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# SVM classification of CWT signal features for predicting sudden cardiac death

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## Abstract

Sudden Cardiac Death (SCD) is a major health problem that is responsible for most of all the heart disease deaths. The Ventricular Tachyarrhythmia's (VT's), especially the Ventricular Fibrillation (VF) are the primary cause of the SCD's. This paper presents a classification method using Support Vector Machine (SVM) algorithm for predicting if there is an SCD occurrence in a signal. This is carried out by comparing certain characteristic features of the ECG signal of a normal healthy person with that of the unhealthy patient prone to SCD. In the time domain, the ECG signal has to be monitored continuously for long hours, which is not feasible and moreover the cardiac arrest in SCD cases occurs for a very short time which is preceded and followed by normal ECG. The noise and some electrical disturbances during measurement also affect the signal feature measurements. So, the signal is transformed into another domain using Wavelet Transformation method (Continuous Wavelet Transform (CWT) to be precise) to extract certain features of the signal and study their pattern while comparing the abnormal ECG signal with that of a normally running ECG signal. The main features that were extracted are the R-peaks, R to R intervals, QRS complexes, QRS complex durations, T-Wave durations and the QT intervals. CWT was used to extract the features information from the ECG signals providing the base. The tests were performed on the data signals taken from the Physionet database [12].

## 1. Introduction

An Electrocardiogram (ECG or sometimes also known as EKG) is used to measure the rate and regularity of a heartbeat, it is used as an indication of the presence of any damage in the heart, and to see the effects of drugs or any devices (such as pacemakers) that are used to regulate the heartbeat. Due to the heart's essential role in human health and disease, and the relative ease of recording and analyzing in a noninvasive manner, the analysis of the ECG has been widely used for diagnosing many cardiac diseases. It is also a routine part of any complete medical evaluation. This research work is carried out with the analysis of such ECG signals (ECG signal records are taken from: normal healthy persons profiles as well as abnormal persons profiles).

The normal clinical features of the ECG signal are shown in figure 1. It shows different wave amplitudes and different characteristic points: P, Q, R, S and T that are marked, in the signal (and sometimes U, although this wave is often hard to identify is also shown) [1]. The remainder of this paper is split into four sections: section 2 contains the basic reminders and the related works, section 3 provides the methodology and experimental setup. The discussion and interpretation of the main obtained results are also described in section 3. Finally, section 4 presents the conclusion.

## 2. General reminders and related works

### 2.1. Sudden cardiac death

Sudden Cardiac Death (SCD) [2] is an unexpected death of a person caused due to Sudden Cardiac Arrest (SCA). SCD and SCA are sometimes used interchangeably. There is a sudden loss of cardiac function and the heart abruptly stops beating. It can also be said as the

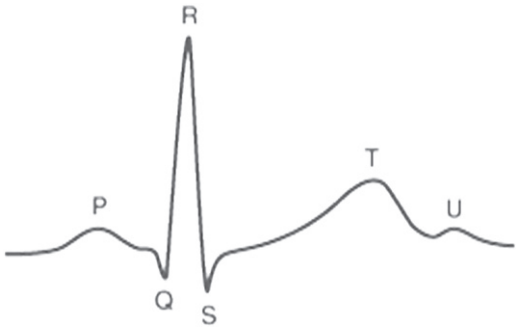


**Figure 1.** Characteristic points in Electrocardiogram.

cessation of normal circulation of blood due to failure of the heart to contract effectively. Delivery of oxygen to body and brain is prevented by SCA and this lack of oxygen to the brain causes loss of consciousness (which may further lead to brain injury if not treated within few minutes), which then results in abnormal or absent breathing. Arrhythmias (heart rhythm disorder) are the primary reason that may cause the SCD.

*2.1.1. Arrhythmias* (*Ventricular Tachyrhythmia*)
Arrhythmia [3, 4] is also known as irregular heartbeat or Cardiac Dysrhythmia. The electrical activity in the heart is abnormal and the heartbeat is non-uniform, it is either too fast or too slow. A very large number of very different conditions are covered in the term Arrhythmia. There are some harmless arrhythmias, which may be distracting for patients, but there are also many arrhythmias, which are harmful that have adverse outcomes such as cardiac arrest, or sudden death. The different types of arrhythmias are:

*Ventricular Tachycardia* (*VT*). These are widened QRS complexes and have usually regular rhythm, but it may be modestly irregular on some occasion. It is defined as three or more consecutive beats of ventricular origin at a rate greater than 100 beats/min.

*Ventricular Flutters* (*VFl*). These are high frequency (250–350min$^{-1}$) beats. Due to high rates of contraction of heart chambers the time of blood flow into the chamber becomes very small, so very little blood flows to the body. The person who is experiencing VFl is close to unconsciousness.

