

ECG based Heartbeat Classification

A Mini Project Report Submitted by

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CERTIFICATE

Certified that the mini project work entitled

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is a bonafide work carried out by

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ABSTRACT

Electrocardiogram (ECG) signals represent the electrical activity of the human hearts and consist of several waveforms (P, QRS, and T). The duration and shape of each waveform and the distances between different peaks are used to diagnose heart diseases. In this work, to better analyze ECG signals, a new algorithm that exploits two-event related moving-averages (TERMA) and fractional-Fourier-transform (FrFT) algorithms is proposed. The TERMA algorithm specifies certain areas of interest to locate desired peak, while the FrFT rotates ECG signals in the time-frequency plane to manifest the locations of various peaks. The proposed algorithm's performance outperforms state-of-the-art algorithms.

Moreover, to automatically classify heart disease, estimated peaks, durations between different peaks, and other ECG signal features were used to train a machine-learning model. Most of the available studies uses the MIT-BIH database (only 48 patients). However, in this work, the recently reported Shaoxing People's Hospital (SPH) database, which consists of more than 10,000 patients, was used to train the proposed machine-learning model, which is more realistic for classification. The cross-database training and testing with promising results is the uniqueness of our proposed machine-learning model.

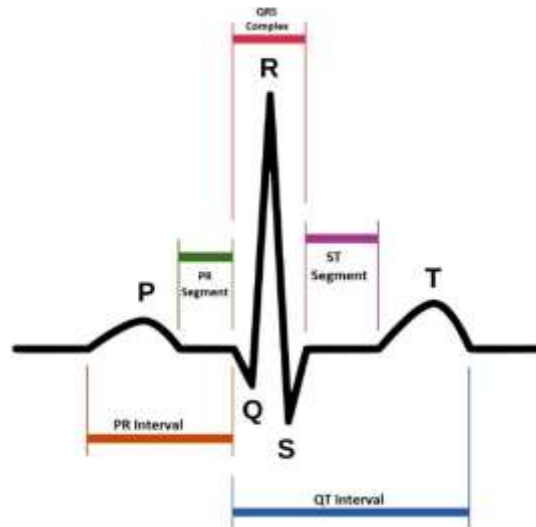
INTRODUCTION

According to the World Health Organization, cardiovascular diseases (CVDs) are the leading cause of death globally. In recent years, various programs and policies have been implemented in increasingly diverse communities to provide tools, strategies, and other best practices for reducing the incidences of initial and recurrent cardiovascular events. To achieve this goal, the electrocardiogram (ECG) has become the most commonly used biosignal for the prompt detection of CVDs. The ECG is a graphical representation of heart electrical activity, and it is used to identify various heart diseases and abnormalities. Doctors have been using ECG signals to detect heart diseases such as arrhythmia and myocardial infarctions for over 70 years. An ECG signal consists of P, QRS complex, and T waves, as shown in Fig. 1. Additionally, a U wave may be present. By analyzing the variations of these waves, many cardiac diseases can be diagnosed. ECG machines are safe and inexpensive. However, noise and other factors, which are called artifacts can produce spikes in ECG signals.

These artifacts can be body movement of patients, electrode movement on a body, and power line interferences. Therefore, noise and artifacts must be removed from the ECG signals to ensure accurate ECG analyses. Different transforms are used for the preprocessing of ECG signals to remove noise and artifacts, and one of the most commonly used transform is the wavelet transform. Several algorithms have been previously reported to detect P, QRS complex, and T waves, so as to realize noise and artifact-free ECG signals, and they have been validated over MIT-BIH arrhythmia database. In8, a rapid-ramp effective algorithm was proposed for the detection of R peaks, which uses the slopes between adjacent signals to determine the occurrence of the R peaks.

This algorithm is only applied to two records of the database and has higher-order complexity. In9, a combination algorithm based on empirical-mode-decomposition and the Hilbert transform was proposed to detect the R peaks in ECG signals. However, this algorithm is complicated and involves a large number of blocks for the detection of R peaks. Moreover, both of these algorithms are restricted to the detection R peaks only.

After enhancement, window sizes are selected based on the duration and repetition intervals of the QRS wave. Next, BOI is generated for each peak using moving averages. The width of each block is calculated and compared with a threshold depending on the window size. Finally, the peaks are detected from each block. For the localization of P and T peaks, the samples before and after the detected R peaks, including the R peak samples, are set to zero depending on the RR interval. This algorithm provides acceptable results with regard to peak detection.



