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# A new method for early detection of myocardial ischemia: cardiodynamicsgram (CDG)

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**Abstract** Early detection of myocardial ischemia via electrocardiographic methods is important and challenging. In the study, based on the standard 12-lead electrocardiography (ECG), a new method called cardiodynamicsgram (CDG) is proposed for early detection of myocardial ischemia. Using a recently proposed deterministic learning algorithm, the cardiodynamics information is extracted from the ST-T segments of standard 12-lead ECG. The CDG is generated by plotting the three-dimensional cardiodynamics information. By analyzing CDG morphology, it is found that significant correlations exist between CDG and ischemia. By evaluating ischemia patients and healthy controls from the Physikalisch-Technische Bundesanstalt (PTB) database and the General Hospital of Guangzhou Military Command, the CDG method achieves a mean sensitivity of 90.3% and a mean specificity of 87.8%, which are higher than those of both the standard 12-lead ECG and the exercise ECG. As it is noninvasive, convenient, and inexpensive, it is hopeful that CDG may become a cost-effective screening method for early detection of ischemic heart diseases.

**Keywords** early detection, myocardial ischemia, cardiodynamicsgram (CDG), ECG, deterministic learning, cardiodynamics

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## 1 Introduction

Cardiovascular disease (also called heart disease) is the leading cause of death worldwide. Myocardial ischemia is a kind of heart disease with insufficient blood flow to the heart muscle. Persistent and severe myocardial ischemia will lead to myocardial infarction (MI) (i.e., heart attack). Thus, early detection of myocardial ischemia prior to heart attack is important because though heart attack (MI) is deadly, it is treatable if ischemia can be detected early [1].

Myocardial ischemia is usually caused by a critical coronary artery obstruction, which is also known as atherosclerotic coronary artery disease (CAD). In hospitals, CAD and myocardial ischemia are diagnosed by various methods, including the resting and exercise ECGs, echocardiography, computed tomography

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angiography (CTA), magnetic resonance imaging, myocardial perfusion imaging (MPI), and coronary angiography (CAG). All these methods except for ECG are based on advanced imaging technologies and require high-level technical expertise to perform the diagnosis [2]. The standard 12-lead ECG (or resting ECG) is an efficient and convenient tool for monitoring heart activities. Compared with other tools used in clinical practice, it is noninvasive, fast, and inexpensive and is available in every hospital. However, the accuracy (sensitivity) of standard ECG for detecting myocardial ischemia is normally low [3]. Exercise ECG is developed to detect myocardial ischemia under stress conditions. It can achieve a moderate accuracy for myocardial ischemia [4,5], nonetheless, many patients are not able to conduct adequate exercise testing. This is the main disadvantage of exercise ECG [6]. Thus, both the resting ECG and the exercise ECG cannot be used as an appropriate screening method for early detection of ischemia. On the other hand, vectorcardiography (VCG) developed by Frank [7] has proved its potential in principle for ischemia diagnosis. However, so far VCG has not been established as a routine method, probably because it is difficult to interpret. There are also some other enhanced electrocardiographic methods (e.g., signal-averaged ECG [8,9], body surface potential mapping [10,11], cardiogoniometry [12,13], and T-wave alternans [14,15]) which are relevant to ischemia diagnosis, but have not become routine screening diagnostic tools [6]. Therefore, it is still of great importance and necessity to improve ECG detection for myocardial ischemia.

To improve the accuracy for detecting ischemia based on ECG, a variety of methods have been proposed. They include signal processing techniques such as time-domain analysis [16–19], and artificial intelligence techniques such as artificial neural networks (ANNs) [20–22], decision tree-based approach [23], and so on. In these methods, information about the severity and duration of cardiac ischemic episodes is extracted from the changes in the ST segments of ECG patterns. One difficulty lies in that the ST segment changes may be caused by nonischemia diseases or situations, which affect the performance of detection algorithms [24].

