.org/10.1016/j.measurement.2010.05.003

Hyvärinen, A., & Oja, E. (2000). Independent component analysis: algorithms and applications. Neural networks 13(4-5), 411-430.. doi.org/10.1016/S0893-6080(00)00026-5

Jain, A. K., Ross, A., & Prabhakar, S. (2004): An introduction to biometric recognition. IEEE Transactions on Circuits and Systems for Video Technology 14(1), 4-20. doi.org/10.1017/S0893-6070(00)00026-5

Kabir, M. A., & Shahnaz, C. . (2011, November): An ECG signal denoising method based on enhancement algorithms in EMD and wavelet domains. In TENCON 2011-2011 IEEE Region 10 Conference. 284-28). doi: 10.1109/TENCON.2011.6129109

Khan, M., Aslam, F., Zaidi, T., & Khan, S. A.(2011). Wavelet based ECG denoising using signal-noise residue method. In 2011 5th International Conference on Bioinformatics and Biomedical Engineering 1-4. doi: 10.1109/icbbe.2011.5780263

Lin, H. Y., Liang, S. Y., Ho, Y. L., Lin, Y. H., & Ma, H.P. (2014). Discrete-wavelet-transform-based noise removal and feature extraction for ECG signals. Irbm 35(6), 351-361. doi.org/10.1016/j.irbm.2014.10.004

Ling, B. W. K., Ho, C. Y. F., Lam, H. K., Wong, T. P. L., Chan, A. Y. P., Tam, P. K. S. (2008): Fuzzy rule based multiwavelet ECG signal denoising. In 2008 IEEE International Conference on Fuzzy Systems, IEEE World Congress on Computational Intelligence, 1064-1068. doi: 10.1109/FUZZY.2008.4630501

Liu, Q., Pitt, D., Wu, X. & (2014). On the prediction of claim duration for income protection insurance policyholders. Annals of Actuarial Science, 8(1), 42-62. doi.org/10.1017/S1748499513000134

Luz, E. J. D. S., Schwartz, W. R., Cámara-Chávez, G., & Menotti, D. (2016). ECG-based heartbeat classification for arrhythmia detection: A survey. Computer methods and programs in biomedicine 127, 144-164. doi.org/10.1016/j.cmpb.2019.105075

Martis, R. J., Chakraborty, C., & Ray, A. K (2009). A two-stage mechanism for registration and classification of ECG using Gaussian mixture model. Pattern Recognition 42(11), 2979-2988. doi.org/10.1016/j.patcog.2009.02.008

Nawal, M., & Purohit, G.N. (2014). based human authentication: a review. Int. J. Emerg. Eng. Res.Technol2(3),178-185. doi.org/10.1016/j.eswa.2014.01.051

Odinaka, I., O'Sullivan, J. A., Sirevaag, E. J., & Rohrbaugh, J.W. (2014). Cardiovascular biometrics: combining mechanical and electrical signals. IEEE Transactions on Information Forensics and Security 10(1), 16-27. DOI: 10.1109/TIFS.2014.2361261

Pal, S., & Mitra, M. (2012). Increasing the accuracy of ECG based biometric analysis by data modelling. Measurement 45(7), 1927-1932. doi.org/10.1016/j.measurement.2012.03.005

Rani, S., Kaur, A., & Ubhi, J.S. (2011). Comparative study of FIR and IIR filters for the removal of

Baseline noises from ECG signal. doi.org/10.48550/arXiv.1807.11359

Sahoo, S. K., Choubisa, T., & Prasanna, S. M. (2012). Multimodal biometric person authentication: A review. IETE Technical Review 29(1), 54-75. doi.org/1016.48550/arXiv.1807.11359

Soorma, N, Jaikaran S., & Mukesh T. (2014). Feature extraction of ECG signal using HHT algorithm, arXiv preprint arXiv:1403.1660 .

Srivastava, V. K., & Prasad, D., (2013), DWT-based feature extraction from ECG signal, American J. of Eng. Research (AJER) 2(3), 44-50. doi**:** 10.1109/TIFS.2013.2361261

Vaidya, M., (2015), A study of biometrics technology methods and their applications-a review. International Journal of Innovations in Engineering and Technology 5(2), 235. doi: 10.1109/TIFS.2014.2361261

Viknesh, V., & P. Prashanth, P.R. (2013). Matlab implementation of ECG signal processing, IOSR Journal of VLSI and Signal Processing 3.1. doi: 10.1106/TIFS.2013.2360430

Wahabi, S., Pouryayevali, S., Hari, S., & Hatzinakos, D., (2014). On evaluating ECG biometric systems: Session-dependence and body posture. IEEE Transactions on Information Forensics and Security 9(11), 2002-2013. doi: 10.1109/TIFS.2014.2360430