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ECG beat classification via deterministic learning

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ABSTRACT

This paper proposes a novel method for the electrocardiographic (ECG) beat classification via deterministic learning. The *dynamics* of ECG beats is used as a unique feature for ECG beat classification, which is fundamentally different from the time/frequency domain features used in literature. It is the essential feature of ECG beats, and contains complete information of ECG beats. Precisely, the deterministic learning allows us to model and represent the *dynamics* of a training beat set as constant radial basis function (RBF) networks. As the classification measure, a set of errors is further obtained through the comparison between the test beat and the estimators constructed by the RBF networks. ECG records taken from the MIT-BIH (Massachusetts Institute of Technology-Beth Israel Hospital) arrhythmia database are selected to test the proposed method. With 5% beats used as training beats, the overall accuracies are 97.78% and 97.21% for global and patient-adapting beat classification, respectively. These results indicate the proposed method is reliable and efficient for ECG beat classification.

1. Introduction

As a valuable tool for patient monitoring or diagnosis in clinical practice, electrocardiogram (ECG) is widely used for the detection of a broad range of cardiac conditions, e.g., arrhythmia, heart rate variability. However, the analysis of thousands of ECG signals is tedious and time-consuming for cardiologists, and the possibility of missing (or misreading) vital information is high. Thus, computer-aided analysis of ECG signals is very important in clinic. Automatic ECG beat classification plays an important role in detecting cardiac disease, particularly for life-threating heart diseases (e.g., ventricular tachyarrhythmia). In general, the procedure of ECG beat classification can be divided into two steps: (i) feature extraction and (ii) classifier designation. Therefore, the beat classification performance is affected immediately or even determined by the characterization capability of the extracted features and the design of the classifier [1]. Features used for beat classification can be extracted in time domain, in frequency domain, or represented as statistical measures (e.g., higher-order statistics) [2]. For features extraction, lots of techniques have been used in literature, such as principal component analysis (PCA) [3–6], wavelet transform (WT) [1,7–9], Hilbert transform [10], and cross-correlation approach [11], Kalman filter [12]. Many algorithms including particle swarm optimization [1,13–16], support vector machines [17–20], nearest neighbor method [9,21–23], linear discriminant analysis [24,25], clustering method [26], mixture-of-experts method [27], discrete cosine transform [28], deep learning [29,30] and artificial neural network (ANN), have also been presented for the classifier designation. In particular, ANNs is one of most powerful tool for designing classifiers [1,31]. A number of effective ANN-based schemes including fuzzy neural networks [33-34], multilayer perceptrons (MLPs) [35–38], modular neural network [39,40], radial basis function network [41,42], learning vector quantization (LVQ) neural network [11,43], probabilistic neural network [44–46] have been used for ECG beat classification.

According to the scope of application, beat classification systems can be divided into two categories: global-classifier approach and patient-adapting approach. The global-classifier approaches aim to classify ECG beat without information from an expert. Unfortunately, the performance of the global-classifier approaches was not good enough in practice [47,48]. The main reason is that there exists large inter-individual variability in the ECG waveforms. For instance, for different patients, identical cardiac disease may have different waveforms, while two various cardiac diseases may have similar waveforms [18]. Furthermore, the large inter-individual variability in ECG waveforms also exists [49] in healthy individuals as well as within different patient categories. To improve beat classification performance, the patient-adapting approaches had been proposed [1,27,47,50,51]. That is, to let the classification algorithm adaptable to the special characteristics of each patient's ECG records [27]. However, the improvement is limited since the large variations in the morphologies of ECG

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waveforms also exist in the same subject under different temporal or physical conditions [1,52].

In fact, ECG signal is a temporal (or dynamical) pattern which is time-varying. Therefore, ECG beat classification is virtually a problem of temporal pattern recognition and classification. As well known, temporal pattern recognition is one of the most difficult task in pattern recognition field [53,54]. In temporal recognition, there are some fundamental issues need to be solved first. The most challenging issue is the appropriate representation of the temporal patterns. Another two difficult and important issues are the definition of similarity and recognition of temporal patterns. In [55], the authors pointed out that the methods for temporal patterns processing should be fundamentally different from those for static patterns processing [53].

Recently, a novel theory [53,56,57], named deterministic learning, was proposed for temporal patterns representation, similarity definition and rapid recognition. With the deterministic learning theory, a temporal pattern dynamics can be accurately modeled and represented as a constant radial basis function (RBF) networks. It is time-invariant and spatial distributed manner. In particular, complete information of both the temporal pattern state and the underlying system *dynamics* is included in the constant RBF networks. Based on the representation, a similarity definition and a rapid recognition mechanism of temporal patterns were successively proposed. Since ECG signals are essentially temporal patterns and the beat classification belongs to the problem of temporal pattern recognition, the deterministic learning is more reasonable and suitable for ECG beat classification.

In the paper, we propose a novel method for ECG beat classification via deterministic learning. The *dynamics* of ECG beats rather than static features (e.g., RR interval, QRS duration) is accurately modeled (i.e., extracted) and used for beat classification. It is more suitable for ECG beat classification than static features since it contains complete information of ECG beat. The *dynamics* of training beats are accurately modeled and represented as constant RBF networks by using the deterministic learning. Based on the representation, a mechanism for ECG beat classification is presented. A set of estimators employed the constant RBF networks is constructed for a test beat to be classified. Through the comparison between the estimators and the test beat, a set of errors is obtained and taken as classification measure between the training beats and the test beat. The test beat is classified according to the smallest error principle. The overview of the proposed method is shown in Fig. 1.

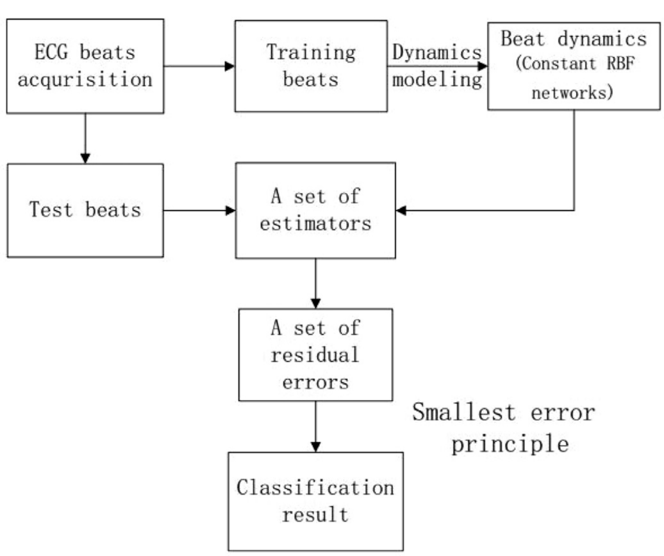


Fig. 1. Block diagram of the proposed system.

ECG records taken from MIT-BIH arrhythmia database [58] are used to evaluate the proposed method. Experimental results demonstrate that it is reliable and efficient for ECG beat classification, whether used as a global-classifier or used as a patient-adapting classifier. The main contributions of this paper are: i) the beat dynamic is first extracted as a unique feature for beat classification; ii) the similarity between beats is first measured by the dynamics; iii) an originality method based on dynamics and the similarity measure is proposed for beat classification.

