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The Cardiodynamicsgram Based Early Detection of Myocardial Ischemia Using the Lempel-Ziv Complexity

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ABSTRACT Background: Electrocardiogram (ECG) is a routine method for detecting myocardial ischemia in clinical practice, but more than half of ECGs are without specific ischemic changes. Cardiodynamicsgram (CDG) is an effective method to detect ischemia with non-diagnostic ECG. The Lyapunov exponent (LYE) and the Fourier transform coefficient are combined to characterize the spatial and temporal features of CDG. However, in some cases, the Lyapunov exponent does not accurately enough describe the degree of irregular morphology of CDG for ischemic patients. In this context, this study aims to improve the characterization of CDG using the Lempel-Ziv (LZ) complexity instead of the Lyapunov exponent. Methods: The cardiodynamics information inside ECG is extracted via deterministic learning from the ST-T segments of ECG and then the CDG is generated by plotting the extracted three-dimensional cardiodynamics information. The Lyapunov exponent and LZ complexity are calculated from CDG and coupled with the Fourier transform coefficient respectively to construct the LYE model and LZ model for detecting myocardial ischemia. Results: 393 subjects presenting non-diagnostic ECG are enrolled in the study. 312 of them are ischemic patients selected as the myocardial ischemia group, and the other 81 non-ischemic subjects are selected as the healthy control group. The average sensitivity, specificity, and accuracy of the LYE model and the LZ model are 90.7% vs 93.4%, 86.4% vs 86.8%, and 89.0% vs 90.8%, respectively. Meanwhile, the proposed method achieves better performance on the PTB database than most of the previous studies in detecting ischemia or infarction. Conclusion: The results indicate that LZ complexity can accurately characterize the cases that cannot be accurately depicted by Lyapunov exponent, and the corresponding model is more accurate for the early detection of myocardial ischemia.

INDEX TERMS Cardiodynamicsgram, Lempel-Ziv complexity, myocardial ischemia, deterministic learning.

I. INTRODUCTION

Early detection of myocardial ischemia is an important clinical issue, which helps reduce the acute myocardial infarction, even sudden death, and other malignant cardiovascular events caused by myocardial ischemia. Myocardial ischemia can cause electrophysiological changes in ventricular repolarization, leading to the heterogeneity of repolarization [1]. At present, the 12-lead electrocardiogram (ECG) is the most common method used to trace the electrical activities of the heart, and the heterogeneity of repolarization results in irregular changes of ST-T segments in ECG [2]–[4].

Numerous ECG analysis methods have been successively proposed based on machine learning or deep learning for the ECG waveform classification, detection, and localization of myocardial ischemia or infarction, combining features

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extracted by the Fourier transform, wavelet transform, and other methods with neural networks, support vector machines (SVM) and other classifiers [5]–[7], or directly using deep neural networks [8], [9]. Sharma *et al.* [5] extracted 72-dimensional multiscale energy and eigenspace features from 12-lead ECG signals and employed SVM for infarction detection with 96% accuracy, 93% sensitivity, and 99% specificity on the PTB database. Furthermore, Acharya *et al.* [8] implemented a convolutional neural network (CNN) algorithm for the detection of infarction using only lead II of ECG signals from the PTB database, and it has achieved 95.22% accuracy, 95.49% sensitivity, and 94.19% specificity. Moreover, Tripathy *et al.* [6] proposed a multiresolution analysis approach of the 12-lead ECG signals for the detection of infarction using Fourier–Bessel series expansion-based empirical wavelet transform (FBSE-EWT), yielding the accuracy, sensitivity, and specificity of 99.74%, 99.87%, and 99.65%, respectively, using the combination of FBSE-EWT-based entropy features and the deep layer least-square support vector machine (DL-LSSVM) formulated with the hidden layers of sparse auto-encoders; and further combined low-order range sub-band signals and CNN for infarction location, and obtained higher accuracy value [7]. Besides, Han *et al.* [9] proposed a 13-layer multi-lead residual neural network combining with feature fusion to detect infarction. The model obtained 95.49% accuracy, 94.85% sensitivity, and 97.37% specificity based on the PTB database. Although the above methods have achieved good performance in the detection of myocardial ischemia or infarction, these studies are almost based on the PTB database, in which most ECG with myocardial infarction has significant ischemic changes, lack of normal or non-specific ECGs. However, the amplitude of ST-T segments corresponding to the heterogeneity of the ventricular repolarization is often changed at the microvolt level, resulting in many patients with myocardial ischemia without significant specific changes in the ST-T segments of ECG, which is not easily observed by the naked eye [10], [11]. It is a great challenge to detect myocardial ischemia early and accurately based on ECG. Therefore, how to effectively extract the information reflecting the irregular weak electrical activity of ST-T segments ECG, and to characterize the degree of the irregular information are the key factors to the early detection of myocardial ischemia.

Cardiodynamicsgram (CDG) has emerged recently as a noninvasive method for detecting myocardial ischemia [12]. CDG is the three-dimensional visualization of the cardiodynamics information extracted from the ST-T segments of ECG using deterministic learning (a machine learning method in the dynamic environment), and it reflects the subtle cardiac dynamics related to myocardial ischemia [13]. Compared with the existing features based on ECG (such as time-domain or frequency-domain features), which recognize limited information of myocardial ischemia [5], [14]–[17], the dynamical features extracted from the CDG can distinguish myocardial ischemia from healthy controls more sensitively [12], [18], [19]. A clinical trial of the detection of myocardial ischemia was carried out using CDG in Beijing FuWai Hospital of Chinese Academy of Medical Sciences [18], where a spatial heterogeneity index (Lyapunov exponent, LYE) and a temporal heterogeneity index (frequency domain index based on Fourier transform) are utilized to characterize the morphology of CDG. The preliminary results showed that CDG can detect myocardial ischemia patients with normal or roughly normal ECG. Nevertheless, in some cases, the Lyapunov exponent does not accurately enough characterize the irregular degree of CDG morphology.