*Ventricular Fibrillation* (*VF*). This is the most dangerous type of arrhythmia. In this case, rhythm is totally uncoordinated with no discriminate waves. VF is a severely abnormal heart rhythm (arrhythmia) and is the most common cause of cardiac arrest. In this, the heart starts to beat too rapidly(350–450 beats/min) then returns back to normal sinus rhythm of the ECG.

The figure 2 shows the onset of Ventricular Tachycardia (annotated by v). We go with the hypothesis that symptoms such as ventricular tachycardia should affect the activity of the heart and apart from having its effects during irregular beat; it should have its after effects during normal sinus rhythm as well. Since frequency is defined as the rate of change, a change in activity of the heart means that the significant spectrum of the signal should be affected as well.

### 2.2. Wavelet transforms

Mathematical transformation methods are used to obtain certain features of the signals which are not readily available in their raw time-domain format (i.e., the signal being measured is a function of time). Fourier transformation is one popular technique which allows us to study the cyclical nature of a time series data in the frequency domain. This transformation however has a serious shortcoming. In particular, the time information is completely lost and thus it becomes harder to distinguish transient relations or to identify when structural changes take place. Therefore, this type of technique is not suitable for non-stationary processes but suitable only for time series data with stable statistical properties, i.e., stationary time series.

Localizing in time can overcome this limitation partly by introducing a sliding time window of fixed length. The local or Short Time Fourier Transform (STFT) provides a degree of temporal resolution by highlighting changes in spectral response with respect to time. As time progressed, a number of alternative time and frequency methods are made available for signal analysis. The wavelet transform is one such alternative that has emerged over recent years as the most favored tools by researchers for analyzing problematic signals across a wide variety of areas in science, engineering and medicine [5].

Wavelet Analysis performs the estimation of the spectral characteristics of a time series data and then reveal how the different periodic components of the time series data change over time. Wavelet transform's major advantage is the ability to perform natural local analysis of a time series: the wavelet stretches into a long function to measure the low frequency components and it compresses into a short function to measure the high frequency component. There has been significant work done using different wavelet transform techniques in the field of research and development. There still exits scope of exploring and developing using various techniques. We make use of CWT for our analysis. More recently, the tools associated with the CWT are becoming more widely used as well. The CWT maps a single function time variable of the original time series variable into a function of frequency and time variables, providing highly redundant information. The CWT though, has the drawback of computational time; it provides a lot of freedom in selecting our wavelets, while this choice is limited in the discrete setting (i.e., DWT). Moreover,

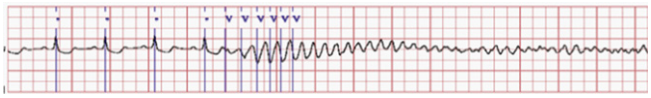

**Figure 2.** ECG of Ventricular Tachycadria (patient's record: 30 m).

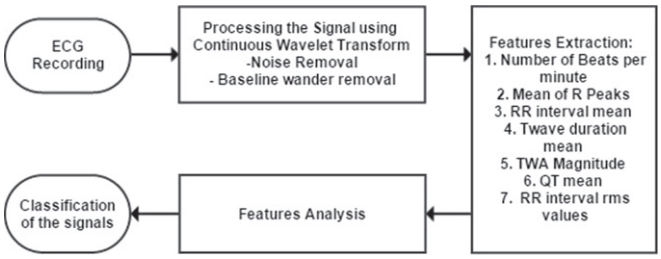


**Figure 3.** Block diagram for methodology used in prediction of SCD.

the redundancy helps in interpreting the results much easier than the results obtained with the DWT.

*Continuous Wavelet Transforms* Like the Fourier Transform, the CWT as shown in equation (1) measures the similarity between a signal (f (t)) and an analyzing function (wavelet, $\psi$). The compressed or stretched versions of a wavelet are compared with the signal in the CWT. Stretching or compressing a function is collectively referred to as dilation or scaling and it corresponds to the physical notion of scale. A function of two variables is obtained by comparing the signal to the wavelet at various scales and positions. If the wavelet is complex-valued, the CWT is a complex-valued function of scale and position. If the signal is real-valued, the CWT is a real-valued function of scale and position. For a scale parameter, a $> 0$, and position parameter, b, the CWT is:

$$C(a, b; f(t), \psi(t)) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \psi^* \left( \frac{t-b}{a} \right) dt \quad (1)$$

Where $^*$ denotes the complex conjugate. Not only do the values of the scale and position affect the CWT coefficients, the choice of wavelet also affects the values of the coefficients. By continuously varying the values of the scale parameter, a, and the position parameter, b, one may obtain the CWT coefficients $C(a, b)$. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal.

### 2.3. SVM classification

The SVM(Support Vector Machine) is defined by a decision hyper plane (the plane with maximum margins) between a set of objects that have different class memberships. Given a pair of training data objects, each of which are marked as belonging to one of two categories, an SVM algorithm builds a model that assigns new data object into one category or the other making it a non-probabilistic binary linear classifier. Along with performing linear classification, SVMs can also efficiently perform a non-linear classification by using what is called the kernel trick, here inputs are mapped into high-dimensional feature spaces.