The rest of the paper is organized as follows. In Section 2, we present brief introductions of the deterministic learning and the MIT-BIH arrythmia database. The proposed method will be presented in Section 3. Experimental results are demonstrated in Section 4. Section 5 and Section 6 are discussion and conclusion, respectively.

2. Materials

2.1. Deterministic learning

The deterministic learning theory was proposed for temporal patterns modeling and rapid recognition. It was first proposed by Wang and Hill [56] and mainly developed utilizing theories and concepts of adaptive control, system identification, and RBF networks. Through deterministic learning, fundamental knowledge on system *dynamics* of temporal patterns can be accurately modeled, stored, and represented as an accurate neural network approximation with constant neural weights [53].

In deterministic learning, a temporal or dynamical pattern is defined as periodic or periodic-like trajectories (including quasi-periodic, almost-periodic, and chaotic trajectories) generated from the following general dynamical systems [59]:

$$\dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}; \mathbf{p}), \quad \mathbf{x}(t_0) = \mathbf{x}_0, \tag{1}$$

where $\mathbf{x} = [x_1, \ldots, x_n]^T \in R^n$ is system state, $\mathbf{F}(\mathbf{x}; \mathbf{p}) = [f_1(\mathbf{x}; \mathbf{p}), \ldots, f_n(\mathbf{x}; \mathbf{p})]^T$ is a vector of continuous but unknown nonlinear functions, and $\mathbf{p}$ is a constant vector of system parameters. *The dynamics of the temporal pattern starting from* x_0 $\boldsymbol{\phi}_\zeta(\mathbf{x}, t; \mathbf{x_0})$ *(or* $\boldsymbol{\phi}_\zeta$ *for brevity) is the unknown function* $\mathbf{F}(\mathbf{x}; \mathbf{p})$.

To achieve the accurate modeling of the unknown system *dynamics* $\mathbf{F}(\mathbf{x}; \mathbf{p}) = [f_1(\mathbf{x}; \mathbf{p}), \ldots, f_n(\mathbf{x}; \mathbf{p})]^T$ underlying the temporal pattern $\boldsymbol{\phi}_\zeta$, an estimator system is employed as follows:

$$\dot{\hat{x}}_i = -a_i(\hat{x}_i - x_i) + \hat{\mathbf{W}}_i^T \mathbf{S}_i(\mathbf{x}), \tag{2}$$

where $\hat{x}_i$ is the estimator state, x_i is system state of (1), $a_i > 0$ is a design constant, $\hat{\mathbf{W}}_i^T \mathbf{S}_i(\mathbf{x})$ is RBF networks and used to approximate the unknown *dynamics* $f_i(\mathbf{x}; \mathbf{p})$ of (1), with $\hat{\mathbf{W}}_i = [w_{i1}, \ldots, w_{iN}]^T \in R^N$ and $\mathbf{S}_i(\mathbf{x}) = [s_{i1}(\| \mathbf{x} - \xi_1 \|), \ldots, s_{iN}(\| \mathbf{x} - \xi_N \|)]^T$, $s_{ij}\ (\cdot)$ being Gaussian function, $\xi_j\ (j = 1, \ldots, N)$ are distinct centers.

According to systems (1) and (2), state estimation error $\tilde{x}_i = \hat{x}_i - x_i$ satisfies the following equation:

$$\begin{aligned} \dot{\tilde{x}}_i &= -a_i\tilde{x}_i + \hat{\mathbf{W}}_i^T \mathbf{S}_i(\mathbf{x}) - f_i(\mathbf{x}; \mathbf{p}) \\ &= -a_i\tilde{x}_i + \tilde{\mathbf{W}}_i^T \mathbf{S}_i(\mathbf{x}) - \epsilon_i, \end{aligned} \tag{3}$$

where $\tilde{\mathbf{W}}_i = \hat{\mathbf{W}}_i - \mathbf{W}_i^*$, $\mathbf{W}_i^*$ is the ideal constant weight vector, and $\epsilon_i = f_i(\mathbf{x}; \mathbf{p}) - \mathbf{W}_i^{*T} \mathbf{S}_i(\mathbf{x})$ is the ideal approximation error. The following law is used to update the weight estimates $\hat{W}_i$:

$$\dot{\hat{\mathbf{W}}}_i = -\boldsymbol{\Gamma}_i \mathbf{S}_i(\mathbf{x})\tilde{x}_i - \sigma_i \boldsymbol{\Gamma}_i \hat{\mathbf{W}}_i, \tag{4}$$

where $\boldsymbol{\Gamma}_i = \boldsymbol{\Gamma}_i^T > 0$, and $\sigma_i > 0$ is a small constant.

By setting initial values $\hat{\mathbf{W}}_i(0) = \mathbf{0}$, it has been shown that for almost every temporal pattern $\boldsymbol{\phi}_\zeta$, accurate modeling (or approximation) of the unknown *dynamics*f_i $(\mathbf{x}; \mathbf{p})$ can be achieved along the trajectory of ϕ_ζ [53,56,57]:

$$f_i(\phi_\zeta;\mathbf{p}) = \hat{\mathbf{W}}_i^T \mathbf{S}_i(\phi_\zeta) + \epsilon_{\zeta i} \\ = \bar{\mathbf{W}}_i^T \mathbf{S}_i(\phi_\zeta) + \epsilon_{\zeta i1}, \tag{5}$$

where $\bar{\mathbf{W}}_i = mean_{t\in[t_a,t_b]}\ \hat{\mathbf{W}}_i(t)$, *mean* is the arithmetic mean, $0 < t_a < t_b$ represents a piece of time segment after the transient process, $\epsilon_{\zeta i1} = O(\epsilon_{\zeta i}) = O(\epsilon_i)$ is the practical approximation error. This implies that the *dynamics* f_i ($\boldsymbol{\phi}_\zeta$; $\mathbf{p}$) underlying almost every dynamical pattern $\boldsymbol{\phi}_\zeta$ can be accurately modeled via deterministic learning.

Remark 1. RBF is a feed-forward network with a single hidden layer, and is widely used for function approximation and pattern classification [60–62]. Its superiority lies in using linear learning algorithms to complete the work formerly handled by nonlinear learning algorithms, and maintaining the high precision at the same time. It owns the characteristics of best approximation, global optimum, fast learning speed, and so on. However, the classification precision is restricted by the feature dimension and the number of training sample. In addition, it is hard to determine the numbers, center and width of the hidden layer's neurons, which constrain the success of training. In deterministic learning, the RBF network is mainly used for function approximation.

2.2. MIT-BIH arrhythmia database

In the paper, ECG records collected from the MIT-BIH arrhythmia database are used to evaluate the proposed method. It was created in 1980 and aimed to motivate the development of techniques for automatic detection and classification of arrhythmia. It contains 48 half-hour ECG records measured from 47 patients. Thereinto, 25 ECG records were chosen to include uncommon, threatening, arrhythmic beat samples and the remaining 23 ECG records were selected randomly [63]. Each record contains two leads, with lead V_1 in 40 records, modified-lead II in 45 records, and lead II, lead V_2, lead V_4 and lead V_5 distributed in 11 records. Especially, each record was annotated both in timing information and beat classification by at least two cardiologists independently.

3. Methods

Using the deterministic learning algorithm, we present the novel method for ECG beat classification in the section. Modeling of ECG beat *dynamics* will be first proposed. Second, a classification mechanism of ECG beat will be proposed.

