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Research Article

Improving the Diagnosis of Sudden Cardiac Death by Using Non-Linear Features of the ECG Signal and Hybrid RBF

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Abstract: Sudden Cardiac Death (SCD) leads to the killing of millions of people worldwide every year. In this article, sudden cardiac death is predicted by utilizing electrocardiogram signal processing. For this purpose, after extracting the signal of heart rate variations from the electrocardiogram signal, temporal and non-linear features have been extracted. In the next step, by applying LDA to the combined feature vector, the feature dimensions are reduced and finally, healthy people and high-risk people are classified through Hybrid-RBF classifiers. The obtained results show that there are features in the signal of heart rate variations related to risk-taking individuals near the occurrence of sudden cardiac death, that completely distinguish them from healthy persons. It has also been shown that from 6 minutes before the occurrence of cardiac death, this increase in the probability of risk is quite evident, so that as we get closer to the occurrence of the accident, the probability of its occurrence also increases, and this is enough time to adopt strategies to prevent it. The simulation results achieved by the data available in the MIT-BIH database prove the ability of the presented methods to achieve accurate diagnosis.

Keywords: Variations in heart rate, sudden cardiac death, linear features, nonlinear features.

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1. Introduction

Cardiovascular diseases are one of the most common diseases of this century. Among them, one of the biggest reasons of death is cardiac arrhythmias in today's societies. Nowadays, in medicine, various tools and methods have been invented to investigate performance of the heart work such as the analysis of the heart's behaviour using the electrocardiogram signal. Of course, there are other methods to measure the behaviour of the heart, such as angiography, MRI, etc., in all these methods, the goal is to obtain different types of structural and functional information from the heart so that the specialist doctor can diagnose both conditions: heart disease and prediction of its occurrence.

Sudden cardiac death is an unexpected event that occurs due to known and unknown factors in a short period of time (less than an hour) [1, 2]. It is estimated that the death caused by Sudden Cardiac Death (SCD) alone is ten times higher than the death caused by accidents in Europe and the United States, so that 300,000 people just die annually in the United States due to Sudden Cardiac Death [3, 4]. Usually, sudden cardiac death begins with a severe arrhythmia such as ventricular tachycardia, ventricular flutter or ventricular fibrillation [5, 6]. Fig. 1 shows the ECG signals of a patient with SCD a few seconds before SCD occurs. Statistics show that SCD increases with age. So that the incidence of SCD in young people (less than 30 years old) is 100 times lower than middle-aged or elderly people [7]. Relatively, women are more immune to SCD than men, although genetic factors also play an important role in the occurrence of sudden cardiac death [7].

Genetic mutations increase the risk factors associated with coronary artery diseases. The results of some studies show that African Americans have a higher risk of SCD than whites. In men, there are many factors that increase the risk of SCD, including various cancers (such as prostate cancer, lung cancer), accidents, chronic respiratory diseases, diabetes, and cerebrovascular diseases. In women, some factors such as lung cancer and cerebrovascular diseases play a more important role than other factors in increasing the risk of SCD [8]. Research shows that nearly 50% of people diagnosed with SCD have not had any heart complications. In this type of people, risk classification is a challenging issue. In addition, 40% of SCD attacks occurred in people who had a history of heart disease with a left ventricular ejection fraction greater than 40%, the remaining 10% of people at risk for SCD are those with structural heart disease and left ventricular ejection fraction. fraction (LVEF) was less than 40%. Therefore, today, risk stratification and treatment tools such as internal cardiac defibrillators have little effect on the overall problem of SCD. It should be noted that a cardiac defibrillator is a battery-operated device that is only slightly larger than a pacemaker. Defibrillators are implanted under the skin, monitor the heart rhythm and correct it if necessary. Calculations based on genetic problems include only 2% of all SCD patients, so considering the high prevalence of SCD in people without a history of heart disease, most methods are focused on identifying and correcting common risk factors. Risk factors for SCD are similar to those for other heart diseases, including smoking, high blood pressure, and diabetes. For example, in Framingham, a US city with a population of 70,000, smoking increased the risk of SCD 2-3 times more than any other factor.

1.1. Previous Works

Studies represent that the QT waveform interval in the ECG signal and heart rate variations are two prominent indicators for assessing the risk of SCD [16, 17]. Despite this measurement, the QT interval is complicated and the results of the review demonstrate that the ability to predict using this method is weak [18]. Studies reveal that analysis based on HRV signal is a strong predictor [19]. Van Hougenhuys et al. [20] have been calculated the standard deviation, the mean value of the RR intervals, as well as the mean value of the standard deviation of the HRV signal. This study proves that the obtained values of the HRV signal in sick people are lower than in young normal people. Although linear methods have been used in HRV analysis, the capability of such methods is not effective in predicting SCD [21, 22]. Nowadays, researchers use non-linear methods to analyze the HRV signal and predict SCD from the HRV signal because these methods provide more information than linear methods [23].

