Myocardial infarction detection using artificial intelligence and nonlinear features based on synthesis of the standard 12-lead and Frank XYZ leads

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Research

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RESEARCH

Myocardial infarction detection using artificial intelligence and nonlinear features based on synthesis of the standard 12-lead and Frank XYZ leads

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Abstract

Nowadays cardiovascular diseases (CVD) is one of the prime causes of human mortality, which has received tremendous and elaborative research interests regarding the prevention of CVD. Myocardial ischemia is a kind of CVD which will lead to myocardial infarction (MI). The diagnostic criterion of MI is supplemented with clinical judgment and several electrocardiographic (ECG) or vectorcardiographic (VCG) programs. However the visual inspection of ECG or VCG signals by cardiologists is tedious, laborious and subjective. To overcome such disadvantages, numerous MI detection techniques including signal processing and artificial intelligence tools have been developed. In this study we propose a novel technique for automatic detection of MI based on disparity of cardiac system dynamics and synthesis of the standard 12-lead and Frank XYZ leads. First, 12-lead ECG signals are reduced to 3-dimensional VCG signals, which are synthesized with Frank XYZ leads to build a hybrid 4-dimensional cardiac vector. This vector is decomposed into a series of proper rotation components (PRCs) by using the intrinsic time-scale decomposition (ITD) method. Second, four levels discrete wavelet transform (DWT) is employed to decompose the predominant PRCs into different frequency bands, in which third-order Daubechies (db3) wavelet function is selected as reference variable for analysis. Third, phase space of the reference variable is reconstructed based on db3, in which the properties associated with the nonlinear cardiac system dynamics are preserved. Three-dimensional (3D) phase space reconstruction (PSR) together with Euclidean distance (ED) has been utilized to derive features. Fourth, neural networks are then used to model, identify and classify cardiac system dynamics between normal (healthy) and MI cardiac vector signals. Finally, experiments are carried out on the PhysioNet PTB database to assess the effectiveness of the proposed method, in which conventional 12-lead and Frank XYZ leads ECG signal fragments from 148 patients with MI and 52 healthy controls were extracted. By using the 10-fold cross-validation style, the achieved average classification accuracy is reported to be 98.20%. The result verifies the effectiveness of the proposed method which can serve as a potential candidate for the automatic detection of MI in the clinical application.

Keywords: myocardial infarction (MI) detection; electrocardiographic (ECG); intrinsic time-scale decomposition (ITD); discrete wavelet transform (DWT); cardiac system dynamics; neural networks

1 Introduction

Cardiovascular diseases (CVD) are the most common cause of human mortality [1]. Measurement of timing intervals and amplitudes of the electrocardiographic (ECG) or vectorcardiographic (VCG) waves provides fundamental feature in CVD diagnostics. Myocardial ischemia is a kind of CVD which will lead to myocardial infarction (MI). Pathological alterations provoked by MI cause slow conduction by increasing axial resistance on coupling between cells. This issue may cause abnormal patterns in the dynamics of the tip of the cardiac vector [2]. Hence analysis of the morphology of ECG or VCG recordings plays an important role in monitoring the variation of dynamics in the pathological alterations of cardiac patterns caused by MI. In order to diagnose CVD, the standard 12-lead ECG has been regarded as the gold standard for monitoring and analyzing alternations in the cardiac activity [3]. From the perspective of medical science, cardiologists have been accustomed to the standard 12-lead system due to its noninvasiveness, inexpensiveness and availability for CVD diagnosis. Traditionally, detection of MI based on the visual inspection of ECG or VCG signals by cardiologists is tedious, laborious and subjective [4]. In addition, it requires expertise in the analysis of long-term ECG or VCG signals [5]. In those application scenarios absence of experts, for example, in emergency situations, computer-aided automatic detection of MI becomes significant.

To overcome the aforementioned disadvantages of the standard 12-lead ECG system, strategies can be taken in two aspects: (1) reduce the number of leads; and (2) employ artificial intelligence tools to analyze and classify cardiac patterns. In the first aspect, several studies have proposed to reduce the number of leads that can reconstruct the 12-lead ECG signals without loss of significant information in diagnosis. These methods can be categorized into two types: using subsets of the 12-lead and using special leads [4, 6]. For the first category, subsets of the leads of the 12-lead ECG are used to reconstruct the standard 12-lead ECG [7–12]. The missing precordial leads are reconstructed from the remaining leads by using either a personalized or a universal transformation. For the second category, special leads are used based on the orthogonal lead system. For example, the orthogonal Frank XYZ leads and EASI leads are well-known for use of fewer leads compared to the widely used 12-lead ECG systems, since it is convenient to implement and can capture more information than Holter leads [6, 13–16].

In the second aspect, ECG or VCG signal based arrhythmia or MI detection techniques including signal processing and artificial intelligence tools have been developed, such as linear [17, 18] and nonlinear methods [19, 20], Wavelet Transform (WT) [21], Complex Wavelet Transform (CWT) [22, 23], Pitch Synchronous Wavelet Transform (PSWT) [24], Discrete Wavelet Transform (DWT) [25], Kalman filtering (KF) [26], Least Mean Squares algorithm (LMS) [27], ensemble learning [28, 29], Artificial Neural Networks (ANN) [30], Adaptive Neuro-fuzzy Inference System (ANFIS) [31], support vector machine (SVM) [20], and deep learning [32–42]. For example, Varatharajan et al. [43] used linear discriminant analysis (LDA) to reduce the features presented in the ECG signal, which followed with a SVM model with a weighted kernel function for the classification of cardiac arrhythmia. Plawiak [44] used the spectral power density to enhance feature performance extracted from ECG signals and employed genetic algorithms for feature selection.

Then several machine learning tools including SVM, k-nearest neighbor, ANN, have been used for the classification of cardiac disorders. Kumar and Inbarani [29] used DWT to extract effective features. Then neighborhood rough set was employed for the ECG signal classification. Acharya et al. [35] used ECG signals of two seconds and five seconds' durations as the input of convolutional neural network (CNN) with eleven-layer to detect different types of cardiac arrhythmia. There is no need for the pre-processing of QRS detection. Kumar et al. [45] used flexible analytic wavelet transform (FAWT) to decompose ECG beats into subband signals. Then sample entropy was computed as features and fed into random forest (RF), J48 decision tree, back propagation neural network (BPNN), and least-squares support vector machine (LS-SVM) classifiers for detection of MI. Yildirim [37] decomposed ECG signals into frequency sub-bands at different scales, which were used as the input of long-short term memory networks (LSTMs) for ECG signal classification. However, it still remains an open problem for the automatic arrhythmia or MI detection with high efficiency and accuracy based on different types of lead system in discriminating between normal and abnormal ECG signals [46].