3.1. Modeling of beat dynamics

In fact, ECG signal is a temporal pattern generated by the heart electrical activities which can be seen as a complex, high-dimensional continuous nonlinear dynamical system. Assume that the nonlinear dynamical system is represented as follows:

$$\dot{\mathbf{V}}(t) = \mathbf{F}(\mathbf{V}(t)) \tag{6}$$

where $\mathbf{V}(t) = [v_1(t), \ldots, v_N(t)]^T$ is the system state which represents the ECG signals, $\mathbf{F}(\mathbf{V}(t)) = [f_1(\mathbf{V}(t)), \ldots, f_N(\mathbf{V}(t))]^T$ is an unknown nonlinear function vector.

As declared in deterministic learning, the function vectors $\mathbf{F}(\mathbf{V}(t))$ is the dynamics of ECG signals, a kind of temporal pattern. The beat *dynamics* can be extracted form the ECG signals dynamics according to the QRS complexes detection. Thus, the modeling of beat *dynamics* can be achieved in two steps: i) modeling the ECG signal dynamics; ii) extracted beat dynamics from the modeling results of ECG signal dynamics according to the QRS complexes detection.

In order to model the ECG signals *dynamics* $\mathbf{F}(\mathbf{V}(t))$ of (6), the following dynamical model is employed:

$$\dot{\hat{\mathbf{V}}}(t) = -\mathbf{A}(\hat{\mathbf{V}}(t) - \mathbf{V}(t)) + \hat{\mathbf{W}}^T\mathbf{S}(\mathbf{V}(t)) \tag{7}$$

where $\hat{\mathbf{V}}(t)$ is the estimation of $\mathbf{V}(t)$ in system (6), $\mathbf{A} = diag\{a_1, \ldots, a_N\}$ is a diagonal matrix, a_i are design constants, $\hat{\mathbf{W}}\mathbf{S}(\mathbf{V}(t))$ is RBF networks and used to approximate $\mathbf{F}(\mathbf{V}(t))$. The following law is used to update the weight estimates $\hat{\mathbf{W}}$:

$$\dot{\hat{\mathbf{W}}} = -\boldsymbol{\Gamma}(\mathbf{S}(\mathbf{V}(t))\tilde{\mathbf{V}}(t) + \sigma\hat{\mathbf{W}}) \tag{8}$$

where $\boldsymbol{\Gamma} = \boldsymbol{\Gamma}^T > 0$, $\tilde{\mathbf{V}}(t) = \hat{\mathbf{V}}(t) - \mathbf{V}(t)$, and $\sigma > 0$ is a small parameter.

Consider the adaptive system consisting of systems (6), (7), and (8). In view of the fact that ECG signal is quasi-periodic, we have:

1. The state estimation error $\tilde{\mathbf{V}}(t)$ converges to zero;
2. $\mathbf{F}(\mathbf{V}(t)) = \bar{\mathbf{W}}^T\mathbf{S}(\mathbf{V}(t)) + \epsilon$, where $\bar{\mathbf{W}}$ is a constant vector computed from $\hat{\mathbf{W}}$ according to some averaging procedure, $\boldsymbol{\epsilon}$ is the modeling error which can be arbitrarily small.

That is, ECG *dynamics* is accurately modeled and is effectively represented as constant RBF networks $\bar{\mathbf{W}}^T\mathbf{S}(\mathbf{V}(t))$, a time-invariant manner. It contains complete information of ECG signals. In other words, a complete information representation of ECG signals is obtained.

To further extract the *dynamics* of each ECG beat, the QRS complexes should be identified first. The QRS complex is the most striking waveform within the ECG. The detection of QRS provides the fundamentals for almost all automated ECG analysis algorithms. There are many approaches to QRS detection, such as algorithms based on artificial neural networks, wavelet transforms, genetic algorithms. In view of the aim of the paper, QRS complex is extracted by choosing a window of -300 *ms* to 400 *ms* around the R-peak [11,64,65], where R-peak is found in the MIT-BIH database annotation. According to the sample frequency of MIT-BIH database, a 252-sample signal vector is extracted which ensure it contains a single QRS complex (i.e., beat) roughly.

With the QRS complexes detection and the modeling results of the ECG signals *dynamics*, beat *dynamics* can be represented as follow:

$$\mathbf{F}(\mathbf{V}_{QRS}) \approx \bar{\mathbf{W}}^T\mathbf{S}(\mathbf{V}_{QRS}) \tag{9}$$

where the $(\cdot)_{QRS}$ represents QRS complexes in ECG signals.

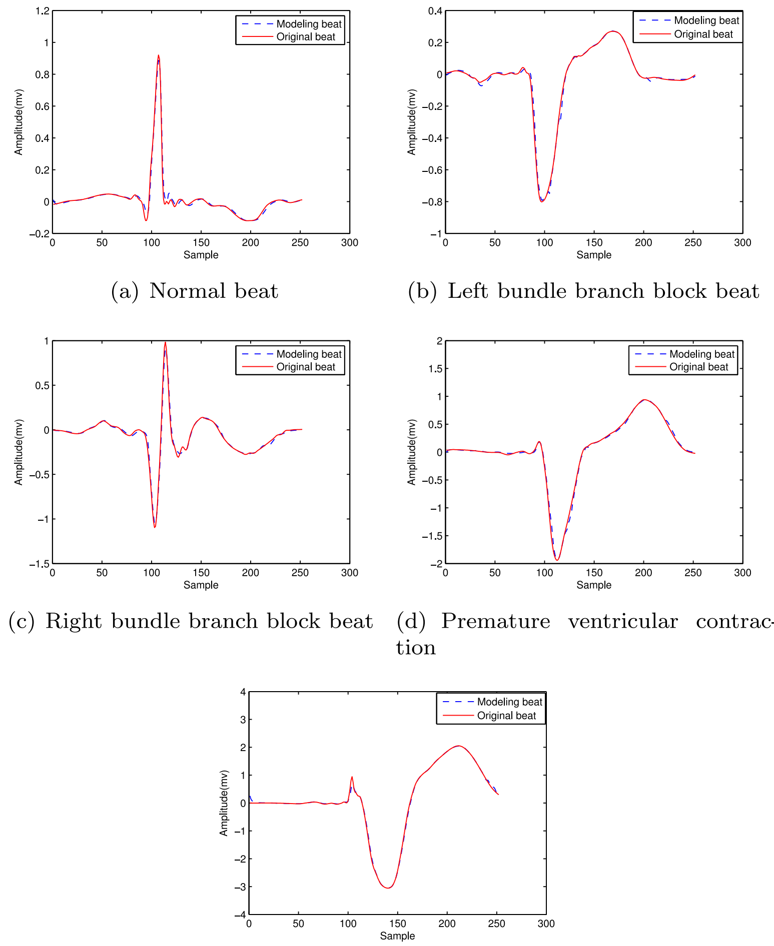
To show the modeling effect of the proposed method, modeling results of five types of beat which will be classified in the paper are shown in Figs. 2 and3. The modeling results are shown only for one lead for space-saving. From Fig. 2 we can see that the ECG beats can be accurately approximated by the modeling beats. The *dynamics* of the five types of beat are shown in Fig. 3. It can be seen that the *dynamics* of different types of beat are very different from each other, which may be used as the classification measure effectively.