In this paper, based on the standard 12-lead ECG, a new method called cardiodynamicsgram (CDG) is proposed for early detection of myocardial ischemia using a recently proposed deterministic learning algorithm. Deterministic learning is proposed for accurate modeling and rapid recognition of temporal or dynamical patterns. This algorithm is applicable to the detection of small oscillation faults generated from nonlinear dynamical systems [25], which is closely related to the detection of myocardial ischemia. First, the cardiodynamics information inside ECG is extracted via deterministic learning from the ST-T segments (the dash line shown in Figure 1) of standard 12-lead ECG. The CDG is generated by plotting the extracted three-dimensional cardiodynamics information. Second, by analyzing CDG morphology, it is found that significant correlations exist between CDG and ischemia. Particularly, it is shown that the shapes of CDG remarkably differ between ischemia patients (irregular shapes) and healthy controls (regular shapes). By evaluating ischemia patients and healthy controls from the PTB database [26] and the General Hospital of Guangzhou Military Command, the CDG method achieves a mean sensitivity of 90.3% and a mean specificity of 87.8%, which are higher than those of both the resting ECG and the exercise ECG. Thus, it is hopeful that CDG may become an effective method for early detection of myocardial ischemia. As CDG is based on the standard 12-lead ECG, it is noninvasive and convenient similar to ECG, and so it may be used as a screening method for ischemia detection in primary healthcare centers.

## 2 Methods

Since ECG signals are essentially temporal patterns generated from electrical activities of the heart, which can be modeled by complex nonlinear dynamical systems, the diagnosis of heart diseases based on ECG signals virtually belongs to the problem of modeling and analysis of temporal or dynamical patterns. However, modeling and feature extraction of temporal or dynamical patterns is among the most difficult tasks in the pattern recognition area [27]. It is supposed in [28] that methods for temporal pattern recognition should be fundamentally different from those for static pattern recognition. Recently, a deterministic learning theory is proposed for modeling nonlinear dynamical systems using radial basis

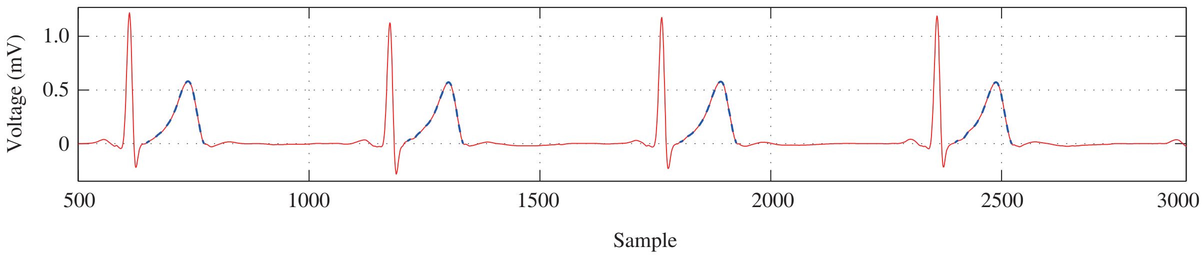


**Figure 1** (Color online) The ST-T segment of ECG used to construct CDG.

function (RBF) neural networks [29–31]. A brief introduction of deterministic learning is given in the following subsection.

### 2.1 Deterministic learning

Deterministic learning theory is proposed for modeling, representation, similarity definition, and rapid recognition of temporal or dynamical patterns. This theory is mainly developed using concepts and theories of system identification, adaptive control, and RBF networks. Using the deterministic learning algorithm, the dynamics of a temporal pattern can be accurately modeled, and the temporal features of the pattern can be effectively extracted and represented in a time-invariant manner [29,30]. Based on the deterministic learning theory, an approach for modeling and detection of small oscillation faults generated from nonlinear dynamical systems was presented in [25]. The detection of abnormal oscillations is of great importance for both theory and practical applications and is closely related to the detection of myocardial ischemia.

In deterministic learning, a temporal or dynamical pattern is defined as the periodic or recurrent signals (or trajectories) generated from the following general nonlinear dynamical system:

$$\dot{x} = F(x;p), \quad x(t_0) = x_0, \tag{1}$$

where $x = [x_1, \ldots, x_n]^{\mathrm{T}} \in \mathbb{R}^n$ is the system state, $p$ is a constant vector of system parameters, and $F(x;p) = [f_1(x;p), \ldots, f_n(x;p)]^{\mathrm{T}}$ is a vector of continuous but unknown nonlinear functions. The system trajectory starting from $x_0$ is denoted as $\phi_\zeta(x,t;x_0)$ or $\phi_\zeta$ for conciseness of presentation. It is assumed that $\phi_\zeta$ is in either a periodic or a recurrent motion. In the rest of this paper, $\phi_\zeta$ is used to represent a temporal or dynamical pattern.

