ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 03, 2021

A NOVEL METHOD FOR DETECTION OF ISCHEMIA IN ELECTROCARDIOGRAM SIGNALS

Nisha Raheja[1], Amit Kumar Manocha[2*]

[1]Department of Electrical Engineering, GZSCCET, Maharaja Ranjit Singh Punjab Technical University, Bathinda, India; Email: nisha.5165@gmail.com

[2]Department of Electrical Engineering, Punjab Institute of Technology, Moga; Maharaja Ranjit Singh Punjab Technical University, Bathinda, India; Email: manocha82@gmail.com

Abstract: We have proposed a novel method for detection of ischemic events based on morphological features are extracted from ST-segment abnormalities in electrocardiogram signals named modified isoelectric energy measuring function (MIEMF). ECG signals are first denoised before going through the delineation process. The ECG data is first loaded from the European ST-T Database, and then wavelet transforms are used to normalize the ECG to baseline references and removed the noises. Next, features of the ECG signal are detected, and from these features, ST-segment is defined and calculated ST deviation for each beat, whether it is normal, elevated, or depressed. The collected features are subsequently sent to clinicians via an Internet of Things (IoT) cloud channel. After usage of this approach, we got average sensitivity (SE) is 98.5%, while the average specificity (SP) is 98.3%. These results outperform those of other methods that have been cited in the literature.

Keywords: ECG, Wavelet transform, ST segment, Baseline wander noise, High-frequency noise, Feature extraction, modified isoelectric energy function

1. Introduction

The citizens are more prone to heart infection or cardiovascular disorders as their immobility increases, as does their worry, which leads to an increase in the need for medicine (CVDs). CVDs have become the leading cause of death in India, with heart disease/CVDs accounting for over 34% of all deaths (Janveja et.al (2020)). The admittance of all persons with the hope of receiving medical services is not met due to deficiency of doctors/specialists and specialists: patient ratio of 1:1700 (Algarni, A. D et.al (2020)). In India, medical personnel are in limited supply in all areas, particularly in rural areas. This is an extremely bad/surprising situation. The World Health Organization (WHO) claims that (WHO), non-communicable and coronary heart disease will account for 75% of global mortality. Atherosclerosis and thrombosis are the main causes of these disorders, which might appear as coronary ischemia syndrome (M. Singh, (2010)). Cardiovascular diseases (CVDs) can be avoided by addressing the risk factors as well as medical therapy and early identification. As a result, researchers' attention is currently focused on providing reliable and prompt detection of ischemia. One of the non-invasive approaches for diagnosing ischemia is an electrocardiogram (ECG). The P wave (depolarization of the atria), QRS complex (depolarization of the ventricles), and T wave are all represented in an ECG (ventricular repolarization). Under typical circumstances, the duration, direction, and amplitude of characteristic spots on an ECG are predictable. An ischemia ECG, on the other hand, has a unique look, indicating a reduction in the amount of oxygen available to heart tissues. During the plateau and resting stages of the ventricular action potential, the flow of damage currents is caused by voltage gradients between ischemia and non-ischemic myocytes. In an ECG, this appears as an elevated or depressed ST segment (G.S. Wagner et.al (2009)). ST-elevation is seen in people with prinzmetal angina and transmural ischemia, whereas depressed ST is seen in patients with subendocardial unstable, stable angina, and ischemia.

ECG signal is normally a time-varying signal with amplitude having a range from 10 μV to 5 mV. The system requires a noiseless ECG signal for the proper detection of heart disease (Singh, B.N et al. (2006)). However, the ECG signal got affected by various noises which are baseline wander, high-frequency noise, which makes it difficult in proper detection, and also feature extraction is affected. The main cause of baseline wander noise is the movement of the patient, improper placement of leads, and change in impedance of skin. During monitoring of ECG signal the baseline wanders between noise in an ambulance and workout plays an important role in artifacts Appathurai, A et.al (2019)). The range of frequency of this artifact is commonly 1 to 10 Hz. The noise's amplitude is changing during breathing by 15% from peak to peak at the frequency range of 0.15 Hz to 0.3 Hz (Friesen, G.M et.al (1990)). If this noise is present in the ECG signal, it may lead to affect the ST segment and other low-frequency components presented in the electrocardiogram signal. The distorted ST segment impacts on the analysis of disease, myocardial infarction, and other abnormalities related to ST segments. In addition to this, when high-frequency noise is present in an electrocardiogram (ECG) signal, it entirely obscures the ECG signal's waveform. It causes a dilemma for doctors when analyzing ECG readings. This is a very high-frequency signal that ranges from 100 to 150