Morphology of a normal ECG

BACKGROUND

To address the drawbacks of the above-mentioned algorithms, based on the fusion of TERMA and fractional Fourier-transform (FrFT), we propose an algorithm that can produce better results. TERMA is used in economics to detect different events in trading, and moving averages are helpful in detecting the signals that contain specific events. Thus, these averages can also be used in ECG signals, which contain events such as P, QRS complex, and T waves. These waves repeat themselves after certain time intervals. Likewise, time-frequency analyses are relevant due to the large variations in P, QRS complex, and T waves. In this paper, we demonstrate how moving averages and time-frequency analyses can be exploited for the detection of these waves. Further, we showed that the proposed algorithm in this paper, has a significantly better performance than the existing algorithms

SCOPE OF PROJECT

The objective is to classify the CVD of a given ECG signal, if any. Classification involves two steps: feature extraction and classifier model selection. Many researchers have worked on the classification of ECG signals using the MIT-BIH arrhythmia database. Different preprocessing techniques, feature extraction methods, and classifiers have been used in previous studies and some of them are discussed in this paper. In 14 features such as the R peak and RR interval were extracted using discrete-wavelet-transform (DWT), and multi-layer perceptron (MLP) was used in ECG classification. The obtained accuracy was 99.9% but a total number of 301 features

were used for classification. Similarly, in15, the R peak location and RR interval were extracted using db4 DWT, and to classify ECG signals, a feed-forward neural-network (FFNN) was trained with backpropagation. The sensitivity, specificity, and accuracy achieved by FFNN were 90%,90%, and 95% respectively. In16,17,18,19,20 different classifiers such as Naive Bayes, Adaboost, support vector machines (SVM) and neural networks were used in classification.

SOME PRELIMINARIES

Here are some important techniques that are used in the proposed methodology.

Discrete wavelet transform

The approximate and detailed coefficients of DWT of a function $x(t)$ are respectively defined as follows24:

$$W_{\phi}(j_o, k) = \frac{1}{\sqrt{M}} \sum_{k=0}^{M-1} x(t) \phi_{j_o, k}(t)$$

and

$$W_{\psi}(j, k) = \frac{1}{\sqrt{M}} \sum_{k=0}^{M-1} x(t) \psi_{j, k}(t),$$

where $j \geq j_o$, j_o is the starting scale, $\phi_{j, k}(t)$ is the scaling function, and $\psi_{j, k}(t)$ is the wavelet function. The inverse discrete-wavelet-transform (IDWT) for given approximate and detailed coefficients is defined as follows:

$$x(t) = \frac{1}{\sqrt{M}} \sum_{j_o=0}^{J-1} W_{\phi}(j_o, k) \phi_{j_o, k}(t) + \frac{1}{\sqrt{M}} \sum_{j=j_o}^{J-1} W_{\psi}(j, k) \psi_{j, k}(t).$$

Moving averages

Moving averages result in smoothing out short-term events while highlighting long-term events. In trading, two moving averages are used together resulting in two crossovers. The use of these averages results in the detection of trading events. These averages can be used in the detection of P, QRS, and T waves. The implementation of the moving average results in higher numerical efficiency with less complexity. Therefore, the idea of using two moving averages is promising in analyzing biomedical signals.

Fractional Fourier transform

The FrFT is the generic form of classical Fourier-transform with a parameter (α) that shows order. It was first introduced in mathematical literature years ago. FrFT is mainly used in solving the differential equations in quantum physics, but it can also be used in interpreting optics related problems. In recent years, the use of FrFT in optical applications has been increasing. Many new applications have been proposed in the field of data processing of signals because of the useful characteristics of FrFT in the time-frequency plane. The FrFT of a signal can be defined as follows:

$$\text{FrFT}^\phi(t, u) = F^\alpha(x(t)) = X_\phi(u) = \int_{-\infty}^{\infty} x(t)K_\phi(t, u)dt$$

