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Three-Dimensional Phase Space Characteristics of Electrocardiogram Segments in Online and Early Prediction of Sudden Cardiac Death

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ABSTRACT

Introduction: Predicting sudden cardiac death (SCD) using electrocardiogram (ECG) signals has come to the attention of researchers in recent years. One of the most common SCD identifiers is ventricular fibrillation (VF). The main objective of the present study was to provide an online prediction system of SCD using innovative ECG measures 10 minutes before VF onset. Additionally, it aimed to evaluate the different segments of the ECG signal (which depend on ventricular function) comparatively to determine the efficient component in predicting SCD. The ECG segments were QS, RT, QR, QT, and ST.

Material and Methods: After defining the ECG characteristic points and segments, innovative measures were appraised using the three-dimensional phase space of the ECG component. Tracking signal dynamics and lowering the computational cost make the feature suitable for online and offline applications. Finally, the prediction was performed using the support vector machine (SVM).

Results: Using the QR measures, SCD detection was realized ten minutes before its occurrence with an accuracy, specificity, and sensitivity of 100%.

Conclusion: The superiority of the proposed system compared to the state-of-the-art SCD prediction schemes was revealed in terms of both classification performances and computational speed.

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Introduction

Sudden cardiac death (SCD) results from severe damage to the heart, which causes the heart system to collapse. Thereby, blood can no longer be pumped to different body parts. Using medical equipment such as defibrillators can reduce the number of these deaths, but there are no good ways to predict sudden cardiac death through which doctors can make appropriate decisions for patients [1]. A heart attack, also known as a myocardial infarction, occurs when a coronary artery, which supplies blood to the heart muscle, becomes suddenly blocked. This abrupt blockage deprives a section of the heart muscle of critical blood supply, resulting in its subsequent death. Ventricular fibrillation, on the other hand, refers to a condition where the electrical signals within the heart, responsible for regulating the timing and coordination of the heartbeat, suddenly become completely chaotic. As a consequence, the heart abruptly ceases to beat, leading to fatal outcomes [2]. So far, many researchers have attempted to predict/detect the event in a sufficient and suitable time, saving the patient's life and reducing the risk from him away.

Electrocardiogram (ECG) is a simple, low-cost tool for evaluating the heart's electrical activity. Previously, ECG has been used in various clinical applications, including diagnosing cardiac abnormalities and arrhythmias [3, 4]. Also, this tool has been used for emotion recognition [5] and human identification [6,7] or even to evaluate environmental conditions such as electromagnetic fields [8] or gravitational stress [9]. The significant role of ECG signal analysis has also been emphasized for SCD diagnosis.

In recent decades, many research works have been accomplished to detect SCD based on signal-processing approaches. These studies used either the electrocardiogram (ECG) signal or the heart rate variability (HRV). The HRV signal, generally derived from the ECG signal, is the variations in the time interval between heartbeats. Different feature extraction approaches for the analysis of cardiac signals and different classifications have been considered in diagnosing and predicting this disease (Table 1).

In Ref. [1], to predict SCD 4 minutes before the occurrence, the researchers extracted linear, time-frequency, and nonlinear features of the heart rate (HR) signal. The best combination of the properties with a reduced dimensionality was selected using principal component analysis (PCA).

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Table 1. A summary of previously proposed systems, as well as their results

Ref	features	Number of features	Classifier	accuracy %	Prediction time (min)	number of: SCD/ NORMAL	Database
1	Time, Frequency, Time-frequency Non-linear	time (5) frequency (4) Time- frequency (11) Non-linear (4)	MLP	73.35	4	35 35	MITBIH (NSR-SCDH)
2	Line-time Line-frequency RMSDD SDNN LF, HF, LF/HF	Line-time 2 Line-frequency 3	SVM	88	30	20 20	MITBIH (NSR-SCDH)
10	Db6 wavelet transform, DFA, FD, H, CD, SAMP ENT, HURST APPROXENT	18	SVM	98.68	4	23 18	MITBIH (NSR-SCDH)
11	Wavelet transform db8 Renyi Entropy activity, mobility and complexity Tsallis Entropy	7	SVM KNN DT	94.7	4	23 18	MITBIH (NSR-SCDH)
12	Time, frequency (Wigner-Ville) BURG, Non -linear Poincare& DFA	time (5) frequency (4) Time- frequency (11)	ME	95	12	35 35	MITBIH (NSR-SCDH)
13	time, frequency	time (5), frequency (4)	MLP KNN	89.27 91.23	2	35 35	MITBIH (NSR-SCDH)
14	linear Time-frequency Nonlinear, entropy, Poincare and recursive graph, spectral properties	Linear (11) Non -linear (3)	SVM KNN	93.03 94.10	5	23 18	MITBIH (NSR-SCDH)
15	Time-frequency STOCK WELL DWT	3	Convolution neural network	-	4	20 18	MITBIH (NSR-SCDH)
16	Nonlinear (entropy and RQA)	14	NB, SVM, KNN DT	95	6	20 18	MITBIH (NSR-SCDH)
17	Energy and Poincare average of HRV	2	KNN, MLP	83.96	4	20 18	MITBIH (NSR-SCDH)
18	(ECG) DWT, time, frequency, DFA & Sample entropy	Linear (11) Non -linear (3)	FPGA	95.08	20	20 18	MITBIH (NSR-SCDH)
19	Linear, Non linear	32 9	DT, KNN, SVM	83.33	10	51	MITBIH (BIDMES, SCDH, NSR)
20	R-R interval, QRS-T, ECG Morphology	21	BILSTEM	99.49	-	-	MITBIH (NSR-SCD)
21	Repolarization and conductivity ratios of QRS morphology, and T	7	SVM, KNN, DT, NB, RF	99.41	30	18 28	MITBIH (SDDB, NSRDB)
22	Select a feature from the local subset: temporal, frequency, time-frequency, and nonlinear	time (5), frequency (4), time-frequency (11)	MLP	83	12	35 35	MITBIH (NSR-SCD)
23	Wavelet transform of T Morphology of the ECG	-	Kalman filter	85	2	20 18	MITBIH (NSR-SCD)
24	Wavelet	4		87.5	4	20 18	MITBIH (NSR-SCD)
25	(ECG), return map, SD1, SD2, SD1/SD2	4	SVM	-	10	23 18	MITBIH (NSR-SCD)
26	Lyapunov exponent, Hurst exponent, Sample entropy, Approximate entropy	4	SVM, subtractive fuzzy clustering, neuro-fuzzy Classifier	94.7	5	18 18	MITBIH (NSR-SCD)

