Deep Learning-Based Classification of Massive Electrocardiogram Data

Yan Yan, Xingbin Qin, Jianping Fan, and Lei Wang

***Abstract*—**

***Index Terms*—big data, electrocardiography classification, sparse autoencoder, deep learning, real-time classification.**

I. Introduction

An era of big data in healthcare is now under way, decades of progress in digitising medical records accumulate vast amounts of medical data, simultaneously mobile healthcare and wearable sensor technologies offer healthcare data from larger population coverage. The noninvasive, inexpensive and well-established technology of electrocardiographic signal in mobile health or personal health has the greatest popularity in heart function analysis. Automated electrocardiography classification provides indispensable assist in long-term clinical monitoring, and a large number of approaches have been proposed for the task, easing the diagnosis of arrhythmic changes as well as further inspection, e.g., heart rate variability or heart turbulence analysis [1].

Lots of algorithms have been proposed for the classification and detection for electrocardiography signals. The electrocardiography classification or detection task had been divided into two parts: the feature extraction process and classifier. Simple classifier such as linear discriminants [2] and kNN [3], more complex classifiers like neural networks [4]–[7], fuzzy inference engines [7], [8], hidden Markov model [9], [10], independent component analysis [11] and support vector machine [3], [12], [13] were also adapted by lots of researchers.

Beyond the classifier, the performance of a recognition system highly depends on the determination of extracted electrocardiography features. Time domain features, frequency domain features, and statistical measures features for six fundamental waves (PQRSTU) had been used in feature extraction process [14]. Time domain features like morphological features include shapes, amplitudes, and durations were adapted primarily in [15]–[17], frequency domain features like wavelet transformation were widely used [18], [19] stationary features like higher order statistics also had been developed. Principal component analysis [20] and Hermite functions [21] have been used in electrocardiography classification and related analysis technologies as well. Almost every single published paper proposes a new set of features to be used, or a new combination of the existing ones [1].

The results from these algorithms or models were not amenable to expert labelling, as well as for the identification of complex relationships between subjects and clinical conditions [22]. But for the ambulatory electrocardiography clinical application, as well as the normal application in daily healthcare monitoring for cardiac function or early warning of heart disease, an automated algorithm or model would have significant meaning. The application of artificial intelligence methods has become an important trend in electrocardiography for the recognition and classification of different arrhythmia types [22]. The data explosion puts forward the new request to the method of data processing and information mining.

Over the past decades computational techniques proliferated in the pattern recognition field, simultaneously the applications in electrocardiography recognition, detection and classification for relevant trends, patterns, and outliers. Most of the literatures in the electrocardiography classification task were focused on the supervised learning methods, as in unsupervised learning methods were infrequently used, which needs a lot of effort in labelling data. The MIT-BIH database [23] was the most widely used data in the classification and detection algorithm developments, while mass unlabelled electrocardiography data had been ignored due to the supervise learning approaches essential. Unsupervised learning methods become crucial in mining or analysing unlabelled data, as the unlabelled electrocardiography data accumulated. Unsupervised learning-based approaches and the application to electrocardiogram classification in literatures mainly include clustering-based techniques [21], [24], [25], self-adaptive neural network-based methods [26], [27] and some hybrid unsupervised learning systems [28].

In this paper, we adopt a big data unsupervised learning approach of sparse autoencoder based deep neural network in large unlabelled ambulatory electrocardiography dataset to learn features automatically, with which the cardiac arrhythmia with electrocardiograms classification task was proposed.

In the following sections, we will first state the experimental setup in Section 2. In Section 3 the experimental methodology we propose the system and algorithm details. Then the experimental results and the discussion are given in Section 4 and

Y. Yan is with the Shenzhen Key Laboratory for Low-cost Healthcare, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. No. 1068, Xueyuan Road, Nanshan District, Shenzhen, Guangdong Province, China-mail: (yan.yan@siat.ac.cn).

X. Qin is with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. No. 1068, Xueyuan Road, Nanshan District, Shenzhen, Guangdong Province, China.

J. Fan is with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. No. 1068, Xueyuan Road, Nanshan District, Shenzhen, Guangdong Province, China.

L. Wang is with the Shenzhen Key Laboratory for Low-cost Healthcare, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. No. 1068, Xueyuan Road, Nanshan District, Shenzhen, Guangdong Province, China.

Manuscript received September 29, 2014; revised

Section 5 respectively.

II. Deep Learning, AE and SAE

A. Deep Learning Methods

The backpropagation neural network architecture had been widely applied since 1989 by its multidimensional mapping ability: any L_2 function from $[0, 1]^n$ to R^n can be implemented to any desired degree of accuracy with a three-layer backpropagation neural network [29]. Until 2006, deep architectures have not been discussed much in the machine learning literature, because of poor training and generalisation errors obtained using the standard random initialization of the parameters [30]. Great successes in speech recognition [31], image recognition [32] had been accomplished via this powerful structure due to the proposed proper training algorithms by Hinton [33]. Deep learning methods attempt to learn feature hierarchies as higher-level features are formed by the composition of lower-level features. The network structure could be first layer-wise initialized via unsupervised training and then tuned with supervised learning methods. Deep models can generate more abstract features at higher levels than the lower ones, better results could be achieved when pre-training each layer with an unsupervised learning algorithm, one layer after the other (the so layer-wised manner), starting with the first layer (that directly takes in input the observed x) [30].