Hz (A. Kumar and M. Singh, 2016). So, the reduction of various noises without distorted the important characteristics of the ECG signal by various methods will make the judgment wrong of the expertise. So, reduction of both the noise i.e., low and high-frequency noise has improved the signal-to-noise ratio [E. S. Analysis, 2020].
Blanco-Velasco et.al (2008) discussed the various denoising algorithm i.e., EMD, wavelet transform, and digital filtering, and also proposed for the reduction of ECG noise, a wavelet transform approach is used. because of their good time-frequency, noise dilution, and compression characteristics ((Xu, Y.; Luo et al. 2017)) proposed the soft and hard threshold function is mostly used for the elimination of different types of artifacts introduced in the electrocardiogram signal. (Han, G et.al (2016)) discussed an improved method based on wavelet denoising called sigmoid function-based thresholding which is employed to maintaining the characteristic peak of the ECG signal (Üstünda G et.al 2012)) discussed a method for denoising the ECG signal using a threshold function. In this function, optimal parameters of fuzzy S-function are calculated for proper denoising of the ECG signal (Singh, P. et.al 2017) proposed the approach for removal of various artifacts in the ECG signal employing non-Local mean method (NLM) and DWT. This method is found better than the other methods after being tested on the MIT-BIH database. In this method, the thresholding is performed on the detail co-efficient for removal of high-frequency noise (Al-Betar et.al, 2017)) proposed an approach i.e., (Beta) – hill climbing with wavelet transform for the pre-processing of ECG signal. In this approach, optimal parameters are calculated for denoising of the ECG signal with the minimum mean square error between the original and noise-free ECG signal. The presented technique provides a better output of the filtering out noise. i.e., low frequency and high-quality ECG signal which is made easy proper detection of ECG signal by the specialist.
Wavelet analysis divides a signal on a time-scale domain into time and scaled domains of the underlying wavelet (Malfait, M et.al 1997)), (Torrence, C. et.al, 1998). This is a signal processing technique that is beneficial for assessing time series with a variety of timescales. In comparison to the Fourier transform, the wavelet transform offers a changeable "time-frequency window" that may be scaled dynamically. Because the window size widens at low frequencies and narrows at high frequencies, it is a useful method for all frequency ranges, resulting in increased accuracy in both frequency and time domains (Manikandan, M.S. et.al, 2014)) presented a technique based on Wavelet for compressing or improving characteristics. Due to the great resolution, Wavelet transform can distinguish the abstract and hidden aspects of ECG signals due to its high frequency and time resolution (Castillo, E et.al (2013)). Morlet, hat, Mexican, Daubechies, Meyer, Symlets and Coiflets, haar, and bi-orthogonal wavelets are some of the wavelet bases. Using the wavelet transform, it is critical to select an appropriate wavelet basis and the number of decomposition levels for the signal of interest. Wavelet bases differ in their properties and suitability for different applications (Enamamu T. et.al 2020), (Clark N. et.al, (2018)) discussed a real-time approach for detecting heart problems in individuals from rural areas using the QRS complex detection in the ECG data. The data will be collected in this system on a single channel, that is joined to and communicates with the Smartphone, which will be controlled and analyzed. The pan-Tomkins technique is used to continuously detect the QRS in an ECG signal (C. Liu et.al, 2019) focused on the issues that QRS and SQA pose for wearable applications. To begin, a combination of diverse signal dependable evidence was offered, as well as a machine learning-based method for further classification of a 10-s ECG signal (J. Wannenburg et.al, 2018) examined a wearable device that used electrodes and an analogous conditioning system to calculate ECG signal and heart rate (HR). Following the collection of data, which is utilized to calculate the fluctuation in RR and the ECG signal's features point. In present research work, we have proposed a novel modified isoelectric energy measuring function for detecting ischemic events based on morphological features are extracted from ST-segment abnormalities in electrocardiogram signals. ECG data are first denoised before going through the delineation process. The data is first loaded from the European ST-T Database, and then wavelet transforms are used to normalize the ECG to baseline references and removed the noises. Next, features of the ECG signal are detected, and from these features, ST-segment is defined and calculated ST deviation for each beat, whether it is normal, elevated, or depressed. Rest of paper is divided in four sections, section 2 represents database and methods, section 3 explains the proposed methodology, section 4 presents results and discussion and section 5 cover conclusion and future work.

2. Database and methods

The European ST-T Database (EDB) entries are expected to be utilized to evaluate the developed method's performance and to validate the outcomes. This database consisting of 90 electrocardiogram recordings with 79 patients having beat-by-beat annotation. Two leads were obtained from MLI, MLIII, V1–V5, and D leads, according to the database. There are 367 ischemic events in the database, according to ST-segment changes lasting anywhere from 30 seconds to several minutes. Each record contains a two-hour recording of two channels with 12-bit resolution and a sampling frequency of 250 samples/s over a nominal 20 mV input range (Taddei et.al, 1992).

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 03, 2021

2.1 Wavelet Transforms

Wavelet transform denotes the wavelet function. This wavelet function is scaled and translated into a daughter wavelet with a finite-length signal is called the mother wavelet transform. Though the wavelet transform divides a continuous signal into scale components, each of which has its frequency range. Each frequency-scaled component is subsequently assigned a resolution, resulting in a multi-resolution analysis. The mother wavelet function in the time domain is defined as having a value in a specific frequency band and zeros elsewhere.

$$Wf(u,s) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{s}} \Psi^* \left(\frac{t-u}{s}\right) dt = f * \Psi_s(u) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

In this paper, discrete wavelet transformations are employed to decompose the ECG signal into two co-efficient, the first of which is the approximate co-efficient and the second of which is the detail co-efficient. The approximate and detail co-efficient contain vital data for the reconstruction of the original signal at each phase. Decomposition tree, also known as Mallat-Tree decomposition, is the name given to this process (A. K. Manocha, M. Singh, 2015).

3. Proposed Methodology

The work presented here introduces novel strategies for smoothing noised waveforms. The full scheme chart for the elimination of low frequency and high-frequency noise, as illustrated in figure 1. In this flow diagram, the data is first loaded from the European ST-T database, and normalized the ECG to baseline references and removed the noises using wavelet transforms followed by detection of features of ECG signal and defined the ST segment after that calculation of ST deviation for each beat whether it is normal, elevated, depressed. Then the extracted features are then delivered to cliniians via an IoT cloud channel (Internet of Things) for further analysis.