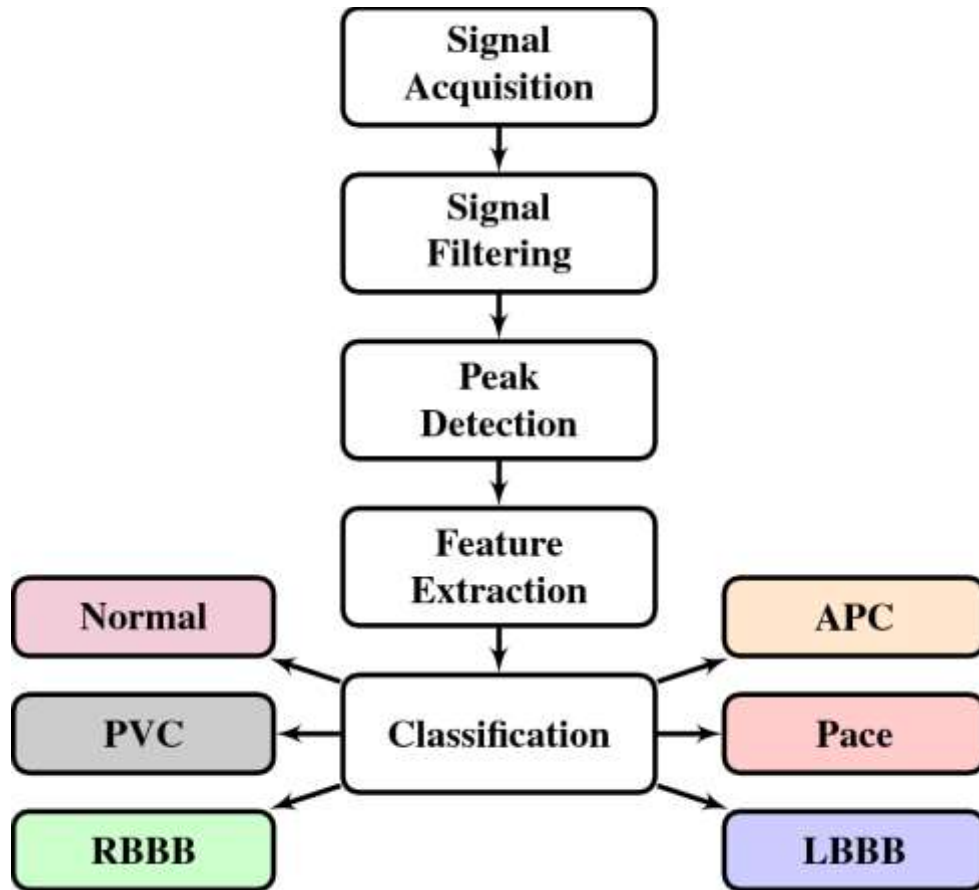
where α is the order of FrFT and $\phi = \alpha\pi/2$ is the angle of rotation. While $F^\alpha(\cdot)$ denotes the FrFT operator and $K_\phi(t, u)$ represents the kernel of FrFT and is defined as

$$K_\phi(t, u) = \begin{cases} \sqrt{\frac{1-j\cot\phi}{2\pi}} \exp(j\frac{t^2+u^2}{2}\cot\phi - jtu\csc\phi), & \phi \neq n\pi \\ \delta(t-u), & \text{for } \phi = 2n\pi \\ \delta(t+u), & \text{for } \phi = 2(n+\frac{1}{2})\pi, \end{cases}$$

where n is an integer.

Proposed methodology

As motioned earlier, for the accurate detection of P, QRS, and T waves, artifacts and noise should be removed from signals. Figure 3 shows the block diagram of the proposed three-step methodology. (1) To remove noise and artifacts, the conventional wavelet-transform-based filtering method is used, (2) for the detection of P, QRS complex, and T waveforms TERMA and FrFT are fused together to improve the detection performance, and (3) machine learning algorithms are applied to classify ECG signals to determine the CVD if any. The individual tasks are discussed in detail in the following subsections.



Signal filtering

The ECG signals are non-stationary, i.e., their frequency response changes with respect to time. Similarly, the noise and artifacts contaminating the ECG signal are non-linear, and their probability-distribution function is time-dependent. Conventional Fourier transform techniques do not provide time localization, while DWT provides time localization. Therefore, DWT can better deal with non-stationary signals. First step is to remove the baseline drift using DWT27. For this purpose, first of all, the central frequency, F_c , (also called F_c factor) is calculated for the wavelet, which ranges from 0 to 1 depending on the similarity between the signal and chosen wavelet.