Lots of deep neural network architectures were proposed since the layer-wised training method was developed by Hinton. Typical structures include deep belief networks (DBNs) [34], deep Boltzmann machines (DBMs) [35], stacked autoencoders (SAEs) [36], and stacked denoising AEs [37]. The autoencoder based deep learning model and stacked autoencoder as the corresponding architecture.

B. Autoencoders

The first research on the potential benefits of unsupervised learning based pre-training might date back to 1987, in which the first unsupervised autoencoder hierarchies were proposed [38]. The lowest-level autoencoder neural network is a single hidden layer which is trained to map input patterns to themselves. Then the x $\hat{x}$

III. Electrocardiography Classification Problem

IV. Experiments Settings

V. Classification With AE Structures

VI. Experimental Results

VII. Discussion and Conclusions

Acknowledgment

This study was financed partially by the National 863 Program of China (Grant No. 2012AA02A604), the Next generation communication technology Major project of National S&T (Grant No. 2013ZX03005013), the Key Research Program of the Chinese Academy of Sciences, and the Guangdong Innovation Research Team Funds for Image-Guided Therapy and Low-cost Healthcare.

References

[1] T. Mar, S. Zaunseder, J. Martinez, M. Llamedo, and R. Poll, "Optimization of ecg classification by means of feature selection," *Biomedical Engineering, IEEE Transactions on*, vol. 58, no. 8, pp. 2168–2177, Aug 2011.

[2] P. de Chazal, M. O'Dwyer, and R. Reilly, "Automatic classification of heartbeats using ecg morphology and heartbeat interval features," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 7, pp. 1196–1206, 2004.

[3] F. Melgani and Y. Bazi, "Classification of electrocardiogram signals with support vector machines and particle swarm optimization," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 12, no. 5, pp. 667–677, Sept 2008.

[4] W. Jiang and S. Kong, "Block-based neural networks for personalized ecg signal classification," *Neural Networks, IEEE Transactions on*, vol. 18, no. 6, pp. 1750–1761, 2007.

[5] T. Olmez, "Classification of ecg waveforms by using rce neural network and genetic algorithms," *Electronics Letters*, vol. 33, no. 18, pp. 1561–1562, Aug 1997.

[6] C.-W. Lin, Y.-T. Yang, J.-S. Wang, and Y.-C. Yang, "A wearable sensor module with a neural-network-based activity classification algorithm for daily energy expenditure estimation," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 16, no. 5, pp. 991–998, Sept 2012.

[7] S. Osowski and T. H. Linh, "Ecg beat recognition using fuzzy hybrid neural network," *Biomedical Engineering, IEEE Transactions on*, vol. 48, no. 11, pp. 1265–1271, Nov 2001.

[8] M. Kundu, M. Nasipuri, and D. Basu, "A knowledge-based approach to ecg interpretation using fuzzy logic," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 28, no. 2, pp. 237–243, Apr 1998.

[9] R. Andreao, B. Dorizzi, and J. Boudy, "Ecg signal analysis through hidden markov models," *Biomedical Engineering, IEEE Transactions on*, vol. 53, no. 8, pp. 1541–1549, 2006.

[10] D. Coast, R. Stern, G. Cano, and S. Briller, "An approach to cardiac arrhythmia analysis using hidden markov models," *Biomedical Engineering, IEEE Transactions on*, vol. 37, no. 9, pp. 826–836, 1990.

[11] Y. Zhu, A. Shayan, W. Zhang, T. L. Chen, T.-P. Jung, J.-R. Duann, S. Makeig, and C.-K. Cheng, "Analyzing high-density ecg signals using ica," *Biomedical Engineering, IEEE Transactions on*, vol. 55, no. 11, pp. 2528–2537, Nov 2008.

[12] A. Kampouraki, G. Manis, and C. Nikou, "Heartbeat time series classification with support vector machines," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 13, no. 4, pp. 512–518, 2009.

[13] A. Khandoker, M. Palaniswami, and C. Karmakar, "Support vector machines for automated recognition of obstructive sleep apnea syndrome from ecg recordings," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 13, no. 1, pp. 37–48, Jan 2009.

[14] C.-P. Shen, W.-C. Kao, Y.-Y. Yang, M.-C. Hsu, Y.-T. Wu, and F. Lai, "Detection of cardiac arrhythmia in electrocardiograms using adaptive feature extraction and modified support vector machines," *Expert Systems with Applications*, vol. 39, no. 9, pp. 7845 – 7852, 2012.