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 03, 2021

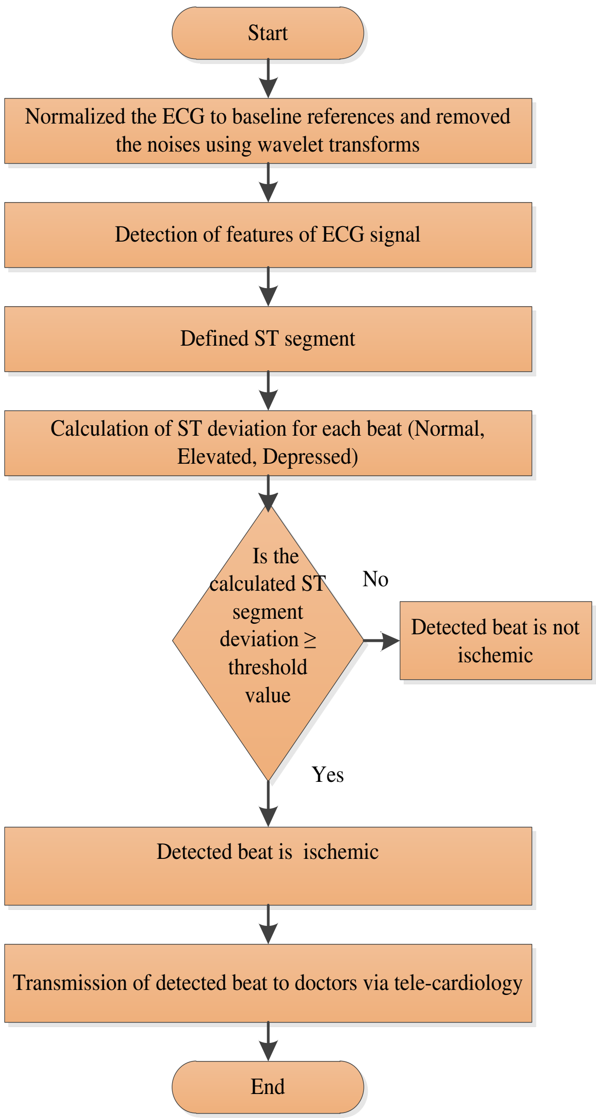


Figure 1: Flow chart of the proposed methodology

3.2 Features for detection of Ischemia

3.2.1 P-QRS-T waveforms detection

The ECG waveform, which is a very weak low-frequency electrical signal, reflects the activity of the heart tissue. The signal frequency is less than 5 mV and the peak amplitude is less than 5 mV is between 0.05 and 100 Hz. ECG waveform is normally comprised of P-waves, QRS complexes, T-waves, and U waves as shown in figure 2. The morphological features include different, peak intervals, peak amplitudes, and QRS complex.

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 03, 2021

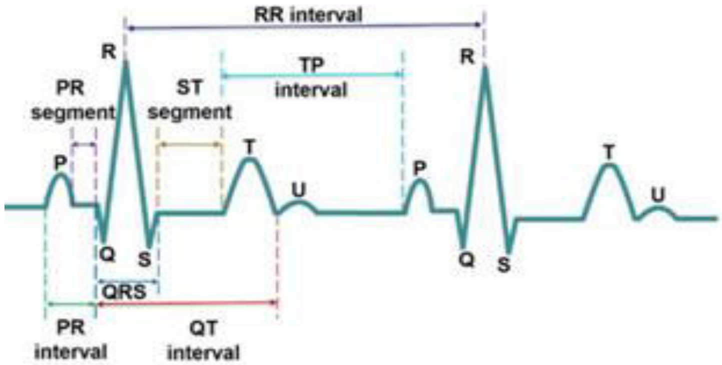


Figure 2: Conduction system of heart electrical activity and the ECG signal [E. S. Analysis, 2020].

3.2.2 Diagnosis of the J point

The J point occurs between 80 -120 milliseconds after the QRS complex and after the S peak, the J point is identified as the primary inflection point.

3.2.3 Isoelectric reference detection

The iso-electric reference (IR) is found in the TP segment of the ECG signal, which is the area between the Toffset of the present beat and Ponset of the next beat.

3.2.4 Calculation of heart rate

The heart rate is calculated by measuring the distance between the two corresponding R–R periods which is reported in beats per minute (bpm). It is the average time of R–R interval.

3.2.5 Measurement of ROI and ST-Segment Deviation

For proper diagnosis of the ST segment and isoelectric reference, we developed an ROI. The benefit of creating ROIs is that it is used only the highest value of samples instead of small values of samples. The ST segment is considered to be located between J point and Tonset, depending on the heart rate, i.e.

Defined ST segment

J+80 ms for heart rate ≤120 bpm
J+60 ms for heart rate >120 bpm

An approach for ROI method according to ST-segment has been developed given below.

ROI_{ST}
ST segment=length (Jpoint: Tonset)
M_{ST}=25% of ST Segment
ROI_{ST} = Jpoint+MST : Tonset- M_{ST}

Similarly, for the ROI corresponding to IR, the procedure is

ROI_{IR}
IR=length(Toffset:Ponset)
M_{ST}=25% of IR
ROI_{IR} = Toffset+M_{ST} : Ponset- M_{IR}

The ST Deviation is calculated by potential difference i.e. $ROI_{ST} - ROI_{IR}$ [A. Kumar and M. Singh, 2016].

3.2.6 Modified Isoelectric Energy Measuring Function (MIEMF)

We have proposed a novel function for the detection of ST deviation. Each sample in the ST segment has its iso-electric energy is quantified, and an isoelectric energy function (IEEF) is proposed in this paper is defined as given in equation (2)

$$IEEF = \sum \frac{[\![ROI_{ST} - ROI_{IR} + \alpha]\!]}{Length\ (ROI_{ST})} * \gamma \tag{2}$$

where i=1, 2, 3——————up to the length of samples in an ST-segment and α= 0.01, which is artificially added regularly to keep IEEF from reaching an infinite value, and ɤ is to maintain the beat's categorization threshold as low as possible. The number of samples in each ST segment of a record is represented by length (ST). The MIEMF is invented with the idea that samples from segments closest to the baseline will provide less energy than samples from segments further away and defined a function that diagnosis these differences in a hard way as an alternative to detecting the elevation or depression of an ST segment with respect to a baseline (isoelectric line). The value of this function should increase as an ST-segment approach the isoelectric reference level, and decrease the ST-segment move below the isoelectric reference level. So, a function we have proposed in this paper based on the threshold for identification of myocardial ischemia [A. Kumar and M. Singh, 2016].