3.2. Classification mechanism

With the time-invariant representation (constant RBF networks) of ECG beat *dynamics*, a mechanism for ECG beat classification will be presented in the subsection. For each training beat, the following dynamical model employing the constant RBF network $\bar{\mathbf{W}}^{k^T}\mathbf{S}(\mathbf{V}_{QRS})$ (for the kth training beat Q_T^k) is constructed:

$$\dot{\bar{\mathbf{V}}}_{QRS}^k = -\mathbf{B}(\bar{\mathbf{V}}_{QRS}^k - \mathbf{V}_{QRS}) + \bar{\mathbf{W}}^{k^T}\mathbf{S}(\mathbf{V}_{QRS}) \tag{10}$$

where $\bar{\mathbf{V}}_{QRS}^k$ and $\mathbf{V}_{QRS}$ are the dynamical model state and a test beat Q_t state respectively, $\mathbf{B} = diag\{b_1, \ldots, b_N\}$ is a diagonal matrix, $b_i > 0$ $(i = 1, \ldots, N)$ being design constants. Then, an error system



(a) Normal beat
(b) Left bundle branch block beat
(c) Right bundle branch block beat
(d) Premature ventricular contraction
(e) Paced beat

Fig. 2. The modeling results of the five types of beat.

corresponding to the dynamical model (10) (for training beat Q_T^k) and the test beat Q_t can be obtained as follows:

$$\dot{\bar{\mathbf{V}}}_{QRS}^k = -\mathbf{B}\tilde{\mathbf{V}}_{QRS}^k + \bar{\mathbf{W}}^{k^T}\mathbf{S}(\mathbf{V}_{QRS}) - \mathbf{F}(\mathbf{V}_{QRS}) \tag{11}$$

where $\tilde{\mathbf{V}}_{QRS}^k = \bar{\mathbf{V}}_{QRS}^k - \mathbf{V}_{QRS}$ is the state estimation (or synchronization) error. It can be inferred from Theorem 2 in [57] that the state estimation errors $\tilde{\mathbf{V}}_{QRS}^k$ can be used as the classification measure between the test beat and the training beats.

From the above analysis, the following procedure is used to classify an unclassified beat based on a set of training beats with annotation:

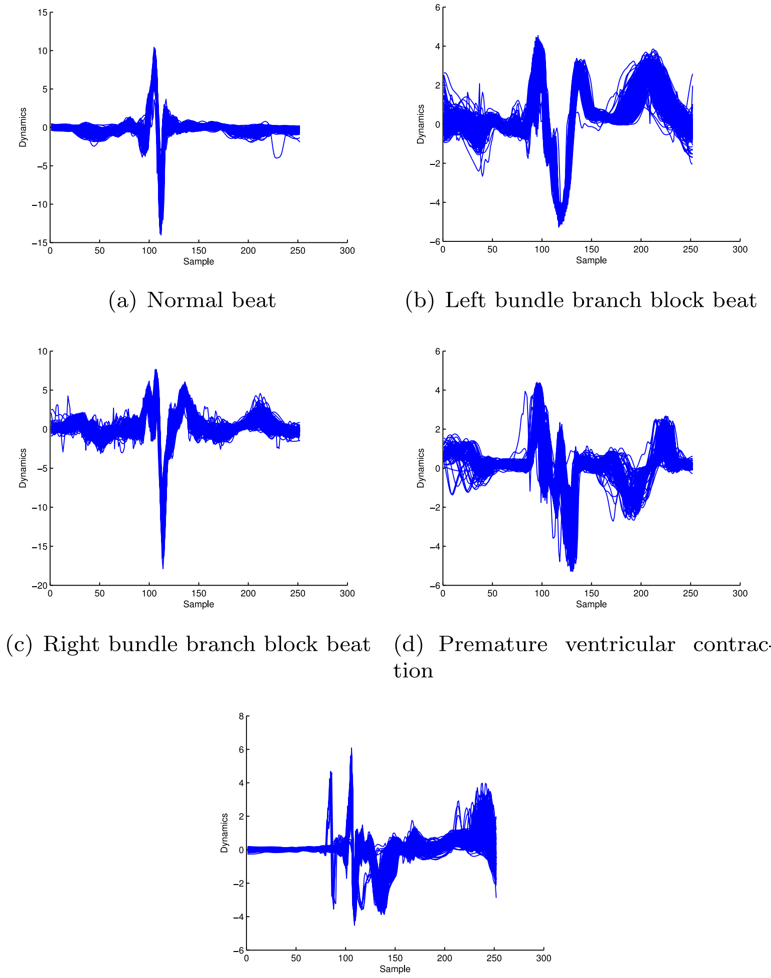
Step 1 Modeling the system *dynamics* of training set of ECG beats Q_T^k, $(k = 1, \ldots, M)$;
Step 2 Construct a dynamical model for each training beat Q_T^k;
Step 3 Take the state $\mathbf{V}_{QRS}$ of an unclassified beat Q_t as the RBF networks input of the dynamical models (10), and compute the average L_1 norm of the state estimation error $\tilde{\mathbf{V}}_{QRS}^k$;
Step 4 Classify the unclassified beat Q_t into the class same with the training beat whose dynamical model yields the smallest $\|\tilde{\mathbf{V}}_{QRS}^k\|_1$.

4. Experiments

The study is focused on the classification of the five largest beat types in MIT-BIH arrhythmia database (almost 95% of all beats) [22]: (i) normal beats (N); (ii) left bundle branch blocks (LBBB); (iii) right bundle branch blocks (RBBB); (iv) premature ventricular contractions (PVC); (v) paced beats (PB). As the *dynamics* of ECG signal will be extracted from the dynamical system (6) whose states are the ECG signals, to classify the ECG beats using the proposed method, the lead system must be identical. In the MIT-BIH database, there are 40 records with identical lead system: modified-lead II and lead $V1$. In our study, the 40 records without considering signal quality are all selected to evaluate the proposed method. Thus, the classification method was applied in ECG signal even with artifacts or noise, which may be reducing the classification accuracy.

The performance of the proposed method is quantified by the following five statistical indices: accuracy (Acc), sensitivity (Se), specificity (Sp), positive predictive value (Pp), and negative predictive value (Np). Accuracy measures the overall performance of the proposed method, the other four indices measure the capacity of the proposed method to distinguish certain beat type from other beat types (e.g., distinguish PVC from non-PVC). The five indices are defined as follows [1]:

$$\begin{aligned} Acc &= \frac{N_t - N_e}{N_t}, \\ Se &= \frac{TP}{TP+FN}, \quad Sp = \frac{TN}{TN+FP}, \\ Pp &= \frac{TP}{TP+FP}, \quad Np = \frac{TN}{TN+FN}, \end{aligned} \tag{12}$$



(a) Normal beat (b) Left bundle branch block beat

(c) Right bundle branch block beat (d) Premature ventricular contraction

(e) Paced beat

Fig. 3. The *dynamics* of the five types of beat extracted by using the proposed method.

where N_t is the total number of beats, N_e is the total number of wrongly classified beats in the files, *TP* (*TN*) is the number of the true positive (negative) classifications; *FP* (*FN*) is the number of the false positive (negative) classifications, respectively [22].