Because of the redundant and discrete-time characteristics of ECG and VCG signals, numerous methods with combination of time and frequency domains and nonlinear analysis have been developed to handle the problem [47]. Especially for the nonlinear analysis, nonlinear parameters extracted through different types of entropies [48], Lyapunov exponent [49], local fractal dimension [50], higher order spectra (HOS) cumulants [51], recurrence quantification analysis (RQA) [52] and Hurst exponent [53], have been employed for automatic detection of abnormal ECG or VCG signals. Despite the fact that the above-mentioned methods have achieved respectable classification accuracy, the potential of nonlinear methods, including the nonlinear features and the modeling and identification algorithms for nonlinear cardiac system dynamics, has not been thoroughly investigated. Considering the characteristics that the ECG signal is highly random, nonlinear, nonstationary and non-Gaussian in nature [54], self-adaptive signal processing methods, such as empirical mode decomposition (EMD) [55, 56], local mean decomposition (LMD) [57] and intrinsic time-scale decomposition (ITD) [58], can be employed to extract effective and predominant features from ECG or VCG signals [59, 60]. In comparison to EMD and LMD, ITD significantly improves the computational efficiency. In addition, with high decomposition efficiency and frequency resolution, ITD can help decompose a complex signal into several proper rotation components (PRCs) and a baseline signal, which leads to the accurate extraction of the dynamic features of nonlinear signals. In the present work we have developed a novel algorithm to compute the representative features based on ITD algorithm and the synthesis of 12-lead and Frank XYZ leads. We hypothesize that these features reflect the abnormal alterations in the dynamics of the cardiac vector and can achieve high sensitivity and specificity simultaneously as a discriminator of MI.

The novelty of this study lies in four aspects: 1) we use the synthesis of 12-lead and Frank XYZ leads to build a new 4-dimensional cardiac vector which may fully reflect the pathological alterations provoked by MI. 2) ITD method is employed to measure the variability of cardiac vector and the first proper rotation components (PRCs) are extracted as predominant PRCs which contain most of the cardiac

vector's energy. 3) Discrete wavelet transform (DWT) decomposes the predominant PRCs into different frequency bands, which are used to construct the reference variables. 4) 3D phase space of the predominant PRCs components is reconstructed, in which the properties associated with the cardiac system dynamics are preserved. 5) Cardiac system dynamics can be modeled and identified using neural networks, which employ the ED of 3D PSR of the reference variables as input features. 6) The difference of cardiac system dynamics between healthy control and MI cardiac vector is computed and used for the detection of MI based on a bank of estimators.

2 Method

In this section, we propose a method to discriminate between normal and MI cardiac vectors using the information obtained from nonlinear cardiac system dynamics for the detection of MI. It is divided into the training stage and the classification stage, which includes the following steps. In the first step, the synthesis of 12-lead and Frank XYZ leads is used to build a new 4-dimensional cardiac vector. In the second step, ITD is applied to decompose the cardiac vector into several PRCs to extract PRC_1 predominant components. In the third step, DWT is employed to decompose the predominant PRCs into different frequency bands. In the fourth step, PSR is applied to extract nonlinear dynamics of cardiac system and Euclidean distances are computed. Finally, feature vectors are fed into the neural networks for the modeling and identification of cardiac system dynamics. The difference of dynamics between normal (healthy) and MI cardiac vector will be applied for the classification task. The flowchart of the proposed algorithm is illustrated in Fig. 1.

2.1 ECG database

In this study we utilize the popular and publicly available PTB database which has been acquired at the Department of Cardiology of University Clinic Benjamin

Franklin in Berlin, Germany, and has been provided to the users of PhysioNet [61, 62]. The database contains 549 records from 290 subjects, in which there are 148 patients with MI and 52 healthy control (HC) subjects. Each subject is represented by one to five records. Hence there are 367 and 78 heart beat records for MI and HC subjects, respectively. Each record includes 15 simultaneously measured signals: the conventional 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) together with the 3 Frank XYZ leads ECGs (vX, vY, vZ). Each signal was digitized at 1000 samples per second.

In this study, the characteristics of the used ECG data obtained from PTB database is presented in Table 1.

Table 1 Description of the PTB database with the selected ECG signals.

Characteristics	HC	MI
Age range	17-81	36-86
Average age	43.4	60.4
Number of participants	52	148
Number of heart beat records	78	367
Ratio of male to female	3	2.89

2.2 Synthesis of 12-lead and Frank XYZ leads

First, transform the 12-lead ECG into 3-dimensional VCG since VCG signals and 12-lead ECG signals can be linearly transformed into each other without loss of useful information content pertaining to the cardiac system dynamics [63]. The transformation relationship is shown as follows [64]:

$$\begin{cases} V_1 &= 0.38x_1 - 0.07x_2 - 0.13x_7 + 0.05x_8 - 0.01x_9 + 0.14x_{10} + 0.06x_{11} + 0.54x_{12} \\ V_2 &= -0.07x_1 + 0.93x_2 + 0.06x_7 - 0.02x_8 - 0.05x_9 + 0.06x_{10} - 0.17x_{11} + 0.13x_{12} \\ V_3 &= 0.11x_1 - 0.23x_2 - 0.43x_7 - 0.06x_8 - 0.14x_9 - 0.20x_{10} - 0.11x_{11} + 0.31x_{12} \end{cases} \quad (1)$$

where x_1 to x_{12} represent the 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6), respectively, V_1, V_2, V_3 represent the transformed 3 VCG signals, respectively. For the Frank XYZ leads,

$$V_4 = \sqrt{X^2 + Y^2 + Z^2} \quad (2)$$

where X, Y and Z represent the lead value of three corresponding axes, V_4 represents the VCG voltage magnitude of the 3 Frank leads by taking the square root of the sum of the squares for the three individual axes.

Here we build a new 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$, which contains useful information content from the 12-lead and Frank XYZ leads. It reduces the dimension of feature vectors instead of using 15 leads ECG signals directly. In addition, the novel cardiac vector may fully reflect the pathological alterations provoked by MI and may be correlated to the disparity of cardiac system dynamics between HC and MI subjects. The examples of the 4-dimensional cardiac vectors from HC and MI subjects are demonstrated in Figs. 2 and 3.

Fig. 2 Examples of the synthesis of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC subject.

Fig. 3 Examples of the synthesis of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from MI subject.

2.3 Intrinsic time-scale decomposition (ITD)

Intrinsic time-scale decomposition (ITD) is suitable for analyzing nonstationary and nonlinear signals such as the ECG and VCG signals. Without resorting to the spline interpolation to signal extrema and sifting in mono-component separation, it decomposes a signal into proper rotation components (PRCs) that are suitable to calculate the instantaneous frequency and amplitude, based on the baseline defined via linear transform. The obtained decomposition result precisely preserves the temporal information of each component regarding signal critical points and riding waves, with a time resolution equal to the time scale of the occurrence of extrema in the raw signal [65]. Based on the single wave analysis, it extracts accurately the inherent instantaneous amplitude and frequency/phase information and other relevant morphological features [58].

