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Postprint: Machine Learning-Based Arrhythmia Signal Classification Algorithms

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Abstract

With the improvement of living standards, cardiovascular diseases have become one of the common diseases threatening modern people' s life and health. The classification and recognition of arrhythmia signals in electrocardiograms (ECGs) constitute an important basis for diagnosing cardiovascular diseases. Based on data files provided by MIT-BIH, 21 sets of feature information from ECG signals were extracted through wavelet transform. This study investigated the classification and recognition of five common types of cardiac rhythm signals, primarily designing and implementing classification algorithms based on Softmax regression and neural networks. Experimental results demonstrate that a suitable neural network algorithm exhibits faster training speed; with fewer iterations, the classification and recognition accuracy remains stable above 90%. Among these, deep neural networks demonstrate superior classification performance in many aspects.

Full Text

Preamble

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Study on Classification Algorithm of Arrhythmia Signals Based on Machine Learning

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Abstract: With the improvement of living standards, cardiovascular diseases have become one of the most common threats to human health. The classification and identification of cardiac arrhythmias in electrocardiograms (ECG) provide an important basis for diagnosing cardiovascular diseases. Based on data files from the MIT-BIH database, this study extracted characteristic information from ECG signals using wavelet transform and investigated the classification and recognition of five common types of arrhythmia signals. We designed and implemented classification algorithms based on Softmax regression and neural networks. Experimental results demonstrate that an appropriate neural network algorithm converges more quickly and achieves a stable classification accuracy of over 90% with fewer iterations, with deep neural networks exhibiting superior classification performance in many respects.

Keywords: arrhythmia signal; classification and identification; wavelet transform; Softmax regression; deep neural network

0 Introduction

With improving living standards, the mortality rate caused by cardiovascular diseases continues to rise annually, making them a major threat to modern human health. Electrocardiograms record the electrical activity of the heart throughout each cardiac cycle and serve as a crucial diagnostic tool for cardiovascular diseases. Traditional ECG analysis relies on manual interpretation, which is not only time-consuming and labor-intensive but also susceptible to subjective misjudgment of certain arrhythmia signals by clinicians. With the rapid development of artificial intelligence, automated ECG analysis has become a research hotspot both domestically and internationally [**?**, **?**]. Although ECG waveform recognition methods and diagnostic criteria are not yet standardized, and automated analysis cannot fully replace human expertise, it provides valuable auxiliary information for clinical practice.

Classification represents an important data mining technique. With the rapid development of the Internet of Things, mobile healthcare has gained widespread attention. The emergence of smart textiles has made physiological signals more accessible, thereby advancing mobile healthcare [**?**, **?**]. The theoretical foundation of mobile healthcare systems based on ECG monitoring lies in the classification and recognition of arrhythmia signals.

In recent years, with the advancement of machine learning, researchers have begun employing various models and algorithms for ECG classification [**?**, **?**]. This study utilizes MIT-BIH arrhythmia signal data, performs waveform recognition and feature extraction on five common signal types using wavelet transform, and constructs a sample database suitable for training and learning. We designed and implemented classification algorithms based on Softmax logistic regression, BP neural networks, and deep neural networks, comparing their performance in terms of training speed, stability, and accuracy. The deep neural network

model not only can process massive ECG signal datasets but also significantly improves classification accuracy.

1.1 MIT-BIH Data Reading

The MIT-BIH database, provided by the Massachusetts Institute of Technology, is one of three internationally recognized standard ECG databases for arrhythmia research [**?**]. In recent years, ECG classification research has remained a hot topic, with increasing applications of the MIT-BIH database.

MIT-BIH offers free downloads of 48 ECG recordings. To minimize file size and storage requirements, MIT-BIH employs a custom format. Each ECG record consists of three components: a header file (.hea), a data file (.dat), and an annotation file (.atr). MATLAB can be used for data reading and visualization. [Figure 1: see original paper] displays the records from files 101 and 109, showing only the first 10 seconds. The numerical markers in the figure correspond to arrhythmia signal types. provides diagnostic information for selected signal types. This study focuses on classifying five common signal types (annotated as 1, 2, 3, 5, and 8).

