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Effective compression and classification of ECG arrhythmia by singular value decomposition

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ABSTRACT

Electrocardiogram (ECG) monitoring systems are widely applied to tele-cardiology healthcare programs nowadays, where ECG signals should always be compressed first during its transmission and storage. Previous studies attempted to achieve high quality decompressed signal with compression ratio as high as possible. In this paper, we investigated the performance on ECG arrhythmia classification on ECG signal decompressed after lossy compression with a high compression ratio. We proposed a simple but efficient method utilizing singular value decomposition (SVD) to decompose ECG signals, then applied the decompressed data to a convolutional neural network (CNN) and supporting vector machine (SVM) for classification. Using the optimization method with accuracy and compression ratio as objective functions, the highest average accuracy obtained is above 96% when the selected number of singular value is only 3. The evaluation results illustrated that the decompressed ECG signal even with a relatively high distortion can still achieve a satisfying performance in the arrhythmia classification.Thus,we proved that the real-time nature of the remote mobile ECG monitoring system can be greatly improved and countless people who are in need of ECG diagnosis can benefit from it.

1. Introduction

Nowadays, the number of people dying from cardiovascular disease each year is the main cause of abnormal human death and has been growing at an alarming rate. Remote ECG monitoring system, ECG monitoring mobile phone terminal, hospital monitoring center server and network communication support are widely used in medical treatment. With the collected electrocardiogram signals, patient's cardiac health condition is able to be monitored and classified [1–9,48,49] in real time under the ECG telemetry systems. The medical professionals can react much more promptly and efficiently to some acute cardiac diseases, making the transmission of ECG signals an indispensable and essential part of the whole procedure.

Fig. 1 shows an typical ECG tele-monitoring system. The ECG signal is obtained through a wearable electronic device of the terminal, and compressed then transmitted to a server for signal classification. Due to multiple cycles and high resolution acquisition, the amount of collected ECG data is large that negatively affected the transmission efficiency and portability of ECG data. This calls for the compression of ECG signals.

In the past few decades, researchers have devoted plenty of efforts into the field regarding compression and proposed a myriad of methods to achieve better performances, which could be divided into lossy and lossless approaches. Lossy compressions are often used in ECG signal compression due to its high compression ratio (CR). A comparison and investigation about earlier work can be found in [10–13]. In general, ECG signal compression techniques can be divided into three types. The basic idea of the first one is to detect redundancy and compress the ECG signals in the time domain, like amplitude zone time epoch coding (AZTEC) [14], scan along polygonal approximation (SAPA) [15], and the coordinate reduction time encoding system (CORTES) [16]. The second type of methods is aimed at extracting and coding particular parameters and features of ECG signals, such as linear prediction method [17], the neural network method [18], and vector quantization [19] and so on. The third type of methods is to analyze the energy distribution by transforming ECG signals from time domain to the frequency or other domains; for example, the Fourier transform [20], Karhunen-Loeve transform (KLT) [21], the discrete cosine transform (DCT) [22], the wavelet transform [23], and the singular value decomposition (SVD) [24,25]. Mostly, every researcher is dedicated to design a better way of compression and seek for a balance to optimize the compression performance between high compression ratio and high quality of reconstruction without compromising either of them. However, while advancing the lossless compression algorithm [26], researchers have overlooked the promising superiority of lossy compression in practical applications, since the performance in some particular applications is slightly influenced by the degree of loss in compression.

In order to ensure the accuracy of the diagnostic results, lossless compression is often used in the field of ECG monitoring and diagnosis, in-

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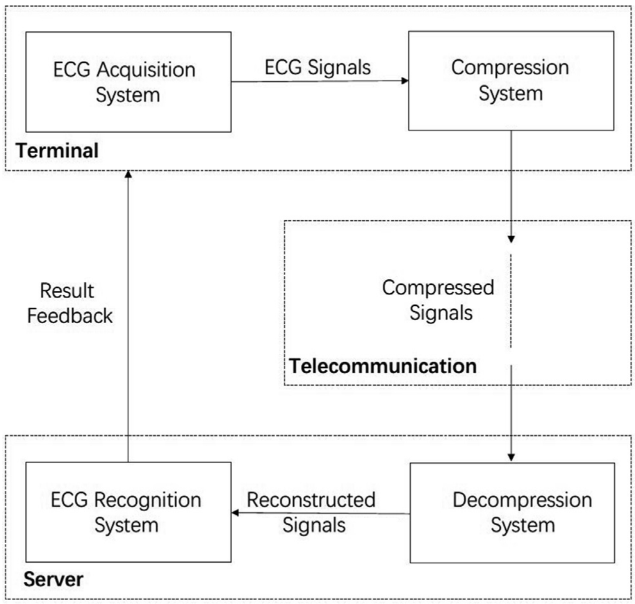

Fig. 1. Diagram of ECG tele-monitoring system.