Applying the multi-layer perceptron (MLP) neural network, healthy and sick individuals were classified with an accuracy rate of 73.35%. Sheela et al. [2] proposed a scheme to predict sudden cardiac arrest 30 minutes before its occurrence. Some time- and frequency-based features were extracted from heart

rate variability (HRV). Different classifiers were implemented to classify SCD from healthy normal. Their results showed the highest classification accuracy of 88% using a support vector machine (SVM). Acharya et al. [10] presented a scheme for SCD detection up to four minutes before the occurrence with an accuracy of 98.68%. To this effect, they implemented discrete wavelet transform and nonlinear attributes of ECG data, including Correlation dimension (CD), Hurst exponent (H), Detrended fluctuation analysis (DFA), approximate entropy, and sample entropy. Using SVM, Fujita et al. [11] predicted SCD up to 94.7% four minutes before its onset utilizing the MIT-BIH arrhythmia database. After HRV extraction, a Daubechies 8 (db8) mother wavelet function was applied, characterized by some nonlinear indices. Ebrahimzadeh et al. [12] could detect SCD 12 minutes before the occurrence. An accuracy of 95% was reported by selecting the features and using a mixture of experts (ME) as a classifier. They evaluated the system on 35 patients (19 males and 16 females) and 35 normal sinus rhythm subjects (17 females and 18 males). The signals were characterized using temporal, time-frequency-based, and nonlinear properties. The time-frequency measures were calculated using the Wigner-Ville method, and nonlinear indices were achieved using Poincare and DFA analysis. In another study [13], the team used linear methods and time-frequency analysis to characterize HRV signals. The linear properties were the average of all RR distances, a standard deviation of all RR distances, the mean square root of consecutive differences, a standard deviation of the difference of adjacent RR distances, the probability of successive distance difference of more than 50 milliseconds, low-frequency (LF), high frequency (HF), and very-low-frequency (VLF) powers. The average energy was also calculated for time-frequency characteristics. They reported that a maximum accuracy of 74.36% for SCD prediction one minute before the occurrence using linear properties and MLP, which increases to 99.6% using time-frequency properties and the KNN classifier. Classification results for two minutes before the SCD were 72.28% using linear methods integrating with MLP and 91.23% for time-frequency indices and KNN.

Houshyarifar et al. [14] used linear and nonlinear HRV features to detect SCD. 18 healthy controls and 20 patients were used to assess the scheme. An accuracy of 92.50% was reported for a time prediction of four minutes by applying some nonlinear measures to the SVM classifier. KNN classification resulted in an accuracy of 92.59% five minutes before the SCD event. In [15], Alizadeh et al. diagnosed SCD four minutes before the occurrence, using time-frequency achieved from STOCK WELL conversion. They used the convolutional neural network.

