Application of ECG Signal Denoising and T-wave Automatic Detection Based on Computer Deep Learning

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Abstract. To address the problems of time-consuming, laborious and costly ECG expert diagnosis in the long-term massive ECG signal automatic denoising and T-wave automatic detection system, resulting in the difficulty to extract features, as well as the poor adaptability and low accuracy of the abnormal diagnosis model, we proposed an ECG signal denoising and T-wave automatic detection method based on deep learning. The method mainly includes four steps as follows: ECG signal denoising preprocessing, segmentation of ECG signal and unification of sampling points, unsupervised heartbeat feature learning, denoising and T-wave automatic detection. The structure of the deep faith network FCMDBN model and the learning denoising and T-wave automatic detection algorithm are proposed. Based on the MIT-BIH heart rate anomaly database, the simulation experiment shows that the signal diagnosis method proposed in this paper has relatively high adaptability and accuracy compared with the denoising and T-wave automatic detection by artificial design based on traditional ECG features.

Keywords: ECG Signal Denoising and T-wave Automatic Detection, Deep Learning, Deep Belief Network

1. Introduction

When the electrode is attached to the body surface, different potential is generated at various positions that changes periodically with time. After the lead wire is connected to the electrocardiograph acquisition circuit board, it can be amplified and filtered\cite{1-2}. Clinical practice shows that the strength of the same electrocardiograph band measured at different positions of the human body is different\cite{3-4}. There are several algorithms for ECG feature point detection: neural network method, wavelet transform method, difference threshold method, template matching method. Among them, the difference threshold method is relatively simple, can process the results efficiently, and is convenient to complete in the environment with low hardware requirements, but the detection accuracy is not high; the template matching method is easy to understand its basic mechanism, but easy to be interfered by...
high-frequency noise and baseline drift; the neural network method can accurately identify the signal features, but in the real environment, the timeliness is not excellent. Compared with the difference threshold method, the wavelet transform method has much more computation[5-6]. However, its localization has better features in time and frequency domain, which improves the detection accuracy. From the above-mentioned literature, although various ECG denoising and T-wave automatic detection systems have achieved high accuracy in specific ECG data sets (such as MIT-BIH, AHA and CSE database), they still face the following problems: 1) the process of feature extraction usually requires the participation of cardiac experts, resulting in the increase of time and cost; 2) due to the artificial design of ECG features, In recent years, with the deep unsupervised feature extraction technology in-depth research, the ECG automatic denoising and T-wave automatic detection system based on deep learning technology has been widely concerned.

This paper proposes a method of ECG signal denoising and T-wave automatic detection combined with deep learning technology. Firstly, the technical process of this method is described, including ECG signal denoising preprocessing, ECG signal segmentation and sampling point unification, unsupervised heartbeat feature learning, fuzzy denoising and T-wave automatic detection, etc.; secondly, the structure and algorithm of deep belief network (DBN) model are proposed, and the DBN construction method for ECG feature extraction and the method for ECG denoising and T-wave automatic detection are introduced. Finally, the simulation experiment based on the MIT-BIH arrhythmia database verifies the effectiveness of this method.

2. ECG denoising preprocessing

In order to improve the accuracy of waveform detection, denoising, and T-wave automatic detection, it is necessary to remove baseline drift, EMG noise, power frequency noise and other interference signals, mainly including digital filter technology, adaptive filter technology and modern high-tech filter technology represented by wavelet transform, mathematical morphology and neural network. Because digital filter has the advantages of good system reliability, low design cost, and flexible and convenient application, It is the simplest and widely used technology of ECG signal preprocessing.

According to the proposed denoising preprocessing method, the 200ms median filter is first used to remove QRS complex and P wave, then use 600ms median filter to remove T-wave, finally use the source signal to subtract the two median filter signals to get baseline drift ECG signal, The EMG and power frequency noise signals are removed by a low-pass filter with 35Hz, 3dB and 12 tap. Finally, the ECG signals that can be used for subsequent processing are obtained.