For a time series signal $I(t)$, define the operator L to extract the baseline signal from $I(t)$ and the residual signal is called the proper rotation component (PRC). The decomposed signal $I(t)$ can be expressed as

$$I(t) = LI(t) + (1 - L)I(t) = B(t) + H(t) \quad (3)$$

where $B(t)$ is the baseline signal and $H(t)$ is the proper rotation.

The decomposition procedure of a nonlinear signal can be summarized by the following steps:

- **Step 1:** Find the local extrema of the signal $I(t)$, denoted by I_k , and the corresponding occurrence time instant $\tau_k, k = 0, 1, 2, \dots$. For convenience $\tau_0 = 0$.
- **Step 2:** Suppose the operators $B(t)$ and $H(t)$ are given over the interval $[0, \tau_k]$, and $I(t)$ is set on the interval $t \in [0, \tau_{k+2}]$. Then on the interval $[\tau_k, \tau_{k+1}]$ between two adjacent extrema I_k and I_{k+1} , the piecewise baseline extraction operator is defined as

$$LI(t) = B(t) = B_k + \left(\frac{B_{k+1} - B_k}{I_{k+1} - I_k} \right) \times (I(t) - I_k), t \in [\tau_k, \tau_{k+1}], \quad (4)$$

where

$$B_{k+1} = \beta[I_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k} \right)(I_{k+2} - I_k)] + (1 - \beta)I_{k+1}, \quad (5)$$

and $0 < \beta < 1$, typically $\beta = 0.5$.

- **Step 3:** After extracting the baseline signal, the operator Θ for extracting the residual signal as PRCs is defined as

$$\Theta I(t) \equiv (1 - L)I(t) = I(t) - B(t) \quad (6)$$

According to the definition, the PRC is a riding wave with the highest frequency on the baseline. Therefore, ITD separates the PRC in a frequency order from high to low. In addition, the PRC is obtained directly by subtracting the baseline from the input signal, without resorting to any sifting within each iterative decomposition.

Thus, ITD has low computational complexity, and more importantly, avoids the smoothing of transients and time-scale smearing due to repetitive sifting [65].

Take the baseline $B(t)$ as the input signal $I(t)$, and repeat steps (1)–(3), until the baseline becomes a monotonic function or a constant. Eventually, the raw signal will be decomposed into PRCs and a trend [65]

$$I(t) = \sum_{i=1}^{\rho} H^i(t) + B^{\rho}(t), \quad (7)$$

where ρ is the decomposition level.

Samples of the ITD of 4-dimensional cardiac vector from the HC and MI subjects are demonstrated in Figs. 4 and 5.

(b) Original V_2 vector and its ITD from HC

(c) Original V_3 vector and its ITD from HC

(d) Original V_4 vector and its ITD from HC

Fig. 4 Samples of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC subject.

(a) Original V_1 vector and its ITD from MI.

(b) Original V_2 vector and its ITD from MI

(c) Original V_3 vector and its ITD from MI

(d) Original V_4 vector and its ITD from MI

Fig. 5 Samples of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from MI subject.

2.4 Discrete wavelet transform (DWT)

Wavelet transform is an effective time-frequency tool for the analysis of non-stationary signals. Discrete Wavelet Transform (DWT) is a procedure for the decomposition of input signal $H(t)$ ($H(t)$ is the PRC of the cardiac vector in this work) into sets of function, called wavelets, by scaling and shifting of mother wavelet function. Consequently, the decomposition i.e. set of wavelet coefficients are formed.

To accomplish this, the signal $H(t)$ can be reconstructed as linear combination of wavelets and weighting wavelet coefficients. The setting of appropriate wavelet function and the number of decomposition levels is of great importance for correctly reconstructing the signal $H(t)$. It was reported that Most of the energy of the ECG signal lies between 0.5 Hz and 40 Hz [66], for which the wavelet coefficients is concentrated in the lower sub-bands. In order to extract five physiological cardiac vector bands, four levels DWT with third-order Daubechies (db3) wavelet function have been used (Table 2 represents the frequency distribution of the DWT-based coefficients of the PRCs of the cardiac vector at 1000 Hz), from which the choice of the mother wavelet is supported by many works in literature [67–69]. Fig. 6 shows samples of cardiac vector channel of HC and MI subjects and their decomposed frequency bands of predominant PRCs. Since the frequency components above 40 Hz is lack of use in ECG analysis, in order to reduce the feature dimension, the advisable sub-band (D4) is selected for feature acquisition. The detailed information of levels 1, 2 and 3 (sub-bands D1, D2 and D3) are discarded since the frequencies covered by these levels are higher than frequency content of the cardiac vector.

Table 2 Frequency band of PRCs of the cardiac vector using fourth level decomposition of DWT

Decomposition levels	Sub-bands	Frequency range (Hz)
1	D1	250-500
2	D2	125-250
3	D3	62.5-125
4	D4	31.25-62.5
4	A4	0-11.25

(a) Four levels DWT of PRC_1 of the V_1 and V_2 vectors from HC.

(b) Four levels DWT of PRC_1 of the V_3 and V_4 vectors from HC.

(c) Four levels DWT of PRC₁ of the V₁ and V₂ vectors from MI.

(d) Four levels DWT of PRC_1 of the V_3 and V_4 vectors from MI.

Fig. 6 Samples of four levels DWT of PRC_1 of the 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC and MI subjects.

2.5 Phase space reconstruction (PSR)

It is sometimes necessary to search for patterns in a time series and in a higher dimensional transformation of the time series [70]. Phase space reconstruction is a method used to reconstruct the so-called phase space. The concept of phase space is a useful tool for characterizing any low-dimensional or high-dimensional dynamic system. A dynamic system can be described using a phase space diagram, which essentially provides a coordinate system where the coordinates are all the variables comprising mathematical formulation of the system. A point in the phase space represents the state of the system at any given time [71, 72]. Every db3 wavelet function of the PRC of the cardiac vector can be written as the time series vector $V = \{v_1, v_2, v_3, \dots, v_K\}$, where K is the total number of data points. The phase space can be reconstructed according to [72]:

$$Y_j = (V_j, V_{j+\tau}, V_{j+2\tau}, \dots, V_{j+(d-1)\tau}) \quad (8)$$

where $j = 1, 2, \dots, K - (d-1)\tau$, d is the embedding dimension of the phase space and τ is a time lag. It is worthwhile to mention that the properties associated with the cardiac dynamics are preserved in the reconstructed phase space.