[15] I. Jekova, G. Bortolan, and I. Christov, "Assessment and comparison of different methods for heartbeat classification," *Medical Engineering & Physics*, vol. 30, no. 2, pp. 248–257, 2008.

[16] I. Christov, G. Gomez-Herrero, I. Krasteva, I. Jekova, A. Gotchev, and K. Egiazarian, "Comparative study of morphological and time frequency ecg descriptors for heartbeat classification," *Medical Engineering & Physics*, vol. 28, no. 9, pp. 876–887, 2006.

[17] C. Ye, B. Kumar, and M. Coimbra, "Heartbeat classification using morphological and dynamic features of ecg signals," *Biomedical Engineering, IEEE Transactions on*, vol. 59, no. 10, pp. 2930–2941, Oct 2012.

[18] O. T. Inan, L. Giovangrandi, and G. T. A. Kovacs, "Robust neural-network-based classification of premature ventricular contractions using wavelet transform and timing interval features," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 12, pp. 2507–2515, 2006.

[19] S. Banerjee and M. Mitra, "Application of cross wavelet transform for ecg pattern analysis and classification," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 2, pp. 326–333, 2014.

[20] T. Stamkopoulos, K. Diamantaras, N. Maglaveras, and M. Strintzis, "Ecg analysis using nonlinear pca neural networks for ischemia detection," *Signal Processing, IEEE Transactions on*, vol. 46, no. 11, pp. 3058–3067, Nov 1998.

[21] M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt, and L. Sornmo, "Clustering ecg complexes using hermite functions and self-organizing maps," *Biomedical Engineering, IEEE Transactions on*, vol. 47, no. 7, pp. 838–848, Jul 2000.
[22] G. D. Clifford, F. Azuaje, and P. McSharry, *Advanced Methods And Tools for ECG Data Analysis*. Norwood, MA, USA: Artech House, Inc., 2006.
[23] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000 (June 13).
[24] H. Nishizawa, T. Obi, M. Yamaguchi, and N. Ohyama, "Hierarchical clustering method for extraction of knowledge from a large amount of data," *Optical Review*, vol. 6, no. 4, pp. 302–307, 1999.
[25] C. Maier, H. Dickhaus, and J. Gittinger, "Unsupervised morphological classification of qrs complexes," in *Computers in Cardiology, 1999*, 1999, pp. 683–686.
[26] S. Palreddy, W. J. Tompkins, and Y. H. Hu, "Customization of ecg beat classifiers developed using som and lvq," in *Engineering in Medicine and Biology Society, 1995., IEEE 17th Annual Conference*, vol. 1, Sep 1995, pp. 813–814 vol.1.
[27] M. Risk, J. Sobh, and J. Saul, "Beat detection and classification of ecg using self organizing maps," in *Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE*, vol. 1, Oct 1997, pp. 89–91 vol.1.
[28] P. Tadejko and W. Rakowski, "Hybrid wavelet-mathematical morphology feature extraction for heartbeat classification," in *EUROCON, 2007. The International Conference on Computer as a Tool*, Sept 2007, pp. 127–132.
[29] R. Hecht-Nielsen, "Theory of the backpropagation neural network," in *Neural Networks, 1989. IJCNN., International Joint Conference on*, 1989, pp. 593–605 vol.1.
[30] Y. Bengio, "Learning deep architectures for ai," *Found. Trends Mach. Learn.*, vol. 2, no. 1, pp. 1–127, Jan. 2009.
[31] G. Hinton, L. Deng, D. Yu, G. E. Dahl, A.-r. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. N. Sainath *et al.*, "Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups," *Signal Processing Magazine, IEEE*, vol. 29, no. 6, pp. 82–97, 2012.
[32] D. C. Ciresan, U. Meier, L. M. Gambardella, and J. Schmidhuber, "Deep, big, simple neural nets for handwritten digit recognition," *Neural computation*, vol. 22, no. 12, pp. 3207–3220, 2010.
[33] G. E. Hinton and R. R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, vol. 313, no. 5786, pp. 504–507, Jul. 2006.
[34] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural computation*, vol. 18, no. 7, pp. 1527–1554, 2006.
[35] R. Salakhutdinov and G. E. Hinton, "Deep boltzmann machines," in *International Conference on Artificial Intelligence and Statistics*, 2009, pp. 448–455.
[36] Y. Bengio, P. Lamblin, D. Popovici, H. Larochelle *et al.*, "Greedy layer-wise training of deep networks," *Advances in neural information processing systems*, vol. 19, p. 153, 2007.
[37] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P.-A. Manzagol, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion," *The Journal of Machine Learning Research*, vol. 11, pp. 3371–3408, 2010.
[38] D. H. Ballard, "Modular learning in neural networks." in *AAAI*, 1987, pp. 279–284.

PLACE PHOTO HERE

Jan Doe Biography text here.

John Doe Biography text here.

Jane Doe Biography text here.