ECG signal segmentation technology has been studied for more than 30 years. It mainly focuses on the detection of P-wave peak and QRS wave group and can effectively detect the key points of P, QRS and T-wave peak, upper and lower edge, etc. Attributing to its simplicity and effectiveness, this method has been extensively used. . It can recognize all kinds of wave shape boundaries of ECG signal to realize the segmentation of ECG signal heartbeat. After calculation, according to the key points obtained from detection, It is easy to segment each heartbeat sample. Because different personal body conditions have different heartbeat cycles, the segmented samples have different number of sampling points, and the ECG feature extraction model needs a unified input. Therefore, it is necessary to unify the sampling points of the heartbeat samples. In this paper, the interpolation algorithm is used
3. Deep belief network model

The data set of ECG signal can be expressed as \( S = [s^1, s^2, \ldots, s^{R+T}] \), represents the sampling data of each ECG signal. \( R \) is the number of training samples, \( t \) is the number of test samples, and \( D \) is the number of sampling points of each ECG signal. Randomly or actively select \( l \) of \( R \) training samples to establish the training samples \( X^l = [x^1, \ldots, x^l] \), \( 1 \leq l \leq R \). The corresponding sample label vector is \( Y^l = [y_1^1, y_2^2, \ldots, y_c^l] \), \( y_i = \begin{cases} 1, & x \text{ belongs to class } i \\ 0, & x \text{ does not belong to class } i \end{cases} \) (1).

Subsequently, the implementation goal of the network model is to find the mapping relationship based on the collected ECG data. The depth network structure proposed in this paper includes two parts: DBN abstract feature extraction, FCM denoising and T-wave automatic detection, as shown in Figure 1. The underlying DBN network model is built by multi-layer undirected restricted Boltzmann machine (RBM). In order to build DBN model, there are two stages: unsupervised learning training and model fine-tuning. The top-level FCM denoising and T-wave automatic detection model are based on the high-level abstract features of DBN output to calculate the clustering center of each kind of ECG signal, Then calculate the shortest distance to carry out the fuzzy denoising and T-wave automatic detection of ECG. In order to build FCM model, the two stages of ECG clustering center and center distance calculation are generally needed.
4. Deep network DBN construction

The classic greedy and unsupervised training RBM method from low to high level is used in DBN model of ECG signal to set the parameters of RBM in-depth network. As the basic module of DBN, RBM has strong non-linear and unsupervised learning ability, can learn useful information from complex data, and has the energy definition for a group of states (V, H). The first level RBM of the model receives the continuous value of ECG signal due to the need, then Gauss Bernoulli RBM (GBRBM) is used, and its energy is defined as equation (2). RBM in other layers of the model is Bernoulli Bernoulli RBM (BBRBM), and its energy is defined as equation (3).

\[ E(v, h; \theta_1) = \sum_{i=1}^{n} \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n} \sum_{j=1}^{m} v_i h_j w_{ij} \]  
\[ E(v, h; \theta_2) = \sum_{i=1}^{n} \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n} \sum_{j=1}^{m} v_i h_j w_{ij} \]  

Where V represents the visible layer unit vector of RBM, h represents the hidden layer unit vector of RBM, which represents the parameter vector of GBRBM and BBRBM respectively, W represents the undirected weight vector between the visible layer unit and the hidden layer unit of RBM, a and b are the offset vector of visible layer unit and hidden layer unit respectively, \( \sigma \) represents the standard deviation vector of Gaussian noise of visible layer unit, n represents the number of visible layer units, M indicates the number of hidden layer units.

4.1. Denoising and T-wave automatic detection

Hypothesis \( H = \{ h_1, h_2, \cdots, h_L \} \) is the abstract feature vector of L ECG samples extracted by the depth DBN model. If the abstract feature dimension is p, then h can be represented by equation (3).

\[ H = \begin{bmatrix} h_{1,1} & h_{1,2} & \cdots & h_{1,p} \\ h_{2,1} & h_{2,2} & \cdots & h_{2,p} \\ \vdots & \vdots & \ddots & \vdots \\ h_{L,1} & h_{L,2} & \cdots & h_{L,p} \end{bmatrix} \]  

(3)

In this paper, FCM algorithm is used to minimize the target function (13) and update the membership and ECG denoising and T-wave automatic detection center until the position of the denoising and T-wave automatic detection center is fixed or the difference between the two iterative target function values is within the allowable range.

\[ J(H; U, V) = \sum_{i=1}^{C} \sum_{l=1}^{L} (u_{i,l})^m (d_{ij})^2 \]  

(4)

Where the ambiguity parameter \( U = (u_{i,j})_{C \times L} \) represents the partition matrix.

4.2. Deep learning algorithm
The traditional fuzzy neural network optimizes the membership function by adjusting the fuzzy parameter $m$ to achieve the goal of denoising and T-wave automatic detection of the target data. In the structure of fuzzy depth network, for the needs of ECG denoising and T-wave automatic detection, the optimization of the model requires collaborative modeling and fine-tuning of ECG sampling data $L$, high-level Abstract ECG feature vector $h$, fuzzy parameter $m$ and corresponding label vector $y$.