In the past few decades, many nonlinear methods have been proposed and applied to the complexity analysis of different waveforms of ECG [20]–[23]. In particular, the Lempel-Ziv (LZ) complexity is a nonparametric complexity measurement of the irregular degree of time series. Its physical significance lies in that it can reflect the rate at which a new pattern appears with the increase of the length of time series [24]. The greater complexity reflects the faster rate of new changes, indicating that the data changes in this period are irregular. On the contrary, the lower complexity indicates the slower rate of new changes and the more regular and periodic changes of data. Since the LZ complexity has good interpretability and has been proved to be more suitable for describing the irregular degree of the quasi-periodic biomedical signals [25], it has been widely used in the analysis of the irregularity of biomedical signals [26]–[33]. Meanwhile, in [34], the authors show that the LZ complexity analysis of the dynamic characteristics of nonlinear dynamical systems can reflect the weak changes of the system signals more sensitively.

In this study, we sought to improve the characterization of CDG using the LZ complexity instead of the Lyapunov exponent.

II. MATERIALS AND METHODS

A. PATIENT POPULATION

393 patients (age, 34 to 84 years, including 87 females and 211 males) with suspicious myocardial ischemia presenting with non-diagnostic ECGs were enrolled in this study. Patients were requested to stay at rest in the supine position for 20 seconds ECG in a relaxing room prior to any catheter insertion. In order to obtain enough ECG beats for analyzing CDG, 20-second 12-lead ECGs [5], [12]–[18] were recorded using a commercially available electrocardiograph (Mindray Bene-Heart R12, Shenzhen, China) with a 1,000-Hz sampling rate and 16-bit resolution before coronary angiography. Patients with valvular heart disease, old myocardial infarction, heart failure, ischemic cardiomyopathy, persistent atrial fibrillation, and severe atrioventricular block were eliminated. ECG was analyzed by two experienced cardiologists blinded to patients. The diagnostic ECG was defined as with the horizontal or downsloping ST deviation $\geqslant 0.05$ mV in 2 contiguous leads and/or T inversion $\geqslant 0.1$ mV in 2 contiguous leads with prominent R wave. The ECG with inconsistencies between two cardiologists was jointly determined

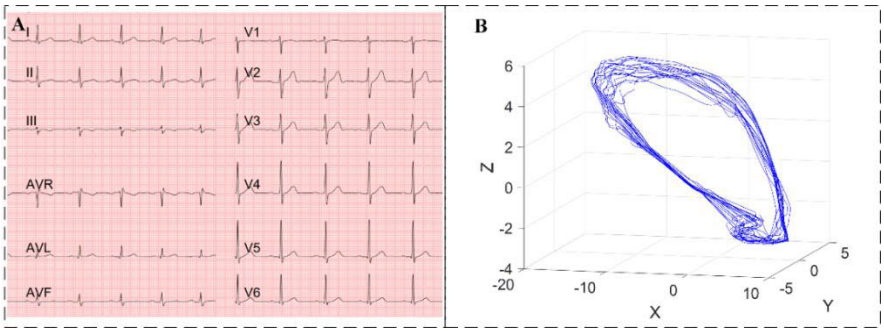


FIGURE 1. A case of a healthy male subject, 47 years old. A: Normal ECG, B: Regular CDG.

by the two experts according to the above acute ischemia criteria. The only patient presenting with non-diagnostic ECG was included in this study. All patients were scheduled for coronary angiography. 312 patients with myocardial ischemia (MI) were confirmed with severe coronary stenosis (>50% stenosis) or coronary slow flow phenomenon existed in one of the 3 main coronary arteries: the left anterior descending artery, the left circumflex artery, and the right coronary artery. Besides, 81 patients without obvious coronary artery lesions or coronary slow flow phenomenon were selected as the healthy control (HC) group. The study was approved by the Institutional Review Board of FuWai Hospital and Shihezi people's hospital (code number: 2016-780).

B. CARDIODYNAMICSGRAM

CDG is recently proposed as a new method to detect myocardial ischemia. The tiny cardiodynamics information related to myocardial ischemia is extracted from the ST-T segments of ECG using deterministic learning, and the CDG is generated by plotting the extracted three-dimensional cardiodynamics information. The 12-lead ECG is reduced to the 3-dimensional vectorcardiography (VCG, $V(t)$) [35].

It is difficult to detect ST-T segments accurately, due to the various shapes of ST-T segments during the onset of the disease in clinical practice. The ST-T segment detection method in [36] utilizes the convex operator to locate the R wave and achieves more than 90% accuracy in detecting the ST-T segment in the European ST-T database using the dynamic search window and difference method. Additionally, this method only requires little computation and can detect the ST-T segment accompanied with the giant or inverted T wave accurately and robustly. Thus, the method proposed in [36] is adopted to detect ST-T segments in this study.

First, the wavelet transform-based multi-resolution analysis is performed to modify the baseline drift and filtering of the original VCG signals. The convex transformation is applied to the preprocessed VCG signals. Then, the threshold method is used to detect the interval of R wave and further locate the peak value of R wave. On this basis, the dynamic search window method is combined with the difference method to detect the onset of ST-segment and the endpoint of T wave.

Thus, ST-T segments $V_{stt}(t)$ are identified and segmented from the VCG signals by combing the convexity operator and dynamic search window. For more technical details, please refer to the reference [36].