### 2.4. Related works

The malfunction in the heart's electrical system causes the body to lose consciousness and this in turn lead to sudden cardiac death. A normal ECG is preceded and followed when the cardiac arrest (which happens for a very short time) takes place [6]. Usually, the frequency domain methods are used to predict sudden cardiac death and also to quantify the autonomous nervous system control [7].

For a patient suffering an SCD, few noteworthy features are: the lower spectral energy and the low frequency range of first lobe [6]. Power Spectral methods analysis of HRV is a useful tool for categorizing the risk of SCD for cardiac patients [8]. For the patients with slightly reduced or preserved left ventricular (LV) function, some Holter variables were used to guess the occurrence of SCD event [9]. T-wave alternans (TWA) and Modified Moving Average (MMA) were also used as tools of predicting and preventing SCD [10, 11]. Spectral analysis and MMA-TWA are both useful to predict arrhythmia-free survival. For patients surviving an acute myocardial infarction, wavelet analysis on the recordings (taken from Hotler database [12]) was used for the detection of SCD risks [13]. Analysis of ECG is important for the primary diagnosis of heart diseases, thus the ECG signal must be clearly represented and filtered to remove all noise and artefacts from the signal. Several studies were made on the use of wavelet transform in characterizing the ECG signals [1, 5, 14–18].

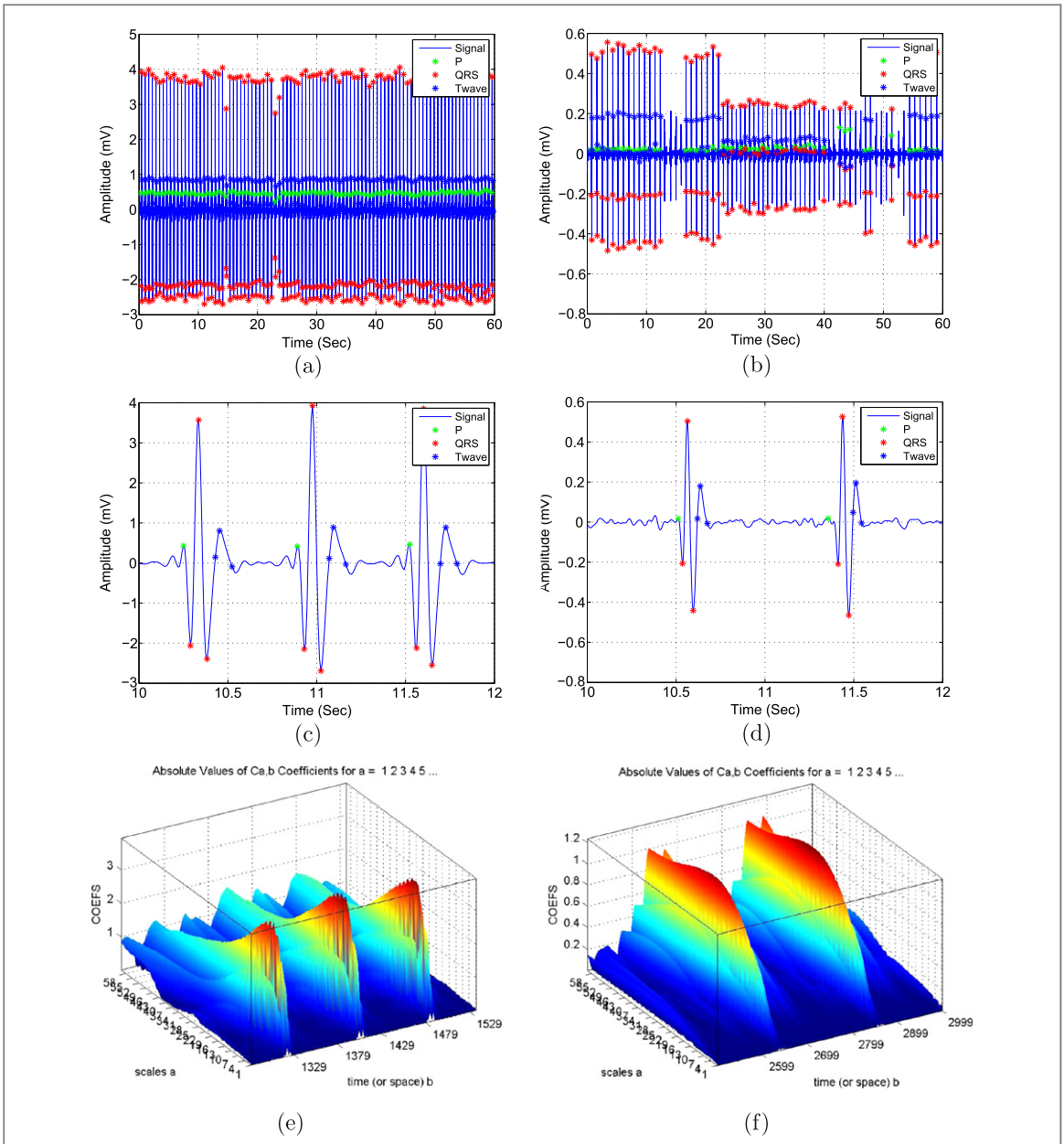


**Figure 4.** (a) and (b): CWT plots of NSR signal and SCD signals, (c) and (d): short interval of CWT plots, (e) and (f): surf plots. NSR record: 16265 m, SCD record: 30 m.