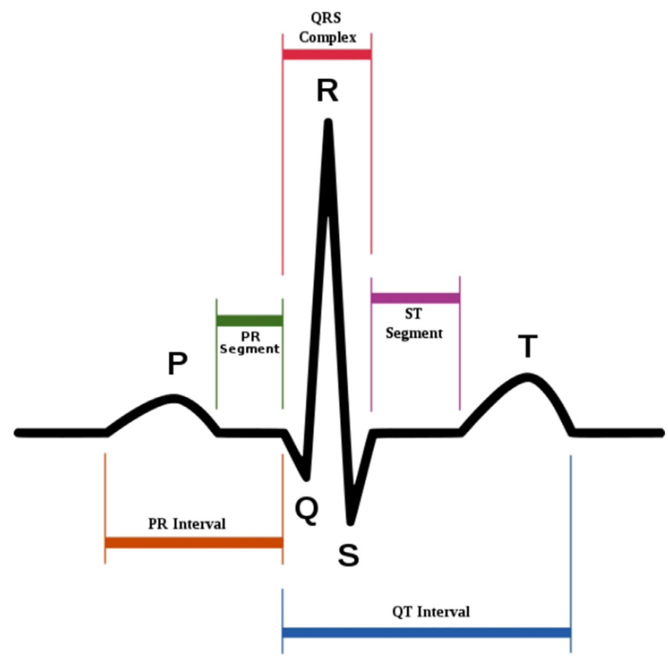

Fig. 2. A typical cycle of ECG signal [32].

evitably leading to a lower transmission efficiency [27–29]. We wonder whether a lossy compression, which can compress data with higher compression ratios than lossless compression, can create lost information in large amount to improve transmission efficiency without compromising the diagnostic accuracy. In fact, if the assumption is proved truth, the real-time nature of the remote mobile ECG monitoring system can be greatly improved and countless people who are in need of ECG diagnosis can benefit from it. This is also the motivation of this paper. The main contributions of this paper are summarized as follows:

1. A SVD-based compression procedure was proposed. Such method has simple implementation and well established theory to guarantee its performance;
2. Both SVM and CNN models were introduced to classify ECG abnormal signals. The evaluation results illustrate that the decompressed ECG signal even with a relatively high distortion can still achieve a satisfying performance in the arrhythmia classification;
3. A multi-objective optimization method was proposed to choose the most appropriate number of singular vectors used in compression for different application scenarios.

The rest of the paper was organized as follows. The main features of ECG signal as well as the basic principles and ideas of singular value decomposition (SVD) and convolutional neural network (CNN) were introduced in Section 2. In Section 3, we presented the procedure of SVD-based compression including period normalization, compression and reconstruction. In Section 4, the CNN and supporting vector machine (SVM) method were adopted into ECG classification on the compressed signals. The experimental results were evaluated and compared in detail. Finally, in Section 5, brief conclusions were presented.

2. Basic signals and methods

2.1. ECG

The electrocardiogram (ECG) signals [30,31] play an important role in arrhythmia detection and classification. However, when using manual analysis by a general physician it is quite time-consuming and possibly makes considerable mistakes. Hence, it calls for a highly accurate automatic classification method for practical applications. In addition, automatic classification will be helpful to paramedical and emergency medical staff in cases where immediate action is required.

As shown in Fig. 2, a typical one-cycle ECG waveform consists of P wave, QRS complex and T wave which are separated by intervals and segments. The horizontal portion prior to the P wave is referred as the baseline. P-wave is the first upward deflection with positive polarity that represents the depolarization of the atrial musculature and has a duration of 80–110 ms. The three waves of the QRS complex, with the duration between 60 and 100 ms, correspond to the combined results of the repolarization of the atria and depolarization of the ventricles. Q wave is the first downward deflection and R wave, as the largest wave, is always the first upward deflection after the Q wave while S wave is the negative one that immediately follows the R wave. Ventricular relaxation follows repolarization of the ventricles and is represented by T wave whose direction is consistent with QRS complex.

The ECG signals used in this study are obtained from MIT-BIH cardiac arrhythmia database [33,34] which is the most widely used database in recent years. MIT-BIH database was provided by the Massachusetts Institute of Technology for the study of cardiac arrhythmias, containing 48 records, with acquisition time length more than 30 min and sampling rate 360 Hz. The MIT-BIH database offers 13 different types of beats corresponding to each heart arrhythmia. To make ECG classification more accurate and monitoring result more comprehensive, four most common types of heart condition have been selected, including normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), ventricular premature beats (PVC). We define R peak as the marker point and each heartbeat contains the first 100 and the last 150 sampling points. Fig. 3 is a schematic diagram of four types of sample beats.

2.2. Singular value decomposition (SVD)

The signal processed by the SVD technology is a periodic signal, it should be segmented before it is applied to the compression algorithm by SVD. During the segmentation procedure, the original ECG signal is divided into m R-to-R segments of length n, via QRS peak detection [35].

The ith ECG segment can be presented as $x_i = [x_i(1), x_i(2), \ldots, x_i(n')]$, where n' is the length of x_i, which can be converted to a segment $y_i = [y_i(1), y_i(2), \ldots, y_i(n)]$ to simplify the calculation. In this way, the signal morphology of x_i is identified with y_i, while their lengths are different.