CDG represents the dynamic changes in $V_{stt}(t)$, which can be described as a 3-th order differential equation

$$\dot{V}_{stt}\,(t) = F(V_{stt1}, V_{stt2}, V_{stt3}), \tag{1}$$

where $F(V_{stt1},\ V_{stt2},\ V_{stt3}) = [f_1(V_{stt}(t)),\ f_2(V_{stt}(t)),\ f_3(V_{stt}(t))]$ is the unknown nonlinear function vector, representing the cardiac dynamic information inside the ST-T signals. Cardiac dynamics information can be extracted along the trajectory of the VCG using deterministic learning:

$$\dot{V}_{stt}\,(t) = F\,(V_{stt}\,(t))\,\big|_{t=t_{start}}^{t=t_{end}} \approx F_{NN}(V_{stt}(t)), \tag{2}$$

where $F_{NN}(V_{stt}(t))$ represents a neural network model that approximates cardiac dynamics. Then, CDG is obtained by plotting the extracted cardiac dynamics information in the three-dimensional space. By analyzing CDG morphology, it is found that the shapes of CDG significantly differ between myocardial ischemic patients and healthy subjects. Under normal conditions, repolarization is a homogeneous process with a regular CDG shape, as shown in Figure 1. Under pathological conditions, such as myocardial ischemia, repolarization is a heterogeneous process with an irregular CDG shape, as shown in Figure 2.

C. FEATURE EXTRACTION

In this paper, the frequency domain feature, the Lyapunov exponent, and the LZ complexity are extracted from CDG to characterize the temporal and spatial heterogeneity of CDG, respectively. The following sections show a brief process of feature extraction.

1) THE TEMPORAL HETEROGENEITY INDEX (THI)

The temporal heterogeneity index based on the Fourier transform is used to describe the temporal characteristics of CDG. First, for each dimension of CDG, the discrete fast Fourier Transform is applied to calculate the spectrum $f_i\,(w)\,, i = 1, 2, 3, w = 1, 2, \ldots, M$, where M is the number of data points in the spectrum. Then, the negative exponential function is used to fit the spectral data $f_i\,(w)$ via the least

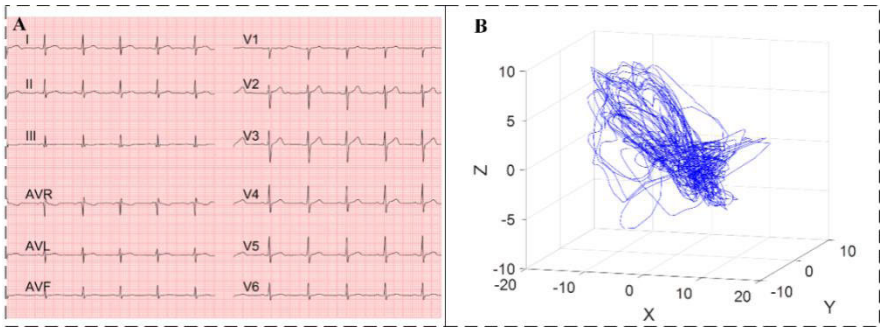


FIGURE 2. A case of an ischemic male patient, 35 years old. A: Normal ECG, B: Irregular CDG.

square method. The curve fitting index λ_i and the THI are calculated according to the following formula:

$$\begin{cases} \lambda_i = min \sum_{w=1}^{M} \left(f_i(w) - k \cdot e^{-0.1\lambda_i} \right)^2, \quad i = 1, 2, 3 \\ THI = \frac{1}{3} \sqrt[2]{\sum_1^3 \lambda_i^2}, \end{cases} \tag{3}$$

where $ke^{-0.1\lambda_i}$ represents a set of negative exponential functions that fit the spectrum curve, and k is the maximum value of the $|f_i(w)|$.

2) THE LYAPUNOV EXPONENT (LYE)

In this paper, the maximum Lyapunov exponent of the multi-dimensional phase space trajectory is computed to describe the spatial heterogeneity of CDG through the Wolf algorithm [37],

For multi-dimensional time series $Y(k) = \{X(1), X(2), \ldots, X(N)\}$, where N represents the length of multidimensional time series, and the distance d_{11} from the initial point $X(1)$ to its nearest neighbor is calculated. Then, the distance d_{12} between the two points after d step evolution is calculated. The above process is repeated until the endpoint of the time series. The number of iterations in the evolutionary process is N/d, and the maximum Lyapunov index (LYE) is

$$LYE = \frac{d}{N} \sum_{n=1}^{N/d} \ln\left(\frac{d_{n2}}{d_{n1}}\right), \tag{4}$$

where d_{n1} represents the distance between the *nth* data point and its nearest data point, and d_{n2} represents the distance between the *nth* data point and its nearest data point after d steps. The optimal value of d used to calculate the maximum Lyapunov index is determined by the T-test method in the above patient population. Figure 3 illustrates the influence of different d values on the Lyapunov exponent. The evolution step size d in formula (4) is set as 10 in this study to balance the calculation speed and accuracy.

3) LEMPEL-ZIV (LZ) COMPLEXITY

The LZ complexity analysis is based on the coarse-graining of the measurements. Before calculating the LZ complexity measure, the time series must be transformed into a finite symbol sequence. Generally, an arbitrary time series

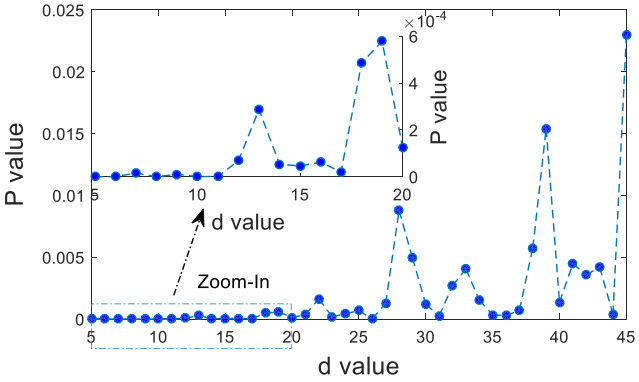


FIGURE 3. T-test results of maximal Lyapunov exponent between myocardial ischemia patients and healthy subjects under different d values.