An algorithm for detection of characteristic points and T waves was proposed in [14]. Such algorithm, based on CWT with Splines enables to determine ventricular activity intervals clinically useful for cardiac diagnosis. DWT had been used among multiple ECG compression methods; it is defined as reversible compression tool offering low compression ratios but permits an exact or near-lossless signal reconstruction [15]. Wavelet transform analysis is also used for denoising by removing the corresponding wavelet coefficients at higher scales. Then each QRS complexes were detected to find the peaks of the individual waves like P and T, and also their deviations [16, 18].

Some algorithms based on WT dedicated for the detection of QRS, T, and P waves of ECG were reported in [1]. Other detailed characteristics, for example, ST segment and R to R rate etc can be obtained easily. Characterization of various morphologies of ECG waveform as normal or abnormal is facilitated by the use of multi-scale analysis, through bi-orthogonal wavelets [1, 17]. Characteristics of even the feeble P-wave, an arrhythmia descriptor, are accurately estimated and the estimates are said to be robust in the presence of noise and baseline wander situations. A good evidence showing the role of lower order higher harmonics when approaching the moment of SCD instant, was provided by characterizing the SCD patient's ECG signal [19].

## 3. Methodology and experimental setup

The wavelet analysis of an ECG signal is performed using Wavelet toolbox available in MATLAB [22], a high performance, interactive system which allows

