Detection of Cardiac Arrhythmias using SVM Classifier

Onkar Singh and Vineet Kumar

Department of ECE, Lovely Professional University, Phagwara- 144411, Punjab, India; onkarsingh1357@gmail.com, vineet.15921@lpu.co.in

Abstract

ECG (Electrocardiogramis a critical non-intrusive clinical instrument for the finding of heart diseases.Thediscovery of cardiovascular arrhythmias is a testing assignment since the little varieties in ECGsignals can't be recognized decisively by human eye. Heart arrhythmias are ordered utilizing Discrete Wavelet Change (DWT) and Double Tree Complex Wavelet Change (DTCWT) procedure.The DWT highlight set involves measurable components extricated from the sub groups got afterdeterioration of QRS complex signs up to 5 scales while the DTCWT highlight set includes waveletcoefficients removed from the fourth and fifth scale disintegration of QRS complex signs. The twoarrangements of elements are affixed independently by two different components (Maximum and minimum) separated from the QRS complex sign of each cardiovascular cycle. These capabilitiesare autonomously grouped utilizing a Support Vector Machine taking into account back spreadcalculation. In this work, 3 sorts of ECG beat (Normal Sinus Rhythm (N), Atrial Fibrillation (AF) and Supraventricular (S)) are characterized from the 48 records of MIT-BIH arrhythmia database.The trial results show that the DTCWT system groups ECG beats with a general affectability of94.78%.

Keywords: Dual-tree complex wavelet transform (DT-CWT), Electrocardiogram (ECG), Empirical mode decomposition (EMD), Support Vector Machine (SVM).

1. Introduction

Electrocardiogram (ECG) signal which is the recording of the cardiac electrical activity has gained so much importance over the few decades. Efficient processing and analysis of ECG signals helps cardiologist make decisions about cardiac arrhythmia more accurately andeasily[1].The condition of cardiovascular heart is by and large reflected fit as a fiddle of ECG waveform and heart rate. ECG arrhythmia is a gathering of conditions in which the heart has sporadic electrical movement which causes pulse to be moderate or quick[2]. As ECG sign is a non-stationary sign, the arrhythmia may happen indiscriminately time interim, which implies the arrhythmia side effects may not distinguished all the time but rather would show at certain unpredictable interims amid the day. In this manner, programmed and PC based investigation of arrhythmia is basic in clinical cardiology, particularly for the treatment of patients in the emergency uni3. In the late years, various analysts have created distinctive strategies in the written works for recognition and order of ECG arrhythmias.

Empirical Mode Decomposition (EMD) is used for analyzing data from non-stationary and non-linear processes. EMD decomposes the signal into few oscillatory functions, Intrinsic Mode Functions (IMFs), where Spectral Flatness (SF) automatically determined noisy IMFs. These noisy IMFs are filtered out to remove the noise components of the signals.

An ECG sign can be disintegrated by utilizing the wavelet change as per scale, in this manner permitting partition of the pertinent ECG waveform morphology descriptors fromthe noise, interference[3], baseline drift, and amplitude variation ofthe original signal.

Be that as it may, among various proposed strategies, discrete wavelet changes has performed detectable part[4]. In any case, DWT has a no. of confinements like absence of movement invariance property, associating, motions, absence of directionality. To conquer these confinements,

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we plan to utilize double tree complex wavelet change system[5] which has rich computational structure containing shift in-difference property and hostile to associating impact particularly for biomedical sign .

At that point, SVM-based classifier is utilized for the identification of Arrhythmia utilizing the parameters of a symmetric ordinary opposite Gaussian earlier that are extricated from DT-CWT sub-groups as components. The capacity of this classifiers in separating ECG signals into a few clinically significant cases has been examined. The execution is measured as far as accuracy, sensitivity, specificity[6].