Authors in [24] have been expressed the nature of the EGC signal with the short-term fractional scaling factor and showed that this factor is an independent and suitable factor for predicting SCD in 446 heart attack survivors with left ventricular function assessment less than 35%. In this research, it is claimed that the fluctuation analysis (Detrended DFAα) has the ability to determine the worst case (cardiac death with and without arrhythmia) during 1200 days of follow-up compared to the standard deviation of RR intervals and ventricular problem. In the research carried out in reference [25], it was shown that the short-term fractal scaling properties of the heart rate increase randomly in the elderly. Authors in [26] presented a new nonlinear algorithm using time-independent dimensions of point correlation extracted from the HRV signal. The accuracy of this method is 100% and its sensitivity is 85% for detecting VF/VT. Authors in [22] extracted time and frequency domain parameters from 26 cardiac patients after heart attack (low risk group and high-risk group) and used non-linear and normal entropy methods. They reported 100% resolution, which was obtained by combining features in all fields. Authors in [21] used time and frequency domain parameters of HRV to predict SCD. They have affirmed that short-term low-frequency power during controlled breathing is a suitable tool for predicting SCD in patients with chronic heart problems. Reference [6] presented a home and personal protection system to predict SCD from ECG signals. They reported an accuracy of 92%. In addition, they used short-term HRV analysis to predict events preceding SCD, using four HRV features including HF, LF, and VHF parameters.

Finally, based on SVM and KNN classification methods in [33], the gained results were about 93% and 95% for SCD detection up to 6 minutes in [26]. In this article, we are trying to apply the Hybrid-RBF classification network to improve the percentages. The rest of this paper is designed as follows: in Section 2 we describe the SCD disease and processing the ECG signal to detect it. Section 3, is for describing the proposed feature extraction and the block diagram of the SCD classification method. Also, the proposed Hybrid RBF classifier is described in Section 3. Section 4, represents the results of SCD detection and Section 5 concludes the results.

2. SCD DIAGNOSING METHOD

In this section, we present the suggested method for diagnosing SCD.

2.1. Generalities

At this step, before starting of cardiac arrest1, we divide the ECG signal into one-minute segments in patients who suffer SCD. It should be noted that the onset of cardiac arrest begins with the onset of a ventricular tachycardia. In this article, we can detect SCD before the onset of an attack, according to the assumption used in most articles. The one-minute intervals before SCD are divided into the first one-minute interval before SCD to the sixth one-minute interval before SCD; These intervals are independent of each other. Fig. 1 shows two minutes before the onset of SCD. For normal people, one-minute intervals were selected independently and at different times.

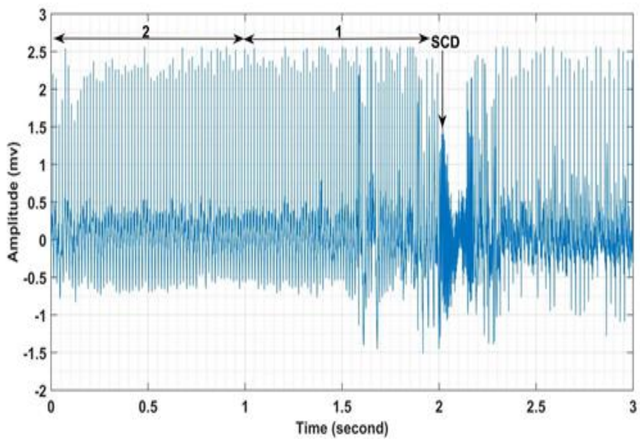

Fig. 1: ECG signal of a patient obtained 2 minutes before the onset of SCD and a few moments after it.

2.1. Noise Elimination

At first, the noise in the ECG signal must be removed. This action is necessary in order to correctly detect the QRS complex. Below are some sources of noise:

2.1.1. City electricity noise

This noise includes the frequency of 51 Hz of city electricity and its harmonics, which can be modelled by the sum of sinusoidal signals. The output of a research explains that the 51 Hz noise in the ECG signal and its harmonics have an amplitude equal to 51% of the peak-to-peak amplitude of the ECG signal [22]. To eliminate the city electricity noise, we use a median filter. Then, after passing the ECG signal through the median filter, we enter it into a band stop-pass filter. Due to the nature of the ECG signal, the coefficients of the band-stop filter are very significant. If coefficients are not selected correctly, it may cause transient states in the ECG signal, which is well explained in reference [26]. Fig. 2 illustrates the city electricity noise and its elimination from ECG signal.

3. Feature Extraction and Reduction Methods

This section as the main part of this article discuss the extraction of features that increase the power of the classification in separating healthy people from risky people. Various features have been used in this article, which are mentioned below.

