

## RESEARCH

# ECG Annotation and Diagnosis Classification Techniques

Yan Yan<sup>\*</sup> and Lei Wang<sup>\*</sup>Correspondence:

yan.yan@siat.ac.cn

Shenzhen Institutes of Advanced  
Technology, Chinese Academy of  
Sciences, Xueyuan, Shenzhen,  
ChinaFull list of author information is  
available at the end of the article<sup>†</sup>Equal contributor**Abstract****First part title:** Text for this section.**Second part title:** Text for this section.**Keywords:** sample; article; author

## Background

The heart is comprised of myocardium which rhythmically contract and thus drive the circulation of blood throughout the human body. A wave of electrical current passes through the entire heart, which triggers myocardial contraction [1]. Electrical propagation spreads over the whole heart in a coordinated pattern generate changes on the body surface potentials which can be measured and illustrated as an electrocardiogram (ECG, or sometimes EKG). Metabolic abnormalities (a lack of oxygen, or ischemia etc.) and pathological changes of the heart engender variety of ECG, consequently ECG analysis has been a routine part of any complete medical evaluation or healthcare applications.

Automated ECG analysis provides indispensable assist in clinical monitoring, a large number of approaches have been proposed for the task, basically the diagnosis of arrhythmic and further the inspection of heart rate variability or heart turbulence analysis [2]. Lots of ECG annotation and diagnosis classification techniques had been proposed in industrial circles and academic communities. As the general steps in a classification problem in a machine learning task, the ECG classification includes data collection, preprocessing, feature extraction, and classification with a classifier. Most of literatures described models which were combined by different classifier with features which extracted from different feature extraction algorithms. The ECG classification methods develops at the same pace with the development of classification theories in machine learning and pattern recognition. Because of the particularity in medical data collection and data annotation, the developments in ECG classification and detection were not as flourishing as the similar research topics like speech recognition, natural language processing and image processing etc.

In this chapter, we first introduce the basic elements and procedures in a typical ECG classification task, then we would review the proposed literatures of ECG classification, in the last we would introduce a new method in unsupervised learning for ECG classification.

## Technology Roadmap

ECG classification methods had been developed for decades. With the development of theories in machine learning and data mining, lots of algorithms had been adopted in this domain. Before the review about the methods, it is quite necessary to mention the common experiment settings and data sets, as well as the framework.

### ECG Acquisition

Acquiring and storing ECG data were the base for a analyzing task. Errors might be creep into an analysis at any possible stage, thus not only the hardware acquisition system, but also the transmission and storage should be carefully designed. The explantation for the acquisition field could be found in [3]. A raw data acquisition task related the digital signal processing and hardware design knowledges would not be further discussed in this chapter, in [4] a typical ECG signal acquisition process was illustrated.

As for the signal acquiring process, different kinds of sample rate might be involved, for common ECG acquisition device the sample rate would be 128Hz, 250Hz, 340Hz or 500Hz, even higher. However, even in murine studies, a sampling rate of 2 kHz is considered sufficiently high [5]. Arbitrary resizing would be an ideal procedure to handle with the different sampling rate from different data source to build the datasets for mining and analysis.

### ECG Signal Preprocessing

Before the segmentation and feature extraction process, the ECG signals were pre-processed. As in the procedure of collecting ECG signals, in addition to the ECG signals, the baseline wander (caused by Perspiration, respiration and body movements), power line interference and muscle noise were recorded as well, which had been described in lots of literatures [6]. When the filtering methods were proposed and adopted in the preprocessing, the desired information should not be altered. The ECG typically exhibits persistent features like P-QRS-T morphology and average RR interval, and non-stationary features like individual RR and QT intervals, long-term heart rate trends [1]. Possible distortions caused by filtering should be quantified in these features.