1. Methodology

The displaying of the ECG signals in DT-CWT space utilizing a NIG likelihood thickness capacity (pdf) and the capacity of the NIG parameters of these signs in segregating them is quickly talked about.In this paper MIT-BIH database is utilized to accept the execution of their proposed strategy and contrast their outcome and previous calculations. The database used, comprises of 24 recordings of each 1 minute duration, These 24 (100-123) recordings correspond to the routine clinical recordings.

a. Empirical mode Decomposition:

EMD deteriorates a sign into couple of oscillatory capacities known as Intrinsic Mode Functions (IMFs)[7]. The IMF in every cycle, characterized by the zero intersections of, includes one and only method of swaying, no perplexing riding waves are permitted. The significant preferred standpoint of EMD is that the premise capacities used to deteriorate a sign are not predefined but rather adaptively gotten from the sign itself. The IMFs speak to the oscillatory method of a specific flag and is gotten by a precise procedure called filtering. An IMF ought to fulfill the accompanying two properties.

1) The maximum difference between the number of extreme and the number of zerocrossings must be either equal or differ at most by 1.
2) At any given point, the mean of the envelopes created by the maximas and minimas should be 0.

First of all, the observed ECG signal is modelled as,

$$x(n) = d(n) + v(n)$$

where d(n) represents the desired ECG signal, and v(n) represents the noise which corrupts the desired signal. The following steps comprises in the EMD algorithm:

(1) Above all else, All the amazing (maxima and minima) of the sign, x(t) are recognized.
(2) The upper and lower envelope are created by the cubic spline interjection of the compelling point created in step (1).
(3) The mean of the upper and lower envelope, m(t) is ascertained.

$$m(t) = x(t) - \frac{1}{2} \{envl(t) + envu(t)\}$$

(4) The difference signal d(t) = x(t)−m(t) is being calculated.
(5) The iteration stop when d(t) gives a zero-mean process and the resulting signal is the first IMF (IMF1(t), representing the highest frequencies); otherwise, go to step (1) and replace x(n) with d(t).
(6) By performing the same process on the residue signal,The second IMF is calculated

$$r1(t) = x(t) - IMF1(t).$$

(7) By rehashing the strategy from steps (1) to (6), new IMF and deposit are gotten, To get IMFn(t), proceed with steps (1)–(6) after n emphasess. The procedure is ceased when the buildup r(t) gets to be monotonic.

Toward the end of the system, we have a buildup r(t) and a gathering of n IMF, named from IMF1(t) to IMFn(t). Presently, the first flag can be spoken to as:

$$x(t) = rk(t) + \sum_{i=0}^{k} IMF\ i(n)$$

The given equation shows that a signal, decomposed by EMD can be recreated easily by simple addition of the IMF components IMFk(t) and the residue signal rk(t)[8].

b. Discrete wavelet transform

The wavelet transform of a signal represents a signal in multiple scales and provides simultaneous resolution in time and frequency domain[9]. Here, the signal is decomposed into dilated (scale) and translated (time) versions of a prototype wavelet by using a lowpass filter and high
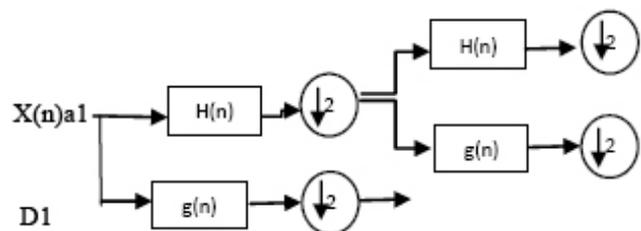

Figure 1. Discrete wavelet transform.

pass filter followed by down-sampling in eachstage. Thus D1 and A1 can be termed as the detailed coefficient of first stage high pass filter and approximationcoefficient of the low pass filter[10]. The 2-scale decomposition of a signal in Figure 1.

c. Dual Tree Complex Wavelet Transform:
Kingsbury in 2001 initially presented the double tree complex wavelet change which beats the primary disadvantage of DWT for the multi-determination signal i.e. the movement change issue of the information signal. The movement fluctuation issue causes the little moved of the information flag that can change the wavelet coefficients swaying in the singularities. This movement difference is happened for the lower examining. This sort of issue can be overcomes by utilizing un-destroyed type of dyadic channel tree. Be that as it may, high excess and high computational many-sided quality in the yield is required. The DT-CWT with an excess variable 2 for 1D sign can conquer this issue.