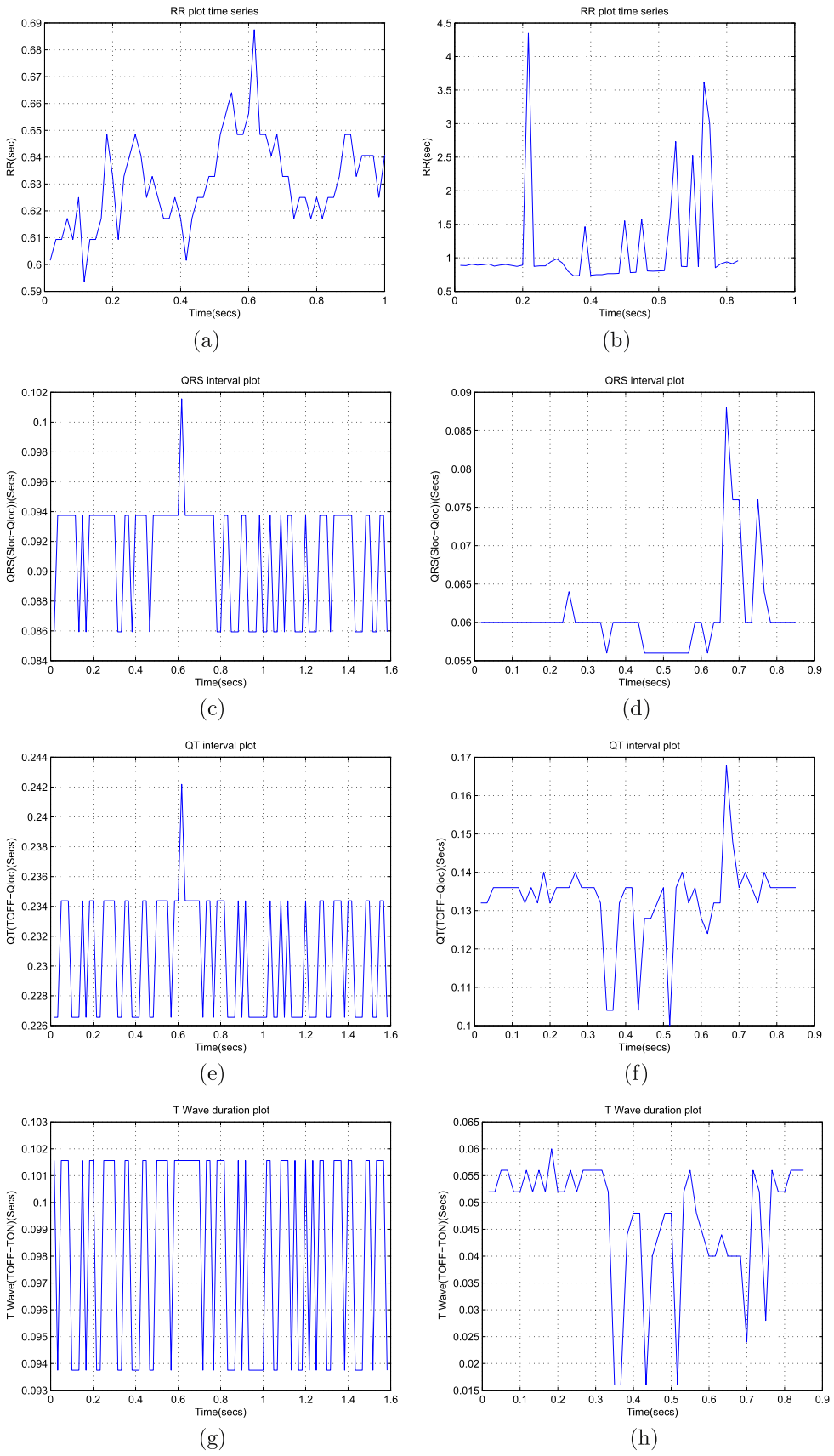


**Figure 5.** (a) and (b): R-R plot of NSR (random 1 minute interval) and SCD signals (1 minute interval prior to SCD event) (c) and (d): QRS complex durations plots(NSR and SCD signal), (e) and (f): QT interval plot. (g) and (h) T wave duration plot. NSR record: 16265 m, SCD record: record 30 m.

solving many technical computing problems). The current task involves working on the 36 data records acquired from Physionet [12] Database. These records are:

1. 18 records of NSR (Normal Sinus Rhythm) signals taken from the section titled 'MIT-Normal Sinus Rhythms'. These include 13 female subjects (between age group of 20 to 45 years) and 5 male subjects (between age group of 28 to 45 years).
2. 18 records of patients who suffered Sudden Cardiac Death taken from the section titled 'Sudden Cardiac Death Hotler Database'. These include 7 female subjects (between age group of 30 to 89 years), 11 male subjects (between age group of 17 to 82 years) and 2 unknown gender persons records.

It is to be mentioned here that the analysis of the two channels ECG signal recordings yielded similar results and therefore, one channel ECG signal's recordings has been considered for the analysis purpose.

Processing of ECG Signals using CWT transform: The block diagram representing the proposed method is shown in figure 3. In the current method, the usage of CWT function(available in MATLAB Bioinformatics Toolboox)removes the raw ECG signals baseline wandering(which are in the range of 0.005 to 1 HZ), low frequency contents due to noise and power line interferences that contains high frequency components which makes the clinical interpretation inaccurate. This in addition with selection of scales for the required wave points detections (namely P,Q,R,S and T wave points) reduces the risk of above interferences.

Figure 4 shows the CWT of two records:NSR signal's Random one minute interval, SCD signal's One minute interval prior to SCD event. These records are taken from Physionet's Databases. The observations that are made from this figure are:

i. After CWT ,the NSR signal has amplitude range between −3 to 4 mV whereas, the SCD signal has an amplitude range between −0.6 to 0.6 mV, which is very less as compared to the NSR signal.

ii. NSR signal has a uniform distribution of approx 3 beats per 2 seconds interval whereas in SCD signal, it has approximately 2 beats per 2 seconds.

iii. The nature of the NSR signal in surf plot shows that it has high amplitude peaks at high frequency (low scales (scale = 10)) and the nature of the SCD signal in surf plot shows that it has high amplitude peaks at high scales (scale = 41).

iv. In NSR, Uniform amplitude peaks occur within 1 minute interval where as in SCD signal there are quite a few low amplitude peaks and it also shows loss of beats.

v. Table 1 shows the differences in certain features of the NSR and SCD signals.

**Table 1.** Differences between NSR and SCD signals in wavelet transformed signals.

| Intervals (seconds) | NSR (seconds) | SCD -18 min (seconds) |
|---|---|---|
| R-R peaks | 0.59 to 0.7 | 0.58 to 4.5 |
| QRS | 0.086 to 0.102 | 0.055 to 0.09 |
| QT | 0.226 to 0.242 | 0.1 to 0.16 |
| T-Wave | 0.093 to 0.102 | 0.015 to 0.006 |

These differences in the parameter values are taken into considerations for determining the abnormality of signals.

CWT provides the time and frequency (scale) component in the signal. At first, the prominent R-spikes in the signal are determined using an *extrema* function developed in MATLAB which provides maximum and minimum points by taking a threshold level at 60 % of the peak values and choosing a window size of over 10 extrema samples each time. These filters out the non-peak points present in the signal.

The R-peaks which occur at high frequencies (i.e., low scale levels) along with Q and S wave points that forms the QRS complex are found to be obtained at low level of scale 10. From R peaks, the successive R to R intervals are determined for analysis purpose. P and T waves in the signals are found to occur at low frequencies (i.e. high scale levels) and so an appropriate scale 41 is chosen after observation in the high scale range. After this, QT time intervals are calculated. Once the T waves are determined, Twave Alternan's magnitudes and intervals of Twave alternans are determined. Even though these all features play important role, to avoid redundancy in ECG analysis, only certain features can be used for classifying normal and abnormal signals.