To achieve modeling of the unknown system dynamics $F(x;p) = [f_1(x;p), \ldots, f_n(x;p)]^{\mathrm{T}}$ underlying the dynamical pattern $\phi_\zeta$, the following estimator system using the RBF network is employed:

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

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

From (1) and (2), the derivative of the state estimation error $\tilde{x}_i = \hat{x}_i - x_i$ satisfies

$$\dot{\tilde{x}}_i = -a_i\tilde{x}_i + \hat{W}_i^{\mathrm{T}} S_i(x) - f_i(x;p) = -a_i\tilde{x}_i + \tilde{W}_i^{\mathrm{T}} S_i(x) - \epsilon_i, \tag{3}$$

where $\tilde{W}_i = \hat{W}_i - W_i^*$, $W_i^*$ is the ideal constant weight vector, and $\epsilon_i = f_i(x;p) - W_i^{\mathrm{T}*} S_i(x)$ is the ideal approximation error. The weight estimates $\hat{W}_i$ are updated by the following law:

$$\dot{\hat{W}}_i = \dot{\tilde{W}}_i = -\Gamma_i S_i(x)\tilde{x}_i - \sigma_i \Gamma_i \hat{W}_i, \tag{4}$$

where $\Gamma_i = \Gamma_i^{\mathrm{T}} > 0$, and $\sigma_i > 0$ is a small value.

By setting initial values $\hat{W}_i(0) = 0$, it has been shown [29–31] that for almost every recurrent trajectory or temporal/dynamical pattern $\phi_\zeta$, locally accurate modeling (or approximation) of the unknown dynamics $f_i(x;p)$ can be achieved along the trajectory of $\phi_\zeta$:

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

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

### 2.2 Cardiodynamicsgram (CDG)

Using the deterministic learning algorithm, we present in this subsection the new CDG method for the detection of ischemia. The CDG is the three-dimensional graphical representation of cardiodynamics information extracted from the standard 12-lead ECG. It is generated in the following steps:

(1) Transformation of ECG into VCG: Since RBF networks are used in the deterministic learning algorithm, when the high-dimensional 12-lead ECG signals are taken as inputs to RBF networks, it will lead to the problem of the curse of dimensionality [32]. Thus, it is required that the dimension of the standard 12-lead ECG signals be reduced. A natural choice is to use the three-dimensional VCG signals, since VCG signals and 12-lead ECG can be linearly transformed into each other without loss of useful information content pertaining to the heart dynamics [33–35]. In this paper, an extension to [33–35] is used to transform the standard 12-lead ECG into VCG [36]. The transformed VCG (denoted as TVCG) can be considered as patterns generated from the following three-dimensional dynamical system:

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

where $V = [v_X, v_Y, v_Z] \in \mathbb{R}^3$ is the system state, which represents three-dimensional TVCG signals, and $F(V) = [f_X(V), f_Y(V), f_Z(V)]^{\mathrm{T}}$ is a unknown nonlinear function vector, that is, the cardiodynamics underlying the TVCG pattern $\phi_V$.

(2) Modeling of TVCG: Based on the deterministic learning algorithm, an extension of the deterministic learning algorithm [37,38] is employed to model the cardiodynamics $F(V)$ of the TVCG pattern. Using three RBF networks $\hat{W}_i^{\mathrm{T}} S_i(\phi_\zeta)$ $(i \in \{X,Y,Z\})$ and setting the initial values $\hat{W}_i(0) = 0$, accurate approximation of the TVCG cardiodynamics $f_i(V)$ $(i \in \{X,Y,Z\})$ can be represented as follows:

$$f_i(\phi_V) = \hat{W}_i^{\mathrm{T}} S_i(\phi_V) + \epsilon_{i1} = \bar{W}_i^{\mathrm{T}} S_i(\phi_V) + \epsilon_{i2}, \tag{7}$$

where $\epsilon_{i1}, \epsilon_{i2}$ are the practical approximation errors, $\bar{W}_i = \mathrm{mean}_{t\in[t_b,t_a]}\hat{W}_i(t)$, mean is the arithmetic mean, and $t_b > t_a > 0$ represents a piece of time segment after the transient process.