3.2.7 Threshold

In this proposed work, we have specified the value of the threshold to differentiate the normal beats from ischemic beats in an ECG signal after measuring isoelectric energy for each ST segment in that record. An ischemic (elevated or depressed) beat will always have a higher IEEF value than a normal beat. Normal heartbeats are marked with a 1 and ischemic heartbeats are marked with a **± 1**.

If isoelectric energy = 1
then detected beat is Normal
else if isoelectric energy = -1
then ST segment is depressed
else if isoelectric energy = +1
Then ST-segment is elevated

4. Results and Discussion

We have proposed a novel modified isoelectric energy measuring function for detecting ischemic events based on morphological features derived from ST-segment abnormalities in electrocardiogram signals. We tested the suggested technique on the European ST-T database's records. ECG records are first pre-processed to remove noises before going through the delineation process. The data is first loaded from the European ST-T Database, and then wavelet transforms are used to normalize the ECG to baseline references and removed the noises as shown in figure 4. Next, features of the electrocardiogram signal are detected shown in figure 5, and from these features, ST-segment is defined and calculated ST deviation for each beat, whether it is normal, elevated for e0103 record, or depressed for e0105 record as shown in figure 6. The collected features are subsequently sent to clinicians via an Internet of Things (IoT) cloud channel.

4.1 Noises in ECG signal

Electrocardiogram signals are normally time-varying signals with amplitude having a range from 10 μV to 5 mV. The system requires a noiseless ECG signal for the proper detection of heart disease [Singh, B.N et al. 2006]. However, the ECG signal got affected by various noises which are baseline wander, high-frequency noise, which makes it difficult in proper detection, and also feature extraction is affected.

4.1.1 Removal of Baseline Wanders

The main cause of baseline wander noise is the movement of the patient, improper placement of electrodes, and changes in skin impedance. During monitoring of ECG signal in an ambulance and exercise, the baseline wander noise plays an important role in artifacts [N. Raheja et al. 2021]. The range of frequency of this artifact is commonly 1 to 10 Hz. The noise's amplitude is changing during breathing by 15% from peak to peak at the frequency range of 0.15 Hz to 0.3 Hz [Friesen, G.M et al. 1990]. If this noise is present in the ECG signal, it may lead to affect the ST segment and other low-frequency components presented in the electrocardiogram signal. The distorted ST-segment impacts the analysis of disease, myocardial infarction, and other abnormalities related to ST segments. Baseline wandering is a low-frequency noise having a frequency range of 0.5–1 Hz, the ECG signal is divided to the tenth level and baseline wander noise is removed using the Daubechies (db4) wavelet transform.

4.1.2 Removal of High-Frequency Noise

When this type of noise appears in an electrocardiogram (ECG) signal, it entirely obscures the ECG signal's waveform. It causes a dilemma for doctors when analyzing ECG readings. This is a very high-frequency signal that ranges from 100 to 150 Hz. As a result, a technique called the wavelet transform is utilized in this research to reduce

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 03, 2021

high-frequency noise [A. Kumar and M. Singh, 2016]. So, the reduction of various noises without distorted the important characteristics of the ECG signal by various methods will make the judgment wrong of the expertise. So, reduction of both the noise i.e., low and high-frequency noise has improved the signal-to-noise ratio. To remove this noise we have employed the Coiflet (Coif4) wavelet function. The noise is first assessed using the approximate coefficients of the ECG signal, known as sigma, and then calculated the value of threshold after employing the sigma value. For elimination of detail co-efficient, the soft thresholding technique is used whereas the approximation coefficients are kept at unity value (Beena et al., 2014; Kumar and Singh, 2015). Figure 4. shows the results of eliminating both baseline wander and high-frequency noise of e0103m record of European ST-T database.

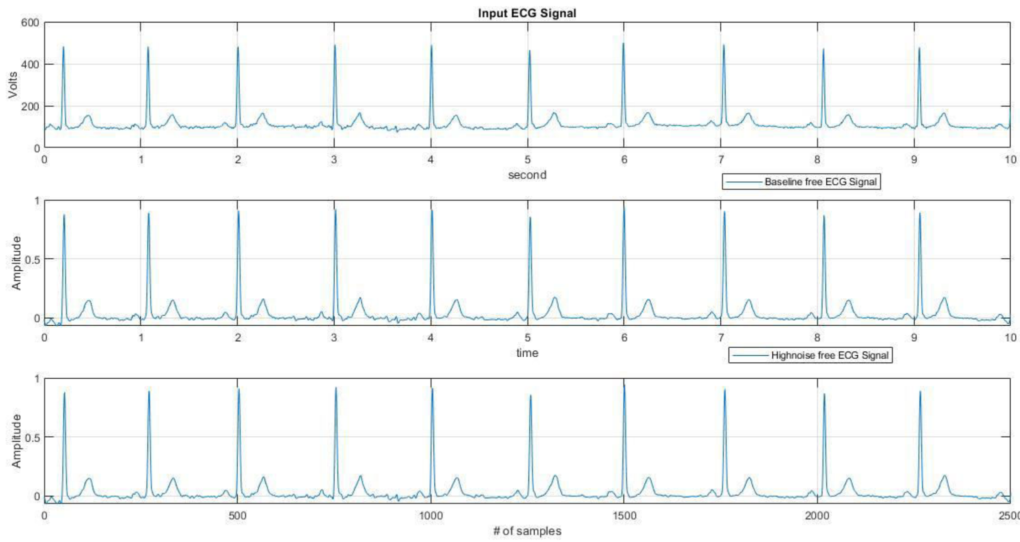


Figure 4. Removal of baseline wander and high-frequency noise for e0103 EDB record