For the analysis purpose, from the 24 hour recordings, random 1 minute segments of the NSR signal and one minute time interval segments of SCD patients prior the SCD event occurs are collected. Different timings prior to SCD event are shown in table 2.

### 3.1. Features extraction

Various features that were extracted from the signals after pre-processing and performing wavelet transformation are:

**Table 2.** Cumulative Means of the 1-minute time interval means.

| Signal | Record | RRmean (Seconds) | QRSmean (Seconds) | QTmean (Seconds) | Tmean (Seconds) |
|---|---|---|---|---|---|
| NSR Signals | 16265 m | 0.6893 | 0.0905 | 0.2294 | 0.0973 |
| | 16272 m | 0.9631 | 0.0856 | 0.2190 | 0.0958 |
| | 16273 m | 0.6470 | 0.0906 | 0.2254 | 0.0935 |
| | 16420 m | 0.6835 | 0.0845 | 0.1999 | 0.0839 |
| | 16483 m | 0.6202 | 0.0827 | 0.1861 | 0.0617 |
| SCD Signals | 30 m | 0.9213 | 0.0605 | 0.1342 | 0.0522 |
| | 31 m | 0.8638 | 0.0626 | 0.1287 | 0.0486 |
| | 32 m | 0.8086 | 0.0528 | 0.1245 | 0.0623 |
| | 33 m | 1.3079 | 0.0689 | 0.1406 | 0.0488 |
| | 34 m | 0.9609 | 0.0546 | 0.1236 | 0.0497 |

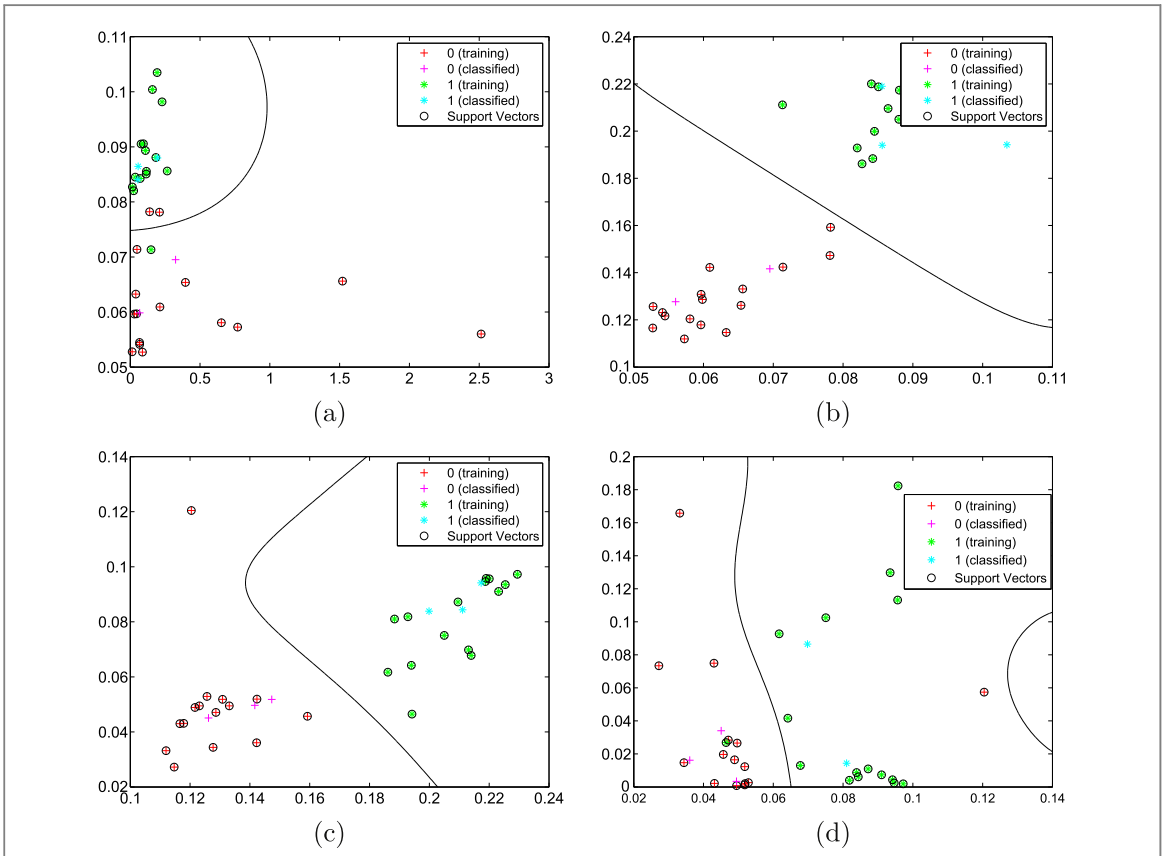


**Figure 6.** Classification based on features sets: (a) RRsd and QRSmean, (b) QRSmean and QTmean, (c) QTmean and Twav_dur_mean, (d) Twav_dur_mean and TWA_mag.