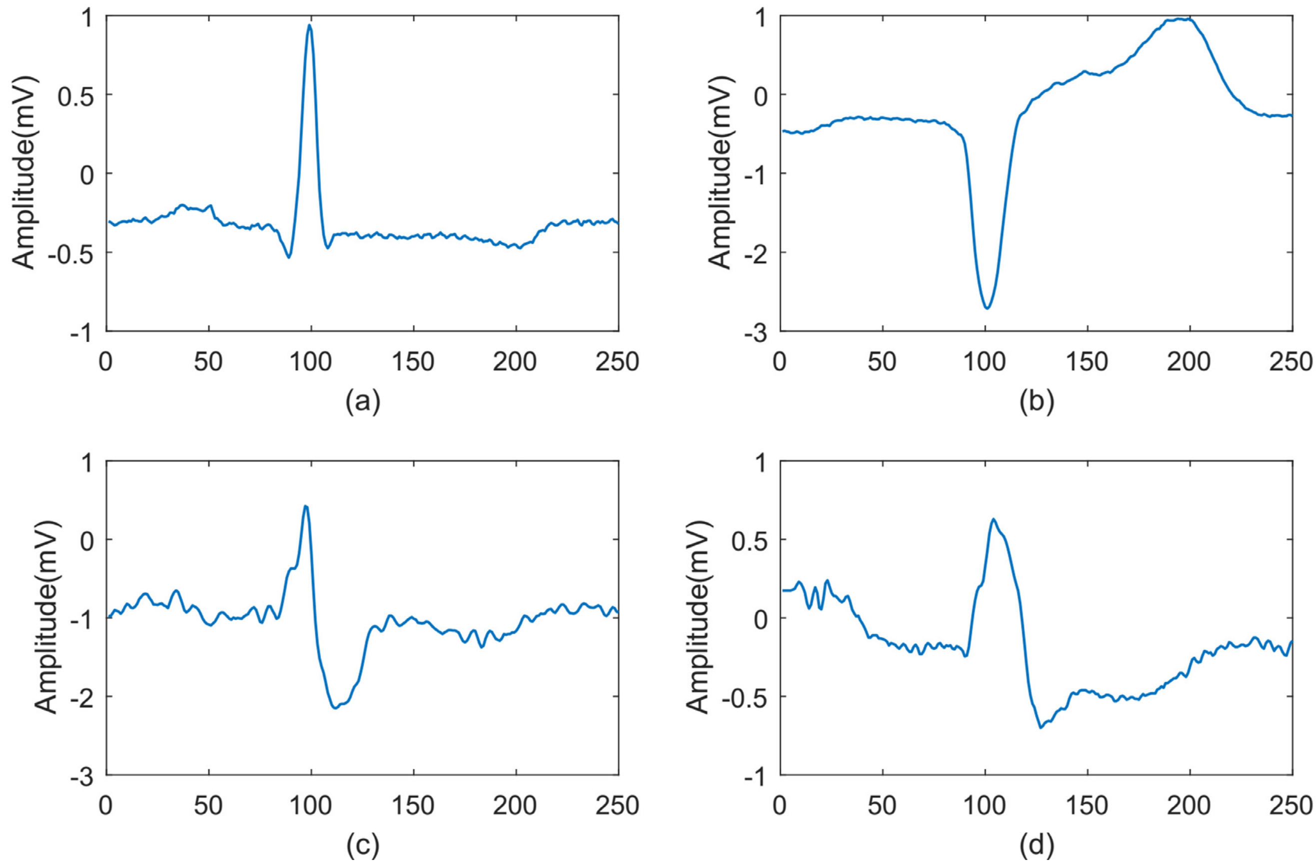

Fig. 3. Four types of heart beat samples: (a) normal (N), (b) ventricular premature beat (PVC), (c) right bundle branch block (RBBB), (d) left bundle branch block (LBBB).

The transformation is stated as follows

$$y_i(j) = x_i(j') + (x_i(j'+1) - x_i(j'))(r_j - j'),$$

where $r_j = (j-1) \times n'/(n-1) + 1$, j' is the integral part of r_j.

Then, by arranging each signal cycle as a row, the ECG signal is transformed to an $m \times n$ matrix Y_{mn}. Let Y be the $m \times n$ matrix composed of the samples of the normalized ECG to be compressed, which can be described as follows:

$$Y = \begin{bmatrix} y_1(1) & y_2(2) & \cdots & y_1(n) \\ y_2(1) & y_2(2) & \cdots & y_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ y_m(1) & y_m(2) & \cdots & y_m(n) \end{bmatrix}. \tag{1}$$

Apply the SVD on the matrix Y yields

$$Y = U_y \Sigma_y V_y^T \tag{2}$$

where $U_y = [u_1^y, \cdots, u_m^y]$, $V_y = [v_1^y, \cdots, v_n^y]$, $U_y^T U_y = I$, $V_y^T V_y = I$, and Σ_y is a diagonal matrix whose diagonal entries $\{\sigma_i^y\}$ are the singular values of Y in descending order. The matrix can also be expressed as

$$Y = \sum_{i=1}^{p} u_i^y \sigma_i^y (v_i^y)^T, \tag{3}$$

where $p = \min(m, n)$, u_i^y and v_i^y are the orthogonal eigenvectors of YY^T and of $Y^T Y$, respectively.

During the decompression process, in order to reduce the redundant data resulted from high correlation among ECG periodic signals, insignificant singular values can be truncated appropriately since information of the periodic signals is primarily focused on significant singular values representing the basic patterns and associated scaling vectors.

In the case of ideal ECGs, according to the decomposition process of SVD, except for the singular value representing the principal component, all other singular values will be zero, and the matrix will become a rank 1 matrix since it is a periodic signal with precise length. Therefore, only one singular value and associated eigenvector pairs are required for restoring the original signal unexceptionably. However, for practical periodic physiological signals, ECG do not manifest perfect waveforms, both the periodic length and waveform pattern may show discrepancy to a certain extent. Therefore, in order to obtain the main information, $q \leq p$ predominant singular values need to be selected from p singular values and related vectors could be used to reconstruct ECG signals with a relatively high quality. Hence, the above matrix Y can be reduced to the following one as $\hat{Y}$

$$\hat{Y} = \sum_{i=1}^{q} u_i^y \sigma_i^y (v_i^y)^T, \quad q \leq p. \tag{4}$$

3. SVD-based compression procedure

The overall procedure of SVD-based compression algorithm is shown in Fig. 4. The ECG data is normalized by the period into a matrix Y, and then the matrix is compressed using SVD. This will be described in more detail below along with the data reconstruction process.