(3) Plotting the cardiodynamics: To extract the cardiodynamics information of ST-T loop, the onset and the offset of ST-T loop should be identified first. Many efficient algorithms had been developed for extraction of ECG feature points. In the study, the algorithm proposed in [39] which is robust and efficient is used to extract the onset $k_S$ and the offset $k_E$ of ST-T loop. This is helpful for achieving good performance of CDG. With the onset $k_S$ and the offset $k_E$ of ST-T loop, the ST-T loop of TVCG pattern can be represented as follows:

$$\phi_{V_{\mathrm{ST}}} = V(v_X, v_Y, v_Z, t)|_{t=t_S}^{t=t_E}.$$

Correspondingly, the cardiodynamics of TVCG ST-T loop can be represented and be locally accurately approximated by

$$F(\phi_{V_{\mathrm{ST}}}) = (f_X(\phi_{V_{\mathrm{ST}}}), f_Y(\phi_{V_{\mathrm{ST}}}), f_Z(\phi_{V_{\mathrm{ST}}})) \approx (\bar{W}_X^{\mathrm{T}} S_X(\phi_{V_{\mathrm{ST}}}), \bar{W}_Y^{\mathrm{T}} S_Y(\phi_{V_{\mathrm{ST}}}), \bar{W}_Z^{\mathrm{T}} S_Z(\phi_{V_{\mathrm{ST}}})), \tag{8}$$

where $\bar{W}_X^{\mathrm{T}} S_X(\phi_{V_{\mathrm{ST}}})$, $\bar{W}_Y^{\mathrm{T}} S_Y(\phi_{V_{\mathrm{ST}}})$, $\bar{W}_Z^{\mathrm{T}} S_Z(\phi_{V_{\mathrm{ST}}})$ are constant RBF networks which achieve locally accurate approximation of the cardiodynamics $f_X(\phi_{V_{\mathrm{ST}}})$, $f_Y(\phi_{V_{\mathrm{ST}}})$, $f_Z(\phi_{V_{\mathrm{ST}}})$ along the trajectories of ST-T loop, respectively. The CDG is obtained by plotting the cardiodynamics information ($\bar{W}_X^{\mathrm{T}} S_X(\phi_{V_{\mathrm{ST}}})$, $\bar{W}_Y^{\mathrm{T}} S_Y(\phi_{V_{\mathrm{ST}}})$, $\bar{W}_Z^{\mathrm{T}} S_Z(\phi_{V_{\mathrm{ST}}})$) in the three-dimensional $XYZ$ coordinate system along the trajectories of TVCG ST-T loop $\phi_{V_{\mathrm{ST}}}$.

**Remark 1.** It is shown that the CDG is generated by extracting the cardiodynamics information from the TVCG ST-T loop, which is transformed from the ST-T segments of standard 12-lead ECG. Note that though VCG has proved its potential in ischemia diagnosis, it has not been established as a routine method in clinical practice [6,40–42], mainly because it uses a different lead system and is difficult to interpret. In the following, it will be shown that by using the cardiodynamics information, CDG is more effective and more convenient in early detection of ischemia and CAD.

## 3 Experiments

### 3.1 Materials

In this study, a total of 385 cases are recruited to verify CDG. They include two groups: (i) the first group is from the PTB database [26], which includes 148 MI subjects and 52 healthy controls and (ii) the second group recruits 86 patients with suspected ischemic heart disease and 99 healthy controls from the General Hospital of Guangzhou Military Command. The PTB database is an ECG collection provided by the National Metrology Institute of Germany for the purposes of teaching, research, and algorithm evaluation. It contains ECG records from 290 subjects. Each record includes 15 simultaneously measured signals, that is, the standard 12-lead ECG together with the 3-lead Frank VCG. Among the 290 subjects, the clinical summary is not available for 22 subjects. From the remaining 268 subjects with detailed clinical summaries, we take all the MI subjects (148) and all the healthy controls (52) as the first group.

It is noticed that there is currently no gold standard for the diagnosis of myocardial ischemia [43,44]. None of the traditional clinical methods, including the resting and exercise ECGs, biochemical markers, and imaging techniques, can be considered as a true "gold standard" for the diagnosis of ischemia [43,44]. This is one of the main challenges faced in the development of any new method for detecting ischemia. In this study, similar to [45], the final hospital diagnosis is used as the "gold standard." The final hospital diagnosis resulted from the analysis of all available clinical data, such as the clinical history, ECG, MPI, CTA, CAG, and so on.