The behaviour of the signal over time can be visualized using PSR (especially when $d = 2$ or 3). In this work, we have confined our discussion to the value of embedding dimension $d = 3$, because of their visualization simplicity. In addition, different studies have found this value to best represent the attractor for human biological system [73, 74]. For τ , we either use the first-zero crossing of the autocorrelation function for each time series or the average τ value obtained from all the time series in the training dataset using the method proposed in [75]. In this study, we consider the values of time lag $\tau = 1$ to test the classification performance. PSR for $d = 3$ has been referred to as 3D PSR.

Reconstructed phase spaces have been proven to be topologically equivalent to the original system and therefore are capable of recovering the nonlinear dynamics of the generating system [76, 77]. This implies that the full dynamics of the cardiac system are accessible in this space, and for this reason, features extracted from it can potentially contain more and/or different information than the common features extraction method [78].

3D PSR is the plot of three delayed vectors V_j, V_{j+1} and V_{j+2} to visualize the dynamics of human cardiac system. Euclidian distance (ED) of a point (V_j, V_{j+1}, V_{j+2}) , which is the distance of the point from origin in 3D PSR and can be defined as [72]

$$ED_j = \sqrt{V_j^2 + V_{j+1}^2 + V_{j+2}^2} \quad (9)$$

ED measures can be used in features extraction and have been studied and applied in many fields, such as clustering algorithms and induced aggregation operators [79].

2.6 Feature extraction and selection

In order to obtain more efficient features, this paper proposes the following extraction scheme.

(1) ITD of the cardiac vector and derivation of predominant PRCs. The signals obtained by ITD method, which are a series of decomposing signals, cannot be directly used to classify because of the high feature dimension. To solve this problem, the Pearson's correlation coefficient is calculated to measure the correlation between the first six PRCs and the original cardiac vector. The PRC component with higher correlation coefficient is more highly correlated to the original signal, which means the signal energy is mostly concentrated in this PRC as well. In the present study most of the energy is concentrated in PRC₁ component, which have the most important information from the cardiac vector and are considered to be the predominant PRCs (seen from Table 3).

Table 3 The average correlation coefficients between each PRC and original cardiac vector from HC and MI subjects in the PTB database.

Cardiac vector type	Average correlation coefficients					
	PRC ₁	PRC ₂	PRC ₃	PRC ₄	PRC ₅	PRC ₆
V ₁ for HC	0.6640	0.3671	0.3390	0.2873	0.1814	0.2889
V ₂ for HC	0.4547	0.2704	0.2717	0.2233	0.2463	0.1556
V ₃ for HC	0.7034	0.2865	0.3271	0.3165	0.1366	0.2643
V ₄ for HC	0.6399	0.3025	0.2997	0.2633	0.1979	0.1732
V ₁ for MI	0.5155	0.3262	0.3124	0.2474	0.2484	0.2086
V ₂ for MI	0.5898	0.2809	0.2524	0.2498	0.2146	0.2073
V ₃ for MI	0.6186	0.2647	0.2346	0.2153	0.2018	0.2034
V ₄ for MI	0.5289	0.3190	0.2706	0.2478	0.2721	0.1972
Mean	0.5894	0.3021	0.2884	0.2563	0.2124	0.2123

(2) Four levels DWT is employed to decompose the predominant PRCs into different frequency bands, in which third-order Daubechies (db3) wavelet function is selected for analysis. D4 of the PRC₁ cardiac vector are regarded as reference variables $[V_1^{\text{PRC}_1^{\text{D4}}}, V_2^{\text{PRC}_1^{\text{D4}}}, V_3^{\text{PRC}_1^{\text{D4}}}, V_4^{\text{PRC}_1^{\text{D4}}}]^T$ and are used for feature derivation.

(3) Reconstruct the phase space of the reference variables with selected values of d and τ ;

(4) Compute ED of 3D PSR of the reference variables. Concatenate them to form a feature vector $[ED_{j_1}^{V_1^{\text{PRC}_1^{\text{D4}}}}, ED_{j_2}^{V_2^{\text{PRC}_1^{\text{D4}}}}, ED_{j_3}^{V_3^{\text{PRC}_1^{\text{D4}}}}, ED_{j_4}^{V_4^{\text{PRC}_1^{\text{D4}}}}]^T$.

For the PTB database, cardiac vectors are analyzed and cardiac system dynamics are extracted by using ITD, DWT and 3D PSR. First, ITD of the cardiac vector is exhibited in Figs. 4 and 5. Four levels DWT of the PRC₁ of cardiac vector from the HC and MI subjects are demonstrated in Fig. 6. The db3 of the PRC₁ is utilized to form the reference variables $[V_1^{\text{PRC}_1^{\text{D4}}}, V_2^{\text{PRC}_1^{\text{D4}}}, V_3^{\text{PRC}_1^{\text{D4}}}, V_4^{\text{PRC}_1^{\text{D4}}}]^T$. Samples of the 3D PSR of the reference variables are exhibited in Figs. 7 and 8. After 3D PSR, features of $[ED_{j_1}^{V_1^{\text{PRC}_1^{\text{D4}}}}, ED_{j_2}^{V_2^{\text{PRC}_1^{\text{D4}}}}, ED_{j_3}^{V_3^{\text{PRC}_1^{\text{D4}}}}, ED_{j_4}^{V_4^{\text{PRC}_1^{\text{D4}}}}]^T$ for cardiac vectors of the HC and MI subjects are derived through ED computation, as demonstrated in Figs. 9 and 10. As we have analyzed before, significant difference in cardiac system dynamics have been reported between HC and MI subjects, which can also be seen obviously from Figs. 7 and 8.

Fig. 7 Samples of 3D PSR of $\text{PRC}_1^{\text{D}4}$ of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC subject.

Fig. 8 Samples of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from MI subject.

(a) Euclidian distance of 3D PSR of PRC_1^{D4} for V_1 .

(b) Euclidian distance of 3D PSR of PRC_1^{D4} for V_2 .

(c) Euclidian distance of 3D PSR of PRC_1^{D4} for V_3 .

(d) Euclidian distance of 3D PSR of PRC_1^{D4} for V_4 .

Fig. 9 Samples of the Euclidian distance of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC subject.

(a) Euclidian distance of 3D PSR of PRC_1^{D4} for V_1 .

(b) Euclidian distance of 3D PSR of PRC_1^{D4} for V_2 .

(c) Euclidian distance of 3D PSR of PRC_1^{D4} for V_3 .

(d) Euclidian distance of 3D PSR of PRC_1^{D4} for V_4 .

Fig. 10 Samples of the Euclidian distance of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from MI subject.

2.7 Training and modeling mechanism based on selected features

In this section, we present a scheme for modeling and derivation of nonlinear cardiac system dynamics derived from the synthesis of 12-lead and Frank XYZ leads from normal and MI subjects based on the extracted features.