3.1. Period normalization

Using the dual-slope processing [36] and low-pass filtering-based R-peak detection technique, it is possible to detect the R-peak and extract a segment between two consecutive R-peaks, that is, cutting out a single ECG cycle. However, since the extracted ECG cycles are not of equal length, periodic normalization is required to equalize them before applying SVD technique to compression. In [37], the method of periodic normalization was introduced. By which the lengths of all cycles can be normalized to the average period length by separating a ECG signal into m cycles.

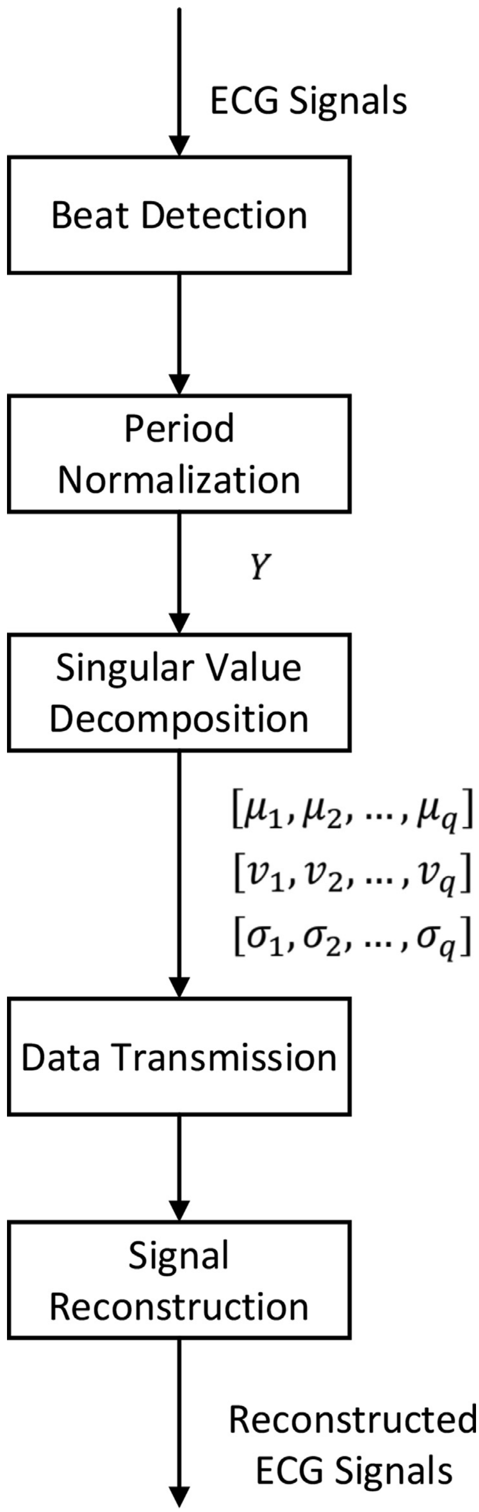

Fig. 4. SVD compression and reconstruction procedure.

3.2. Performance evaluation index

In order to evaluate the performance of the proposed method, some commonly used indicators are adopted in this study, like

Compression Rate (CR): it is the ratio of the number of bits required to store the original signal to that required to store the compressed signal, measuring the degree of data compression.

$$CR = \frac{bits\ of\ the\ original\ signals}{bits\ of\ the\ compressed\ signals} \tag{5}$$

Percent Root Mean Square Difference (PRD): it measures the error between the reconstructed signal and the original signal, that is, the quality of the reconstruction.

$$PRD = \sqrt{\frac{\sum_{k=1}^{L} \left(x_0(k) - x_r(k)\right)^2}{\sum_{k=1}^{L} x_0^2(k)}} \times 100, \tag{6}$$

where L is the number of sampling points.

The Normalized version of PRD (PRDN): it is defined as

$$PRDN = \sqrt{\frac{\sum_{k=1}^{L} \left(x_0(k) - x_r(k)\right)^2}{\sum_{k=1}^{L} \left(x_0(k) - \bar{x}\right)^2}} \times 100. \tag{7}$$

Root Mean Square Error (RMS): it represents differences between signals' energy before and after the compression.

$$RMS = \sqrt{\frac{1}{L} \cdot \sum_{k=1}^{L} \left(x_0(k) - x_r(k)\right)^2} \times 100. \tag{8}$$

Signal-to-Noise Ratio (SNR):

$$SNR = 10 \log_{10} \left(\frac{\sum_{k=1}^{L} (x_0(k))^2}{\sum_{k=1}^{L} (x_0(k) - x_r(k))^2} \right). \tag{9}$$

Quality Score (QS): it considers both the compression ratio and the quality of the reconstructed signal, used to measure the overall performance of data compression. The higher the QS, the better the compression performance.

$$QS = \frac{CR}{PRD}. \tag{10}$$

3.3. Performance on compression and reconstruction

In practice, most of the signal information is contained in the primary components of matrix Y, which can be used to recover original signal with a high quality. By performing SVD method and determining the number of singular values, three matrices u, s, v are obtained, the compressed signal can be reconstructed as $Y' = s \times u \times v'$. Fig. 5 shows the original waveform and the normalized recovered signal from the compressed one. From the comparison of the compressed and the decompressed signals, it can be found that most information of ECG signals is preserved, especially that of the QRS complex. As for the rest of signals, though the waveforms are retained, they becomes slightly smoother because some high frequency components are lost during the compression.