Among the 385 cases in the study, 21 patients in the second group were excluded from the final analysis due to incomplete diagnosis information or inaccuracy for data acquisition. Therefore, the total study population comprised 364 cases, 200 cases in the first group and 164 cases in the second group (65 inpatients and 99 healthy controls). All the healthy controls in the first and second groups were considered as nonischemia cases. On the other hand, all the 148 MI subjects from PTB database were considered as ischemia patients according to the clinical summary of the ECG records. Of the 65 inpatients in the second group, 27 were discharged with a final diagnosis of CAD or ischemia. The remaining 38 patients with normal arteries were diagnosed as nonischemia cases.

### 3.2 Results

As shown in Section 2, the cardiodynamics information can be extracted from the ST-T segments of standard 12-lead ECG, and the CDG is generated by plotting the extracted three-dimensional cardiodynamics information. By analyzing CDG morphology, it is found that the shapes of CDG remarkably differ between healthy controls (regular shapes) and ischemia patients (irregular shapes). This implies that significant correlations exist between CDG and ischemia. Consequently, CDGs with irregular or even chaotic shapes are considered as positive, and CDGs with regular shapes are considered as negative. As shown in Figure 2, the CDGs of two healthy controls in the first and the second groups are both negative with regular shapes. On the other hand, the CDGs of two patients in the first and the second groups are both positive with irregular shapes, as shown in Figure 3.

Among the healthy controls in the first and the second groups, there are 43 and 92 cases, respectively, that are negative in CDG. Thus, the specificity for the first and the second groups of healthy controls is 82.7% (43/52) and 92.9% (92/99), respectively. On the other hand, among the 148 MI subjects in the first group of PTB database, 135 cases are positive in CDG. Thus, the sensitivity for this is 91.2% (135/148). The results are shown in Table 1. Among the 65 patients included in the second group, 35

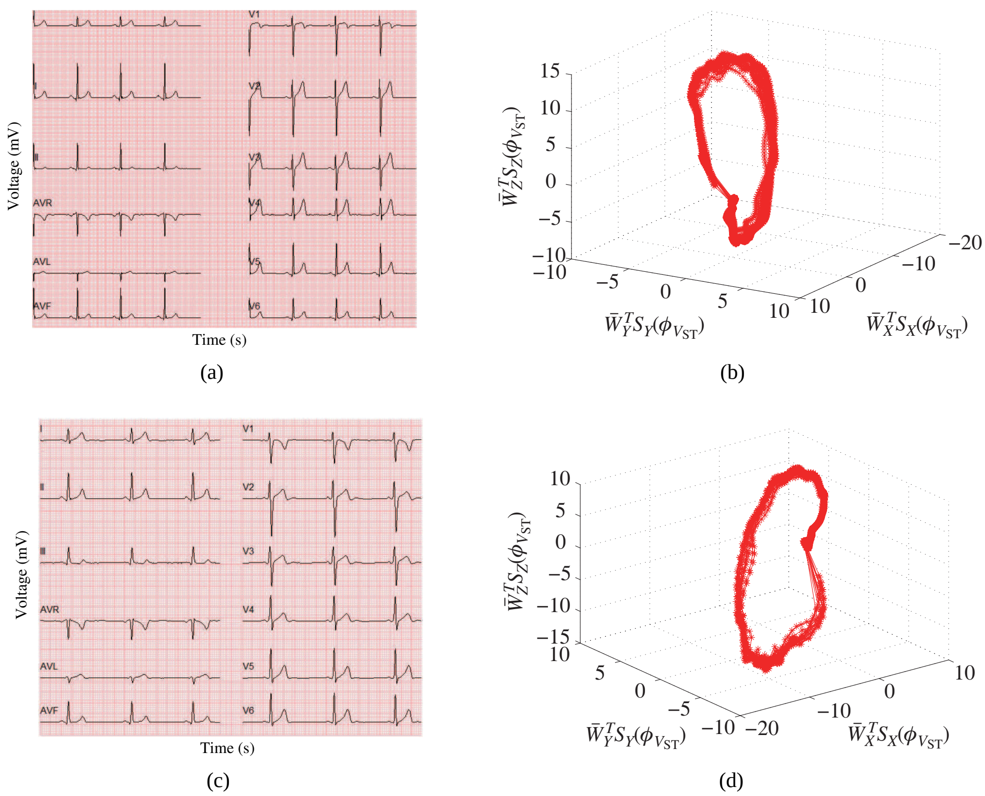


**Figure 2** (Color online) The ECGs and CDGs of two healthy subjects: P165, male, 26 years; A222, male, 23 years. (a) The ECG of P165; (b) the CDG of P165; (c) the ECG of A222; (d) the CDG of A222.