$\{x(i) | i = 1, 2, \ldots, n\}$ is converted into a binary series. By comparing with the threshold, $x(i)$ is converted into a 0-1 series $\{S(i) | i = 1, 2, \ldots, n\}$ as follows:

$$S(i) = \begin{cases} 0, & x(i) < x_{ave} \\ 1, & x(i) \geq x_{ave}, \end{cases} \tag{5}$$

where x_{ave} is the mean of the time series of $x(i)$. The corresponding LZ complexity is called binary LZ complexity (BLZC) and the measurement of complexity is $c(n)$. Under the assumption of large enough sequence length and the symbol set consisting of 2 elements [38], it has been proven that the upper bond of $c(n)$ is

$$\lim_{n \to \infty} c(n) = b(n) = \frac{n}{log_2 n}. \tag{6}$$

To obtain a complexity measure that is independent of the series length, $c(n)$ should be normalized via $b(n)$

$$0 \leq C = \frac{c(n)}{b(n)} \leq 1, \tag{7}$$

where the normalized complexity index C is called the LZ complexity. $c(n)$ can be established only if sample length n is large enough.

The spatial LZ complexity (SLZC) is proposed to characterize CDG in the following steps:

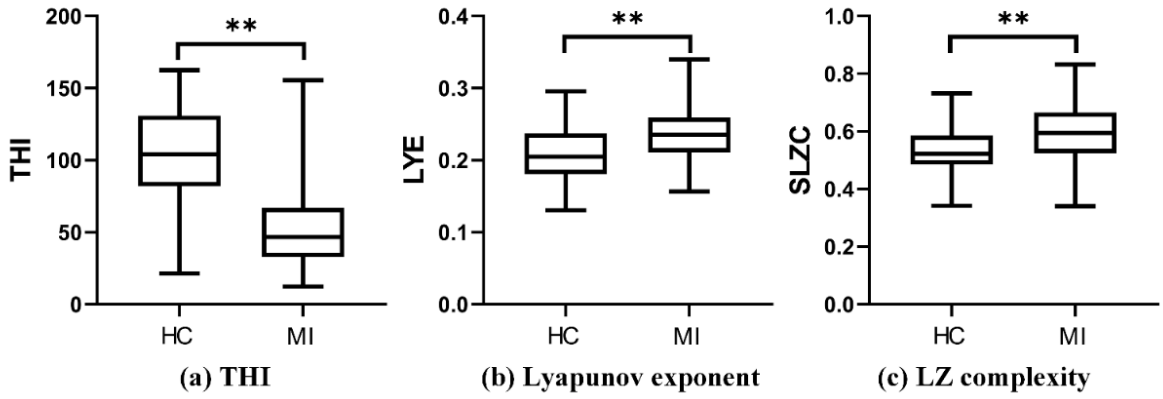


FIGURE 4. The box plots for the CDG features between the myocardial ischemia (MI) group and the healthy control (HC) group.

Step 1: The directional derivative of the dynamic trajectory of a nonlinear system represented by a data sequence $\{y(i)|i = 1, 2, \ldots, n\}$ can be approximately calculated and stored as slope sequence Z.

$$Z_k(r) = \begin{cases} \dfrac{y_k(r+1) - y_k(r)}{\sqrt{\sum_{i=k+1}^{N} (y_i(r+1) - y_i(r))^2}}, & k = 1 \\ \dfrac{y_k(r+1) - y_k(r)}{\sqrt{\sum_{i=1}^{k-1} (y_i(r+1) - y_i(r))^2 + \sum_{i=k+1}^{N} (y_i(r+1) - y_i(r))^2}}, & 1 < k < D \\ \dfrac{y_k(r+1) - y_k(r)}{\sqrt{\sum_{i=1}^{k-1} (y_i(r+1) - y_i(r))^2}}, & k = D, \end{cases} \tag{8}$$

where n is the length of each data sequence y_k, $k \in \{1, \ldots, D\}$, $D = 3$, $r \in \{1, 2, \ldots .n-1\}$.

Step 2: The normalized complexity SC_k of each directional derivative sequence Z_k is obtained by

$$SC_k = c_k(m) / \frac{m}{\log_2 m}, \tag{9}$$

where $m = n - 1$ is the length of the directional derivative sequence. Then, the corresponding SLZC of the nonlinear system dynamic is given by

$$SLZC = \frac{1}{3} \sqrt[2]{\sum_{k=1}^{3} SC_k^2}. \tag{10}$$

The directional derivative sequence reflects the change rate of the nonlinear dynamic trajectory in the space-domain. The corresponding normalized LZ complexity SLZC is taken as a spatial complexity measurement.

D. CLASSIFICATION–SVM

The support vector machine (SVM) is a large margin classifier used to solve the binary classification. It tries to find the hyperplane with a large margin to distinguish samples of different categories. Where the margin is defined as the distance between samples of different categories and the classification hyperplane. In the real world, the training data is linearly separable rarely and is often approximately linearly separable. In this case, a linear support vector machine or soft margin support vector machine is used. The performance of the SVM is affected by the penalty parameter which determines the number of support vectors and the maximum margin. The decision function is