Performances measured by the above indicators including CR, PRD(%), PRDN(%), RMS, SNR and QS in terms of values are presented in Table 1, where the average value of CR is 53.77 and its maximum value can be 66.15 as obtained from record 117, which demonstrates the considerable and satisfying compression ratio. Considering PRD(%), the average value of which is only 9.23 and in the worst case (record 117), it is as low as 3.39. This indicates that the quality of reconstructed

Table 1
Results obtained for 11 MIT-BIH records (q=5).

Rec.	CR	PRD	PRDN	RMS	SNR	QS
100	50.70	6.16	11.55	2.23	18.75	8.23
101	58.54	7.76	11.29	3.05	18.95	7.54
103	54.16	7.46	9.16	2.96	20.76	7.26
107	53.12	14.02	14.53	12.47	16.76	3.79
109	46.43	10.73	11.83	5.87	18.54	4.33
111	53.39	13.77	16.40	4.16	15.70	3.88
115	56.77	5.36	8.94	3.27	20.97	10.59
117	66.15	3.39	12.43	3.01	18.11	19.49
119	56.03	5.99	10.28	5.95	19.76	9.36
214	50.84	16.10	17.03	7.99	15.37	3.16
223	45.38	10.81	17.49	7.12	15.14	4.20
Ave.	53.77	9.23	12.81	5.28	18.07	5.83

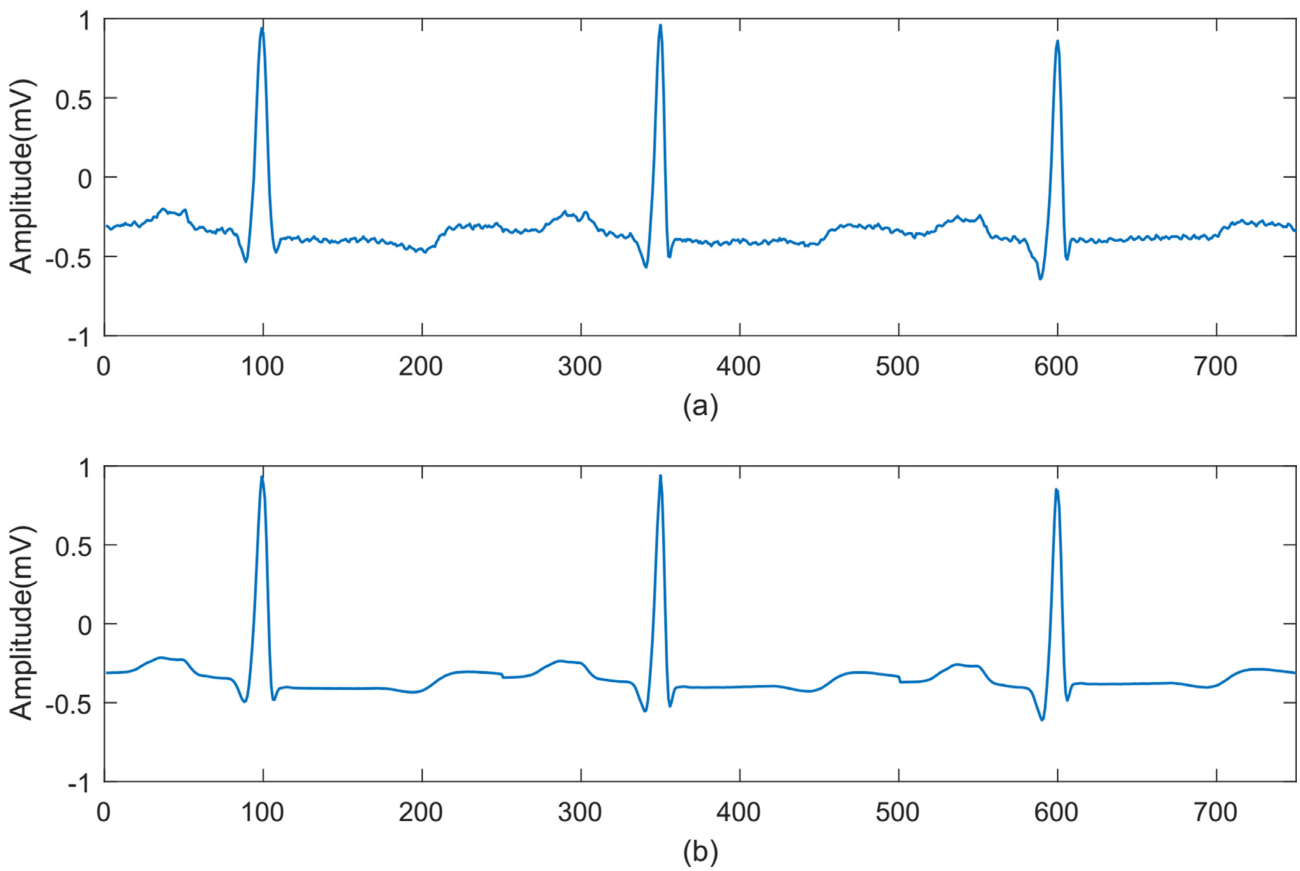

Fig. 5. (a)Original ECG signals of MIT-BIH record 100; (b)The compressed ECG signals with the singular values equals 5 ($q = 5$).

Table 2
Performance comparison of proposed method with Ref.[38] for MIT-BIH Records 100 and 117.