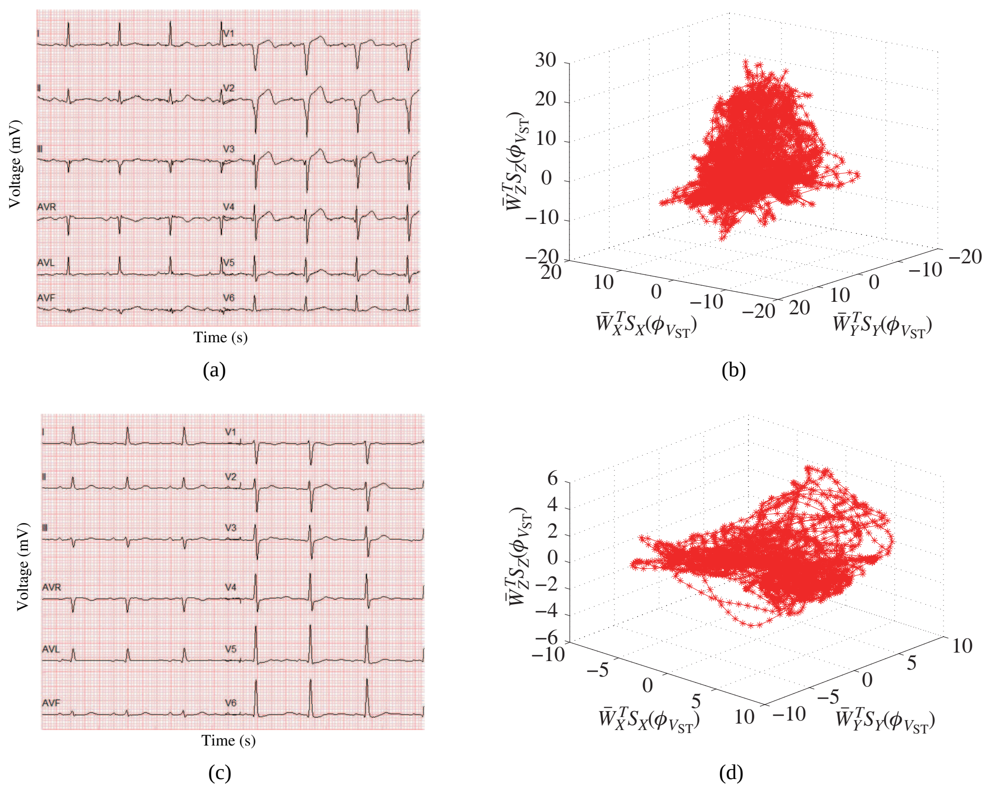


**Figure 3** (Color online) The CDG of two patients with ischemia: P004, male, 69 years, MI; T234, male, 74 years, severe coronary stenosis. (a) The ECG of P004; (b) the CDG of P004; (c) the ECG of T234; (d) the CDG of T234.

**Table 1** The results of the experiments, where N and P represent negative and positive[a)]

| Experiments | Results of CDG | | Number of TP, TN, FP, and FN | | | | SEN (%) | SPE (%) | Accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|
| | N | P | TN | TP | FN | FP | | | |
| PTB's 148 MI patients | 13 | 135 | | 135 | 13 | | 91.2 | | 91.2 |
| PTB's 52 healthy controls | 43 | 9 | 43 | | | 9 | | 82.7 | 82.7 |
| ZYY's 65 patients | 35 | 30 | 31 | 23 | 4 | 7 | 85.2 | 81.6 | 83.1 |
| ZYY's 99 healthy controls | 92 | 7 | 92 | | | 7 | | 92.9 | 92.9 |
| Total 364 cases | 183 | 181 | 166 | 158 | 17 | 23 | 90.3 | 87.8 | 89.0 |

a) TN, TP, FN, and FP represent true negative, true positive, false negative, and false positive; and ZYY represents the General Hospital of Guangzhou Military Command, respectively.

cases are negative in CDG and 30 cases are CDG positive. Using the final hospital diagnosis as the gold standard for the diagnosis of ischemia, the 35 CDG negative patients include 31 nonischemia cases, and the 30 CDG positive patients include 23 ischemia cases. Therefore, the CDG sensitivity, specificity, and accuracy of the 65 patients are 81.0%, 88.2%, and 85.5%, respectively.