Khazaei et al. [16] extracted entropy features and recurrence quantification analysis (RQA) of HRV. Then, a one-way ANOVA test was applied to select significant features. The accuracy was 95% using a decision tree. Ebrahimzadeh et al. [17] proposed a framework for predicting SCD four minutes before the event. HRV was characterized by time-frequency measures like mean energy and nonlinear indices such as Poincare's diagrams. They examined KNN and MLP, and the highest accuracy of 83.96% was reported. In [18], Sanchez et al. proposed a model for predicting SCD 20 minutes before the occurrence. Using the ECG, the highest accuracy was 95.2%. Dewey et al. [19] proposed a new, multi-class approach to predicting SCD at the early stages (ten minutes before the occurrence) with an accuracy rate of 83.33%. An accuracy of 99.49% was reached using BILSTEM neural network [20]. They used the P-QRS-T wave morphology and the distances of the R-R peaks. In Ref. [21], the authors proposed an automated method for identifying the primary SCD hazard using machine learning. Some conductivity characteristics of ECG signals were extracted and fed into the random forest (RF) classification. The results showed an accuracy of 99%. Another attempt [22] reported an accuracy of 83% with a prediction time of 12 minutes using the local subset feature selection. They selected 11 features from the Wigner-Ville technique, four indices of the BURG method, and five measures for the time-domain analysis.

Applying cardiac signal processing and a generalized Kalman filter, Kahroba et al. [23] could diagnose SCD two minutes before the occurrence with an accuracy rate of 85%. In [24], Shen et al. proposed a home system for SCD prediction. The accuracy was 87.05% using the wavelet analysis. They also assessed short-term HRV analysis using LF, HF, and VHF. They reported an accuracy of 67.44%. Moghadam et al. [25] could detect the SCD 10 minutes before the event using nonlinear features and a return map with SVM. Murugappan et al. [26] predicted SCD 5 minutes before the event with an accuracy of 94.7% using the SVM. They used sample entropy, approximate entropy, Lyapunov exponents, and Hurst exponent. Table 1 summarizes the results of previous approaches.

By reviewing the above literature, the following items are perceived. (1) Most articles used HRV signals, while the HRV is derived from the ECG. (2) MIT-BIH arrhythmia database has been generally used. It is noted that the database provides a two-channel ECG. Some researchers have considered them as two participants to increase the observations and accuracy of the method. (3) Among the temporal features, SDNN and RMSSD have been used in most references [2, 14]. (4) Among the frequency-based measures, LF, HF, and LF/HF had been frequently used in most articles. Ref. [2] and Ref. [19] have used these three features exclusively. (5) Among the time-frequency measures, the non-parametric wavelet method and the Wigner-Ville distribution were widely

used [1, 2, 12-15, 19, 24]. (6) Among the nonlinear features, Poincare's measures and DFA have been frequently used in [10, 12, 14, 18, 19, 22]. (7) Concerning prediction time, most articles have diagnosed SCD up to four minutes before the event [10, 11, 15, 17, 24]. However, Refs. [21] and [2] reported the earliest prediction time, 30 minutes before SCD. (8) Regarding the number of samples, most articles considered 38 samples [10, 11, 14-18, 23, 24]. However, it reached 70 in some literature [1, 12, 13, 22]. (9) In terms of the type of classification, the most common type of classification approach was SVM, KNN, and MLP [1, 2, 10, 11, 14, 17, 19, 22].

The approach of the present study concerning the above studies will be as follows. (1) Instead of HRV, the ECG signal has been used in this experiment. (2) According to the previous studies, we will use the MIT-BIH arrhythmia database. Besides, we will consider each channel as a separate observation. (3) Since the ECG is a nonlinear and dynamic signal, conventional temporal and spectral properties cannot provide sufficient information about cardiac behavior, so we use a nonlinear-based approach. Various nonlinear properties have been used in the references. Here, we aimed to propose novel three-dimensional phase space-based measures. Two-dimensional phase space measures with other nonlinear features have been used in some references [12, 14, 16, 17]. Zimmerman et al. [27] proposed a scheme for ST events classification as ischemic or non-ischemic using a reconstructed phase space. Each ST segment and T wave was embedded in a 6-dimensional phase space with a time lag of 5 and classified using Gaussian Mixture Models (GMM). The highest sensitivity of 81% and specificity of 88.1% were reported. Despite the use of this method in the diagnosis of ischemia, no attempts have been made for SCD detection by evaluating the signal trajectory in a higher dimension. The current study provides some innovative properties of three-dimensional phase space for the first time. (4) In terms of prediction time, we will increase this time up to 10 minutes instead of 4 minutes before the SCD event. (5) In some literature, a specific segment/part of the signal has been evaluated [20, 21, 23, 26]. The present study will evaluate different ECG segments related to ventricular function. (6) Most references implemented the SVM classification. Currently, we apply it as a classification approach.

Materials and Methods

The following block diagram (Figure 1) shows the suggested process of the research. The scheme embraces four key modules, including the ECG data, the preprocessing, the feature extraction, and the classification. All of them are described comprehensively in the subsequent sub-sections.

ECG data

This work used two the MIT-BIH arrhythmia database databases, including the Normal Sinus Rhythm (NSR) and SCD Holter databases. The former was utilized to obtain normal ECG, and the latter was used for SCD prediction. SCD database includes ECG signals of 18 subjects (15 men and three women, aged 17 to 82 years), and the NSR database incorporates the ECG of 18 participants (5 men and 13 women, with the age range of 20 and 45 years). Data were obtained directly from hospitals around Boston using Holter recording. The sampling rate of the NSR databases is 128, and for the SCD database is 256 [28, 29].