4.2 Features Extraction

During the recording of electrical impulses generated by cardiac muscles, an ECG is a tool used for the measurement of regular or irregular breathing activity of cardiac. As a result, it's critical to get as much useful clinical information out of ECG signals as feasible. Doctors frequently make the diagnosis by examining the morphological properties of P-QRS-T waves, which is time-consuming and highly dependent on the doctors' experience. The efficiency and accuracy of ECG analysis have substantially increased using a technique i.e., computer-aided based on feature engineering. ECG signals with significant information can have a small number of features such as morphology, peak amplitude, entropy distribution, energy, and frequency content, and the number of event intervals, that can be used to show characteristics of the electrocardiogram signal. Morphological features, frequency-domain features, P-QRS-T features, statistical features, and other more sophisticated characteristics are routinely used in ECG diagnosis and provide effective tools for clinicians' judgment. We computed the numerous morphological features by completing the correct analysis in our proposed work. P wave, QRS complex, T wave, and ST-segment are the morphological features [A. Kumar and M. Singh, 2016]. Figure 5 shows the measurements of morphological features for the European ST-T database of the e0103 record.

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 03, 2021

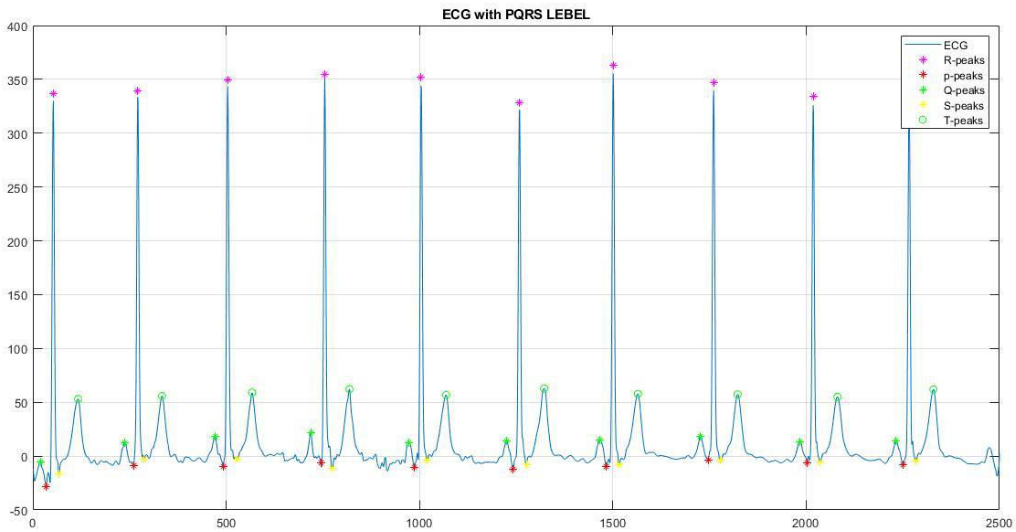


Figure 5. Detection of P, QRS, and T wave of ECG signal

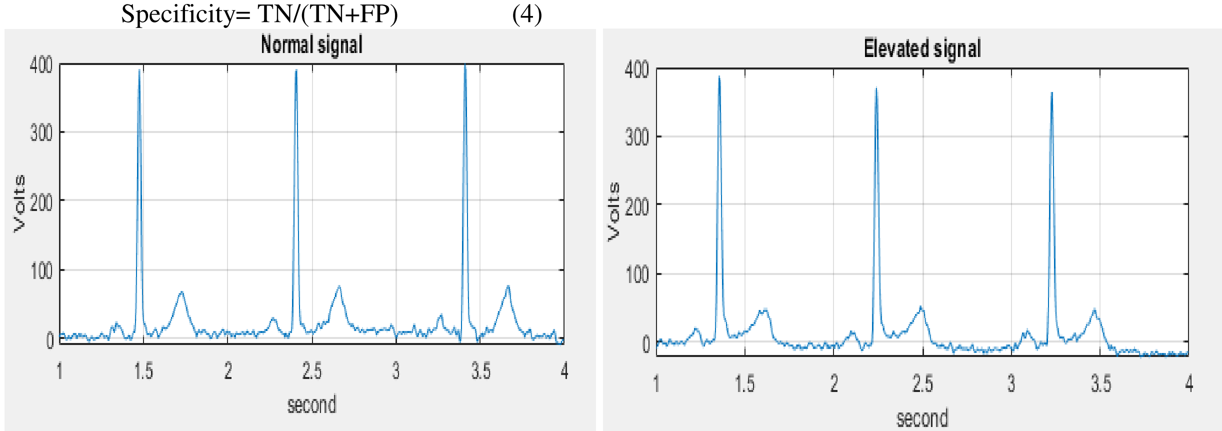
4.9 Detection of ST Deviation

On the ECG, the ST segment is the area between the start of ventricular repolarization and the end of ventricular depolarization. In other words, it is the area between the end of the QRS complex and the beginning of the T wave. The ST segment is the interval during which the heart continues to contract to evacuate blood from the ventricles. ST deviation (elevation or depression) is the most common ECG change caused by myocardial ischemia; The investigation of cardiac ischemia around the applied lead is based on the elevation and depression of the ST segment with a reference in the electrocardiogram signal. Patients with transmural (sub-epicardial) ischemia usually have elevated ST segments, whereas patients with sub-endocardial ischemia usually have depressed ST segments (or episodes) (Goldberger, 1981; Park et al., 2012). The detection of ST-segment (Normal, Elevated) for record of e0103 and depressed signal for record of e0105 of European ST-T database shown in figure 6. We have tested the total number of diagnosis beats for ten number of records i.e., for e0103, e0104, e0105, e0108, e0113, e0114, e0147, e0159, e0162 and e0206. For the examination of the performance of each class, we have proposed the average sensitivity and average specificity that are used for evaluating performance in the field of recognition. Equations (3), (4) are used for the calculation of sensitivity, and specificity. Sensitivity, on the other hand, is an assessment of the degree of true positives, defined as