In summary, for the 364 cases included in this study, 181 cases showed positive in CDG with 158 cases of ischemia and 23 cases of nonischemia; 183 cases showed negative in CDG with 166 cases of nonischemia and 17 cases of ischemia. The diagnosis sensitivity of ischemia is 90.3% (158/175), the specificity is 87.8% (166/189), and the accuracy is 89.0% (324/364). The results are shown in Table 1.

**Remark 2.** The three indices sensitivity (SEN), specificity (SPE), and accuracy are defined as follows:

$$\begin{aligned}
&\text{Sensitivity} :\overset{\text{def}}{=} \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}\ (\%),\\
&\text{Specificity} :\overset{\text{def}}{=} \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}}\ (\%),\\
&\text{Accuracy} :\overset{\text{def}}{=} \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}\ (\%),
\end{aligned}$$

where true positives (TP) and true negatives (TN) are the number of correctly recognized patients with and without myocardial ischemia, and false positives (FP) and false negatives (FN) are the number of erroneously recognized patients with and without myocardial ischemia.

## 4 Discussion

In the following, two more cases are given to show the effectiveness of CDG: one ischemia patient with essentially normal ECG (T540), and another one nonischemia patient being misclassified (T123). Patient T540 was with essentially normal ECGs (as shown in Figure 4(a)). The patient was finally diagnosed as CAD with ischemia after CAG showing severe coronary stenosis. The CDG result of T540 is shown in Figure 4(b), which is positive (with irregular shape) and is consistent with CAG and the final hospital diagnosis. On the other hand, patient T123 was with the symptom of acute chest pain and abnormal ECGs (as shown in Figure 4(c)), thus the patient was first misclassified as MI. After CAG showing no coronary stenosis, the patient was finally diagnosed as pneumatocele, a kind of nonischemia lung disease. The CDG result of T123 is shown in Figure 4(d), which is negative (with regular shape) and is consistent with CAG and the final hospital diagnosis.

Therefore, compared with the standard 12-lead ECG, which is widely available but also insensitive for detection of myocardial ischemia, it is shown that CDG achieves a much higher sensitivity and specificity. Compared with the exercise ECG, which can achieve a moderate accuracy for ischemic heart diseases but is of limited feasibility due to the restriction of performing exercise testing, CDG is more accurate and can be conducted at rest, thus it is with increased feasibility. Compared with other electrocardiographic methods, including VCG and a variety of enhanced analysis tools using different lead systems, CDG is easier to be clinically accepted as routine diagnostics since it is based on the standard 12-lead ECG.