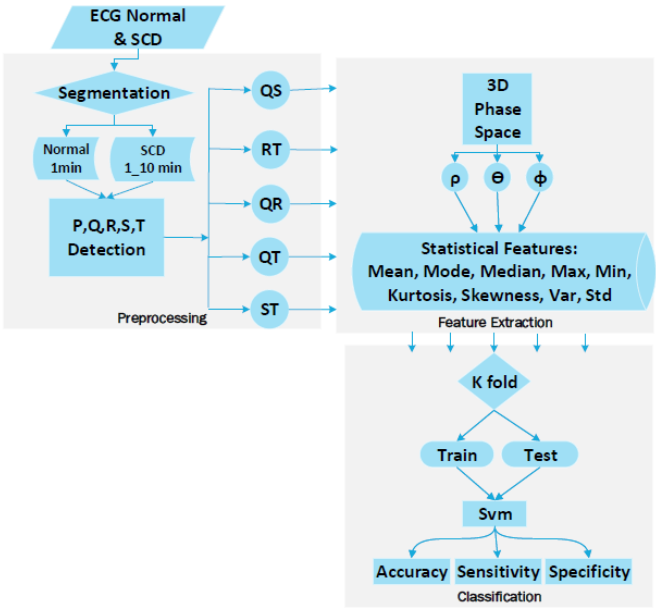

Figure 1. Proposed procedure

A two-channel ECG signal is provided. For further analysis, we assessed (1) each channel as a separate observation and (2) each channel separately. Channel 1 is identical to lead II, and channel 2 is equivalent to V6. For uniformity, the sampling rate was reduced to 128 using the down-sampling approach.

Preprocessing

First, the segmentation is performed on the data, such that the ECG signals at a one-minute duration are obtained. For SCD groups, this segmentation proceeded up to ten minutes before the onset of SCD. However, a one-minute ECG segment was selected randomly for healthy normal because of no pathological effect on the signal of this group. Figure 2 illustrates a sample segmentation procedure. First, the event occurrence time is indicated (SCD onset). The part of the signal that precedes the event is divided into ten pieces at one-minute intervals.

Next, the ECG characteristic points are determined. In a typical ECG, five deflections are incorporated, including the P, Q, R, S, and T. To extract them, we used the Augsburg Biosignal Toolbox (AUBT) [30]. After defining the ECG characteristic points, the data between each pair of points is an ECG segment. Specifically, these segments are QS, RT, QR, QT, and ST (Figure 3). All of which are dependent on ventricular activity.

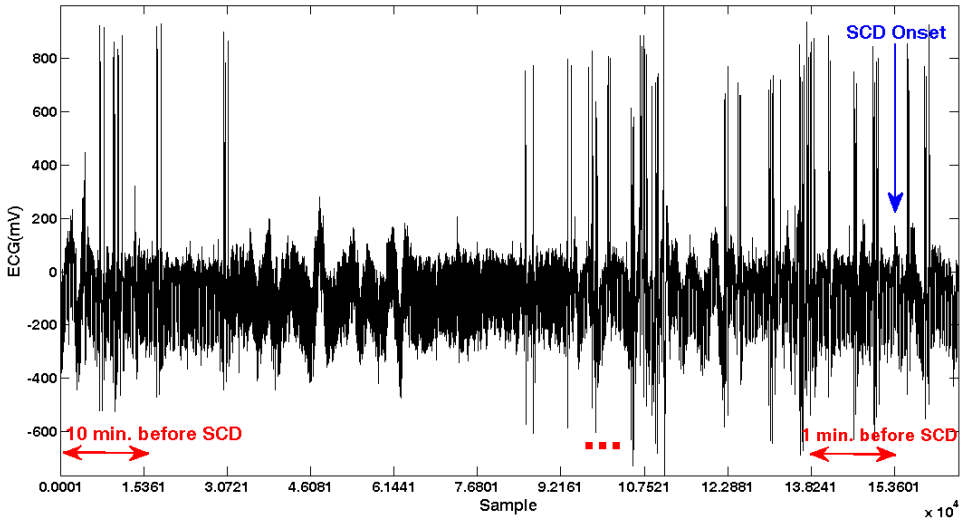

Figure 2. Segmentation of the ECG signal from the SCD database (record 48 of the MIT-BIH SCD Holter database). The SCD onset is firstly determined. The signal is then separated into 10 segments at one-minute intervals before the SCD onset.