1.2 Simple Denoising of ECG Signals

As evident in [Figure 1: see original paper], ECG signals from the MIT-BIH database contain baseline drift and high-frequency noise that hinder waveform recognition and feature extraction. Therefore, denoising is necessary. Discrete Wavelet Transform (DWT) achieves this objective. In MATLAB, the wavelet decomposition function is `wavedec`. After decomposing the signal using a db5 wavelet at multiple levels, the `appcoef` and `detcoef` functions extract low-frequency and high-frequency information, respectively. By zeroing out coefficients at certain scales before signal reconstruction, baseline drift and artifacts can be effectively removed. [Figure 2: see original paper] shows a segment of ECG waveform from record 101 after processing, demonstrating that baseline drift and noise have been substantially eliminated without loss of useful frequency components.

2 ECG Signal Feature Extraction

A normal ECG cycle consists of the QRS complex, P wave, and T wave, each of which carries important physiological information. Arrhythmias manifest as abnormalities in these waveform components. As the most prominent waveform component, QRS complex detection forms the basis for waveform recognition. One effective method for R-wave detection employs discrete wavelet multi-scale analysis. [Figure 3: see original paper] illustrates record 101 after decomposition using a quadratic spline wavelet at different scales.

The zero-crossing point between the modulus maxima produced by each Q and S wave corresponds to the R-wave location. Due to the complex characteristics

of ECG signals, low scales contain numerous other modulus maxima that can interfere with R-wave detection. As scale increases, the modulus maxima pairs corresponding to each ECG band become increasingly clear. This study selects the fourth scale for R-wave identification. After determining QRS band feature points, P-wave and T-wave locations can be identified using the same method. The extracted ECG features consist of two categories: interval information and amplitude information, with 21 feature values for each signal type. Partial waveform recognition results are shown in the figures below.

This study classifies five signal types annotated as 1, 2, 3, 5, and 8. In the MIT-BIH database, record 101 contains normal ECG signals (1); record 109 contains left bundle branch block signals (2); record 118 contains right bundle branch block signals (3); record 208 contains premature ventricular contraction signals (5); and premature atrial contraction signals (8) are extracted from record 232. The five ECG signal types can be accurately identified at each band, providing a reliable sample database for subsequent research.

3 Softmax Regression-Based Classification Algorithm

With recent machine learning advances, researchers have applied various algorithms to ECG classification \cite{8~11}. Common classification algorithms include K-nearest neighbors, decision trees, naive Bayes, and support vector machines—all among the "top ten data mining algorithms." K-nearest neighbors, which typically uses Euclidean distance calculations, is relatively straightforward to implement and may yield good results when feature values are homogeneous. However, for ECG features containing both interval and amplitude information, this approach ignores the impact of dimensional differences. Decision trees are intuitive but relatively difficult to implement. Naive Bayes is a probability-based classification method.

3.1 Softmax Regression Algorithm

This section constructs a Softmax regression model for classifying common arrhythmia signals, building upon the principles of Logistic regression. Logistic regression, commonly used for binary classification with class labels of 0 or 1, can be extended to multi-class problems through Softmax regression. In this classification task with five possible class labels, different arrhythmia signals possess distinct feature information. The dependent variable represents class labels, while independent variables are the extracted feature values. Softmax regression identifies optimal parameters—weights for independent variables—to determine which features are critical for each signal type, thereby achieving classification. An appropriate Softmax regression model is realized by minimizing the cost function.

The cost function is a crucial concept in machine learning algorithms, as model training essentially optimizes this function. Any function measuring the discrepancy between predicted and actual values can serve as a cost function. For large

sample sets, the mean value of the cost function can be computed, denoted as $J(\theta)$. Cost functions are not unique to each algorithm; in logistic regression, cross-entropy is most commonly used. Assuming feature vector x, class label y, and training set size m, the logistic regression cost function is:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log h_\theta(x^{(i)}) + (1-y^{(i)})\log(1-h_\theta(x^{(i)}))\right]$$

where θ represents the parameters to be trained to minimize the cost function. Since Softmax regression extends logistic regression to multi-class problems, their cross-entropy cost functions are similar, with the primary difference being that Softmax sums over multiple class label values:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{k}1\{y^{(i)}=j\}\log\frac{e^{\theta_j^T x^{(i)}}}{\sum_{l=1}^{k}e^{\theta_l^T x^{(i)}}}$$