$$f(x) = sign\left(w^* x + b^*\right), \tag{11}$$

where *sign* is the sign function

$$sign(x) = \begin{cases} +1, & x \geq 0 \\ -1, & x < 0. \end{cases} \tag{12}$$

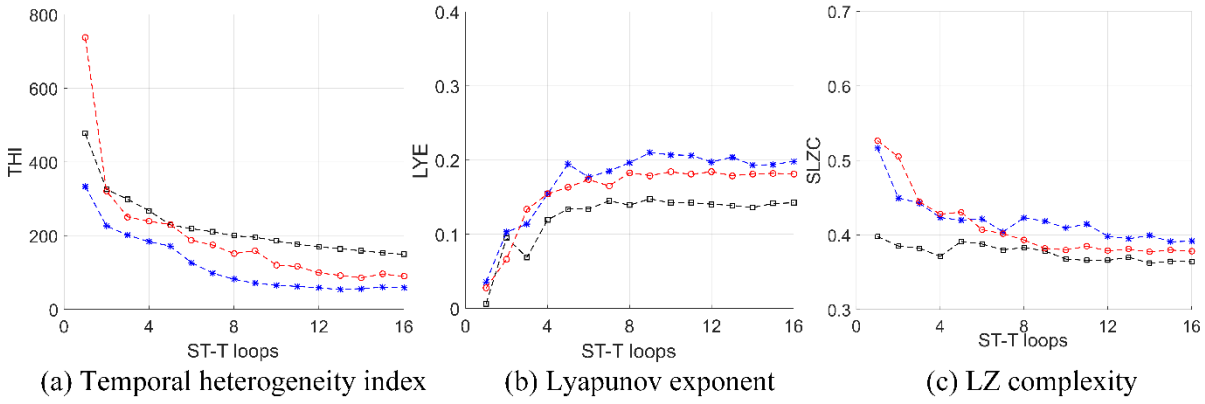
The distance from the sample to the classification boundary was calculated as the CDG value. In this study, the training data is approximately linearly separable, so the soft margin SVM is used.

III. RESULTS

The box plot (Figure 4) describes the differences between features of the THI and the spatial heterogeneity index (including the Lyapunov exponent and the LZ complexity), which extracted from CDG between patients with myocardial ischemia and healthy controls. The THI in ischemic patients significantly differs from that of healthy subjects ($p < 0.001$), and values are almost completely separating between the two groups. Although the values of Lyapunov exponent and LZ complexity largely overlap between normal individuals and ischemic patients, there are significant statistical differences in these two features ($p < 0.001$). Meanwhile, the recognition performance using only THI, LYE, or LZ complexity for myocardial ischemia was also evaluated respectively in the study population, as shown in Table 1. The THI has a better ability to recognize myocardial ischemia, while the LYE and the LZ show better performance in some indexes. It suggested that both of them are helpful to distinguish myocardial ischemia from healthy

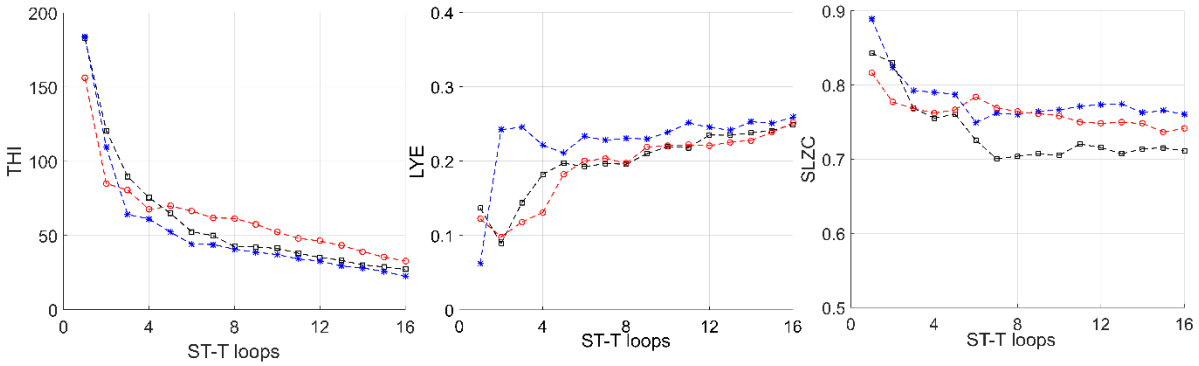
TABLE 1. Results of CDG models for detecting myocardial ischemia on the proposed database.

Type of Model	Samples		Predictions				Accuracy (%)	Sensitivity (%)	Specificity (%)
	Positive	Negative	TP	FN	TN	FP			
THI	312	81	260	52	69	12	83.7 ± 1.9	83.3 ± 2.1	85.2 ± 3.9
LYE			272	40	39	42	79.1 ± 2.1	87.2 ± 1.9	48.2 ± 5.5
LZ			179	133	60	21	60.8 ± 2.5	57.4 ± 2.8	74.1 ± 4.9
LYE Model (LYE+THI)	3150	800	2857	293	691	109	89.0 ± 7.4	90.7 ± 4.4	86.4 ± 11.8
LZ Model (LZ+THI)			2942	208	694	106	90.8 ± 7.9	93.4 ± 5.8	86.8 ± 6.6



(a) Temporal heterogeneity index (b) Lyapunov exponent (c) LZ complexity

FIGURE 5. Convergence analysis of indices of three regular CDGs.



(a) Temporal heterogeneity index (b) Lyapunov exponent (c) LZ complexity

FIGURE 6. Convergence analysis of indices of three irregular CDGs.

individuals, and can couple with the THI to construct the ischemia detection model.

At the same time, we also investigate the influence of the number of beats contained in the 12-lead ECG records on the accuracy of the LZ complexity and the LYE quantized CDG. Three CDGs with regular morphologies are randomly selected to analyze the convergence performance of the LZ complexity, the LYE, and the THI, as shown in Figure 5. Meanwhile, three CDGs with irregular morphologies are also randomly selected to investigate the convergence performance of those indices, as shown in Figure 6. Figure 5 indicates that the convergence of those indices is robust enough for the regular CDG. However, for the irregular CDG, Figure 6 indicates that the convergence of the LYE and the THI is not robust enough. It suggests that the myocardial ischemia detection model based on the LZ complexity and THI may be more effective than that of the LYE and THI.

TABLE 2. Results of CDG models for detecting myocardial ischemia on the PTB database.