Consider a general nonlinear cardiac system dynamics in the following form:

$$\dot{x} = F(x; p) + v(x; p) \quad (10)$$

where $x = [x_1, \dots, x_n]^T \in R^n$ are the system states which represent the features $[ED_j^{V_1^{\text{PRCD}^4}}, ED_j^{V_2^{\text{PRCD}^4}}, ED_j^{V_3^{\text{PRCD}^4}}, ED_j^{V_4^{\text{PRCD}^4}}]^T$ is a constant vector of system parameters. $F(x; p) = [f_1(x; p), \dots, f_n(x; p)]^T$ is a smooth but unknown nonlinear vector representing the cardiac system dynamics, $v(x; p)$ is the modeling uncertainty. Since the modeling uncertainty $v(x; p)$ and the cardiac system dynamics $F(x; p)$ cannot be decoupled from each other, we consider the two terms together as an undivided term, and define $\phi(x; p) := F(x; p) + v(x; p)$ as the general cardiac system dynamics. Then, the following steps are taken to model and derive the cardiac system dynamics via deterministic learning theory [80–82].

In the first step, standard RBF neural networks are constructed in the following form

$$f_{nn}(Z) = \sum_{i=1}^N w_i s_i(Z) = W^T S(Z), \quad (11)$$

where Z is the input vector, $W = [w_1, \dots, w_N]^T \in R^N$ is the weight vector, N is the node number of the neural networks, and $S(Z) = [s_1(\|Z - \mu_1\|), \dots, s_N(\|Z - \mu_N\|)]^T$, with $s_i(\|Z - \mu_i\|) = \exp[-\frac{(Z - \mu_i)^T(Z - \mu_i)}{\eta_i^2}]$ being a Gaussian function, $\mu_i (i = 1, \dots, N)$ being distinct points in state space, and η_i being the width of the receptive field.

In the second step, the following dynamical RBF neural networks are employed to model and derive the cardiac system dynamics $\phi(x; p)$:

$$\dot{\hat{x}} = -A(\hat{x} - x) + \hat{W}_j^T S_j(x) \quad (12)$$

where $\hat{x} = [\hat{x}_1, \dots, \hat{x}_n]$ is the state vector of the dynamical RBF neural networks, $A = \text{diag}[a_1, \dots, a_n]$ is a diagonal matrix, with $a_i > 0$ being design constants, localized RBF neural networks $\hat{W}_j^T S_j(x) = \sum_{i=1}^N w_{ij} s_{ij}(x)$ are used to approximate the unknown $\phi(x; p)$, where $\hat{W}_j = [w_{1j}, \dots, w_{Nj}]^T$, $S_j = [s_{1j}, \dots, s_{Nj}]^T$, for $j = 1, \dots, n$.

The following law is used to update the neural weights

$$\dot{\hat{W}}_i = \dot{\tilde{W}}_i = -\Gamma_i S_i(x) \tilde{x}_i - \sigma_i \Gamma_i \hat{W}_i \quad (13)$$

where $\tilde{x}_i = \hat{x}_i - x_i$, $\tilde{W}_i = \hat{W}_i - W_i^*$, W_i^* is the ideal constant weight vector such that $\phi_i(x; p) = W_i^{*T} S_i(x) + \epsilon_i(x)$, $\epsilon_i(x) < \epsilon^*$ represents the neural network modeling error, $\Gamma_i = \Gamma_i^T > 0$, and $\sigma_i > 0$ is a small value.

With Eqs. (10)-(12), the derivative of the state estimation error $\tilde{x}_i$ satisfies

$$\dot{\tilde{x}}_i = -a_i \tilde{x}_i + \hat{W}_i^T S_i(x) - \phi_i(x; p) = -a_i \tilde{x}_i + \tilde{W}_i^T S_i(x) - \epsilon_i \quad (14)$$

In the third step, by using the local approximation property of RBF neural networks, the overall system consisting of dynamical model (14) and the neural weight updating law (13) can be summarized into the following form in the region Ω_ζ

$$\begin{bmatrix} \dot{\tilde{x}}_i \\ \dot{\tilde{W}}_{\zeta i} \end{bmatrix} = \begin{bmatrix} -a_i & S_{\zeta i}(x)^T \\ -\Gamma_{\zeta i} S_{\zeta i}(x) & 0 \end{bmatrix} \begin{bmatrix} \tilde{x}_i \\ \tilde{W}_{\zeta i} \end{bmatrix} + \begin{bmatrix} -\epsilon_{\zeta i} \\ -\sigma_i \Gamma_{\zeta i} \hat{W}_{\zeta i} \end{bmatrix} \quad (15)$$

and

$$\dot{\tilde{W}}_{\bar{\zeta} i} = \dot{\tilde{W}}_{\bar{\zeta} i} = -\Gamma_{\bar{\zeta} i} S_{\bar{\zeta} i}(x) \tilde{x}_i - \sigma_i \Gamma_{\bar{\zeta} i} \hat{W}_{\bar{\zeta} i} \quad (16)$$

where $\epsilon_{\zeta i} = \epsilon_i - \tilde{W}_{\zeta i}^T S_{\zeta i}(x)$. The subscripts $(\cdot)_\zeta$ and $(\cdot)_{\bar{\zeta}}$ are used to stand for terms related to the regions close to and far away from the trajectory $\varphi_\zeta(x_0)$. The region close to the trajectory is defined as $\Omega_\zeta := \{Z | \text{dist}(Z, \varphi_\zeta) \leq d_\iota\}$, where $Z = x, d_\iota > 0$ is a constant satisfying $s(d_\iota) > \iota$, $s(\cdot)$ is the RBF used in the network, ι is a small positive constant. The related subvectors are given as: $S_{\zeta i}(x) = [s_{j1}(x), \dots, s_{j\zeta}(x)]^T \in R^{N_\zeta}$, with the neurons centered in the local region Ω_ζ , and $\tilde{W}_{\zeta i}^* = [w_{j1}^*, \dots, w_{j\zeta}^*]^T \in R^{N_\zeta}$ is the corresponding weight subvector, with $N_\zeta < N$. For localized RBF neural networks, $|\tilde{W}_{\bar{\zeta} i}^T S_{\bar{\zeta} i}(x)|$ is small, so $\epsilon_{\bar{\zeta} i} = O(\epsilon_i)$.

By the convergence result, we can obtain a constant vector of neural weights according to

$$\bar{W}_i = \text{mean}_{t \in [t_a, t_b]} \hat{W}_i(t) \quad (17)$$

where $t_b > t_a > 0$ represent a time segment after the transient process. Therefore, we conclude that accurate identification of the function $\phi_i(x; p)$ is obtained along the trajectory $\varphi_\zeta(x_0)$ by using $\bar{W}_i^T S_i(x)$, i.e.,

$$\phi_i(x; p) = \bar{W}_i^T S_i(x) + \epsilon_{i2} \quad (18)$$

where $\epsilon_{i2} = O(\epsilon_{i1})$ and subsequently $\epsilon_{i2} = O(\epsilon^*)$.