4.1. Global classifier

Global classifier is used to classify ECG beat without information from an expert. Thus, for a test beat to be classified using the global classifier, the training set should not contains beats from the same patient or record. To evaluate the proposed method as a global classifier, 3%, 4% and 5% of the total beats are randomly selected and used as three global training sets (established from a large ECG database). To be precise, of the 89647 beats (N: 65360, 72.91%; LBBB: 8053, 8.98%; RBBB: 5714, 6.37%; PVC: 6810, 7.60%; PB: 3710, 4.14%;) detected from the 40 records, 2755 beats, 3622 beats, 4524 beats are randomly selected used as global training set (for classification of test beats selected from 1 record, training beats are selected from the other 39 records). The ratio of each beat type in the training set is same as the ratio of each beat type in the total beat set. The remaining 86892 beats, 86025 beats, 85123 beats are used as test sets in the three experiments respectively. The extreme skewness between the training set and testing set can examine the generalization capability of the proposed method. The summary of the classification results of the three experiments are presented in Table 1 as classification matrixes. The

Table 1
The summary of the classification results of the first three experiments. The beat annotations in the database are depicted on the vertical axis, whereas the classifications are shown horizontally.

	Beat type	N	LBBB	RBBB	PVC	PB
	N	62424	278	149	372	128
	LBBB	83	7711	6	4	1
Experiment 1	RBBB	36	6	5488	7	2
	PVC	979	69	164	5279	110
	PB	78	0	3	4	3511
	N	61853	231	183	376	76
	LBBB	64	7650	5	7	2
Experiment 2	RBBB	24	8	5441	9	1
	PVC	804	54	106	5447	124
	PB	44	0	0	4	3512
	N	61313	212	153	305	79
	LBBB	57	7577	5	6	2
Experiment 3	RBBB	17	4	5398	6	1
	PVC	690	57	133	5467	119
	PB	39	0	1	2	3480

statistical indices of the three experiments are listed in Table 2, the respective and their graphical representation is illustrated in Fig. 4.

From Tables 1 and 2, we can see that the overall accuracy of the three experiments are all above 97.10%, and most of the indices are quite promising, except the sensitivity of PVC beat classification, only 81.33%, 84.96%, 86.14% in the three experiments. This may be

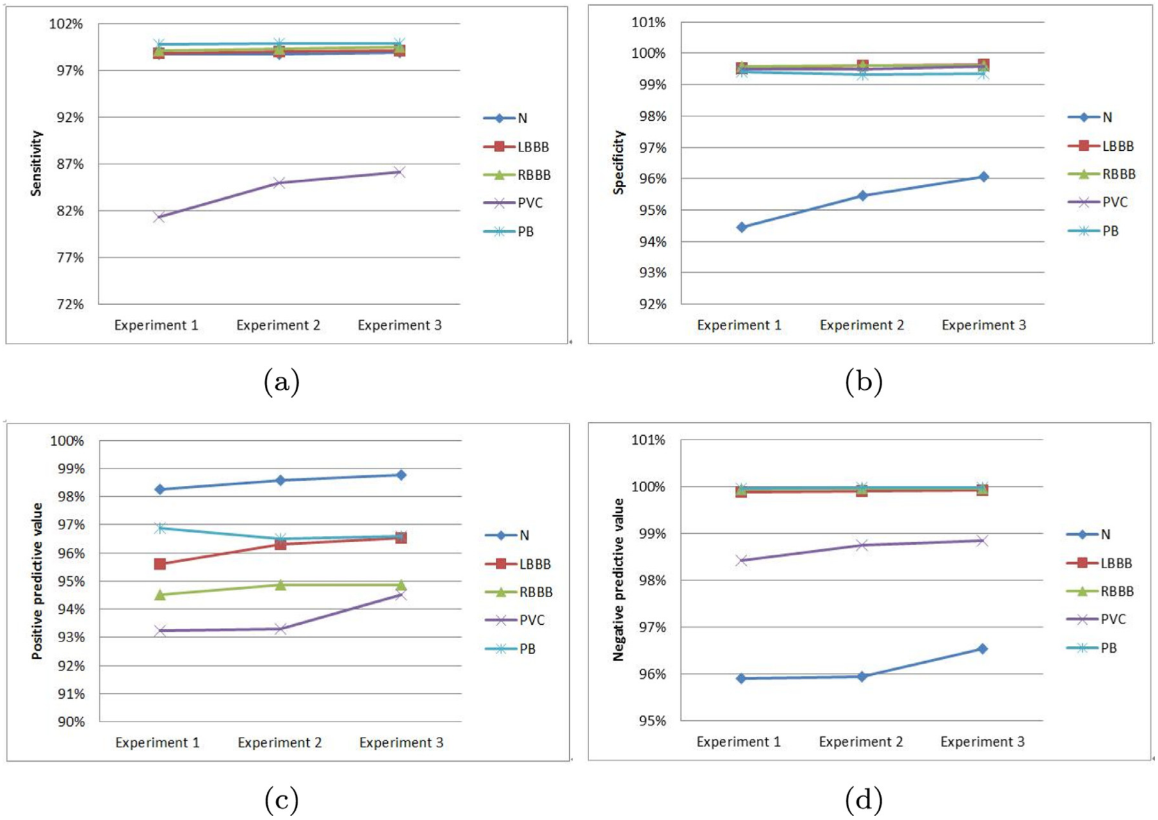


Fig. 4. Statistical indices of the first three experiments.

Table 2
Statistical indices of the first three experiments.

	Beat type	Se(%)	Sp(%)	Pp(%)	Np(%)	Acc(%)
Experiment 1	N	98.74	94.46	98.27	95.91	97.15
	LBBB	98.81	99.53	95.62	99.88	
	RBBB	99.12	99.59	94.51	99.94	
	PVC	81.33	99.50	93.24	98.43	
	PB	99.80	99.40	96.88	99.96	
Experiment 2	N	98.74	95.45	98.58	95.95	97.53
	LBBB	99.02	99.61	96.31	99.90	
	RBBB	99.25	99.62	94.87	99.95	
	PVC	84.96	99.48	93.29	98.74	
	PB	99.89	99.33	96.51	99.98	
Experiment 3	N	98.92	96.07	98.77	96.53	97.78
	LBBB	99.11	99.63	96.52	99.91	
	RBBB	99.50	99.62	94.88	99.96	
	PVC	86.14	99.58	94.52	98.84	
	PB	99.91	99.35	96.61	99.98	

attributed to the fact that PVC is a common event occurring in a person of any age [11], while age is not considered in the paper. Furthermore, the 6810 PVC beats are evenly distributed across 27 records (details can be seen in Table 4), for a test record, a small number of training PVC beats is selected randomly from the other 26 records which were measured from different patients. It makes that there are various of PVCs in the training set since the large inter-patient variation of ECG waveforms. With the increase of PVC training beats, the performance is improved slightly (details can be seen in Table 2). It indicates that the small number of training PVC beats is another reason for the poor performance of PVC classification.

From Fig. 4 we can see that classification performance is improved slightly with the increase of training beat number. The indices of experiment 2 for N beat classification are only 0.31(Pp), 0.04(Np) percentage points higher than experiment 1. Classification indices of the other four types of beat are also increased slightly. The most increased index is the sensitivity of PVC beat classification, experiment 2 is 3.63 percentage points higher than experiment 1. These show that the classification performance can be improved by increasing the number of the training beats. On the other hand, these also show that good performance can also be achieved with very small training set (3% beats) by using the proposed method.