Type of Model	Samples		Predictions				Accuracy (%)	Sensitivity (%)	Specificity (%)
	Positive	Negative	TP	FN	TN	FP			
LYE Model (LYE+THI)	1480	520	1410	70	470	50	94.0 ± 3.7	95.3 ± 1.7	90.6 ± 10.0
LZ Model (LZ+THI)			1410	70	490	30	95.0 ± 2.4	95.3 ± 1.7	94.2 ± 4.8

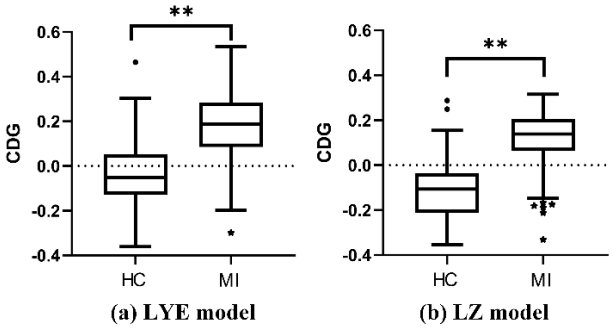


FIGURE 7. The CDG differences of the LYE model (LYE + THI) (a) and the LZ model (LZ + THI) (b) between the myocardial ischemia (MI) group and the healthy control (HC) group.

In this part, the Lyapunov exponent and the LZ complexity are combined with the THI to construct the classification model for detecting myocardial ischemia, respectively. The soft margin SVM and 5-fold cross-validation technique for the detection of myocardial ischemia are employed. Specifically, the entire dataset consisting of 393 12-lead ECG records is divided into 5 equal parts randomly, which has almost the same sample distribution from the two classes for myocardial ischemia detection. 314 records are regarded as the training set, and the other 79 records are used as the testing set. Furthermore, the 5-fold cross-validation is repeated 10 times, which is called 10-times 5-fold cross-validation, to reduce the influence of randomness introduced by data split [39]. Different metrics including accuracy, sensitivity, and specificity are used as the performance measure criterion for ischemia detection. These metrics are derived from the confusion matrix consisting of True Positive (TP, the number of patients detected correctly), True Negative (TN, the number of healthy subjects detected correctly), False Positive (FP, the number of healthy subjects detected incorrectly) and False Negative (FN, the number of patients detected incorrectly).

The overall performance of different features is recorded in Table 1 and Figure 7. Figure 7 shows the differences in CDG values generated from two different SVM models between the ischemia patients and the healthy controls. Figure 7-a represents the CDG values from the LYE model based on the LYE and THI, and Figure 7-b is the CDG values from the LZ model based on LZ complexity and THI. It is shown that the LZ model for detecting myocardial ischemia based on the LZ complexity and the THI achieves slightly higher accuracy, sensitivity, and specificity, and the overall performance is superior to the LYE model based on the Lyapunov exponent and THI. The average accuracy, sensitivity, and specificity of the LYE model and the LZ model are 89.0% vs 90.8%, 90.7% vs 93.4%, and 86.4% vs 86.8%, respectively.

In this subsection, the study for detecting myocardial ischemia based on CDG is carried out in the PTB database (https://www.physionet.org/content/ptbdb/1.0.0/). The study population includes 148 patients with myocardial infarction and 52 healthy controls (HC) obtained from the PTB database. A standard 12-lead ECG is selected for each subject. CDGs are generated by dynamical modeling for all ECGs, and then the THI, LYE, and LZ complexity are extracted. Based on THI plus LYE and THI plus LZ complexity respectively, ischemia detection models are learned and verified using the soft margin and 10-times 5-fold cross-validation. The results of this study were compared with those of the existing myocardial ischemia detection methods in the PTB database, as shown in Table 2. It can be seen from Table 2 that the ischemia detection model based on THI and LZ complexity extracted from CDG achieves better performance, with accuracy 95.0%, sensitivity 95.3%, and specificity 94.2%.

IV. DISCUSSION

Myocardial ischemia induces a series of electrophysiological modifications affecting the ventricular repolarization, leading to a heterogenous repolarization process. It has been observed that ischemia increases repolarization dispersion between normal and ischemic fibers, which is a phenomenon appearing in the ECG as a consistent fluctuation in the repolarization morphology on an ''every-other-beat'' basis. This fluctuation refers to a beat-to-beat variability in the amplitude of the ST segments. This repolarization alternans (dispersion) is usually of microvolts in amplitude and cannot be appreciated visually. CDG is a noninvasive method for subtle cardiac dynamics information analysis within ECG. By analyzing the CDG morphology, it is found that significant correlations exist between CDG and ischemia, even with normal or roughly normal ECG. Particularly, it is indicated that the shapes of CDG remarkably differ between ischemia patients (irregular shape) and healthy subjects (regular shape). Compared with the static features of ECG signals, CDG represents spatiotemporal variations in the repolarization phase of cardiac electrical activation, which is more sensitive than the surface ECG modifications. Two cases are selected to illustrate this property of CDG as shown in Figure 8 and Figure 9.