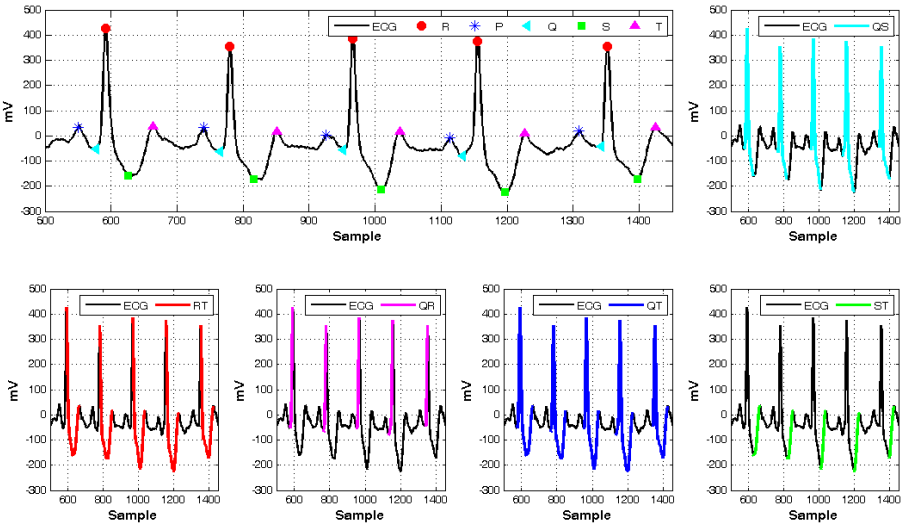

Figure 3. ECG characteristic points and the corresponding segments, i.e. QS, RT, QR, QT, and ST

Feature Extraction

3D phase space

Consider an ECG segment as a scalar vector $x_i(i=1, 2, \ldots, N)$. A delayed data vector to the phase space is shown as Eq. (1):

$$X(k)=[x_k, x_{k+\tau}, x_{k+2\tau}, \ldots, x_{k+(d-1)\tau}] \quad (1)$$

for $k=1, 2, \ldots, N-(d-1)\tau$

where $X(k)$ is the delayed vector, d is the embedding dimension, and τ is the embedding delay. In conventional phase space, τ is 1. Here, for a 3D phase space, $d=3$ is considered.

Spherical coordinate system

For constructing a 3D phase space, the X-axis is X_k, the Y-axis takes in X_{k+1}, and the Z-axis is X_{k+2}. In a Cartesian system, each point is defined by (X, Y, Z). For a spherical coordinate system, a triple (ρ, θ, φ) is used to describe the position of a point (P) in a 3D space (Figure 4). (ρ, θ, φ) can be obtained from the (X, Y, Z) Cartesian coordinates as follows.

$$\rho=\sqrt{X^2+Y^2+Z^2} \quad (2)$$

$$\varphi=\arccos\frac{Z}{\sqrt{X^2+Y^2+Z^2}} \quad (3)$$

$$\theta=\arctan\frac{Y}{X} \quad (4)$$

(ρ, θ, φ) of all points in the 3D phase space were calculated.

Figure 5 illustrates a 3D phase space plot of ECG signals for healthy and SCD participants. As the figure shows, the trajectory pattern of the two signals is quite different. The figure also indicates a higher dispersion of the phase space points for a healthy person than a patient.

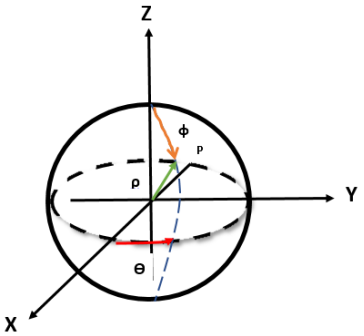

Figure 4. A triple (ρ, θ, φ) which is used to describe the position of a point in a three-dimensional space

Statistical features

Several statistical features were extracted, including mean, mode, median, maximum (max), minimum (min), kurtosis, skewness, variance (var), and standard deviation (std), to quantify each measure of the spherical coordinate system.

An indicator of how the set members is scattered is called the average. A number that is more or less 50% of the data is called the median. The most frequent figure is known as the mode. Maximum and minimum determine the uppermost and the lowermost expansion points. The variance is the mean square value of the difference between values and the mean. The standard deviation is the root of the variance and also shows the scatter of data relative to the mean. Skewness indicates the degree of symmetry of a variable around the mean. Kurtosis is a measure of the flatness of the data distribution.

SVM Classification

SVM mapped the attributes into a high-dimensional space to categorize the data readily. Depending on the applied features, the learning process is repeatedly implemented to produce the most satisfactory hyperplane with the maximum margin between the groups in a high-dimensional feature space. At last, by applying the maximum-margin hyper-planes, the decision borders over the data groups are sketched.