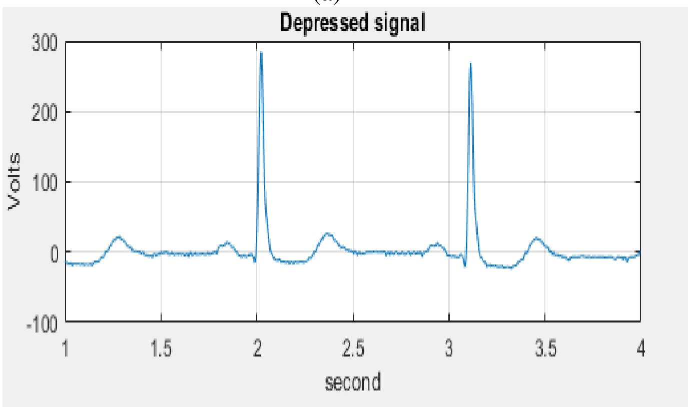
$$\text{Sensitivity} = TP / (TP + FN) \qquad (3)$$

Where TP denotes true positivity, TN denotes true negativity, FP denotes false positivity, and FN denotes false negativity. Specificity, on the other hand, is a measurement of the degree of true negatives, defined as

$$\text{Specificity} = TN/(TN+FP) \qquad (4)$$



(a) (b)



(c)

Figure 6. (a) Normal ST-segment of e0103 record of EDB; (b) Ischemic (elevated) ST segment of e0103 record of EDB (c) Ischemic (depressed) ST segment of e0105 record of EDB.

Comparison with the Existing Approaches

This research presents a new modified function for detecting ischemia in ECG signals named as modified isoelectric energy measuring function, which does not require any sophisticated calculations. The algorithm's performance was tested against existing approaches using the entries from the European ST-T database stated above. This dataset serves as a common reference for categorizing ischemic beats. Every annotated record in the dataset, in particular, was expected to contain just ischemic beats. Our outcome approach cannot compare to other approaches indicated [N. Maglaveras et al. 1998] since they were either examined with different databases or used different outcome measurements or databases. The achieved results are superior to those obtained using other methods [T.P. Exarchos et al. 2007]. Most previously described approaches assessed an ST-segment after point J having constant lengths, while the suggested approach uses window length. In ischemia episode detection, HMM [R.V. Andreao et al. 2004] achieves the best average statistics, but it is ineffective for detecting non-ischemic episodes. For the analysis of rules, fuzzy logic [M.G. Tsipouras et al. 2007] based systems are very important in the diagnosis of ischemia, but they still require further research to improve the diagnosis performance and authors got the results i.e., average sensitivity (SE) is 91.2%, while the average specificity (SP) is 90.9%. The neural network-based systems with hidden layers [C. Papaloukas et al. 2002], [C. Papaloukas et al. 2002] can identify ischemia more accurately than other presented methods, they are, however unable to deliver an interpretation of a detection. In this paper, the authors achieved an average sensitivity (SE) is 81%, while the average specificity (SP) is 84%. Genetic algorithm [C. Papaloukas et al. 2004], support vector machine [J. Park et al. 2012], and kernel density estimation [S. Don et al. 2013] are examples of this. [Cong wang et al. 2014] proposed a new approach termed cardiodynamicsgram (CDG) for early diagnosis of myocardial ischemia based on standard 12-lead electrocardiography (ECG). The cardiodynamics information is retrieved from the ST-T segments using a recently suggested deterministic learning technique. The CDG approach obtains a mean sensitivity of 90.3 percent and a mean specificity of 87.8 percent by evaluating ischemia patients. [A. Kumar et al. 2016] described an approach for the prediction of ischemic events based on statistical features derived from ST-segment abnormalities in ECG signals. For the filtration of false beats in ischemic episodes, the window characterization algorithm was devised. The kurtosis, coefficient of variation (COV), and form factor are used to detect ischemic episodes. For 90 records from the annotated European STT database, the results reveal an average sensitivity (Se) of 97.71 percent and positive predictivity (+P) of 96.89 percent. [Kenichi Nakajima et al.2018] used a Japanese multicenter database, an artificial neural network was retrained to identify myocardial ischemia. AUC=0.98 for version 1.1 (sensitivity 88 percent, specificity 100 percent) and 0.88 for version 1.0 in patients who had neither coronary revascularization nor an old myocardial infarction (p =0.0093): Version 1.1 generated intermediate ANN probabilities between 0.1 and 0.7 more frequently than version 1.0, contributing to better diagnostic accuracy. [Ronghua Li et al. 2021] proposed a method for identifying MI based on the T-wave area curve (TWAC). It was discovered that there is a substantial association between the morphology of TWAC and MI by observation and study of clinical data. In this paper, the presented approach for detecting MI has a sensitivity, specificity, and accuracy of 84.3, 83.6, and 84 percent, respectively. [Marious Reto Bigler et al.