The filtered ECG signals then were segmented into individual heartbeat waveforms depends on the detected R peaks in a classification task. The ECG segmentation can be seen as the decoding procedure of an observation sequence in terms of beat waveforms [7]. Dynamic time warping [8], time warping [9], Bayesian framework [10], hidden Markov models[7], weighted diagnostic distortion [11], morphology and heartbeat interval based methods [12] and genetic methods [13] had been used in this sub-task. The state accuracy rate was close to 100%, which would be accurate enough in most online and offline applications.

### ECG Feature Extraction and Classification

After the segmentation for the ECG records, we got plenty of ECG waveform samples with variety categories. Since different physiological disorder may reflect on different type of abnormal heartbeat rhythms. For the task of classification, it is quite important to determine the classes which would be used. In the early literatures, there were no unified class labels for an ECG classification problem. As in the

open database MIT-BIH arrhythmia database annotations [14, 15], the class label system was build with five beat classes recommended by ANSI/AAMI EC57:1998 standard, i.e., normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB), fusion of a normal and a VEB, or unknown beat type were used in most literature on the classification problems instead of early diversity sub class labels, which could be appropriate in the task since the widely acceptance.

### **Supervised learning Methods in ECG classification**

To be added....

### **Unsupervised learning Methods in ECG classification**

To be added....

### **Deep Learning in ECG Classification: A Preliminary Study**

Deep learning methods attempt to learn feature hierarchies as higher-level features are formed by the composition of lower-level features. The electrocardiography interpretation has been judged by the medical professionals, which was based on the abstractions of the perceptible features. In this model we consider the higher-level abstractions as the perceptible features, with whose composition the medical professionals can make arrhythmia judgement. The deep architecture automatic learning method is especially important for high-level abstractions, which human often do not know how to specify explicitly in terms of raw sensory input [16]. As [17] discussed, deep learning methods are based on learning internal representations of data, another important advantage they offer is the ability to naturally leverage: (a) unsupervised data and (b) data from similar tasks to boost performance on large and challenging problems that routinely suffer from a poverty of labelled data. In the electrocardiography classification problem, we got plenty of unsupervised data, and the labelled data was limited as well, so it is a spontaneously idea to adapt deep learning method in this classification problem.

#### **Deep Neural Networks**

The artificial neural network had been widely used in different applications, the basic 3-layer model (with only one hidden layer) is a fairly shallow network which means only shallow features can be learned via the structure. Deep neural networks were the structures in which we have multiple hidden layers, with which we can compute much more complex features from the input. Each hidden layer computes a non-linear transformation of the previous layer, a deep network can have significantly greater representational power (i.e., can learn significantly more complex functions) than a shallow one. A typical deep neural network structure makes no different from the normal multi layer neural network.

#### **Autoencoders and Sparsity**

An autoencoder is trained to encode the input  $x$  into some representation  $c(x)$  so that the inputs can be reconstructed from that representation. High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors

and such "autoencoder" networks works better than principal components analysis as a tool to reduce the dimensionality of data [18]. Principal Component Analysis (PCA) is a linear reduction technique that seeks projection of the data into the directions of highest variability [19], while autoencoders do the same task in a different way with a wider scope (PCA is method that assumes linear systems where as autoencoders do not). Since in the neural network the hidden layer is nonlinear, the autoencoder behaves differently from PCA, which has the ability to capture multi-modal aspects of the input distribution (the representation of the input). The related literature experiments reported in [20] suggest that in practice, when trained with stochastic gradient descent, nonlinear autoencoders with more hidden units than inputs (called overcomplete) yield useful representations (in the sense of classification error measured on a network taking this representation in input). A farther defence of autoencoder can be accessed from [21]. As the theory illustrated, the electrocardiography signal representations can be learned via the autoencoder structures and algorithms.