2.8 Classification mechanism

In this section, we present a scheme to classify normal and MI cardiac vectors.

Consider a training dataset consisting of cardiac system patterns φ_ζ^k , $k = 1, \dots, M$, with the k th training pattern φ_ζ^k generated from

$$\dot{x} = F^k(x; p^k) + v^k(x; p^k), \quad x(t_0) = x_{\zeta 0} \quad (19)$$

where $F^k(x; p^k)$ denotes the cardiac system dynamics, $v^k(x; p^k)$ denotes the modeling uncertainty, p^k is the system parameter vector.

As demonstrated in Subsection 2.7, the general cardiac system dynamics $\phi^k(x; p^k) := F^k(x; p^k) + v^k(x; p^k)$ can be accurately derived and preserved in constant RBF neural networks $\bar{W}^{k^T} S(x)$. By utilizing the learned knowledge obtained in the training stage, a bank of M estimators is constructed for the training cardiac system patterns as follows:

$$\dot{\bar{\chi}}^k = -B(\bar{\chi}^k - x) + \bar{W}^{k^T} S(x) \quad (20)$$

where $k = 1, \dots, M$ is used to stand for the k th estimator, $\bar{\chi}^k = [\bar{\chi}_1^k, \dots, \bar{\chi}_n^k]^T$ is the state of the estimator, $B = \text{diag}[b_1, \dots, b_n]$ is a diagonal matrix which is kept the same for all estimators, x is the state of an input test cardiac system pattern generated from Eq. (10).

In the classification phase, by comparing the test cardiac system pattern (standing for a HC or MI cardiac system pattern) generated from the cardiac system (10) with the set of M estimators (20), we obtain the following test error systems:

$$\dot{\tilde{\chi}}_i^k = -b_i \tilde{\chi}_i^k + \bar{W}_i^{k^T} S_i(x) - \phi_i(x; p), \quad i = 1, \dots, n, \quad k = 1, \dots, M \quad (21)$$

where $\tilde{\chi}_i^k = \bar{\chi}_i^k - x_i$ is the state estimation (or synchronization) error. We compute the average L_1 norm of the error $\tilde{\chi}_i^k(t)$

$$\|\tilde{\chi}_i^k(t)\|_1 = \frac{1}{T_c} \int_{t-T_c}^t |\tilde{\chi}_i^k(\tau)| d\tau, \quad t \geq T_c \quad (22)$$

where T_c is the cycle of cardiac vector.

The fundamental idea of the classification between HC and MI cardiac vectors is that if a test cardiac system pattern is similar to the trained cardiac system pattern s ($s \in \{1, \dots, k\}$), the constant RBF network $\bar{W}_i^{s^T} S_i(x)$ embedded in the matched estimator s will quickly recall the learned knowledge by providing accurate approximation to the cardiac system dynamics. Thus, the corresponding error $\|\tilde{\chi}_i^s(t)\|_1$ will become the smallest among all the errors $\|\tilde{\chi}_i^k(t)\|_1$. Based on the smallest error principle, the appearing test cardiac system pattern can be classified. We have the following classification scheme.

Classification scheme: If there exists some finite time t^s , $s \in \{1, \dots, k\}$ and some $i \in \{1, \dots, n\}$ such that $\|\tilde{\chi}_i^s(t)\|_1 < \|\tilde{\chi}_i^k(t)\|_1$ for all $t > t^s$, then the appearing cardiac system pattern can be classified and MI can be detected.

3 Results

Experiments are implemented using matlab software and tested on an Intel Core i7 6700K 3.5GHz computer with 64GB RAM. We assign feature vector sequences for all the heart beat records of HC and MI subjects in the PTB database. According to the method described in Subsection 2.6, we extract features, which means the input of the RBF neural networks $[ED_j^{V1^{\text{PRC}^{\text{P}^4}}}, ED_j^{V2^{\text{PRC}^{\text{P}^4}}}, ED_j^{V3^{\text{PRC}^{\text{P}^4}}}, ED_j^{V4^{\text{PRC}^{\text{P}^4}}}]^T$. In order to eliminate data difference between different features, all feature data are normalized to $[-1, 1]$.

Several experiments are carried out to verify the effectiveness of the proposed method on the 78 HC and 367 MI heart beat records. The classification results will

be evaluated with the 10-fold cross-validation style in which the variance of the estimate for the classifiers is reduced. The data are divided into the training and test subsets. For the 10-fold cross-validation, the data set is divided into ten subsets. Each time, one of the ten subsets is used as the test set and the other nine subsets are put together to form a training set. As such, every fold has been used nine times as train data and one time as test data. The final result is the average of the 10 implementations. For the evaluation, six performance parameters are used including the Sensitivity (SEN), the Specificity (SPF), the Accuracy (ACC), the Positive Predictive Value (PPV), the Negative Predictive Value (NPV) and the Matthews Correlation Coefficient (MCC). These measurements are defined as follows [83]:

$$\text{SEN} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100(\%) \quad (23)$$

$$\text{SPF} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100(\%) \quad (24)$$

$$\text{ACC} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \times 100(\%) \quad (25)$$

$$\text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100(\%) \quad (26)$$

$$\text{NPV} = \frac{\text{TN}}{\text{TN} + \text{FN}} \times 100(\%) \quad (27)$$

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FN} \times \text{FP}}{\sqrt{(\text{TP} + \text{FN})(\text{TP} + \text{FP})(\text{TN} + \text{FN})(\text{TN} + \text{FP})}} \quad (28)$$

where TP is the number of true positives, FN is the number of false negatives, TN is the number of true negatives and FP is the number of false positives. To be accurate, a classifier must have a high classification accuracy, a high sensitivity, as well as a high specificity [84]. For a larger value of MCC, the classifier performance will be better [83, 85].

The classification results on HC and MI subjects have been illustrated in Table 4 with 10-fold cross-validation style. Our study demonstrates the accuracy improvements to differentiate between HC and MI. Overall, our classification approach achieves good performance, which indicates that the proposed pattern recognition system can effectively classify MI by using nonlinear features and neural network based classification tools.

Table 4 Performance of the proposed classification approach evaluated by 10-fold cross-validation method.

Evaluation methods	Predicted groups	Actual groups		SEN (%)	SPF (%)	ACC (%)	PPV (%)	NPV (%)	MCC
		HC	MI						
10-fold cross-validation	HC	76	2	98.37	97.44	98.20	99.45	92.68	0.9395
	MI	6	361						

4 Discussion

Experimental results of this study revealed that MI subjects could be differentiated from HC subjects automatically by means of nonlinear features and neural networks based upon hybrid signal processing methods. The proposed scheme focuses not only on providing evidence to support the claim that MI subjects demonstrate altered cardiac system dynamics in comparison to HC subjects, but also on providing an automatic and objective method to detect MI cardiac vectors.