2021] proposed a deep learning method such as convolutional neural networks (CNN) for the extraction of data-derived features and recognize natural patterns. As a result, CNN provides an unbiased perspective on well-known clinical phenomena such as myocardial ischemia. In this paper, the authors achieved the results i.e., sensitivity is 80 percent, specificity 92 percent at a cut-off of 0.279mV using coronary patency or occlusion as a reference for absent or present myocardial ischemia. In this paper, we have calculated the isoelectric energy measuring function using ST-segment deviations, but we could also use other ST-segment morphological properties. There are two significant advantages to the proposed method. The approach can be used to analyze the findings. This is crucial in the development of a medical support decision-making system. This would also be beneficial for CCU patients who have no past references. Second, direct analysis based on isoelectric energy is used rather than a sophisticated algorithm, and the collected features are subsequently sent to clinicians via telecardiology for proper analysis of heart diseases with which has not been defined in the existing state of artworks. Tele-cardiology-based systems also save the lives of human beings in golden hours. After usage of this proposed approach, we got the average sensitivity (SE) is 98.5%, while the average specificity (SP) is 98.3%. These results outperform those of other methods that have been cited in the literature.

5. Conclusion & Future Scope

We proposed a novel modified isoelectric energy measuring function for detecting ST deviation (normal, elevation, or depression) events in ECG records. Even though this is successful research in diagnosing ischemia and produced the best results, with the numerous hurdles to overcome. The study was conducted with the help of the European ST-T datasets. The database records may be absolute, and new types of ischemic and normal ST segments may be integrated, for the created approach to be employed in the clinic. In this paper, the ECG signal is first pre-processed to remove noises before going through the delineation process. The data is first loaded from the European ST-T Database, and then wavelet transforms are used to normalize the ECG to baseline references and removed the noises. Next, features of the ECG signal are detected, and from these features, ST-segment is defined and calculated ST deviation for each beat, whether it is normal, elevated, or depressed. Present research work may be extended for detection of ischemic episodes in ECG signals and diagnosis over tele-cardiology domain.

References

- Janveja, M., Paul, B., Trivedi, G., Vijayakanthi, G., Agrawal, A., Jan, P., &Němec, Z, "Design of Efficient AES Architecture for Secure ECG Signal Transmission for Low-power IoT Applications," In 2020 30th International Conference Radioelektronika (RADIOELEKTRONIKA) (pp. 1-6). IEEE, 2020.
- Algarni, A. D., Soliman, N. F., Abdallah, H. A., & Abd El-Samie, F. E, "Encryption of ECG signals for telemedicine applications ," Multimedia Tools and Applications, 1-25, 2020.
- M. Singh, "Introduction to Biomedical Instrumentation," Prentice Hall of India, New Delhi, India, 2010.
- G.S. Wagner, P. Macfarlane, H. Wellens, et al., AHA/ACCF/HRS recommendations for the standardization and interpretation of the electro-cardiology rhythm society: endorsed by the international society for computerized on clinical cardiology; the American College of Cardiology Foundation; and the Heart American Heart Association Electrocardiography and Arrhythmias Committee, Council, Circulation 119, 2009.
- Singh, B.N.; Tiwari, A.K. Optimal selection of wavelet basis function applied to ECG signal denoising. *Digit. Signal Process., 16*, 275–287, 2006.
- Appathurai, A.; Jerusalin Carol, J.; Raja, C.; Kumar, S.N.; Daniel, A.V.; Jasmine Gnana Malar, A.; Fred, A.L.; Krishnamoorthy, S, "A study on ECG signal characterization and practical implementation of some ECG characterization techniques," *Measurement*, *147*, 106384, 2019.
- Friesen, G.M.; Jannett, T.C.; Jadallah, M.A.; Yates, S.L.; Quint, S.R.; Nagle, H.T, "A comparison of the noise sensitivity of nine QRS detection algorithms,"*IEEE Trans. Biomed. Eng.*, *37*, 85–98, 1990.
- A. Kumar and M. Singh, "Ischemia detection using Isoelectric Energy Function," vol. 68, pp. 76–83, 2016.
- Blanco-Velasco, M.; Weng, B.; Barner, K.E. ECG signal denoising and baseline wander correction based on the empirical mode decomposition. *Comput. Biol. Med. 38*, 1–13, 2008.
- Xu, Y.; Luo, M.; Li, T.; Song, G. ECG Signal De-noising and Baseline Wander Correction Based on CEEMDAN and Wavelet Threshold. *Sensors*, *17*, 2754, 2017.
- Han, G.; Xu, Z. Electrocardiogram signal denoising based on a new improved wavelet thresholding. *Rev. Sci. Instrum.*, *87*, 084303, 2016.