The denominator normalizes the probability distribution to ensure probabilities sum to 1. Minimizing $J(\theta)$ is an optimization problem, with gradient descent algorithms being most commonly used. The gradient direction determines parameter update direction during training, while the learning rate controls step size. Parameters can be updated using partial derivatives and learning rate. To prevent overfitting, adding a weight decay term to the cost function renders $J(\theta)$ strictly convex, guaranteeing convergence to the global optimum. [Figure 8: see original paper] illustrates the Softmax regression algorithm flowchart.

3.2 Data Preparation

Richer feature information improves classification accuracy. This study extracted 21 features from each ECG signal type, primarily comprising interval and amplitude information, totaling 400 samples forming a 400×21 matrix. These 400 samples contain five different arrhythmia signal types as model inputs. The label matrix uses a 1×5 format: normal ECG signals are labeled [0 0 0 0 1]; left bundle branch block signals as [0 0 0 1 0]; and the final arrhythmia type as [1 0 0 0 0]. Models trained on unnormalized data typically exhibit poor performance. Since R-wave peak amplitude creates large variations in the input vectors, this study normalized the sample data. Twenty-five percent of the samples were used as a test set for evaluating model performance.

3.3 Classification Results

Python has gained increasing popularity among developers due to its unique advantages. All classification algorithms in this study were implemented using Python with TensorFlow. [Figure 9: see original paper] shows the Softmax regression classification results. After numerous iterations, the cost function converges to the global minimum with classification accuracy approximately

90%. Notably, after major fluctuations subside, small periodic variations persist. Ideally, algorithms should avoid such oscillations and converge smoothly. Additionally, convergence speed should be improved to achieve stable results with fewer iterations.

4 Neural Network-Based Classification

Neural networks have been applied to various classification tasks (e.g., air quality, personal performance, logistics efficiency). Arrhythmia signal classification can also benefit from neural networks, potentially achieving better performance [**?**]. While researchers employ various neural network structures, multi-layer BP network-based classification is relatively straightforward to implement and yields satisfactory results. Using the same 25% test set allocation, [Figure 10: see original paper] shows the basic structure of a two-layer BP neural network.

The BP neural network classification results are shown in [Figure 11: see original paper]. An appropriate neural network algorithm achieves stable classification accuracy after few iterations, outperforming Softmax regression. Experiments reveal that the number of neurons in hidden layers significantly impacts network performance. To further improve accuracy, a deeper neural network model can be established.

4.2 Deep Neural Network

While common machine learning algorithms and simple neural networks meet basic requirements with relatively small sample sets, room for improvement remains. With the advent of deep learning and deep networks, neural network classification performance has achieved a new leap forward, succeeding across numerous academic fields \cite{13~16}. Notably, Professor Andrew Ng' s Stanford research group has achieved promising results in arrhythmia signal recognition.

[Figure 12: see original paper] presents the deep neural network established in this study, consisting of an input layer, three hidden layers, and an output layer. The input layer receives the extracted ECG signal features—21 feature groups per signal—with each hidden layer containing multiple neurons, forming a more powerful classification model. The Softmax function serves as the output layer activation function for multi-class tasks, determining the class label corresponding to the maximum probability.

The model' s classification results appear in [Figure 13: see original paper]. In this study, the deep neural network algorithm demonstrates greater stability. Despite the limited sample set, classification accuracy reaches 99% or even 100% within a small number of iterations. With the emergence of smart textiles and mobile healthcare, massive ECG datasets have become more accessible. As sample sizes become extremely large, basic models and algorithms face bottlenecks that are difficult to overcome. Deep neural networks consistently exhibit superior classification performance. With deep learning' s rise, computational power and data scale have advanced rapidly. Establishing an appropriate deep

neural network model for normal ECG signals and additional arrhythmia types can achieve higher and more stable classification accuracy.