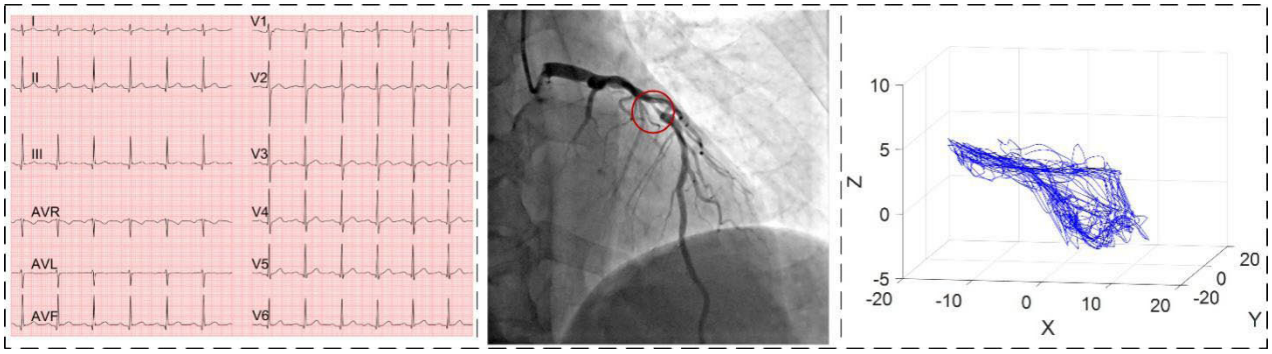


FIGURE 8. A case of an ischemic male patient with coronary artery stenosis, 50 years old. LEFT: Normal ECG; MIDDLE: The left anterior descending branch of the coronary artery is with stenosis 80 %; RIGHT: Irregular morphology of CDG.

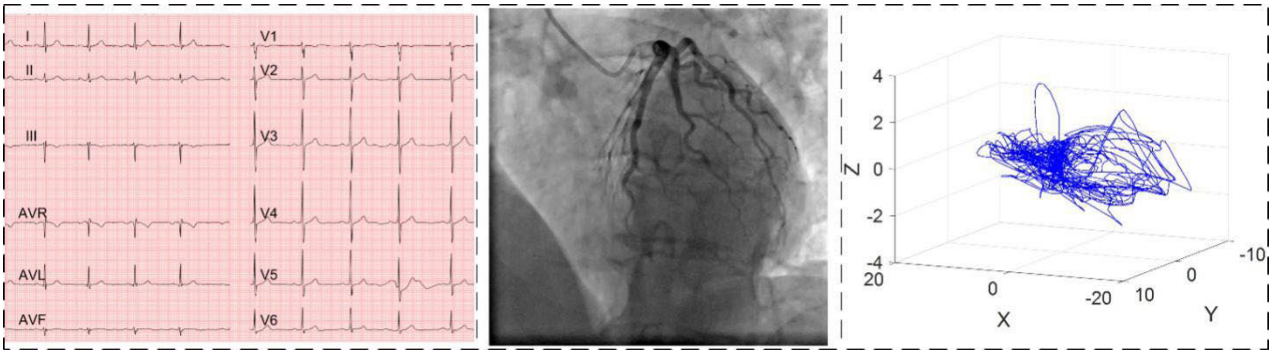


FIGURE 9. A case of an ischemic male patient with the slow coronary flow, 48 years old. LEFT: Normal ECG; MIDDLE: The left anterior descending branch of the coronary artery is with the coronary slow flow; RIGHT: Irregular morphology of CDG.

TABLE 3. Comparison of the proposed method based on LZ plus THI with previous studies for detecting myocardial ischemia.

Author, Year	Features, Number	Classifier	Processing	Accuracy (%)	Sensitivity (%)	Specificity (%)
Acharya et al, 2017 [8]	--, --	CNN	Beats, class specific	93.53	93.71	92.83
Diker et al, 2018 [40]	Morphological and statistical features, and wavelet features, 9	SVM	Records, patient specific	87.80	86.97	88.67
Han et al, 2019 [41]	Energy entropy and morphological and statistical features, 22	SVM	Frames, patient specific	92.7	81.0	81.0
Zhang et al, 2019 [42]	sparse high-dimensional features, --	SVM	Beats, patient specific	93.17	93.91	89.20
Han et al, 2020 [9]	--, --	A multi-lead residual neural network	Frames, patient specific	95.49	94.85	96.92
Proposed	LZ and THI (Proposed work), 2	SVM	Records, patient specific	95.0	95.3	94.2

The complexity analysis is a promising way to describe the morphology of CDG. To achieve the quantitative analysis of CDG in detecting myocardial ischemia, a temporal heterogeneity index (the frequent index based on the Fourier transform) and two spatial heterogeneity indices (the Lyapunov exponent and LZ complexity) are used to characterize the CDG morphology. However, the number of ST-T cycles available in the 20 second period is not too much, resulting in the incompletely converged Lyapunov exponent (there is still a trend to continue to increase), which may lead to the inappropriate characterization of the CDG morphology. The LZ complexity, on the other hand, has a faster convergence speed and strong robustness, and it can accurately describe the spatial heterogeneity of the CDG morphology.