Moreover, 10-fold cross-validation is used to further verify the reliability and stability of the proposed method for global beat classification. To be precise, the set of all beats is divided into 10 subsets, and the proposed method is repeated 10 times. Each time, one of the 10 subsets containing 8964 beats (N: 6536, L: 805, R: 571, P: 681, PB: 371) is used as the test set and the other 9 subsets are put together to form a training set. Then, the average accuracy across all 10 trials is computed. The classification results of the 10-fold cross-validation are shown in Table 3. It can be seen the average accuracy is up to 99.22%.

4.2. Patient-adapting classifier

The patient-adapting classifier is used to classify ECG beat for a specific patient, the training set and the test set are both selected from the records of the same patient. To evaluate the performance of the proposed methods for specific patient, another three experiments are preformed, test set and training set are selected from the same record.

As records 101, 111, 112, 113, 115, 121, 122, 209, 220, 222, 230, 232 only contain one beat type of the five beat types studies in the paper, so the 12 records are excluded from the three experiments. The remaining 28 records with 30-min interval are used in

Table 3
The 10-fold cross-validation results for global beat classification. 'C-' represents the correct classification.

Fold	C-N	C-L	C-R	C-P	C-PB	Acc(%)
1	6495	804	568	635	368	98.95
2	6502	798	570	640	366	99.02
3	6509	803	569	629	371	99.07
4	6518	800	571	637	365	99.19
5	6520	799	567	654	369	99.39
6	6522	804	564	635	370	99.23
7	6512	796	566	659	371	99.33
8	6527	800	571	648	370	99.46
9	6514	799	569	651	366	99.27
10	6521	803	569	638	370	99.30
Average accuracy						99.22

the three experiments. For each record, 3%, 4%, 5% beats are randomly selected as training set and all the beats are used as test beats. The experimental results are given in Tables 4, 5 and 6.

Remark 2. Since LBBB, RBBB, PB beats are only contained in a few records, the indices Se, Sp, Pp, Np are not discussed in the second three experiments.

From Tables 4, 5 and 6, we can see that the overall accuracy of the three experiments are 96.76%, 97.03%, 97.21% respectively. The classification accuracy are higher than 95% for most of records, lower than 90% only for a handful of records. As the training set is very small and selected randomly, and the records are not selected based on the quality of the signal, the results are quite promising. It is shown that the proposed method is reliable in patient-adapting beat classification, which may be used for patient-adapting arrythmia detection. In addition, classification accuracy increases slightly with increasing the number of training beats for most of the records. The overall accuracy of experiments 5 (experiment 6) higher than experiments 4 (experiment 5) only 0.27 (0.18) percentage points. These demonstrate, once again, good performance of beat classification can also be achieved with very small training set using the proposed method .

Similarly with the global classifier, we use 10-fold cross-validation to further verify the reliability and stability of the proposed method for patient-adapting beat classification. The set of all beats of each record is divided into 10 subsets, and each time one of the 10 subsets is used as the test set and the other 9 subsets are put together to form a training set. Then, the average accuracy across all 10 trials is computed. The classification results of the 10-fold cross-validation for the beat classification of the 28 records are shown in Table 7. It can be seen that the beat classification accuracies of the 28 records are 98.36% to 99.62%.

5. Discussion

In the paper, a novel method is proposed for ECG beat classification. Different from the existing methods, beat *dynamics* is used as a unique feature for beat classification. Most of the methods using time domain features or frequency domain features can not express the subtle changes in the ECG signals and the hidden complexities clearly [44]. As the *dynamics* contains complete information of beat, the subtle changes in the ECG beats are also included. Thus, it would be more suitable for the beat classification, specially for the classification of beats with wide variations in waveforms. This is the main feature of the proposed method.

To show the advantage of the proposed method directly, comparative evaluations based on several state-of-the-art methods for ECG beat classification will be given in this section. Table 8 summarizes the experimental results of several state-of-the-art methods for ECG beat classification using the MIT-BIH arrhythmia database.

Table 4
Classification results of experiment 4, where 'a-' represents the annotated beat type and 'c-' represents the classified beat type using the proposed method. The training set is 3% beats.

Record	N		LBBB		RBBB		PVC		PB		Acc(%)
	a-N	c-N	a-L	c-L	a-R	c-R	a-V	c-V	a-pb	c-pb	
105	2518	2503	0	0	0	0	41	35	0	0	99.18
106	1503	1371	0	0	0	0	518	395	0	0	87.38
107	0	0	0	0	0	0	59	27	2070	2070	98.50
108	1731	1731	0	0	0	0	17	0	0	0	99.03
109	0	0	2485	2484	0	0	37	28	0	0	99.60
116	2293	2214	0	0	0	0	109	106	0	0	96.59
118	0	0	0	0	2160	2160	16	0	0	0	99.26
119	1537	1536	0	0	0	0	444	413	0	0	98.38
200	1735	1265	0	0	0	0	826	729	0	0	77.86
201	1621	1621	0	0	0	0	198	198	0	0	100.00
202	2052	2052	0	0	0	0	19	0	0	0	99.08
203	2521	2462	0	0	0	0	444	162	0	0	88.50
205	2563	2560	0	0	0	0	71	52	0	0	99.16
207	0	0	1457	1454	85	82	105	64	105	98	96.92
208	1581	1390	0	0	0	0	989	970	0	0	91.83
210	2415	2415	0	0	0	0	192	50	0	0	94.55
212	914	912	0	0	1825	1823	0	0	0	0	99.85
213	2630	2630	0	0	0	0	220	216	0	0	99.86
214	0	0	1995	1995	0	0	255	234	0	0	99.07
215	3185	3176	0	0	0	0	164	141	0	0	99.04
217	244	244	0	0	0	0	162	136	1535	1530	98.40
219	2075	2075	0	0	0	0	63	31	0	0	98.50
221	2023	2023	0	0	0	0	396	380	0	0	99.34
223	2021	2021	0	0	0	0	473	424	0	0	98.04
228	1684	1683	0	0	0	0	360	281	0	0	96.09
231	314	314	0	0	1248	1242	2	0	0	0	99.49
233	2222	2222	0	0	0	0	828	788	0	0	98.69
234	2692	2692	0	0	0	0	3	0	0	0	99.89
Total	44074	43112	5937	5933	5318	5307	7011	5860	3710	3698	96.76

Table 5
Classification results of experiment 5, where ‘a-’ represents the annotated beat type and ‘c-’ represents the classified beat type using the proposed method. The training set is 4% beats.