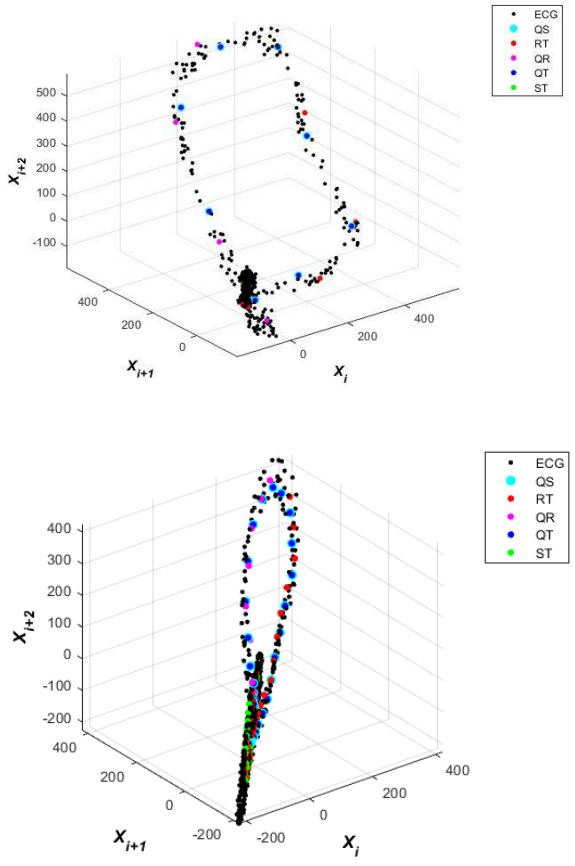

Figure 5. Reconstruction of a three-dimensional phase space for (a) healthy, and (b) SCD data.

For a binary classification problem $y_i \in \{+1, -1\}$, where y_i denotes each group, consider a data set of $\{(x_i, y_i)_N\}$, where N is the data dimension. A linear function of x is deliberated as a hyperplane for linear classification, such that $y_i(f(x))=y_i(<w\cdot x>+b)>0$,

where *w* indicates the weight vector and *b* designates the bias (a scalar measure). The separating hyperplane is recognized when $f(x) =< w \cdot x > +b = 0$. The greater the distance between the hyper-planes and data points in the different groups, the higher the classification rates. When the precise distinction of the two classes is difficult or impossible, implementing SVM kernel tricks is recommended. The current study used a radial basis function (RBF) as a kernel.

The SVM performances were appraised in a binary classification problem using 5-fold cross-validation (CV). Accuracy (AC) , sensitivity (SE), and specificity (SP) were calculated as equations (5), (6), and (7) to estimate the performance of the classification module:

$$AC(\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (5)$$

$$SE(\%) = \frac{TP}{TP+FN} \times 100 \quad (6)$$

$$SP(\%) = \frac{TN}{TN+FP} \times 100 \quad (7)$$

where TP = true positive, TN = true negative, FP = false positive, and FN = false negative.

Results

As mentioned above, different segments of the ECG signal depending on ventricular function were characterized by the proposed indices and fed to the SVM to determine the best ECG segment for SCD prediction. These segments were QS, RT, QR, QT, and ST. The following subsections show the performance of each ECG segment. The classifier was run five times, and the mean, standard deviation, and maximum performances are presented here.

Table 2 shows the performance of the SVM classifier using the proposed features of the ECG segments. Precisely, the table shows the values of accuracy, specificity, and sensitivity of the classifier for different ECG segments, using (1) both channels simultaneously, (2) exclusively using channel 2, and (3) exclusively using channel one.

Performance of QS segment

The classifier achieved the highest classification accuracy, sensitivity, and specificity of 100% six minutes before the onset of SCD using each ECG channel as an observation. In this case, the average accuracy was 84.29%, specificity was 82.64%, and sensitivity was 86.67%.

The classifier accomplished the highest classification accuracy, sensitivity, and specificity of 100% one minute before the SCD onset using channel 2. In this case, the mean accuracy was 78.76%, specificity was 73%, and sensitivity was 72%.

The classifier reached the highest classification accuracy, sensitivity, and 100% specificity six minutes before the SCD onset using channel 1. In this case, the mean accuracy was 82.85%, specificity was 78.33%, and sensitivity was 83%.

Performance of RT segment

The highest classification accuracy was 86.67% for 2 minutes before the SCD event applying both ECG channels, where the highest specificity and sensitivity were 90.91% and 87.5%, respectively. The second-best maximum accuracy was for a prediction time of 9, where accuracy was 85.71%. Regarding the highest average accuracy, the best performance was for 9 minutes before the onset of SCD. In this case, the average accuracy was 72.53%.

Table 2. Performance of SVM classifier using 3D phase space-based measures of different ECG segments

	ECG Segment	Prediction time	Accuracy		Specificity		Sensitivity	
			Mean%± std	Max%	Mean%± std	Max%	Mean%± std	Max%
Two-channels	QS	6	84.29±0.11	100	82.64±0.15	100	86.67±0.08	100
	RT	2	72.42±0.11	86.67	80.66±0.12	90.91	74.21±0.18	87.50
	QR	10	89.23±0.09	100	81.79±0.13	100	86.94±0.09	100
	QT	8	88.57±0.11	100	84.5±0.21	100	89.33±0.15	100
	ST	2	87±0.07	93.33	89.99±0.06	100	87.94±0.08	100
Channel2	QS	1	76.78±0.13	100	73±0.19	100	72±0.19	100
	RT	6	82.86±0.18	100	76.67±0.32	100	84±0.21	100
	QR	7	91.43±0.07	100	100±0.01	100	100±0.01	100
	QT	7	91.43±0.07	100	90±0.13	100	90±0.13	100
	ST	5	97.5±0.05	100	96±0.08	100	95±0.11	100
Channel1	QS	6	82.85±0.11	100	78.33±0.21	100	83±0.17	100
	RT	2	76.07±0.12	87.5	78±0.22	100	78.57±0.16	100
	QR	7	91.43±0.07	100	100±0.01	100	100±0.01	100
	QT	10	78.57±0.13	100	55±0.38	100	77±0.15	100
	ST	7	88.57±0.06	100	78.33±0.21	100	87.67±0.11	100