Banerjee and Mitra [22] employed cross wavelet transform (XWT) to produce wavelet cross spectrum (WCS) and wavelet coherence (WCOH) for the analysis of spectral differences between HC and MI subjects. The reported accuracy with threshold based classifier was 97.6% based on lead-III ECG signals. Arif et al. [86] extracted 117-dimensional features from ST-T region and Q wave region of each beat by using lead-wise principal components analysis (PCA). Features were derived from 12-lead ECG signals and fed into the back propagation neural networks (BPNN) classifier for classification, which was with the reported accuracy of 93.7%. Al-Kindiet et al. [87] used R-complex time index detection method to extract features from Q, R, S waves and J points, which could serve as an clinical indicator of MI. 12-lead ECG signals were derived from 20 normal and 20 MI subjects and the reported sensitivity was 85% for the detection of MI subjects. Liu et al. [88] fitted a given ECG signal with a 20th order polynomial function to derive new ECG features. They reported 94.4% classification accuracy with J48 decision tree model for the diagnosis of MI. Sharma et al. [89] calculated multiscale wavelet energies and eigenvalues of multiscale covariance matrices to act as as diagnostic features. The reported accuracy with the SVM RBF kernel classifier was 96%. Sharma and Sunkaria [90] calculated sample entropy, normalized sub-band energy, log energy entropy and median slope over selected bands of 6-lead ECG signals. These vectors were used as features and fed to the SVM classifier for the classification of MI and HC ECG signals. The reported accuracy was 98.84%. Acharya et al. [91] constructed an end-to-end learning structure without any hand-crafted feature extraction by using a single lead ECG signal. The reported accuracy for the automated detection of normal and MI ECG beats (with noise and without noise) by using deep learning algorithm (CNN) was 93.53% and 95.22%, respectively. Strodthoff and Strodthoff [92] also built an end-to-end learning structure without any hand-crafted feature extraction by including different combinations of leads, which could estimate the relative amount of information that these channels contribute to the classification decision. The reported accuracy for the automated detection of normal and MI ECG beats by using CNN was 96.1%. Lih et al. [93] proposed combined 16-layer CNN and Long Short-Term Memory (LSTM) models for the detection of MI with automatic feature extraction and selection. The reported accuracy was 98%.

Different from the above discussed methods, this study proposes a hybrid method to extract nonlinear features using ITD, DWT, PSR and ED tools based on the

synthesis of traditional 12-lead and Frank XYZ leads. These features are fed into dynamical estimators which are consisting of constant RBF neural networks to classify MI and HC subjects. Comparison of the classification performance to other state-of-the-art methods on the same database is demonstrated in Table 5. The proposed method provides an average classification accuracy of 98.20% through 10-fold cross-validation style. Due to the use of 10-fold cross-validation, the classification performance is robust. The method studied in this paper has the potential to serve as a supportive technical means to other approaches such as coronary arteriography and cardiac ultrasound for the diagnosis of MI. Although our classification accuracy is not higher than that reported in [90], we present a new classification tool together with building a novel feature vector rather than using directly the ECG signals. In addition, we used 4 features which are less than the 10 features used in [90]. Modeling, identification and classification of cardiac system dynamics were employed instead of putting feature vectors directly into the classifier in comparison to other methods. This provides another candidate tool for the detection of MI.

Table 5 Summary of classification performance on the HC and MI subjects obtained from the same PTB database in the literature.

References	Number of leads	Feature extraction	Classifiers	10-fold cross-validation	Performance
Banerjee and Mitra (2013) [22]	One lead (lead III)	Using XWT to yield WCS and WCOH	Threshold based classifier	No	Accuracy=97.6%
Arif et al. (2010) [86]	12 leads	Using PCA to extract 117 features from ST-T segment and Q wave	back propagation neural network	No	Accuracy=93.7%
Al-Kindi et al. (2011) [87]	12 leads	R complex time index extracted from Q, R, S waves and J points	Not mentioned	No	Sensitivity=93%
Liu et al. (2015) [88]	12 leads	20th order polynomial function measured by the Akaike information criterion	348 decision tree	No	Accuracy=93.7%
Sharma et al. (2015) [89]	12 leads	Multiscale wavelet energies and eigenvalues of multiscale covariance matrices	SVM with RBF kernel	No	Accuracy=96%
Sharma and Sonikarla (2018) [90]	6 leads	Sample entropy, normalized sub-band energy, lag energy entropy and median slope	SVM	Yes	Accuracy=98.84%
Acharya et al. (2017) [91]	One lead (lead II)	End-to-end learning structure without any hand-crafted feature extraction	CNN	Yes	Accuracy=95.22%
Strodtzoff and Strodtzoff (2019) [92]	15 leads	End-to-end learning structure without any hand-crafted feature extraction	CNN	Yes	Accuracy=96.1%
Lih et al. (2020) [93]	One lead (lead II)	Automatic feature extraction and selection with deep learning method	CNN-LSTM	Yes	Accuracy=98%
Proposed work	15 leads	Extracted through ITD, DWT, PSR and ED	Dynamical estimators	Yes	Accuracy=98.20%

5 Conclusions

In this study, a novel feature extraction technique including ITD, DWT, PSR and ED is proposed for detection of myocardial infarction, which is computationally simple and easy to implement. The results of this study indicate that the pattern classification of cardiac vector based on the synthesis of traditional 12-lead and Frank XYZ leads can offer an objective method to assess the disparity of cardiac system dynamics between HC and MI subjects. Synthesis of 12-lead and Frank XYZ leads to build a new 4-dimensional cardiac vector may fully reflect the pathological alterations in the abnormal patterns of cardiac system dynamics provoked by MI. ITD could extract most important information of the cardiac vector through predominant PRCs. DWT decomposes the predominant PRCs into different frequency bands, which are used to construct the reference variables. PSR plots cardiac system dynamics along the advisable db3 sub-bands (D4) of predominant PRCs trajectory in a 3D phase space diagram and visualizes the cardiac system dynamics. ED measures and derives features, which are fed into RBF neural networks for the modeling, identification and classification of cardiac system dynamics between HC and MI subjects. However, some limitations such as the relatively small size of the database, the regulation principle of the embedding dimension and time lag, still need to be improved and overcome. Future work will include a clinical validation of the proposed technique with a larger number of patients. Assessments of the relationship between the embedding dimension, time lag and the classification accuracy can also be considered in future investigations. It would be of interest to develop strategy for adaptive selection of PSR parameters which could create best classification performance. Features introduced in other methods such as various entropies, Hurst exponent, fractal dimension and other nonlinear features, can also be

explored in the proposed framework to evaluate its classification performance. The proposed automated MI detection system can assist cardiologists in cross-checking their diagnosis. In addition, it can be extended to grade the severity of MI.