3.1. Non-Linear Features of the Time-Domain

The features of the time- domain have simple relationships, and due to the non-linear nature of the HRV signal, these types of features are not very useful in distinguishing healthy from unhealthy people, but the combination of these types of features with other non-linear features will increase the resolution of the classifier. Some important features of this area are as following

-Standard deviation of all NN (SDNN) distances:

$$DNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RR_i - Mean)^2} \tag{1}$$

- The standard deviation of the average NN (SDANN) intervals in all the minutes that exist in are same time interval:

$$SDANN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Mean_i - Mean_{all})^2} \tag{2}$$

In the above equation, N is the total number of one-minute parts of NN intervals in a given part, and $Mean_i$ is the mean of NN intervals in one-minute segment. $Mean_{all}$ also indicates the average of all one-minute segments.

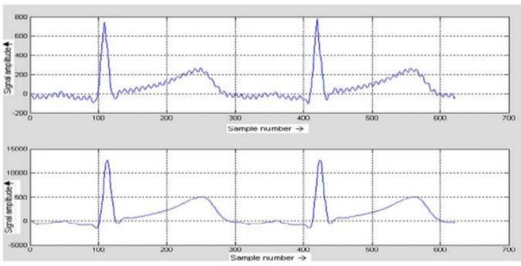

Fig. 2: The consequence of the eliminating city electricity noise from the ECG signal.

- The number of NN intervals whose difference is more than 51 ms:

$$NN50 = \sum_{i=1}^{N}\{|RR_{i+1} - RR_i|\} > 50ms \tag{3}$$

- The value of NN50 is divided by the total number of NN distances in a specific segment:

$$SPNN50 = \frac{NN50}{N} \times 100 \tag{4}$$

- root mean square difference of NN intervals:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{5}$$

- The mean standard deviation of all NN distances for all one-minute segments in a specific part:

$$SDNN_{ind} = \frac{1}{N}\sum_{i=1}^{N} SDNN_i \tag{6}$$

- Heart rate standard deviation:

$$SDHR = \sqrt{\frac{1}{N}\sum(\text{Mean}_{(i)} - \text{Mean HR}_{ah})^2} \tag{7}$$

where Mean HR is the average heart rate.

After extracting these features, we reduce them using the linear discriminant analysis (LDA) feature selection method which itself improves our results dramatically.

Fig. 3 shows the block diagram which indicate the performance of the offered general method.

3.2. Classifier

In [32], Hybrid-RBF network was presented and presented to outperform the support vector machine (SVM) classifier. Fig. 4 shows the Hybrid RBF classifier. This network uses the k-means algorithm to train its hidden layer, which includes radial functions with decision capabilities. After finding the appropriate centres and variances for each radial function in the hidden layer, it is time to find the weights of the output layer, which we do through the adaptive algorithm. Although, as mentioned, there are other methods for this purpose. It should be noted that since the relationship between the data of the hidden layer and the output is linear, adaptive algorithms can be used to update the weights.

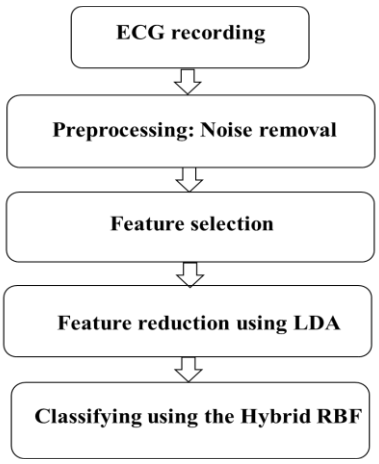

Fig. 3: Block diagram of the general method used in this article to predict sudden cardiac death.

The algorithm of this article is LMS, whose equations are as follows:

$$e(n) = d(n) - W^T(n)\Phi(x_i) \quad (8)$$

$$W(n+1) = W(n) + 2\mu e(n)\Phi(x_i) \quad (9)$$

where $d(n)$ is the desired output value known in the training phase and we estimate it in the testing phase. $W(n)$ is the general vector of weights w_i and $\Phi(x_i)$ defines the general vector of $\phi(x_i)$). $e(n)$ is the error value and μ is the step size, which is assumed constant here. This algorithm adjusts the weights of the values of the radial functions according to the error between the estimated and the actual values. Therefore, we have the following two steps up to this section:

1) Using the unsupervised algorithm (k-means) to obtain centers and variances of radial functions.

2) Using the LMS algorithm to update the coefficients of the output layer.

As mentioned in [32] the classification procedure of the Hybrid RBF classifier can be at least 30 percent less than the SVM that is used in many SCD classification papers including [21].