Method	Record 100	Record 117
SVD-WDR [38]	26.65	19.44
SVD-ASWDR [38]	21.36	20.38
Proposed	31.5 ($q = 8$)	12.6 ($q = 22$)

signal is poor. However, our goal is to increase the compression ratio and to keep the performance on classification on the compressed signal. Hence, we have no critical requirements on reconstruction quality.

In Table 2, we compare the performance of our method with reference [38] on MIT-BIH Records 100 and 117. With singular value equals to 8, our proposed method achieve higher compression rate for MIT-BIH record 100. While for record 117 our method has poor performance. However, Ref.[38] only used some indeces like PRD and SNR to show that SVD can achieve higher compression rate with comparable quality on reconstruction. In this paper, we use both SVM and CNN to show that due to the characteristics of ECG arrhythmia and a wise optimized strategy, the decompressed ones even with a relatively high distortion can still achieve a satisfying performance in the ECG arrhythmia classification.

4. Performance study on classification

After acquiring the compressed signal, we perform classification on them to see whether they still have high accuracy on signal classification.

Some ECG temporal features were used for our analysis, i.e., the QRS complex duration, the RR interval (the time span between two consecutive R points representing the distance between the QRS peaks of the present and previous beats), and the RR interval averaged over the ten last beats. These three features are less interfered by noise than other time domain features (such as P wave duration, T wave duration), because it is difficult to accurately locate the starting point and end point of P wave and T wave. Because of the unbalance of the MIT-BIH dataset, we cannot divided the date in a totally random way. Moreover, this is our first attempt to study the ECG signal classification, and we only consider the following four classes: N, LBBB, RBBB,PVC. We selected both SVM and CNN using the same 20,000 samples (5000 samples per class) in study, for which half for the training and half for the test.

The ECG signal is a one dimensional signal representing a time series, hence we designed a quite simple 1-dimensional CNN with 2 convolutional layers, 2 pooling layers, and 1 fully connected layer, trained using stochastic gradient descent (SGD). We select CNN because nowdays the deep learning methods have achieved successful applications like [41–44]. Here, the width of the filter is 5 and we use some standard preprocessing procedures to do the ECG classification task. The batch size is 256 and we train the CNN algorithm with Intel i5-7300HQ processors with 16GB of RAM and GTX1050 as GPU. We classified the compressed signals with q of 1–5, and the accuracy obtained will be studied in the following sections.

4.1. Performance of SVM method

Table 3 and Fig. 6 (a) show the accuracy of classification with decompressed signals under SVM method where 9921 in 10,000 training samples are correctly classified, and the average accuracy is 99.21%. Among all the categories, the accuracy of N beat is the highest, which is 99.88% while that of PVC beat is the lowest, which is 98.58%.

As is shown in Fig. 6 (b), which presents both specific and average accuracy of different categories under different q, q has little effect on R,

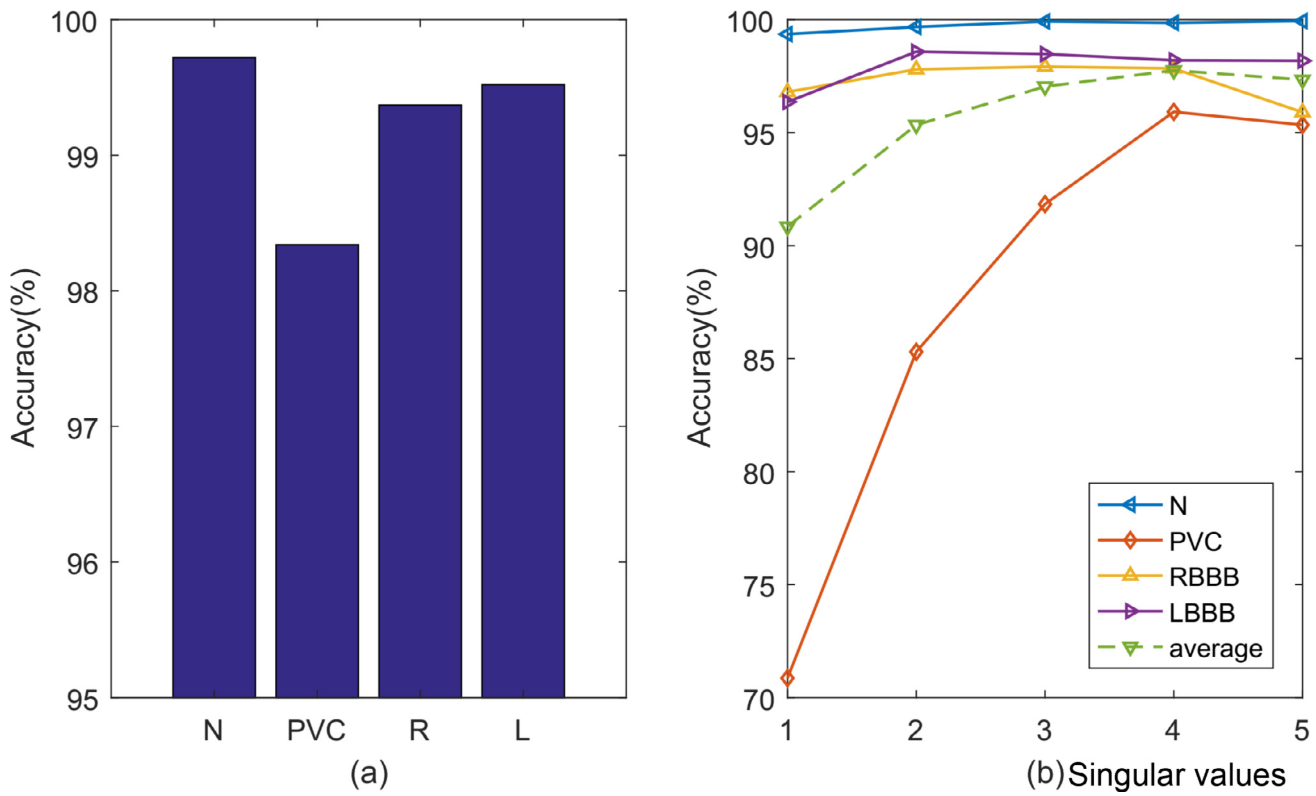

Fig. 6. (a) Accuracy of the original signals under SVM method; (b) Compressed signals accuracy of different q under SVM method.