## Conclusions

Text

## References

### References

1. Clifford, G.D., Azuaje, F., McSharry, P., *et al.*: Advanced Methods and Tools for ECG Data Analysis. Artech House, Boston (2006)
2. Mar, T., Zauneder, S., Martinez, J.P., Llamado, M., Poll, R.: Optimization of ecg classification by means of feature selection. Biomedical Engineering, IEEE Transactions on **58**(8), 2168–2177 (2011)
3. Clifford, G.D., Azuaje, F., McSharry, P.: Advanced Tools for ECG Analysis. <http://www.ecgtools.org/>
4. Silva, C.V., Philominraj, A., del Río, C.: A DSP Practical Application: Working on ECG Signal. INTECH Open Access Publisher, ??? (2011)
5. Ai, H., Cui, X., Tang, L., Zhu, W., Ning, X., Yang, X.: [studies on the time domain and power spectrum of high frequency ecg in normal mice]. Sheng li xue bao:[Acta physiologica Sinica] **48**(5), 512–516 (1996)
6. Blanco-Velasco, M., Weng, B., Barner, K.E.: Ecg signal denoising and baseline wander correction based on the empirical mode decomposition. Computers in biology and medicine **38**(1), 1–13 (2008)
7. Andreão, R.V., Dorizzi, B., Boudy, J.: Ecg signal analysis through hidden markov models. Biomedical Engineering, IEEE Transactions on **53**(8), 1541–1549 (2006)
8. Vullings, H., Verhaegen, M., Verbruggen, H.: Automated ecg segmentation with dynamic time warping. In: Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE, pp. 163–166 (1998). IEEE
9. Vullings, H., Verhaegen, M., Verbruggen, H.B.: Ecg segmentation using time-warping. In: Advances in Intelligent Data Analysis Reasoning About Data, pp. 275–285. Springer, ??? (1997)
10. Sayadi, O., Shamsollahi, M.: A model-based bayesian framework for ecg beat segmentation. Physiological Measurement **30**(3), 335 (2009)
11. Zigel, Y., Cohen, A., Katz, A.: The weighted diagnostic distortion (wdd) measure for ecg signal compression. Biomedical Engineering, IEEE Transactions on **47**(11), 1422–1430 (2000)
12. De Chazal, P., O'Dwyer, M., Reilly, R.B.: Automatic classification of heartbeats using ecg morphology and heartbeat interval features. Biomedical Engineering, IEEE Transactions on **51**(7), 1196–1206 (2004)
13. Gacek, A., Pedrycz, W.: A genetic segmentation of ecg signals. Biomedical Engineering, IEEE Transactions on **50**(10), 1203–1208 (2003)
14. Mark, R., Schluter, P., Moody, G., Devlin, P., Chernoff, D.: An annotated ecg database for evaluating arrhythmia detectors. In: IEEE Transactions on Biomedical Engineering, vol. 29, pp. 600–600 (1982)
15. Moody, G.B., Mark, R.G.: The mit-bih arrhythmia database on cd-rom and software for use with it. In: Computers in Cardiology 1990, Proceedings., pp. 185–188 (1990)
16. Erhan, D., Manzagol, P.-A., Bengio, Y., Bengio, S., Vincent, P.: The difficulty of training deep architectures and the effect of unsupervised pre-training. In: International Conference on Artificial Intelligence and Statistics, pp. 153–160 (2009)
17. Collobert, R., Weston, J.: A unified architecture for natural language processing: Deep neural networks with multitask learning. In: Proceedings of the 25th International Conference on Machine Learning, pp. 160–167 (2008). ACM
18. Hinton, G.E., Salakhutdinov, R.R.: Reducing the dimensionality of data with neural networks. Science **313**(5786), 504–507 (2006)
19. Duda, R.O., Hart, P.E., Stork, D.G.: Pattern Classification. John Wiley & Sons, ??? (2012)
20. Bengio, Y., Lamblin, P., Popovici, D., Larochelle, H., *et al.*: Greedy layer-wise training of deep networks. Advances in neural information processing systems **19**, 153 (2007)

21. Bengio, Y.: Learning deep architectures for ai. *Foundations and trends® in Machine Learning* **2**(1), 1–127 (2009)