Table 1: A comparison of the methods between previous researchers and the time domain and bi-spectrum methods four minutes before SCD and earlier

Features and reference number	Number of features	classifier	Percent correctness of 4 to 6 minutes before SCD
Combined-linear, nonlinear, and TF methods [27]	Linear time domain (5), Linear time domain (4), TF (11) and nonlinear (4)	KNN, MLP	4 min before = 83.96%
nonlinear and TF methods [28]	Nonlinear features (18), Sudden Cardic Death Index	DT,SVM	4 min before = 92.11% (SVM)
Combined-linear, nonlinear and TF methods [17]	Bispectrum features of HRV signal (6) time-domain features (2)	SVM, KNN With LDA	4 min before= 94.46% (SVM) 5 min before = 91.07% (KNN) 6 min before = 92.77% (KNN)
Non-linear features [26]	Non-linear RQA (13), IncEn (2)	KNN, DT-SVM. Naïve Bayes	6 min before = 95% (KNN, DT-SVM. Naïve Bayes)
[18]	Linear (time, frequency domain), TF domain and, nonlinear methods (PP, DFA)	MLP	95.23% (4 min before) 83.88% (12 min before)
[19]	Linear (time, frequency domain), TF domain, and nonlinear methods (PP, DFA)	MLP, SVM, KNN	95.24% (4 min before) 84.28% (13 min before)
[20]	EEMD, linear (time, frequency domain), TF domain, and nonlinear methods (Ren, FuEn, dispersion entropy, Renyi distribution entropy (RdisEn), and improved multiscale permutation entropy	KNN	94.7% (4 min before) 96.1% (14 min before)
[21]	DWT, Nonlinear methods (Fractal Dimension (FD), DFA Hurst's exponent (H), Sample Entropy, Approximate Entropy, and Correlation Dimension (CD))	KNN, SVM, DT	92.11% (4 min before)
This work	Bispectrum features of HRV signal (6) time-domain features (2)	Hybrid-RBF	4 min before= 96.36% (Hybrid-RBF) 5 min before = 96% (Hybrid-RBF) 6 min before = 96% (Hybrid-RBF)

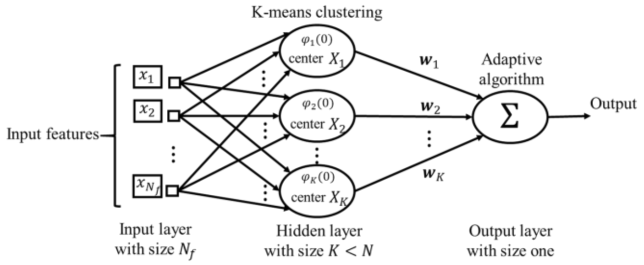

Fig. 4: Order of performance for K-means and adaptive algorithms in RBF network.

4. Results

In this section, we will review and compare the results presented in this article and the previous work. To this end, we use a common database with the rest of the research.

4.1. Article Database

In this article, the database available on the reliable site Physionet [15] and the MIT-BIH database have been utilized. This database is used by many authoritative articles and is very useful for comparison with the work of other researchers in the field of sudden cardiac death. Table 1 shows the comparison of the SCD detection results for various papers and our proposed method.

As we can see, the results are based on two factors, first the number of minutes before SCD and the next one is accuracy. Our experience showed that as we get closer to the happening of the SCD, the detection of it becomes easier and the accuracy rises. For example, the detection of SCD, 4 minutes before its happening is more accurate than detecting it in 6 minutes before SCD. Also, our proposed method works superior than most of the given results in the literature in all the three cases of 4, 5 and 6 minutes detection before SCD.

5. Conclusion

In this paper, we introduce two methods to predict sudden cardiac death (SCD) with linear and nonlinear features extracted from heart rate variability (HRV) signal. It is a challenge to predict five and six minutes before the onset of SCD. This method includes four steps: pre-processing, feature extraction, feature reduction and classification. In the first step, QRS complexes are identified from the electrocardiogram (ECG) signal and then the HRV signal is extracted. In the second step, the linear and non-linear features of the HRV signal are obtained. In the next step, these features are reduced to one feature by the linear discriminant analysis (LDA) technique. Finally, the Hybrid-RBF classifier is used to classify the HRV signals. We utilized two databases, the MIT/BIH Sudden Cardiac Death (SCD) database and the Physiobank Normal Sinus Rhythm (NSR) database. In this work, we achieved the prediction of the occurrence of SCD for five and six minutes before SCD with an accuracy of more than 96%.

CRediT Authorship Contribution Statement

Afshin Koliji: Methodology, Software, Writing - original draft, Writing - review & editing. **Sara MihanDoost:** Supervision, Validation. **Ehsan Mostafapour:** Supervision, Validation. **Ehsan Mostafapour**: Conceptualization, Roles/Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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Afshin Koliji was born in Mohabad, Iran in 1980, he received his B. Sc. In 2001 and currently pursuing his M. Sc. In telecommunications engineering in Urmia University of technology, Urmia, Iran. His main field of research is Signal and image processing.

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