For the ECG signals, Daubichie-4 (db4) has the highest F_c factor, which is approximately equal to 0.7. Next, pseudo-frequency, F_a , is calculated at each scale using the expression.

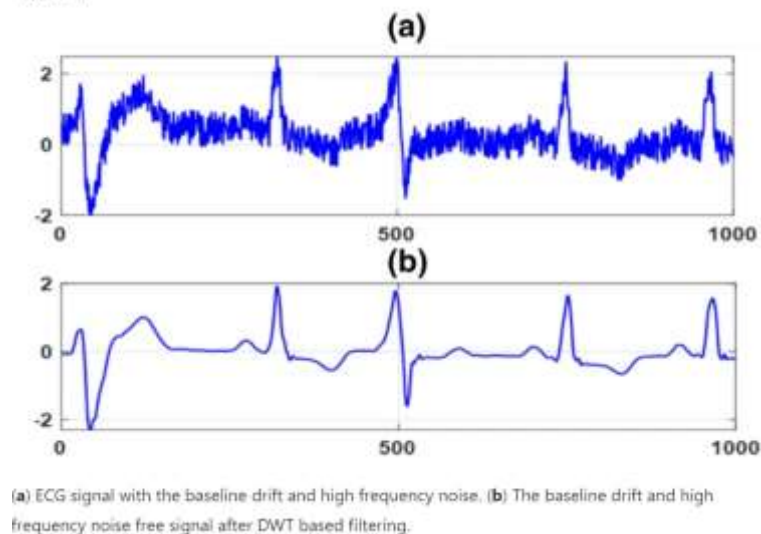
$$F_a = \frac{F_c F_s}{2^a},$$

where a and F_s represent the scale and sampling frequency of the ECG signals, respectively. The baseline drift is mostly localized around 0.5Hz. For the MIT-BIH $F_s=360$, therefore using (2), the scales corresponding to different pseudo frequencies can be easily calculated. Decomposition should be up to scale 9 that corresponds to $F_a=0.5$. Therefore, the ECG signal is decomposed into approximation and detailed coefficients using the db4 wavelet up to scale 9. The approximate coefficients corresponding to the baseline drift are removed, and the signal is reconstructed using IDWT to obtain a baseline drift-free signal.

Once the baseline drift-free signal is obtained, the next step is to remove high frequency noise. It was reported in, that most of the QRS complex energy is concentrated within the range of 8 to 20 Hz. The SNR has been calculated at different levels, which shows that decomposition up to level 6 is required to capture the QRS complex wave. Therefore, the signal is reconstructed using the detailed coefficients of levels 4, 5, 6 and the approximation coefficients of level 6.

The detailed coefficients of levels 1, 2 and 3 contain high frequencies ranging from 50 Hz to 100 kHz. These frequencies belong to muscle contraction noise. Therefore, at these levels, the details are discarded, and the approximations are retained to remove high-frequency noise. The resulted signal has highest SNR because the high frequency detailed coefficients are discarded. Figure 4 shows the baseline drift and high frequency noise-free signal. In the TERMA algorithm, to detect peaks, the artifact and noise free signal is squared to enhance the peak values, a BOI is generated for each wave, and thresholding is finally applied. In the following subsection, we showed how the TERMA algorithm detection performance can be improved by exploiting FrFT.

Figure 4



R peak detection using the fusion algorithm

In the ECG signal, the maximum change in frequency occurred at the R peak. By taking the Fourier transform of the ECG signal, the time localization can be lost. Therefore, in this step, FrFT was applied to the noise-free signal to rotate the signal in the time-frequency plane. As seen in the preliminaries, the FrFT operation comprises a chirp multiplication, followed by a chirp convolution, and lastly another chirp multiplication. Rotating the signal with a higher value of α is like moving closer to the frequency domain of the signal, while rotating it with a lower value of α is like moving toward the time domain of the signal. In R-peak detection, time localization is very important.