Table 3
Accuracy of the original signals under SVM.

Labels	Correct number	Error number	Test accuracy
N	2488	3	99.88
PVC	2426	35	98.58
RBBB	2509	16	99.37
LBBB	2498	25	99.11
Total	9921	79	99.21

Table 4
Accuracy of the original signals under CNN.

Labels	Correct Number	Error Number	Test accuracy
N	2449	3	99.88
PVC	2479	27	98.92
RBBB	2555	7	99.73
LBBB	2456	24	99.03
Total	9939	61	99.39

LBBB, and RBBB whose accuracy can be maintained above 95%. However, the accuracy of PVC heart beat is greatly affected by q, and the overall performance increases with the increase of q. When $q \geq 4$, the accuracy rate can reach over 95%.

4.2. Performance of CNN method

Table 4 and Fig. 7 (a) show the classification performance of the original signal under CNN method where 9939 in 10,000 training samples are correctly classified, and the average accuracy rate is 99.39%. Among all categories, the accuracy of N beat is the highest, which is 99.88% while that of the PVC beat is the lowest, which is 98.92%.

Compared to Fig. 6 (b), Fig. 7 (b) shows the performance on different q. It can be seen that each recognition accuracy of N, RBBB and LBBB beats is above 95%, and there is no significant downward trend with the decrease of the singular value q. However, only when the q is greater than 4, the accuracy of PVC is more than 95%, same as SVM method, the accuracy of PVC beat is increased with the increase of q.

4.3. Performance study on selected number of singular values

The results of SVM and CNN have some similarities with each other: changes of q value have no obvious influence on the accuracy of N, RBBB and LBBB, and can maintain a high accuracy rate which is higher than 95%. In both methods, q has a significant impact on the accuracy of PVC beat. However, when $q \geq 4$, the accuracy of PVC beat in both methods can be more than 95%. Therefore, it can be concluded that the lossy compression of ECG signals can still achieve a high accuracy as long as the appropriate q is obtained.

4.4. Multi-objective optimization

The previous section confirmed that when $q \geq 4$, all the four types of compressed beats have satisfactory accuracies. Two factors, CR and accuracy have to be considered in choosing an appropriate value of q. If a higher accuracy is needed, q should at least equal 4 or even larger while a more efficient transferring rate is needed, q should be smaller than 4, which of course will compromise the accuracy of PVC beat classification. This section describes how to use multi-objective optimization to select the appropriate parameters q for different application scenarios. Here we use the multi-goal programming [39] to deal with the two conflicting objectives.

$$\text{Minimize} \quad \mathcal{O} \equiv \eta_1 \delta_1^- + \eta_2 \delta_2^+,$$

$$\text{subject to} \begin{cases} \mathcal{C}(\vec{x}) - \delta_1^+ + \delta_1^- = \Delta_C \\ \mathcal{A}(\vec{x}) - \delta_2^+ + \delta_2^- = \Delta_A \\ \delta_1^\pm, \delta_2^\pm \geq 0 \end{cases} . \tag{11}$$