Abbreviations

CVD: cardiovascular diseases; MI: myocardial infarction;
 ECG: electrocardiographic; VCG: vectorcardiographic;
 ITD: intrinsic time-scale decomposition; DWT: discrete wavelet transform;
 PSR: phase space reconstruction; PRCs: proper rotation components;
 db3: third-order Daubechies; 3D: Three-dimensional;
 ED: Euclidean distance; PSR: phase space reconstruction;
 WT: Wavelet Transform; CWT: Complex Wavelet Transform;
 PSWT: Pitch Synchronous Wavelet Transform; DWT: Discrete Wavelet Transform;
 KF: Kalman filtering; LMS: Least Mean Squares;
 ANN: Artificial Neural Networks; ANFIS: Adaptive Neuro-fuzzy Inference System;
 SVM: support vector machine; LDA: linear discriminant analysis;
 FAWT: flexible analytic wavelet transform; RF: random forest;
 BPNN: back propagation neural network;
 LS-SVM: least-squares support vector machine; LSTMs: long-short term memory networks;
 HOS: higher order spectra; RQA: recurrence quantification analysis;
 EMD: empirical mode decomposition; LMD: local mean decomposition;
 SEN: Sensitivity;
 SPF: Specificity; ACC: Accuracy;
 PPV: Positive Predictive Value; NPV: Negative Predictive Value;
 MCC: Matthews Correlation Coefficient; XWT: cross wavelet transform;
 RBF: radial basis function; WCS: wavelet cross spectrum;
 WCOH: wavelet coherence; PCA: principal components analysis;

Declarations

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analyzed during in current study are available from the corresponding author on reasonable requests.

Competing interests

The authors declare that they have no competing interests.

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Author's contributions

Study concept and design (WZ); drafting of the manuscript (WZ, ZL and CY); critical revision of the manuscript for important intellectual content (WZ and CY); obtained funding (WZ); administrative, technical, and material support (WZ); study supervision (WZ). All authors read and approved the final manuscript.

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Figure Legends

Fig. 1. Flowchart of the proposed method for the MI classification using syntheses of lead system, ITD, DWT, PSR, ED and neural networks.

Fig. 2. Examples of the synthesis of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC subject.

Fig. 3. Examples of the synthesis of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from MI subject.

Fig. 4. Samples of the ITD of 4-dimensional cardiac vector from HC subject.

Fig. 5. Samples of the ITD of 4-dimensional cardiac vector from MI subject.

Fig. 6. Samples of four levels DWT of PRC_1 of the 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC and MI subjects.

Fig. 7. Samples of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC subject.

Fig. 8. Samples of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from MI subject.

Fig. 9. Samples of the Euclidian distance of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from HC subject.

Fig. 10. Samples of the Euclidian distance of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1, V_2, V_3, V_4]^T$ from MI subject.

Figures

Figure 1

Flowchart of the proposed method for the MI classification using syntheses of lead system, ITD, DWT, PSR, ED and neural networks.

(a) V_1

(b) V_2

(c) V_3

(d) V_4

Figure 2

Examples of the synthesis of 4-dimensional cardiac vector: $V = [V_1; V_2; V_3; V_4]^T$ from HC subject.

(a) V_1

(b) V_2

(c) V_3

(d) V_4

Figure 3

Examples of the synthesis of 4-dimensional cardiac vector: $V = [V_1; V_2; V_3; V_4]^T$ from MI subject.

(a) Original V_1 vector and its ITD from HC.

(b) Original V_2 vector and its ITD from HC

(c) Original V_3 vector and its ITD from HC

(d) Original V_4 vector and its ITD from HC

Figure 4

Samples of the ITD of 4-dimensional cardiac vector from HC subject.

(a) Original V_1 vector and its ITD from MI.

(b) Original V_2 vector and its ITD from MI

(c) Original V_3 vector and its ITD from MI

(d) Original V_4 vector and its ITD from MI

Figure 5

Samples of the ITD of 4-dimensional cardiac vector from MI subject.

(a) Four levels DWT of PRC_1 of the V_1 and V_2 vectors from HC.

(b) Four levels DWT of PRC_1 of the V_3 and V_4 vectors from HC.

(c) Four levels DWT of PRC_1 of the V_1 and V_2 vectors from MI.

(d) Four levels DWT of PRC_1 of the V_3 and V_4 vectors from MI.

Figure 6

Samples of four levels DWT of PRC_1 of the 4-dimensional cardiac vector: $V = [V_1; V_2; V_3; V_4]^T$ from HC and MI subjects.

(a) 3D PSR of PRC_1^{D4} for V_1 .

(b) 3D PSR of PRC_1^{D4} for V_2 .

(c) 3D PSR of PRC_1^{D4} for V_3 .

(d) 3D PSR of PRC_1^{D4} for V_4 .

Figure 7

Samples of 3D PSR of PRCD_4 1 of 4-dimensional cardiac vector: $V = [V_1; V_2; V_3; V_4]^T$ from HC subject.

(a) 3D PSR of PRC_1^{D4} for V_1 .

(b) 3D PSR of PRC_1^{D4} for V_2 .

(c) 3D PSR of PRC_1^{D4} for V_3 .

(d) 3D PSR of PRC_1^{D4} for V_4 .

Figure 8

Samples of 3D PSR of PRC_1^{D4} of 4-dimensional cardiac vector: $V = [V_1; V_2; V_3; V_4]^T$ from MI subject.

(a) Euclidian distance of 3D PSR of PRC_1^{D4} for V_1 .

(b) Euclidian distance of 3D PSR of PRC_1^{D4} for V_2 .

(c) Euclidian distance of 3D PSR of PRC_1^{D4} for V_3 .

(d) Euclidian distance of 3D PSR of PRC_1^{D4} for V_4 .

Figure 9

Samples of the Euclidian distance of 3D PSR of PRCD4 1 of 4-dimensional cardiac vector: $V = [V_1; V_2; V_3; V_4]^T$ from HC subject.

(a) Euclidian distance of 3D PSR of PRC_1^{D4} for V_1 .

(b) Euclidian distance of 3D PSR of PRC_1^{D4} for V_2 .

(c) Euclidian distance of 3D PSR of PRC_1^{D4} for V_3 .

(d) Euclidian distance of 3D PSR of PRC_1^{D4} for V_4 .

Figure 10

Samples of the Euclidian distance of 3D PSR of PRCD4 1 of 4-dimensional cardiac vector: $V = [V_1; V_2; V_3; V_4]^T$ from MI subject.