Using the hit and trial method, we found that the value of $\alpha=0.01$ appropriately enhances R-peaks and makes them easy to detect. After applying FrFT, the R peak was more enhanced by squaring each sample. After the enhancement, two moving averages based on event and cycle were calculated as follows:

$$\begin{aligned} \text{MA}_{event}(n) &= \frac{1}{W_1} \sum_{k=-l}^l x(n+k), \\ \text{MA}_{cycle}(n) &= \frac{1}{W_2} \sum_{k=-p}^p x(n+p), \end{aligned}$$

where W_1 depends on the duration of the QRS complex, and W_2 depends on the heartbeat duration. The mean (μ), of the enhanced signal is calculated and multiplied by a factor (β) whose optimum value was chosen by hit and trial method. The output number is denoted by $\gamma=\beta\mu$, and was added to MA_{cyclic} to generate threshold values. Each value of the MA_{event} was compared with the corresponding threshold value. If $\text{MA}_{event}(n)$ was greater than the n th threshold, one is assigned. Otherwise, zero is assigned in a new vector.

This way, a train of nonuniform rectangular pulses is generated. Finally, the pulses that have widths equivalent to W_1 are the blocks that contain the desired event as shown in Fig. 5a. In each block, the maximum value in the corresponding enhanced signal is considered an R peak value. This process is explained in detail in. Figure 6a shows that the R peaks were accurately detected after applying the proposed algorithm.

Classification of The ECG signal

In this section, to classify the given ECG signal according to CVD, machine learning was applied. In machine learning, training datasets with corresponding labels are fed in an algorithm, where different features are extracted from each dataset and a model is formed to predict test data labels. This is called supervised machine learning. It helps in the automatic decision-making process by building different models from sample data. Data training includes two steps, feature extraction and classification, as discussed in the following subsections.

Feature extraction

Different features can be extracted from the ECG signal. For example, the estimation of different peaks can be used to find the time intervals between different peaks. Since these time intervals represent different cardiac conditions, they can be considered as features. Moreover, auto-regressive (AR) model coefficients of the ECG signal can be used as a feature. The AR model of order p , $AR(p)$, can be defined as follows:

$$x(n) = \sum_{i=1}^p a(i)x(n-i) + e(n),$$

where $a(i)$ is the i th coefficient of AR model, $e(n)$ is a white noise with a zero mean, and p is the order. The optimum order of the AR model depends on the number of factors. Higher order AR model yields more accurate modeled signals but at the cost of higher computational complexity in calculating the coefficient values. Similarly, other features, such as the wavelet transform coefficients, mean, variance, age, sex, and cumulant, can be extracted to classify the CVD of the ECG signal. Feature extraction is very important because it shows which type of inputs can better represent the signal. In this work, MIT-BIH arrhythmia and SPH database signals were used.

Feature matrix

The feature matrix contains feature information of ECG beats taken from different records of the arrhythmia database. Each row of the matrix shows the feature information of a single heartbeat. Each row includes different features of heartbeats taken from the datasets. For example, if we take four coefficients from the AR model, n coefficients from the FrFT of the given heartbeats, and two intervals PR and RT as features, the feature vector can be written as follows: $\{a_1, a_2, a_3, a_4, f_1, f_2, \dots, f_n, PR, RT\}$. The feature matrix can be formed with such multiple rows.

Supervised machine learning algorithms

The classification of the ECG signal is a very important and challenging task. It can provide substantial information about the CVDs of a patient without the involvement of a cardiologist. Only a technician is required to attach the probes, and the machine learning based solution can automatically diagnose the CVDs of the patient. This technique can immediately prioritize the patients that need urgent medical attention. In this work, the SVM and MLP supervised learning algorithms were used for classification and they were briefly discussed in the following subsections.

Support vector machine classifier

The SVM algorithm can be used in classification and regression problems³⁶. In SVM, data is plotted in an l - dimensional space, where l denotes the number of features. After plotting the data, classification is performed by finding a hyperplane that differentiates between different classes. The maximization of the margin optimizes the hyperplane. Then, the hyperplane, that is at a higher distance from the closest data points among other hyperplanes, is chosen. The SVM solves the following quadratic problem:

$$\begin{aligned} \max_{\alpha \geq 0} & \left(\sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i,j=1}^l \alpha_i \alpha_j y_i y_j K(X_i, X_j) \right) \\ \text{subject to} & \quad \sum_{i=1}^l \alpha_i y_i = 0 \\ & \alpha_i \leq C, i = 1, 2, \dots, l, \end{aligned}$$

where X_i, X_j are input features, y_i, y_j are class labels, $\alpha_i \geq 0$ are Lagrangian multipliers, C is a constant, and $K(X, X_1)$ is a kernel function³⁷. A very common kernel function is the Gaussian radial basis function:

$$K(X, X_1) = \exp - \frac{\|X - X_1\|^2}{2\sigma^2},$$

The SVM is very effective in higher dimensional spaces and when the number of dimensions is greater than the number of samples.