Conclusion

The classification and recognition of arrhythmia signals in ECGs provide an important basis for diagnosing cardiovascular diseases. Efficient classification algorithms can significantly save clinicians' time and effort while providing valuable auxiliary information. Feature extraction from arrhythmia signals is particularly critical in ECG classification research. After preprocessing MIT-BIH data, this study selected the fourth scale of wavelet transform for feature extraction, choosing 21 features from 400 samples across five arrhythmia signal types. Using a 25% test set, we implemented three classification algorithms: Softmax regression, BP neural network, and deep neural network. Experimental results demonstrate that deep neural networks offer superior classification performance.

Several avenues remain for future work. The current study focuses on classifying only a limited number of arrhythmia types with relatively small sample sizes. Collaborating with medical institutions to expand the sample database would enable classification of more arrhythmia types. Additionally, exploring parameter design and optimization of deep model structures could further improve ECG automatic diagnosis accuracy and stability. Finally, porting classification algorithms to wearable devices and building cloud servers would enable mobile healthcare equipment to provide more personalized services.

References

[1] Li Q, Rajagopalan C, Clifford G D. A machine learning approach to multi-level ECG signal quality classification [J]. Computer Methods and Programs in Biomedicine, 2014, 117(3): 435-447.

[2] Kong Fei. The study of ECG classification and recognition based on wavelet transform and neural network [D]. Chengdu: University of Electronic Science and Technology of China, 2015.

[3] Zhu Yuhong, Niu Qun. Design and implementation of wearable ECG monitoring equipment [J]. Machinery & Electronics, 2016, 34(8): 59-62.

[4] Lin Shida, Zhu Jijun. Wearable ECG monitoring system based on textile electrodes [J]. Chinese Journal of Sensors and Actuators, 2017, 30(6): 893-897.

[5] Jambulia S H, Dabhi V K, Prajapati H B. Classification of ECG signals using machine learning techniques: a survey [C]//Computer Engineering and Applications. 2015: 714-721.

[6] Meng Yan, Zheng Gang, Dai Min, et al. Design and implementation of wearable ECG signal acquisition and analysis system [J]. Computer Science, 2015, 42(10): 39-42.

[7] Wan Jing, Zhang Xiaorui, He Yunbin, et al. Feature extraction and clustering of 12 lead high frequency electrocardiogram signals [J]. Application Research of Computers, 2015, 32(10): 2934-2939.

[8] Seera M, Lim C P, Wei S L, et al. Classification of electrocardiogram and auscultatory blood pressure signals using machine learning models [J]. Expert Systems with Applications, 2015, 42(7): 3643-3652.

[9] Wang Zhiqiong, Wu Chengyang, Xin Junchang, et al. Algorithm of left bundle branch block diagnosis based on ELM [J]. Chinese Journal of Biomedical Engineering, 2017, 36(3): 293-299.

[10] Rahhal M M A, Bazi Y, Alhichri H, et al. Deep learning approach for active classification of electrocardiogram signals [J]. Information Sciences, 2016, 345(C): 340-354.

[11] Kiranyaz S, Ince T, Gabbouj M. Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks [J]. IEEE Transactions on Biomedical Engineering, 2016, 63(3): 664-675.

[12] Yuan Danyang. Classification of ECG signals based on wavelet packet and neural network [D]. Tianjin: Tianjin Polytechnic University, 2017.

[13] Ferrer L, Lei Y, Mclaren M, et al. Study of senone-based deep neural network approaches for spoken language recognition [J]. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2016, 24(1): 105-116.

[14] Li Yandong, Hao Zongbo, Lei Hang. Survey of convolutional neural network [J]. Journal of Computer Applications, 2016, 36(9): 2508-2515.

[15] Deng Kan, Ou Zhijian. Adaptation method for deep neural network-based speech recognition [J]. Application Research of Computers, 2016, 33(7): 1966-1970.

[16] Ren Rongrong, Zhou Mingquan, Geng Guohua, et al. The multi-scale features extraction method based on deep neural network [J]. Journal of Northwest University: Natural Science Edition, 2017, 47(2): 215-221.

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