Double Tree Complex Wavelet Transform creates complex coefficients by utilizing a double tree of wavelet channels to acquire their genuine and nonexistent parts. The DTCWT of a sign, x(n) is executed utilizing two fundamentally inspected DWTs as a part of parallel on the same information. Both the channels composed in the upper and lower DWTs are distinctive and are intended to translate the sub-band signs of the upper DWT as the genuine part and lower DWT as the fanciful part of a perplexing wavelet change. DT-CWT coefficients are non-swaying with an almost move invariant greatness and altogether lessened associating with more directionalities when contrasted with the DWT.

In this paper, the different sub-groups of a four-level DT-CWT deterioration of the sifted ECG signals evaluates the parameters of a NIG pdf. The ECG signal X (0–60 Hz), is deteriorated into its higher determination segments z1 (30–60 Hz) and lower determination parts, y1 (0–30 Hz) after the main level of disintegration.
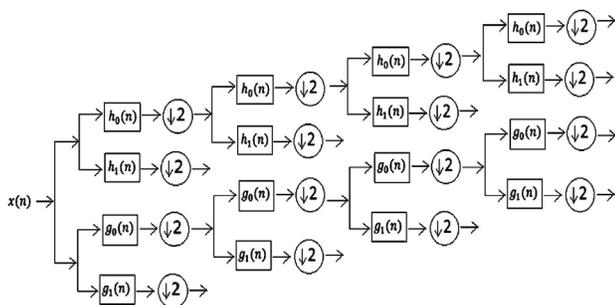

Figure 2. 1D dual-tree complex wavelet transformation.

Essentially, in the second level, the y1 segment is decayed intoz2 (15–30 Hz) and y2 (0–15 Hz). This procedure continues for the four levels as shown in figure 2. Thus, the components obtained after four levels of decomposition include the sub-bands y4 (0–4 Hz), z4 (4–8 Hz), z3 (8–15 Hz), z2 (15–30 Hz), and z1 (30–60 Hz.

d. Support Vector Machine (SVM)
A bolster vector machine (SVM) is a twofold classifier, which works in the high dimensional element space framed by the nonlinear mapping, φ(x)of the n-dimensional information vector into a K-dimensional element space and in this manner deciding the best hyper-plane to isolate the information in the anticipated space. SVM has its wide use in thickness estimation, design characterization and relapse. A legitimate piece capacity for a particular issue relies on the particular information [. As the outspread premise capacity (RBF) part performs better when contrasted with the other bit capacities, so the RBF bit is utilized as a part of this paper. As the SVM is a twofold classifier, it can likewise be utilized to take care of multi-class issues by joining a few of its kind. Along these lines, mistake revising yield coding (ECOC) approach acquired from advanced correspondence is utilized for that reason. Here, we have prepared A most extreme of 2n−1 − 1 SVMs for isolating n classes. For instance, there are three classes A, B and C. To isolate these, three classifiers are utilized: the main SVM will orders A from B and C, the second B from An and C, and the third C from An and B. The yield code of the classifier for an example is a mix of focuses of all the SVMs independently. In the past illustration, vectors from classes A, B and C have codes (1, −1, −1), (−1, 1, −1) and (−1, −1, 1) individually. On the off chance that each of the different SVMs groups an example accurately, the classifier-target code is finished and no blunder for that example will be accounted for by the ECOC approach.

e.The proposed classification method
The proposed technique basically consists of three main stages as shown in Fig. 3, (i) Pre-processing, (ii) Feature extraction and (iii) Classification. In the pre-processing stage, the artifacts/noises present in the ECG data get minimized by using two noble methods differently.