**No of Beats per minute:** the count of the high amplitude pulses present in the time interval of the signal.

**Mean of R-peaks (mV):** mean value of the signal's Peaks termed as R peaks.

**Rmax (mV):** array of signal points containing Maxima values of the signal.

**Rmin (mV):** array of signal points containing the minima points of the signal.

**RRmean (secs):** mean values of the RR interval in each time interval.

**RRrms (secs):** root mean square values of the RR intervals in each time interval.

**RRsd (secs):** standard deviation of RR interval inside each period.

**RR_ad (secs):** RMS values of the difference between adjacent RR intervals.

**RR_std_ad (secs):** Standard Deviation of the difference between adjacent RR intervals.

**RRmax-RRmin (secs):** difference between the maximum of RR intervals and minimum of RR intervals.

**Table 3.** Evaluation with Features: RRsd (secs) and QRSmean (secs).

| Time before SCD event | TP (10 trials Averaged) | TN (10 trials Averaged) | FP (10 trials Averaged) | FN (10 trials Averaged) | Sensitivity (%) | Specificity (%) | Positive Predictive Value (%) | Accuracy (%) |
|---|---|---|---|---|---|---|---|---|
| 30 min prior SCD | 16 | 17 | 1 | 2 | 88.89% | 94.44% | 94.12% | 91.67% |
| 24 min prior SCD | 17 | 17 | 1 | 1 | 94.44% | 94.44% | 94.44% | 94.44% |
| 18 min prior SCD | 17 | 17 | 1 | 1 | 94.44% | 94.44% | 94.44% | 94.44% |
| 12 min prior SCD | 17 | 17 | 1 | 1 | 94.44% | 94.44% | 94.44% | 94.44% |
| 6 min prior SCD | 17 | 17 | 1 | 1 | 94.44% | 94.44% | 94.44% | 94.44% |
| 1 min prior SCD | 16 | 17 | 1 | 2 | 88.89% | 94.44% | 94.12% | 91.67% |

**Table 4.** Evaluation with Features: QRSmean (secs) and QTmean (secs).

| Time before SCD event | TP (10 trials Averaged) | TN (10 trials Averaged) | FP (10 trials Averaged) | FN (10 trials Averaged) | Sensitivity (%) | Specificity (%) | Positive Predictive Value (%) | Accuracy (%) |
|---|---|---|---|---|---|---|---|---|
| 30 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 24 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 18 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 12 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 6 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 1 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |

**QRSmean (secs):** the mean value of the QRS complexes.

**QTmean (secs):** the mean value of the QT time duration.

**Twave_dur_mean (secs):** the mean value of the T waves present in the signals time interval.

**TWA_mag (mV):** the magnitude of the T wave Alternans in the given time interval.

Table 2 shows the Cumulative Means of the 1-minute time interval means of Different Features. Means are of: (a) various random 1-minute intervals of NSR signals and (b) 1-minute intervals prior to the SCD event occurrence of SCD signals). Five selective NSR records and five SCD records are chosen to show the means of different features namely R-R peaks mean, QRS complex mean, QT mean, and T-Wave mean. The tabular values of different features clearly indicates that the abnormality that exists in the SCD signals when compared to the NSR signals. The changes occur because of non-uniform heartbeat and various other conditions of the heart. Similar distorting values were observed when the analysis was done on different records.

### 3.2. Evaluation:

The performance evaluation of the SVM classifier prior to the SCD event is done using the parameters : Sensitivity (SN) given by equation (2), Specificity(SP) given by equation (3), Positive Predictivity (P) given by equation (4) and Accuracy (AC) given by equation (5). The equations are as follows:

$$Sensitivity\,(\%) = \left(\frac{TP}{TP + FN}\right)100 \tag{2}$$

$$Specificity\,(\%) = \left(\frac{TN}{TP + FP}\right)100 \tag{3}$$

$$PoitivePredictivity\,(\%) = \left(\frac{TP}{TP + FP}\right)100 \tag{4}$$

$$Accuracy\,(\%) = \left(\frac{TP + TN}{TP + TN + FP + FN}\right)100 \tag{5}$$

TP : True positive, (correctly classified SCD).
TN : True Negative, (correctly classified NSR).
FP : False Positive, (incorrectly classified SCD).
FN : False Negative, (incorrectly classified NSR).

From the 36 records used (18 NSR records and 18 SCD records),the SVM classifier is trained with 14 NSR signals and 14 SCD signals. 4 NSR signals and 4 SCD signals are then tested for classification. Figures 6(a)–(d) shows the classification results using different feature sets at 30 minutes prior to the SCD event.

Testing is performed at different time intervals namely 1, 6, 12, 18, 24 and 30 minutes before the SCD event by choosing different feature sets. Each such trial is repeated 10 times. The resulting values of the classification tasks are then averaged and tabulated as shown in the tables (3 – 6).