Multi-layer perceptron classifier

Artificial-neural-network (ANN) algorithms classify regions-of-interest using a methodology that performs functions similar to those of the human brain, such as understanding, learning, solving problems, and making decisions. The ANN architecture consists of three layers. The first layer is the input layer, and the input parameters determine the number of neurons in this layer. The last layer is the output layer, and the number of neurons in this layer represents the number of output classes. The layers between the input and output layers are called the hidden layers. MLP was used in this work, and it is a subclass of the feed-forward ANN.

SIMULATION RESULTS

This section is divided into three parts, which are dedicated respectively to peak detection, classification, and cross-database training and testing.

Detection of ECG peaks

In the first part of the simulation, using our proposed FrFT-based algorithm, the P, R, and T peaks are detected, and the proposed algorithm is validated over all the 48 records of the MIT-BIH database. Lead II (MLII) data is used in this paper. Our algorithm works independent of the amplitude of the waveform, so any lead data can be used for the peak detection. Moreover, the performance is assessed using different metrics reported in the literature, such as sensitivity, positive predictivity, and error-rate, which are defined as follows:

$$\begin{aligned}\text{Sensitivity (SE)} &= \frac{TP}{TP + FN}, \\ \text{Positive Predictivity (+Pr)} &= \frac{TP}{TP + FP}, \\ \text{Error Rate (Err)} &= \frac{FP + FN}{TP},\end{aligned}$$

where TP denotes the true-positive, FN denotes the false-negative defined as the annotated peaks not detected by the algorithm, and FP denotes the false-positive defined as the peaks detected by the algorithm but not actually present. If a peak is detected within the 30 ms interval of the annotated peak, it is defined as TP. To assess the performance of the algorithm, we observed TP, FN, and FPs. In Table 1, the R peak detection performance of our proposed algorithm is compared with the TERMA algorithm. Both algorithms were tested over the 48 records of the MIT-BIH arrhythmia database. As seen, the proposed algorithm performed slightly better than the TERMA algorithm.

Algorithms	SE (%)	+Pr (%)	Err
Proposed algorithm	99.83	99.90	0.00259
TERMA ¹²	99.78	99.87	0.00298

Table 1. Performance comparison of the R-peak detection for the 48 records of the MIT-BIH database.

Similarly, the detection performance of the proposed algorithm in the detection of P and T waves was compared with that of TERMA algorithm as shown in Table 2. In Table, we compared the reported performance of TERMA algorithm in, where only 10 records of MIT-BIH database were selected. It can be seen that our proposed algorithm outperforms TERMA algorithm.

10 Records	Detection of P Peaks		Detection of T Peaks	
Algorithms	SE (%)	+Pr (%)	SE (%)	+Pr(%)
Proposed algorithm	99.28	99.05	99.94	99.83
TERMA ¹³	98.05	97.11	99.86	99.65
38 Records				
Proposed algorithm	75.8	0.40	67.5	0.51
TERMA ¹³	59.2	1.04	42.8	1.15

Table 2. Performance comparison of P and T-peak detection for the first 10 and remaining 38 records of the MIT-BIH database.

In Table 2, both algorithms were also tested on the remaining 38 records of the MIT-BIH database. Here, significant difference can be seen in the detection performance of both algorithms. For the P peak detection, our proposed algorithm resulted in SE of an 75.8% and an Err of 0.40 compared with an SE of 67.5% and Err of 0.51 in the case of TERMA. For the T peaks detection, proposed algorithm results in SE of 59.2% and Err of 1.04 compared with an SE of 42.8% and Err of 1.15 in the case of the TERMA algorithm as shown in the table. This shows that the detection performance of the TERMA algorithm is limited to a few CVDs, while our proposed algorithm performs very well for the other CVDs in the MIT-BIH database.

Overall, it was found that our proposed algorithm performs better than the TERMA algorithm and other previously presented algorithms.