The best results were for six minutes before VF with an average accuracy of 82.86%, specificity of 76.67%, and sensitivity of 84% for channel 2. While channel 1 achieved the highest performance two minutes before the start of the SCD with an average accuracy of 76.07%, specificity of 78%, and sensitivity of 78.57%.

Performance of QR segment

The highest classification performances were achieved for 10 minutes before the onset of the event using both ECG channels, where the highest classification accuracy, sensitivity, and specificity was 100%, with average accuracy, specificity, and sensitivity were 89.23%, 81.79%, and 86.94%, respectively.

Seven minutes before the start of VF, the classification results in an average accuracy of 91.43%, specificity, and sensitivity of 100%, using channel 2. Similar results were obtained for channel 1.

Performance of QT segment

Classifier reached the uppermost classification accuracy, sensitivity, and specificity of 100% eight minutes before the SCD occurrence using two ECG channels. In this case, the average accuracy of 88.57%, specificity of 84.5%, and sensitivity of 89.33% were found.

Seven minutes before the start of VF, the classifier reached an average accuracy of 91.43%, specificity of 90%, and sensitivity of 90% for channel 2. Ten minutes before the occurrence of SCD, channel 1 resulted in an average accuracy of 78.57%, specificity of 55%, and sensitivity of 77%.

Performance of ST segment

The results reveal that the maximum classification performances were obtained for 1 to 5 minutes before the SCD event using both channels, where the maximum accuracy was 93.33% with specificity and sensitivity of 100%. However, the highest average classification accuracy was achieved two minutes before the SCD occurrence. In this case, the average accuracy was 87%, with a specificity of 89.99% and a sensitivity of 87.94%.

Channel 2 resulted in an average accuracy of 97.5%, specificity of 96%, and sensitivity of 95% five minutes before the start of VF. Using channel 1, seven minutes before the SCD onset, the average accuracy, specificity, and sensitivity rates were 88.57%, 78.33%, and 87.67%, respectively.

Performance of a test algorithm

A testing algorithm was performed to evaluate the computational speed of the proposed algorithm and compare it with other nonlinear methods. In this approach, after segmentation of the signal, instead of extracting the properties based on the 3D phase space, detrended fluctuation analysis (DFA), sample entropy, and Shannon's entropy were used [26]. We chose entropy and DFA because of their frequent usage in previous studies [10, 11, 18, 26]. The rests of the steps were identical to the proposed algorithm.

The results were calculated from the ST segment 5 minutes before the SCD occurrence, with the algorithm execution time. Similarly, the execution time for 5 minutes before the onset of SCD was calculated by the proposed algorithm using the ST segment. All analyses were performed utilizing a Dell Inspiron 5010 laptop with an Intel Core i3 CFI i3 330M 2.13 GHz processor.

Table 3 provides the performance of the SVM classifier using the test algorithm.

A comparison of the results of Table 2 with Table 3 reveals that the performance of the proposed 3D phase space measures was superior to that of the other nonlinear indices of the test algorithm.

Also, the calculation of the test algorithm took 35138.463375 seconds. The calculation time of the proposed algorithm was only 13.865072 seconds. Therefore, the proposed algorithm outperformed the test algorithm regarding execution speed.

Statistical significance

A statistical test, McNemar's test, was performed to compare machine learning results. McNemar is one of the tests for examining the differences in classification outputs for different modes. Table 4 presents the p-value of McNemar's test. The extremely low p-value indicates that the QT is better in a statistically significant manner.

Table 3. Performance of SVM classifier using DFA, sample entropy, and Shannon entropy *of ST segment (Test algorithm)*

Prediction time	Accuracy		Specificity		Sensitivity	
	Mean%± std	Max%	Mean%± std	Max%	Mean%± std	Max%
1	77.75±0.96	93.33	85.88±0.15	100	82.22±0.21	100
2	81.67±0.05	86.67	77.03±0.19	100	77.28±0.17	100
3	69.75±0.11	80	70.72±0.17	85.71	67.09±0.23	87.50
4	67.08±0.05	73.33	67.20±0.13	85.71	64.89±0.15	80
5	71.17±0.07	80	61.02±0.35	85.71	66.06±0.17	83.33

Table 4. P-values of the McNemar's test for comparing the classification outputs of different ECG segments.