**Table 5.** Evaluation with Features: QTmean (secs) and Twav_dur_mean (secs).

| Time before SCD event | TP (10 trials Averaged) | TN (10 trials Averaged) | FP (10 trials Averaged) | FN (10 trials Averaged) | Sensitivity (%) | Specificity (%) | Positive Predictive Value (%) | Accuracy (%) |
|---|---|---|---|---|---|---|---|---|
| 30 min prior SCD | 17 | 18 | 1 | 0 | 94.44% | 100.00% | 100.00% | 97.22% |
| 24 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 18 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 12 min prior SCD | 18 | 18 | 0 | 0 | 100.00% | 100.00% | 100.00% | 100.00% |
| 6 min prior SCD | 17 | 18 | 0 | 1 | 94.44% | 100.00% | 100.00% | 97.22% |
| 1 min prior SCD | 17 | 18 | 0 | 1 | 94.44% | 100.00% | 100.00% | 97.22% |

**Table 6.** Evaluation with Features: Twav_dur_mean (secs) and TWA_mag (mV).

| Time before SCD event | TP (10 trials Averaged) | TN (10 trials Averaged) | FP (10 trials Averaged) | FN (10 trials Averaged) | Sensitivity (%) | Specificity (%) | Positive Predictive Value (%) | Accuracy (%) |
|---|---|---|---|---|---|---|---|---|
| 30 min prior SCD | 16 | 17 | 1 | 2 | 88.89% | 94.44% | 94.12% | 91.67% |
| 24 min prior SCD | 17 | 17 | 1 | 1 | 94.44% | 94.44% | 94.44% | 94.44% |
| 18 min prior SCD | 17 | 17 | 1 | 1 | 94.44% | 94.44% | 94.44% | 94.44% |
| 12 min prior SCD | 16 | 17 | 1 | 2 | 88.89% | 94.44% | 94.10% | 91.67% |
| 6 min prior SCD | 16 | 17 | 1 | 2 | 88.89% | 94.44% | 94.10% | 91.67% |
| 1 min prior SCD | 16 | 17 | 1 | 2 | 88.89% | 94.44% | 94.12% | 91.67% |

**Table 7.** Comparative results in the literature.

| Method | Literature | Time before Event | Prediction Accuracy |
|---|---|---|---|
| Wavelet Analysis (ANN) | Shen *et al* [20] | 2 minute prior | 87.5% |
| LMS (Neural Networks) | Shen *et al* [20] | 2 minute prior | 67.4% |
| MLP | E Ebrahimzadeh *et al* [21] | 2 minutes prior | 98.74% |
| k-NN | | | 96.42% |
| MLP | E Ebrahimzadeh *et al* [21] | 3 minutes prior | 95.78% |
| k-NN | | | 93.63% |
| Proposed Method | Towfeeq Fairooz, Hedi Khammari, 2015 | 30 minutes prior (least features set) | 91.67% |
| Proposed Method | Towfeeq Fairooz, Hedi Khammari, 2015 | 30 minutes prior (best features set) | 100% |

### 3.3. Discussion

To evaluate the performance in classification, the classification accuracy is shown with different combinations of the features obtained. The results obtained from the proposed method are compared with the previous results as shown in the table 7.

Comparing the results reported by Shen *et al*, Ebrahimzadeh *et al*, and our findings, it is clear that, the proposed method in which the SVM algorithm based classification with different best features combinations performs the prediction operation more accurately.

In the raw time domain, there is not much distinction between a normal person ECG signal and that of SCD patients signal, however, it can be seen that the CWT transformed signal provides us with significant features which are used for the prediction of SCD. In our investigations it was observed that, by processing the ECG signal for classification even as early as 30 minutes prior to SCD event, it is possible to provide information indicating the risk of SCD. It can be seen from the table 4. That the features namely QRSmean and QTmean performs the classification task more accurately (100% accuracy) than the other features. The table 5. Also shows that the other feature sets also provides us with very good accuracy as compared to the earlier works as reported in table 7.

## 4. Conclusion

The study characterizes the signal at times preceding the SCD. It is observed that in the CWT surf plots of the SCD signals,the higher amplitudes peaks occurring at low frequency(higher scales) and the non-uniform beat rate indicates the possible occurrence of SCD. This pattern has been observed for different patients suffering from Sudden Cardiac Death. In this paper we present a methodology for classifying the features obtained from CWT based on SVM algorithm. From the classification results, it is possible to efficiently

predict the possible occurrence of an SCD event. The classification results table 7 indicates the evaluation performances by using the combinations of different features. The best features combination (QRSmean and QTmean) provides an accuracy of up to 100% and the least best features combination (RRsd and QRSmean) provides an accuracy of up to 91.67%. Predicting the the occurrence of SCD, 30 minutes prior to the event can help the doctors diagnose the patients accurately and treat the SCD prone patients immediately. In future, we intend to work on methods using this transformation to predict other heart related issues apart from SCD.

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