- Üstünda˘g, M.; Gökbulut, M.; ¸Sengür, A.; Ata, F. Denoising of weak ECG signals by using wavelet analysis and fuzzy thresholding. *Netw. Modeling Anal. Health Inform. Bioinform.*, *1*, 135–140, 2012.
- Singh, P.; Pradhan, G.; Shahnawazuddin, S. Denoising of ECG signal by non-local estimation of approximation coefficients in DWT. *Biocybern. Biomed. Eng.*, *37*, 599–610, 2017.
- Al-Betar, M.A. β-Hill climbing: An exploratory local search. *Neural Comput. Appl. 28*, 153–168, 2017.
- Malfait, M.; Roose, D. Wavelet-based image denoising using a Markov random field a priori model. *IEEE Trans. Image Process. 6*, 549–565, 1997.
- Torrence, C.; Compo, G.P. A Practical Guide to Wavelet Analysis. *Bull. Am. Meteorol. Soc. 79*, 61–78, 1998.
- Manikandan, M.S.; Dandapat, S. Wavelet-based electrocardiogram signal compression methods and their performances: A prospective review. *Biomed. Signal Process. 14*, 73–107, 2014.
- Castillo, E.; Morales, D.P.; Botella, G.; García, A.; Parrilla, L.; Palma, A.J. Efficient wavelet-based ECG processing for single-lead FHR extraction. *Digit. Signal Process. 23*, 1897–1909, 2013.
- Enamamu, T.; Otebolaku, A.; Marchang, J.; Dany, J, "Continuous m-Health Data Authentication Using Wavelet Decomposition for Feature Extraction," *Sensors 20*, 5690, 2020.
- N. Clark, E. Sandor, C. Walden, I. S. Ahn, and Y. Lu, ''A wearable ECG monitoring system for real-time arrhythmia detection,'' in Proc. IEEE 61st Int. Midwest Symp. Circuits Syst. (MWSCAS), pp. 787–790), Aug. 2018.
- C. Liu, X. Zhang, L. Zhao, F. Liu, X. Chen, Y. Yao, and J. Li, ''Signal quality assessment and lightweight QRS detection for wearable ECG Smart Vest system,'' IEEE Internet Things J., vol. 6, no. 2, pp. 1363–1374, Apr. 2019.
- J. Wannenburg, R. Malekian, and G. P. Hancke, ''Wireless capacitive-based ECG sensing for feature extraction and mobile health monitoring,'' IEEE Sensors J., vol. 18, no. 14, pp. 6023–6032, Jul. 2018.
- A. Taddei, G. Distante, M. Emdin, P. Pisani, G.B. Moody, C. Zeelenberg, C. Marchesi, "The European ST-T database: standard for evaluating systems for the analysis of ST-T changes in ambulatory electrocardiography," Eur. Heart J. 13, 1164–1172, 1992.
- Manocha, A. K, Singh. M, "Optimal Selection of Wavelet Function and Decomposition Level for Removal of ECG Signal Artifacts," Journal of Medical Imaging and Health Informatics, vol. 5, 138–146, 2015.
- A. Kumar and M. Singh, "Statistical analysis of ST segments in ECG signals for detection of ischaemic episodes," 2016.
- N. Raheja and A. K. Manocha, "Removal of Artifacts in Electrocardiograms using Savitzky-Golay Filter: An Improved Approach," J. Inf. Technol. Manag., vol. 12, pp. 62–75, 2021.
- Beena MM, Prabavathy S, Priestly BS, et al, " Robust rule based de-noising scheme using wavelets," Journal of Medical Imaging and Health Informatics 4(4): 457–468, 2014.
- Goldberger A, "Electrocardiogram in ischemic heart disease," The Western Journal of Medicine 135(2): 104–109, 1981.
- N. Maglaveras, T. Stamkopoulos, C. Pappas, Strintzis M, "ECG processing techniques based on neural networks and bidirectional associative memories," J. Med. Eng. Technol. 22 106–111, 1998.
- T.P. Exarchos, M.G. Tsipouras, C.P. Exarchos, C. Papaloukas, D.I. Fotiadis, L.K. Michalis, , "A methodology for the automated creation of fuzzy expert systems for ischemic and arrhythmic beat classification based on a set of rules obtained by a decision tree,"Artif. Intell. Med. 40, 187–200, 2007.
- R.V. Andreao, B. Dorizzi, J. Boudy, J.C.M. Mota, "ST segment analysis using hidden markov model beat segmentation: application to ischemia detection," Comput. Cardiol. 31, 381–384, 2004.
- M.G. Tsipouras, V. Costas, D.I. Fotiadis, "A framework for fuzzy expert system creation application to cardiovascular disease, "IEEE Trans. Biomed. Eng. 54, 2089–2105, 2007.
- C. Papaloukas, D.I. Fotiadis, A. Likas, L.K. Michalis, "An expert system for ischemia detection based on parametric modelling and artificial neural networks," Proc. Eur. Med. Biol. Eng.Conf.Vienna,742–743,2002.
- C. Papaloukas, D.I. Fotiadis, A. Likas, L.K. Michalis, "An ischemia detection method based on artificial neural networks," Artif. Intell. Med. 24, 167–178, 2002.
- C. Papaloukas, T. Goletsis, D.I. Fotiadis, L.K. Aristidis Michalis, "Automated ischemic beat classification

using genetic algorithm and multi-criteria decision analysis," IEEE Trans. Biomed. Eng. 51, 1717–1725, 2004.

- J. Park, W. Pedrycz, M. Jeon, "Ischemia episode detection in ECG using kernel density estimation, support vector machine and feature selection," Biomed. Eng. Online 11, 1–22, 2012.
- S. Don, D. Chung, D. Min, "Analysis of electrocardiogram signals of arrhythmia and ischemia using fractal and statistical features," J. Mech. Med. Biol. 13 1350008-1–1350008-8,2013.
- C. Wang, X. Dong, S. Ou, W. Wang, J. Hu, and F. Yang, "A new method for early detection of myocardial ischemia: cardiodynamicsgram (CDG)," *Sci. China Inf. Sci.*, vol. 59, no. 1, pp. 1–11, 2016.
- K. Nakajima *et al.*, "Artificial neural network retrained to detect myocardial ischemia using a Japanese multicenter database," *Ann. Nucl. Med.*, vol. 32, no. 5, pp. 303–310, 2018.
- R. Li, X. Zhao, Y. Gong, J. Zhang, R. Dong, and L. Xia, "A New Method for Detecting Myocardial Ischemia Based on ECG T-Wave Area Curve (TWAC)," *Front. Physiol.*, vol. 12, no. March, pp. 1–8, 2021.
- M. R. Bigler and C. Seiler, "Detection of myocardial ischemia by intracoronary ECG using convolutional neural networks," *PLoS ONE*, vol. 16, no. 6 June. 2021.