Record	N		L		R		V		pb		Acc(%)
	a-N	c-N	a-L	c-L	a-R	c-R	a-V	c-V	a-pb	c-pb	
105	2518	2505	0	0	0	0	41	38	0	0	99.37
106	1503	1377	0	0	0	0	518	456	0	0	90.70
107	0	0	0	0	0	0	59	32	2070	2070	98.73
108	1731	1731	0	0	0	0	17	0	0	0	99.03
109	0	0	2485	2484	0	0	37	28	0	0	99.60
116	2293	2287	0	0	0	0	109	105	0	0	99.58
118	0	0	0	0	2160	2160	16	0	0	0	99.26
119	1537	1535	0	0	0	0	444	414	0	0	98.38
200	1735	1455	0	0	0	0	826	633	0	0	81.53
201	1621	1621	0	0	0	0	198	198	0	0	100.00
202	2052	2052	0	0	0	0	19	0	0	0	99.08
203	2521	2381	0	0	0	0	444	226	0	0	87.93
205	2563	2555	0	0	0	0	71	64	0	0	99.43
207	0	0	1457	1455	85	81	105	67	105	100	97.20
208	1581	1401	0	0	0	0	989	978	0	0	92.57
210	2415	2411	0	0	0	0	192	58	0	0	94.71
212	914	910	0	0	1825	1816	0	0	0	0	99.53
213	2630	2629	0	0	0	0	220	214	0	0	99.75
214	0	0	1995	1994	0	0	255	227	0	0	98.71
215	3185	3181	0	0	0	0	164	126	0	0	98.75
217	244	228	0	0	0	0	162	58	1535	1535	93.82
219	2075	2075	0	0	0	0	63	39	0	0	98.88
221	2023	2023	0	0	0	0	396	383	0	0	99.46
223	2021	2021	0	0	0	0	473	435	0	0	98.48
228	1684	1684	0	0	0	0	360	277	0	0	95.94
231	314	314	0	0	1248	1247	2	0	0	0	99.81
233	2222	2222	0	0	0	0	828	801	0	0	99.11
234	2692	2692	0	0	0	0	3	0	0	0	99.89
Total	44074	43290	5937	5933	5318	5304	7011	5857	3710	3705	97.03

Table 6
Classification results of experiment 6, where ‘a-’ represents the annotated beat type and ‘c-’ represents the classified beat type using the proposed method. The training set is 5% beats.

Record	N		L		R		V		pb		Acc(%)
	a-N	c-N	a-L	c-L	a-R	c-R	a-V	c-V	a-pb	c-pb	
105	2518	2506	0	0	0	0	41	36	0	0	99.34
106	1503	1305	0	0	0	0	518	473	0	0	87.98
107	0	0	0	0	0	0	59	29	2070	2070	98.59
108	1731	1731	0	0	0	0	17	0	0	0	99.03
109	0	0	2485	2484	0	0	37	28	0	0	99.60
116	2293	2236	0	0	0	0	109	108	0	0	97.59
118	0	0	0	0	2160	2160	16	0	0	0	99.26
119	1537	1536	0	0	0	0	444	413	0	0	98.38
200	1735	1533	0	0	0	0	826	734	0	0	88.52
201	1621	1621	0	0	0	0	198	198	0	0	100.00
202	2052	2052	0	0	0	0	19	0	0	0	99.08
203	2521	2427	0	0	0	0	444	180	0	0	87.93
205	2563	2563	0	0	0	0	71	10	0	0	97.68
207	0	0	1457	1452	85	81	105	72	105	102	97.43
208	1581	1482	0	0	0	0	989	931	0	0	93.89
210	2415	2415	0	0	0	0	192	61	0	0	94.98
212	914	913	0	0	1825	1820	0	0	0	0	99.78
213	2630	2630	0	0	0	0	220	213	0	0	99.75
214	0	0	1995	1995	0	0	255	185	0	0	96.89
215	3185	3178	0	0	0	0	164	141	0	0	99.10
217	244	239	0	0	0	0	162	136	1535	1534	98.35
219	2075	2074	0	0	0	0	63	47	0	0	99.20
221	2023	2023	0	0	0	0	396	376	0	0	99.17
223	2021	2020	0	0	0	0	473	419	0	0	97.79
228	1684	1682	0	0	0	0	360	296	0	0	96.77
231	314	314	0	0	1248	1246	2	0	0	0	99.74
233	2222	2222	0	0	0	0	828	781	0	0	98.46
234	2692	2692	0	0	0	0	3	0	0	0	99.89
Total	44074	43394	5937	5931	5318	5307	7011	5867	3710	3706	97.21

Table 7
The 10-fold cross-validation results for patient-adapting beat classification. 'AAcc' represents the average accuracy.

File	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10	AAcc(%)
105	99.62	99.23	100.0	100.0	98.46	98.85	99.62	99.23	98.08	99.23	99.23
106	98.51	99.01	99.01	100.0	98.02	99.50	100.0	99.01	97.52	98.02	98.86
107	98.58	99.53	99.06	99.06	98.11	100.0	98.58	99.53	99.53	98.11	99.01
108	99.43	100.0	98.86	98.86	100.0	98.29	98.85	98.29	99.43	98.86	99.09
109	99.60	99.21	100.0	98.81	99.60	100.0	98.81	100.0	100.0	98.41	99.44
116	100.0	99.58	99.58	100.0	99.17	97.92	99.17	98.75	98.33	98.75	99.13
118	99.08	100.0	99.54	100.0	100.0	98.17	98.62	96.79	97.71	99.54	98.94
119	99.49	98.99	97.98	100.0	98.48	98.99	100.0	98.48	97.98	98.48	98.89
200	97.27	99.61	99.22	100.0	97.66	98.05	98.44	98.83	97.27	97.27	98.36
201	100.0	99.45	100.0	100.0	98.35	99.45	100.0	99.45	99.45	100.0	99.62
202	100.0	100.0	99.03	99.52	98.55	100.0	100.0	99.03	99.52	99.52	99.52
203	99.33	98.65	100.0	99.66	99.33	98.99	99.66	99.66	99.66	98.99	99.39
205	98.86	99.24	99.24	100.0	98.48	98.10	97.72	98.86	99.62	98.86	98.90
207	99.43	98.29	100.0	97.71	98.86	98.86	99.43	98.29	99.43	100.0	99.03
208	99.22	99.61	98.83	99.22	98.44	99.61	99.22	97.28	99.22	99.61	99.03
210	99.62	98.85	99.23	98.08	98.46	99.62	99.23	98.85	99.62	100.0	99.15
212	98.90	99.27	98.53	100.0	99.63	99.27	99.27	98.90	98.53	98.17	99.05
213	99.65	98.25	98.95	98.95	98.60	100.0	98.60	99.30	99.65	99.65	99.16
214	99.11	99.11	97.78	98.22	100.0	100.0	97.33	97.78	99.56	99.56	98.84
215	99.10	99.10	99.10	100.0	98.51	99.10	99.10	99.10	99.10	100.0	99.22
217	99.48	98.97	99.48	100.0	100.0	98.97	99.48	98.45	100.0	100.0	99.48
219	100.0	100.0	99.07	98.13	98.60	100.0	99.53	98.13	100.0	100.0	99.35
221	98.35	99.59	99.17	100.0	98.76	99.17	99.17	100.0	99.59	99.17	99.30
223	100.0	98.80	98.80	99.60	98.39	100.0	100.0	99.20	99.60	99.20	99.36
228	99.02	98.04	100.0	99.51	100.0	100.0	99.51	99.02	99.51	99.51	99.41
231	99.36	99.36	100.0	99.36	100.0	100.0	98.08	100.0	99.36	99.36	99.49
233	98.36	98.69	100.0	100.0	99.67	98.69	99.02	100.0	100.0	99.67	99.41
234	100.0	99.63	99.26	100.0	100.0	99.63	98.15	98.89	97.78	100.0	99.33

Table 8
Comprehensive summary of ECG beat classification using the MIT-BIH arrhythmia database.