Segment	P-Value
QT vs. RT	2.65×10^{-4}
ST vs. RT	2.65×10^{-4}
QS vs. RT	0.11
QR vs. RT	2.65×10^{-4}
QS vs. QT	2.65×10^{-4}
QS vs. QR	0.02
QT vs. QR	5.72×10^{-7}
QT vs. ST	7.35×10^{-7}
QS vs. ST	0.002
QR vs. ST	0.04

Discussion

This experiment aimed to provide an online system that early predicts participants at the risk of SCD. First, different ECG segments were extracted, including QS, RT, QR, QT, and ST. Then, innovative 3D phase space measures of each ECG segment were calculated. The sets were input in the decision-making part, which applied SVM to classify a healthy control group versus a person at risk of SCD. The MIT-BIH SCD Holter, and Normal Sinus Rhythm databases, were used to validate the proposed scheme.

Table 1 compares the proposed structure with other existing studies using identical databases.

Relating to prediction time, the proposed algorithm examined up to 10 minutes before the event onset, which was earlier than the prediction time studied in most literature [1, 10, 11, 14, 16, 26]. The ECG duration is about an hour for the MIT-BIH SCD Holter database. However, the onset of the event shortly occurred for some signals. For longer prediction time, this signal must inevitably be discarded. As a result, the number of samples decreases for event detection longer than 10 minutes.

Most investigations used an HR signal [1, 11, 12, 14, 16]. Few studies have been done on ECG signals [10, 18, 21, 26]. Some literature [21, 23, 26] studied only one segment of ECG signal, while the present study has comprehensively examined the efficiency of different ECG segments in SCD detection.

This study presented a nonlinear approach for analyzing the 3D phase space geometry of the signal. Previously, nonlinear methods have been frequently evaluated [16, 21, 26], but in almost all, dynamic approaches have been used with other conventional features [1, 10-12, 14, 18]. Few works that have used these features alone [26] implemented a heavy computational load algorithm that requires a lot of execution time (to illustrate this, we analyzed some of them in the results section and reported the algorithm execution time). As a result, these procedures are unsuitable for online applications.

In terms of the classification algorithm, we used SVM. It is comparable to other studies because some have used the same classification approach [10, 11, 18, 16, 21, 26].

The results showed that using the QR segment, the SCD can be predicted at a rate of 100% up to 10 minutes before the event occurrence. Therefore, this work outperforms the previously published studies regarding the accuracy rate.

Regarding the importance of ECG segments, RT achieved the lowest mean rate. In this case, the mean detection rates fluctuated from 62 to 72.5%, and the highest rates were about 85.71 to 86.67%. Therefore, RT has the least important in SCD detection. In contrast, the highest mean accuracy rates were from 77.14 to 88.57% utilizing the QT segment, where the maximum SCD detection rates varied from 85.71 to 100%. Consequently, QT is the most significant ECG segment in SCD diagnosis. The results also revealed the significance of ST and QR in SCD detection. The present study emphasized the changes in the QT segment as an influential component in distinguishing pathological from healthy participants. This finding does not coincide with early research, which shows ECG with normal QT intervals in SCD [31]. In contrast, many recent studies confirm the association between QT changes and SCD [32-35]. The association of ST-segment variations with SCD was also emphasized by other scientists [31, 36].

We examined the classification performance in three modes, (1) each channel was considered as an observation, (2) only channel "1" was considered, and (3) exclusively channel "2" was considered. Table 2 reveals higher performances for channel 2 in terms of higher classification rates. Compared to other studies in which each channel was primarily considered an observation, our study showed that merely one channel usage could improve classification performance.

A low-cost scheme with encouraging accuracy rates was proposed for SCD detection. The suggested system paved the way for designing an online early SCD detector using geometrical ECG indices. However, some specific restrictions and limitations should also be deliberated for following systems design. (1) The framework was examined using an available dataset containing the ECG signals of 30 people at SCD risk. The system generalization should be evaluated using a richer databank with more samples. (2) This study extracted 27 indices from 3D phase space, all applied to the classification module. Future work should incorporate feature selection algorithms to reduce data dimensionality and thus increase computational speed. (3) In this study, we used the conventional phase space with a delay of 1. Future works should investigate the performance of the phase space with optimal delay. (4) This experiment used the popular SVM algorithm for classification. Future work should test other machine learning algorithms for inspecting the possibility of increasing the number of accurately classified ECG segments. (5) Since ECG is unstable in high-risk patients and often affected by factors such as age, gender, and medication taken by patients, future works should test the proposed model on other databases providing supplementary demographic information.

Conclusion

The ECG signal of healthy normal does not look different from the ECG of individuals on the verge of SCD. On the other hand, early prediction of the event can help to increase a person's chances of survival. Although many advanced algorithms have been proposed for SCD detection, providing a fast and accurate scheme is still a challenge among cardiologists. The current study evaluated the potential of different ECG segments in early SCD prediction. This issue has not been studied so far. For the first time, new three-dimensional phase space-based measures have been proposed to characterize ECG segments. The proposed scheme was prominent from the performance and computational speed perspectives. The highest accuracy rate was 100% for detecting SCD 10 minutes before the event onset using QR measures. The high system performance advocates that it can be used confidently as an online and early predictor of SCD.

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