Classification of CVDs

In the second part of the simulation, we classify the ECG signals according to their CVDs. Here, for all simulations 70% of the feature data was allocated to train the machine learning model while 30% was kept for testing. Therefore, different features were extracted from the signals for the classification. Then, the extracted features were passed into the SVM and MLP classifiers to classify the input ECG signals as normal, PVC, APC, LBBB, RBBB, and PACE heartbeats. To compare the performance of the proposed classifier with that of the existing ones, the following performance metrics were used:

$$\begin{aligned}\text{Overall Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN}, \\ \text{Precision} &= \frac{TP}{TP + FP}, \\ \text{Recall} &= \frac{TP}{TP + FN}, \\ f_1\text{-Score} &= 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}},\end{aligned}$$

where TN denotes a true-negative, which is defined as, the patient has a CVD and the classifier also predicts that the patient is not normal.

As we know, the MIT-BIH database contains limited ECG signals from only 48 patients. For machine learning algorithms, the quantity of data is crucial. Therefore, for classification, we tested the proposed algorithms on the recently reported Shaoxing SPH database²³. This database contains 12 lead ECG signals from 10,646 patients. In contrast to the MIT-BIH ECG signal sampling rate of 360 samples/s, the sampling rate of the SPH ECG signal is 500 samples/s. The data set consists of four folders containing ECG raw data, ECG denoised data, diagnosis data, and attributes. This database consists of 11 common rhythms and 67 additional cardiovascular conditions. Each of the 12 lead signals is 10 s long i.e., 5000 samples for each lead. In this database, 11 rhythms are merged into four groups SB, AFIB, GSVT, and SR. The SB group only includes sinus bradycardia, the AFIB group consists of atrial fibrillation and atrial flutter (AF), the GSVT group contains supra ventricular tachycardia, atrial tachycardia, atrioventricular node reentrant tachycardia, atrioventricular reentrant tachycardia, and sinus atrium to the atrial wandering rhythm, while the last SR group includes sinus rhythm and sinus irregularity.

For the first classification-simulation, the extracted features were passed to the SVM classifier. The parameter values of C and $\gamma=1/2\sigma^2$ were respectively adjusted to 65536 and 2.44×10^{-4} . The scikit-learn library of Python was used for machine learning model building⁴¹. In³⁷, to classify an ECG signal, 36 features are extracted from it, where 32 features were the DWT (db4) of the signal and 4 were the coefficients of AR model. However, in the proposed classifier, a feature matrix was generated using only four features, where two features were extracted using the estimated P, R, and, T peaks, which are PR and RT intervals, whereas the other two were age and sex. Both classifiers were trained and tested on the records of the MIT-BIH and SPH databases.

In the case of MIT-BIH database, the number of heartbeats extracted from the Normal, LBBB, RBBB, PACE, PVC, and APC records was 2237, 2490, 2165, 2077, 992, and 1382 respectively. However, in the case of SPH, the features were extracted from all heartbeats of 10,646 patients. The corresponding performances of both classifiers for the MIT-BIH and SPH databases is shown in Table 3. In the case of the MIT-BIH database, the overall accuracy of the classifier proposed in³⁷ with 36 features was 99.6%.

However, in the case of the SPH database, it significantly decreased to 37.1%. Nevertheless, in the case of the MIT-BIH database, the accuracy of our proposed classifier with only four features was 82.2%, but it became 84.2% in case of the SPH database, so it is much better and more stable than that of the proposed classifier in³⁷. The computational complexity comparison of the feature extraction for both classifiers is also shown in the Table 3.

CONCLUSION

In this work, a fusion algorithm based on FrFT and TERMA was proposed to detect R, P, and T peaks. Conventional wavelet transform method were used to denoise signals, whereas the use of FrFT in the TERMA algorithm significantly improved the peak detection performance. We applied the proposed peak detection algorithm in the MIT-BIH arrhythmia database, and it performed slightly better than the TERMA algorithm in the detection of the R peak, while significantly better than it in the detection of the P and T waveforms. Moreover, in contrast to the TERMA algorithm, the performance was independent of CVDs. After the peak detection, the results were used to find the PR and RT intervals as two features of the ECG signal for the classification. We used two classifiers with different features and found that MLP performs better than SVM for a variety of ECG signals. Both classifiers were tested on the two databases. Finally, we designed a classifier for cross-database training and testing. This is a challenging task, and as far as we know, there have not been any available works in this direction. Our initial results are promising and to further improve the results, will be our future work.

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