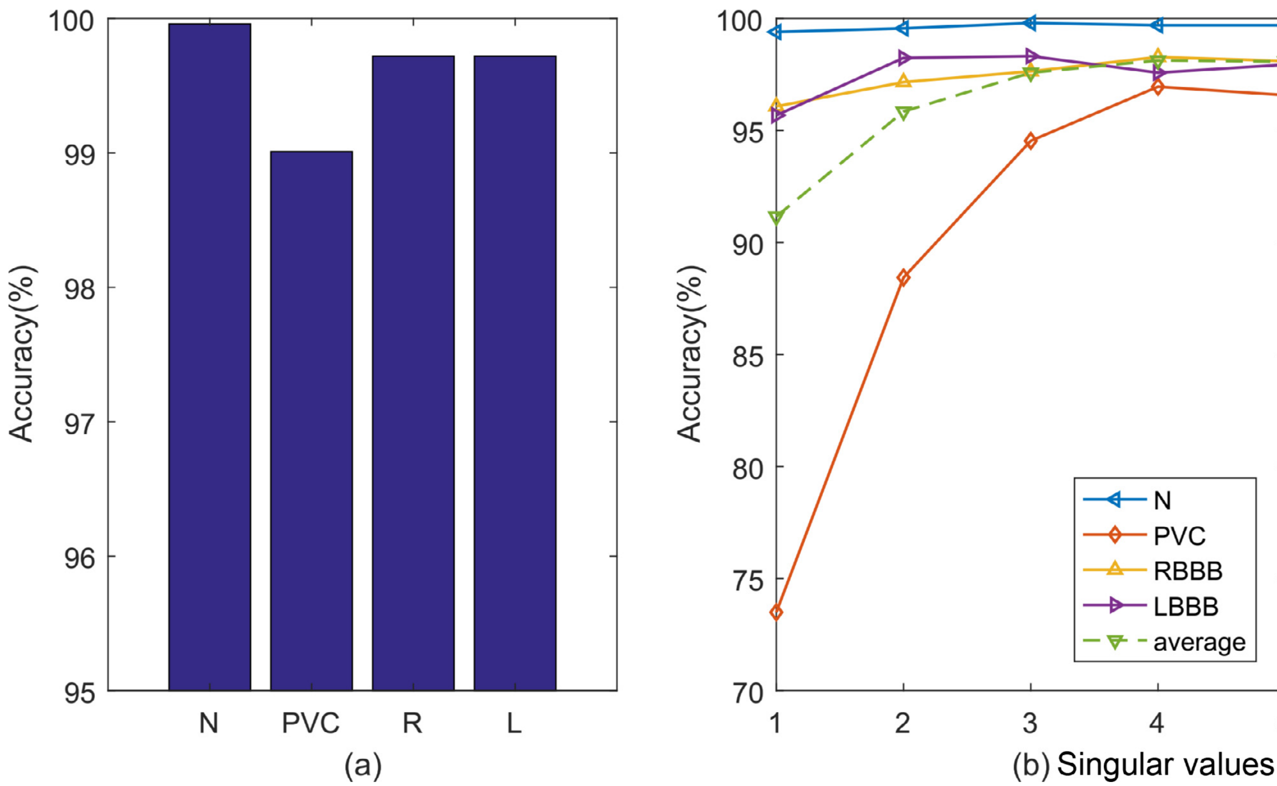

Fig. 7. (a) Accuracy of the original signals under CNN method; (b) Compressed signals accuracy of different q under CNN method.

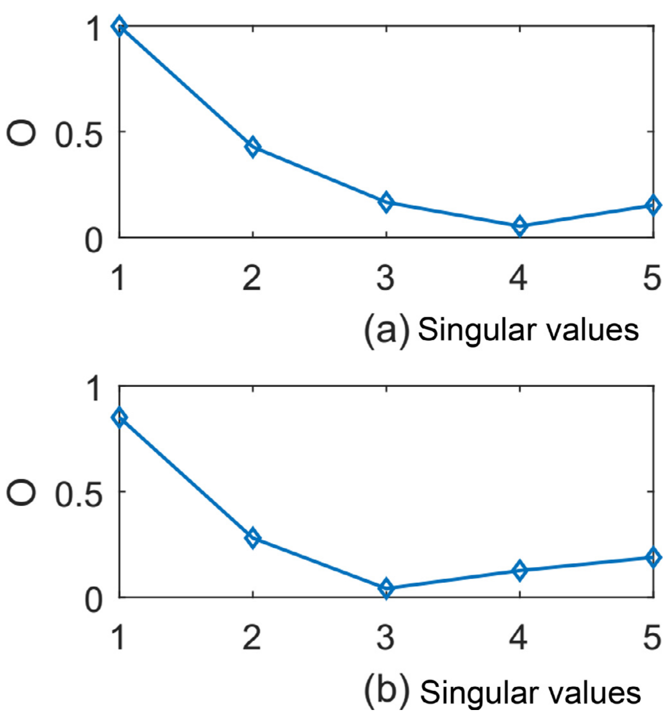

Fig. 8. (a) Optimization results under different parameters: (a)$\Delta_A = 2\%$, $\Delta_C = 75$, $\eta_1 = \eta_2 = 1$; (b) $\Delta_A = 3\%$, $\Delta_C = 90$, $\eta_1 = \eta_2 = 1$.

Here, Δ_C and Δ_A are positive parameters represent the admissible CR and permissible error, respectively. The weight factors η_1 and η_2 are given positive number, and represent the relative priority of objectives.

We use the average error rate obtained under the CNN method to represent A and CR to represent C. Δ_A and Δ_C represent the ideal error rate and compression for different application scenarios respectively, while η_1 and η_2 represent the weights of Δ_A and Δ_A, respectively. Figure 9 shows the optimization results for different parameters. The abscissa represents the number of singular values q, and the ordinate represents the value of the multi-objective function O. As can be seen from the above, the optimal result is when q minimizes O. Fig. 8 (a) and Fig. 8 (b) show the ideal parameter requirements for different scenarios. Fig. 8 (a) shows the need for a lower error rate where parameters are chosen as Δ_A =2% and Δ_C=75, and optimal result is $q = 4$; Fig. 8 (b) shows that a requirement for a higher compression ratio where parameters are selected as Δ_A=3% and Δ_C=90, and the optimal result is $q = 3$. According to requirements under different scenes, the most suitable q can be gained by optimization.

5. Conclusions

In this paper, the SVD technology is used to compress and reconstruct the ECG signal. The obtained compressed ECG signals are then classified and detected using two kinds classifiers. Based on the experimental results, we can find that even if some information are lost, i.e., the quality of reconstructed signal is low, satisfying and high-quality classification result can be achieved with the lossy compression under the appropriate classifier. This result reduces the need for high-quality data compression in the field of ECG arrhythmia classification, thus simplifying the complexity of the problem. Furthermore, with the Error Rate and Compression Ratio as objective functions, multi-objective optimization method is introduced to choose the most appropriate q in different application scenarios.

There are also some points needing for improvement in our further works. For example, we can consider more types of heart conditions and use more complex CNN models to improve the classification performance. Further researches are necessary to carry out to make ECG signal classification more practical and effective. In addition, we can try to get inspiration and ideas from other ECG classification problems [34,40] to solve some related problems.

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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