In algorithm 1, the training, denoising and T-wave automatic detection process of FCMDBN are described. As the ECG signal sampled is continuous data, in the initial DBN stage, the lowest RBM type is GBRBM, and the other RBM type is BBRBM; the number of hidden layer units, model layers, training times and batch size are determined according to the ECG data dimension and sample set size; The initial value of momentum learning rate, learning rate, penalty rate and initial bias need to be assigned by experience; the weight vector of RBM initialization is randomly generated; the number of fuzzy denoising and T-wave automatic detection and clustering termination threshold is set according to the specific ECG signal denoising and T-wave automatic detection requirements, and the fuzzy parameter also needs to be assigned by experience.

5. Experiment and result analysis

5.1. Experimental data
The experimental data comes from MIT-BIH arrhythmia database, which is developed by MIT. All the data are collected in the arrhythmia Laboratory of Beth Israel Hospital. Each record in MIT-BIH arrhythmia database takes about 30 minutes to collect ECG signal, sampling frequency is 360hz, 18 types of heartbeat have been labeled and annotated. There are 48 records in total, 23 ECG records can be used as representative samples of routine clinical records, and the other 25 records contain complex ventricular, junctional and supraventricular arrhythmia problems. Referring to the method of ECG signal preprocessing in literature [3], five types of arrhythmias were selected for denoising and T-wave automatic detection, It includes normal heartbeat (NORM), left bundle branch block (LBBB), right bundle branch block (RBBB), ventricular premature beat (PVC) and atrial premature beat (APC). The five types of experimental data sets of rhythm obtained are shown in Table 1, in which DS1 is the training data set and DS2 is the test data set.

| Data set | Types | Heartbeat record | NORM | LBBB | RBBB | PVC | APC | Total |
|----------|-------|------------------|------|------|------|-----|-----|-------|
| DS1      | Training dataset | 100, 105, 108, 111, 114, 116, 118, 201, 203, 207, 208, 209, 215, 219, 222, 228, 233103, 106, 109, 119, 124, 205, 214, 221, 223, 231, 232 | 30179 | 3578 | 2251 | 3387 | 892 | 40287 |
| DS2      | Test dataset    | 14560 | 1999 | 3182 | 2247 | 1462 | 23450 |
5.2. Experiment and result analysis

In the experiment, the DBN structure of FCMDBN model is \{200-400-300-100-50-10\}. The first layer 200 receives the continuous data of ECG signal of uniform width, and the sixth layer 10 outputs the high-level abstract feature information of ECG signal. The model defines the dynamic learning rate=\{0.4,0.3,0.2,0.1,0\}, batch size=100, training times=50, penalty rate=zero point zero zero zero two; the number of FCM fuzzy denoising and T-wave automatic detection=5, Fuzziness parameter \(m=1.2\), cluster termination threshold=zero point zero one. In the experiment, a desktop computer is used for simulation, and the device is configured as Intel core I 7-4790, CPU 3.6GHz ,RAM 16GB, and GPU Intel HD graphics 4600.

Based on the data of 10 ECG features extracted from DBN samples, this paper analyzes and calculates the cluster center points of each type of rhythm. Box line figure 1 describes the information of each type of rhythm feature values. The results in Figure 2 show that the values of norm, LBBB, RBBB, PVC, and apc5 have distinct distribution range.

![Figure 2. Distribution range of characteristic values of cardiac rhythm](image)

6. Conclusion

Given the problem in the automatic analysis and diagnosis of ECG signal with massive data volume, a heart disease diagnosis method combining deep learning, fuzzy denoising, and T-wave automatic detection. Deep learning is currently the most extensively studied automatic feature extraction technology with research results in multiple application fields. In this paper, the deep belief network (DBN) based on RBM is used to extract the high-level abstract features of continuous ECG signals as the feature vector data foundation for rhythm denoising and T-wave automatic detection. Subsequently, the clustering algorithm is combined to establish the ECG denoising and T-wave automatic detection model. Simulation experiments suggest that compared with the traditional ECG features based on artificial design, the proposed method in this paper has higher accuracy and more robust adaptability for denoising and T-wave automatic detection. In the future, the application of other deep learning methods combined with the denoising and T-wave automatic detection algorithm in the automatic denoising and T-wave detection of ECG signals can be further studied to construct a library of various automatic analysis algorithms for physical signs.
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