Literature	Training set	Testing set	Classes	Acc(%)
Global-Classifier				
Thomas et al. [66]	10% of all beats	90% of all beats	5	97.68
Kaur and Arora [24]	20% of 1325 beats [b]	80% of 1325 beats [b]	5	99.06
Rai et al. [67]	16.7% of 2990 beats [b]	83.3% of 2990 beats [b]	5	99.60
Inan et al. [65]	2% of 18 records [a]	93281 beats	3	95.16
Dutta et al. [11]	5% of 18 records [a]	93246 beats	3	95.24
Martis et al. [68]	90% of 34989 beats	10% of 34989 beats	5	93.48
Martis et al. [69]	90% of 34989 beats	10% of 34989 beats	5	94.52
Khalaf et al. [70]	90% of 6259 beats	10% of 6259 beats	5	98.60
Proposed	5% of 89647 beats	85123 beats	5	97.78
Patient-adapting				
Ince et al. [1]	16.67% of each record [b]	83.33% of 44 records [b]	5	95.58 [d]
Hu et al. [27]	8.33% of 13 records [b]	91.67% of 20 records [b]	2	94.00
Chazal and Reilly [47]	28% of each record [b]	72% of 22 records [b]	5	93.89 [d]
Jiang and Kong [50]	24 records	49600 beats [d]	5	94.50 [d]
Llamedo and Martínez [51]	100 records [c]	48 records	3	93.00
Proposed	5% of each record	66050 beats of 28 records	5	97.21

[a] The actual number of beats was not given in the paper.
[b] The percentages of training set and testing set are computed based on the segment length used as training and testing set provided in the paper.
[c] This training set consists of 78 records of MIT-BIH supraventricular arrhythmia database and 22 records of the MIT-BIH arrhythmia database.
[d] It is computed on the strength of the classification matrix provided in the paper.

From Table 8, it can be seen the performance of the classification accuracy reported in [65] ([11]) is 95.16% (95.24%), 3 types of beat were classified with training set containing 2% (5%) representative beats taken from 18 records. 10-fold cross-validation strategy (90% beats were used as training set and 10% beats were used as test set) was used to evaluate the classification systems provided in [68–70], accuracies of 93.48%, 98.6%, 94.52% were achieved for classifying 5 types of beat, respectively. In comparison, the proposed method could produce a classification accuracy of 97.78%, with 5% beats (selected randomly) used as training set, for 5 types of beat classification. It can be seen that the accuracy reported in [70] is higher than the proposed method. There are two main reasons for this: i) The ratio between the training beats and test beats is 9:1 in [70], while this ratio is 1:19 in this paper. This ratio is a main factor for the classification accuracy. ii) The total beats (89647) used in the paper is more than 14 times greater than used in [70] (6259). It is another main factor for the classification accuracy. Especially, in [24,66,67], 5 beat types that are identical with this paper were classified. In [66], all of the beats in the MIT-BIH database are used in experiments, while 10% of total beats are used as training set which is more than this paper (5%), and the accuracy is lower (97.68%) than the proposed method (97.78%). Although the accuracies reported in [24,67] (99.06%, 99.60%) are higher than the proposed method, the percentage of the training sets in the total beats (20%, 16.7%) used in experiments are much higher than this paper (5%), and the total beats (1325, 2990) used in experiments are much less than this paper (89647). Additionally, the reliability and stability of the proposed method is verified by 10-fold cross-validation and the beat classification accuracies of the 10 folds are up to 98.95% to 99.46% (Table 3), higher than the accuracies reported in [68–70]. From the comparison and the 10-fold cross-validation results, it can be inferred that the proposed method is more reliable and preferable for beat classification than other major techniques in the literature.

For patient-adapting beat classification, the paper introduces the classification of 5 types of beat using the proposed method, and achieved an overall accuracy of 97.21% with training set containing 5% beats (selected randomly) of each record. In comparison, the accuracy reported in [27] was 94.0% for distinguishing ventricular ectopic beat from non-ventricular ectopic beat; in [1,47,50], accuracies of 95.58%, 93.89%, 94.5% were achieved for 5 types of beat classification respectively; in [51] the maximum accuracy was 93% for 3 types of beat classification. In addition, the 10-fold cross-validation results in Table 7 are up to 98.36% to 99.62% which show that the proposed method has good reliability and stability for patient-adapting beat classification. These indicate that the proposed method is also reliable and efficient for patient-adapting beat classification.

What's more, a number of methods were tested only on limited data set and the generalization performance on large ECG databases was not evaluated [44]. For instance, Korüek and Doğan [13] obtained average sensitivity and specificity in the beat classification of 95.24% and 98.99% considering a limited data (836 N beats, 605 PVC beats). In addition, some of methods were evaluated using large training set and the generalization capability can also not be checked. For instance, Sumathi et al. [71] achieved an accuracy of 98.24% for classification of 5 types of beat, with 70% of data set used as training and 30% of data set used as testing set. In comparison, the proposed method is tested on a large data set and achieved 93.28% (94.45%, 94.80%) average specificity and 98.24% (98.53%, 98.64%) average sensitivity, with 3% (4%, 5%) of the total beats used as training set. It is shown that the proposed method has good generalization capacity.

Finally, the classification procedure does not need to extract features (whether statics features or temporal features) from the test beat. As finding the right feature combinations is, indeed, a hard task [36], most literature selects the optimal features used for beat classification by trial and error. While the hard task is avoided in the proposed method. In addition, the classification process takes place from the beginning of measuring the state of the test beat and ends within the period of the test beat, and it dose not need to compare directly the dynamics of the test and training beats by any form of numerical computation. These make the proposed method could be implemented in real-time. In practice, it may be used to monitor some arrhythmia in ambulance or intensive care rooms, based on a few of beats (at the beginning of the ECG record) with annotations given by physicians.

6. Conclusion

In our study, a novel method for ECG beat classification is proposed. The *dynamics* of ECG beat is accurate modeled and used for beat classification. For a beat need to be classified, a set of errors can be obtained based on the modeling results of a training beat set, and the beat can be classified according to the smallest error principle. Experimental results indicate that the proposed method is reliable and efficient for beat classification, whether for global beat classification or for patient-adapting beat classification, and has good generalization capacity.

The main contribution of the paper is that a novel method based on dynamics is proposed for beat classification. The dynamics is the deeper nature of ECG beat, and first used as feature for beat classification. Compared with existing features (e.g, durations, amplitude, frequency) used in literature, it contains complete information of ECG beat and can characterize various variations of the ECG beat more accurately. It is the main reason that comprehensive performance of the proposed method is superior to other major approaches in literature. Moreover, it does need to extract feature from the test beat, which is essential in literature. Thus, it is expected to be implemented in real-time and used in some arrhythmia monitors, based on the modeling results of some beats annotated by physician at the beginning of the ECG record.

There are also some limitations in the study. As the *dynamics* is a description of the heart electrical activities which is influenced by many factors such as age, gender and physiological status, information of these factors is contained in the *dynamics*. While, these factors are not considered in the paper. This will influence the classification performance of the proposed method. It is also one of the main reasons for the low *Se* of PVC. In the following work, we intend to study the beat classification considering various factors, and the classification performance of the proposed method would be further improved. Specially, we will further study the classification of ECG signals according to various heart diseases, and desirable to provide some assistance in ECG automatic diagnosis. The classification of other biomedical signals, such as electroencephalogram, the pulse of traditional Chinese medicine, will also be studied since they are all temporal patterns.

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