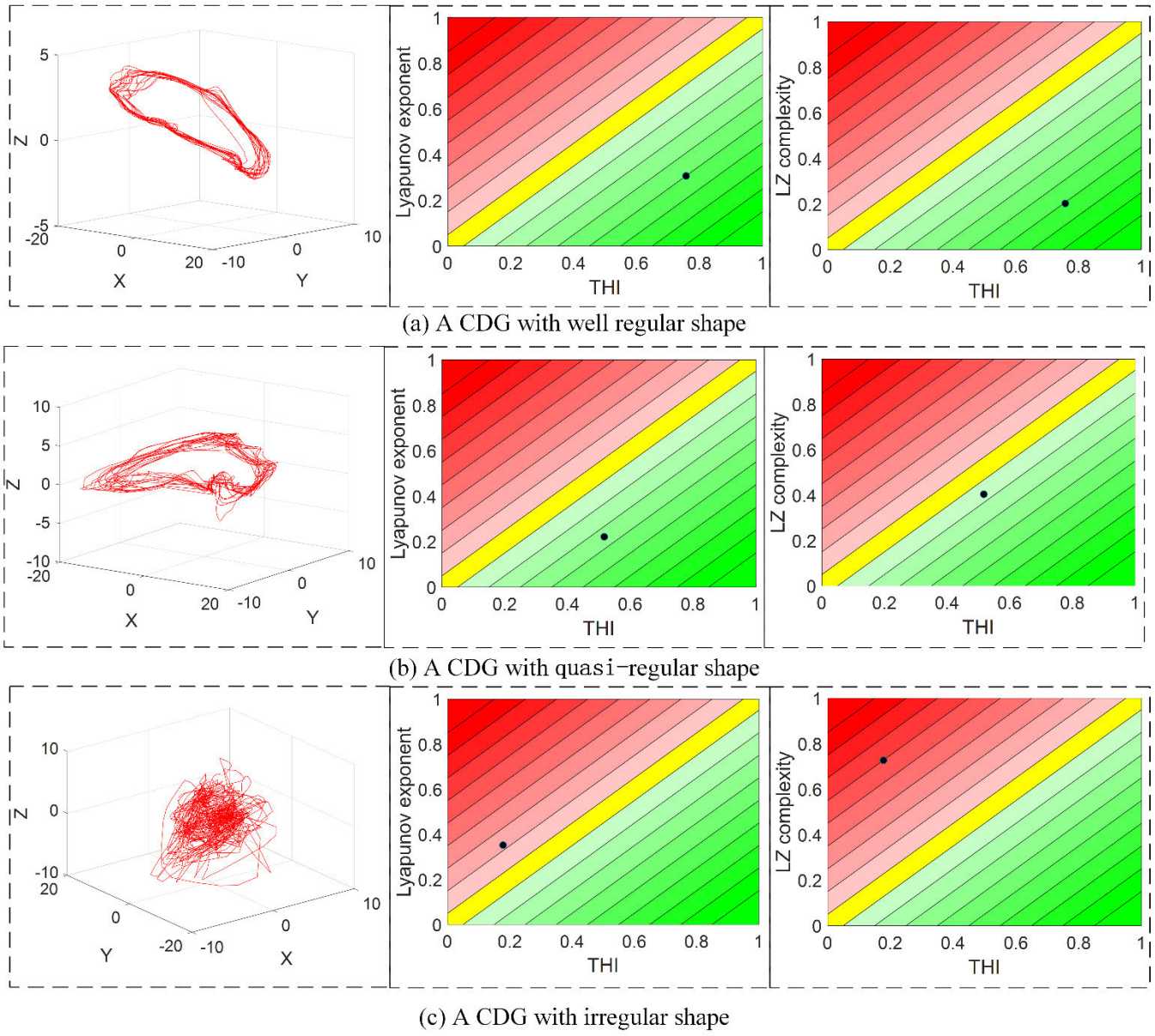


FIGURE 10. CDG (Left) and the detection results of the LYE model (Middle) and LZ model (Right). The red area represents positive, and the green area represents negative.

Table 3 summarizes previous studies regarding myocardial ischemia/infarction detection based on the PTB database. Note that most of the studies used a single ECG beat [8], [42] or a frame consisting of multiple beats [9], [41], rather than a complete ECG record [40]. Although most of the studies achieved good results in detecting patients with myocardial ischemia, these studies adopted high-dimensional features or deep networks generally. In this paper, the proposed method achieves better performance than most of the previous studies in detecting ischemia or infarction only using two features extracted from CDG. More importantly, results based on a small number of features are easier for clinicians to understand and explain to patients the basis of diagnosis.

It can be seen from Table 1 that the LYE-based and LZ-base models in this paper achieve good performance in detecting myocardial ischemia with normal or roughly normal ECG. However, compared with the LYE-based model for myocardial ischemia detection, the LZ-based ischemia detection model achieves slightly improved performance. The weak changes in ST-T segments reflect the heterogeneity of ventricular repolarization: the disorder morphology of CDG reflecting the more serious heterogeneity of ventricular repolarization, whereas the regular morphology of CDG reflecting the less heterogeneity of ventricular repolarization. Compared with the LYE, LZ complexity can more accurately characterize the order or disorder CDG (as shown in Figure 10-a and 10-c). However, in some cases, it is not easy

to evaluate which of the two characteristics of the LYE and LZ complexity is more accurate in describing CDG, as shown in Figure 10-b. Meanwhile, the results of the proposed method for myocardial ischemia detection in the self-built database with normal or roughly normal ECG are significantly lower than the results obtained in the PTB database. It demonstrates that it is more difficult and challenging to detect myocardial ischemia with normal ECG. Therefore, combining the LYE and LZ complexity may be better, since they can complement each other in quantifying CDG.

This study focuses on myocardial ischemia patients with normal or roughly normal ECG, which is clinically common but frequently overlooked. This completely differs from the previous studies on ischemia detection using significantly abnormal ECG from the PTB database, and the result of this study is more applicable to the clinical practice. Previous studies [12], [18], [43] demonstrated that CDG is an effective method for the detection of myocardial ischemia with normal or approximately normal ECG. This study further suggests that accurate quantification of CDG can improve the performance of CDG in detecting ischemia. However, the results of the LZ complexity-based ischemic detection model are obtained from small numbers of patients, therefore, whether accurate quantification of CDG can improve its clinical performance needs more and more cases to be verified.

V. CONCLUSION

The morphology of CDG is found to be related to myocardial ischemia significantly. The Lyapunov exponent is used to depict the morphology of CDG in previous studies, but it is not accurate enough in some cases. This paper investigates the cause of the inaccuracy of the Lyapunov exponent and reveals that its incomplete convergence results in the inappropriate characterization of the CDG morphology. Further, the LZ complexity is used to characterize the irregular degree of CDG morphology. Based on a total of 393 suspected patients with myocardial ischemia with nondiagnostic ECG, the average accuracy, sensitivity, and specificity of the LZ model for detecting myocardial ischemia are 90.8%, 93.4%, and 86.8%, respectively. The results indicate that LZ complexity is more precise than Lyapunov exponent in quantifying CDG morphology in some cases, which further improves the performance of CDG in detecting myocardial ischemia.

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