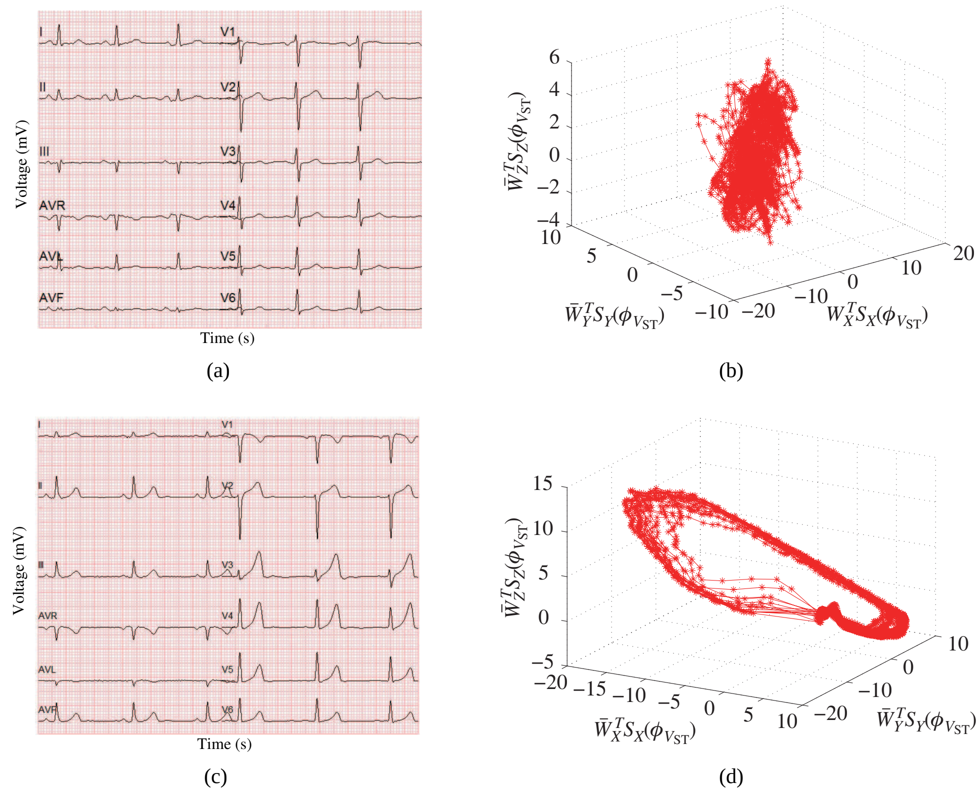


**Figure 4** (Color online) The ECGs and CDGs of one patient being ignored with normal ECG (T540) and one patient being misclassified (T123). (a) The ECG of T540; (b) the CDG of T540; (c) the ECG of T123; (d) the CDG of T123.

Thus, CDG may become a practical, cost-effective screening method for improving ECG diagnosis of myocardial ischemia/CAD in primary health care.

The CDG is generated by extracting the cardiodynamics information from the ST-T segments of the standard 12-lead ECG via deterministic learning, and then by plotting the cardiodynamics information in the three-dimensional $XYZ$ coordinate system. Using the more in-depth dynamics information of the heart rather than using the static features of ECGs, it is shown that CDG is more sensitive since the shapes of CDG remarkably differ between ischemia patients (irregular shapes) and healthy controls (regular shapes), while a resting or exercise ECG might miss the ischemia sign when the ST segment changes are subtle. On the other hand, the imaging results from CAG or CTA provide only morphological information on coronary artery stenoses that may partly correlate with the presence of ischemia [46–48]. Note that even in the absence of severe or moderate stenoses, different levels of ischemia may occur, which in turn lead to electrophysiological alterations. These electrophysiological changes may be more sensitively detected by the cardiodynamics information in CDG, thus even patients with silent myocardial ischemia [49] may be detected early by CDG.

There are some limitations in the study. First, as indicated in [46–48], one of the main challenges for the diagnosis of myocardial ischemia is that there is no “gold standard”. In this study, we use the final hospital diagnosis similar to [49] as the gold standard for the diagnosis of ischemia. The final hospital diagnosis is reliable since it comes from the analysis of all available clinical data by an independent experienced cardiologist. For example, in our study several inpatients with chest pains or other symptoms of ischemia are classified as nonischemia according to the final hospital diagnosis, because noncardiac mechanism is found as the cause of chest pain; and the absence of moderate or severe stenosis on CAG or CTA is confirmed. Second, the number of cases in the study is limited. Patients enrolled in the study are required to have complete clinical information to make the final diagnosis. This requirement precluded the recruitment of patients in the second group. Further studies with greater patient numbers are needed.

## 5 Conclusion

In this study, a new method called CDG has been proposed for early detection of myocardial ischemia. The cardiodynamics information is extracted from the ST-T segments using deterministic learning algorithm and is plotted in the three-dimensional $XYZ$ coordinate system. It is found that there exist significant correlations between CDG and ischemia. By evaluating ischemia patients and healthy controls from the PTB database and the General Hospital of Guangzhou Military Command, the CDG method achieves a mean sensitivity of 90.3% and a mean specificity of 87.8%, which are higher than those of both the resting ECG and the exercise ECG. As it is based on standard 12-lead ECG and is noninvasive, convenient, and inexpensive, it is hopeful that CDG may become a cost-effective screening method for early detection of ischemic heart diseases. Further studies with larger populations are necessary with regard to a prospective validation of the method for early detection of myocardial ischemia.

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**Conflict of interest** The authors declare that they have no conflict of interest.

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