This novel noise filtering technique is

empirical mode decomposition (EMD)[11]. Now, the output of the pre-processing stage is applied to the Feature extraction stage.At this stage, the separated ECG information is connected to two unique plans that are Dual Tree
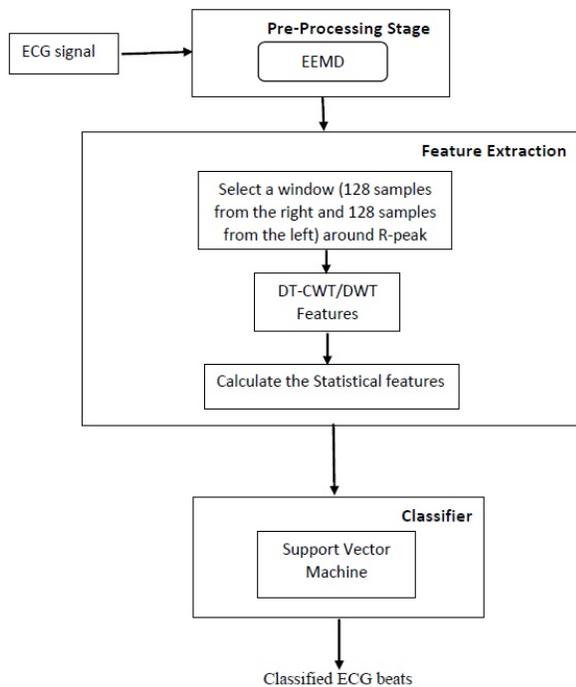
Figure 3. Methodology for the proposed work.

Continuous Wavelet Transform (DTCWT) and Discrete Wavelet Transform (DWT) for removing the elements of the ECG signal. The execution of these list of capabilities is contrasted and measurable elements that are separated from the sub-groups got after disintegration of the QRS complex sign utilizing discrete wavelet change (DWT) and Dual Tree Continuous Wavelet Transform (DTCWT). Next, these capabilities are connected to the Support Vector Machine (SVM) classifier for the order of arrhythmia.

f. Experimental Result

The performance of the system is evaluated using 2 parameters that are accuracy and the sensitivity of the system [12]. These parameters can be defined as:

a) Accuracy (Ac): The Accuracy of the system is characterized as the general execution of the framework when contrasted with all ECG beats. It is computed as the proportion between the accurately group beats to the aggregate no. of the ECG beats.

$$Ac\ (\%) = \frac{TP\ +\ TN}{TP\ +\ TN\ +\ FP\ +\ FN} * 100$$

b) Sensitivity (Se): It can be calculated as effectively characterized beats of the specific class to the aggregate beats of same specific class.

$$Se\ (\%) = \frac{TP}{TP\ +\ FN} * 100$$

Table 1. ECG beats used for the training and testing

Class	Training beats	Testing beats
N (Normal Sinus Rhythm)	970	1455
AF (Atrial Fibrillation)	540	810
SV (Supraventricular)	860	1290
Total	2370	3555

Table 2. Performance of the system

Class	Ac (%)	Se (%)
N	96.24	98.76
AF	92.43	94.91
SV	90.93	90.69

Overall sensitivity=94.78

Where the TP stands for the true positive, which includes a set of beats dealing to the true class, TN stands for the true negative which incorporates the arrangement of beats that are not having a place with the genuine class. While FN stands for the false negative which have the arrangement of genuine beats which are delegated non-genuine beats. FP stands for the false positive which has an arrangement of non-genuine beats which are delegated genuine beats

g. Classification Performance:

The SVM utilized as a part of this work is direct based SVM classifier. It is prepared by utilizing the 30 documents of the MIT-BIH arrhythmia database. The testing is done on the 45ECG records. The aggregate no. of ECG beats utilized for preparing and their testing is shown the given table 1.

The table 2 shows the performance of the system in terms of the Accuracy and Sensitivity.

The system has trained over 2370 beats and tested over 3555. The features has been classified N, AF and SV beats with a sensitivity of the 98.76%, 94.91% and 90.69%.

3. Conclusion

Through this work, the capacity of DT-CWT has been investigated for the characterization of the cardiovascular arrhythmia. The multi-determination property of this change make it all the more capable for the issue acknowledgment. As the DWT is the time variation in light of the down inspecting operation at each stage. So to beat this downside, the Double tree-CWT is utilized. The change breaks down the information ECG signal into genuine

and fanciful parts and register its greatness data. The components are separated up to the 5 levels. The detail coefficients up to 5th level and approximation coefficients of the 5th level are taken into account. The statistical features are calculated from these coefficients. These feature are then applied to SVM classifier. The experimental results shows that the features shows a better results as compared to the previous results. This study is performed on the 45 databases of MIT-BIH arrhythmia databases and shows the better sensitivity of 94.78%.

4. References

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