www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 6 Issue 11 November 2017, Page No. 23233-23235
Index Copernicus value (2015): 58.10 DOI: 10.18535/ijecs/v6i11.25

Wavelet Packet and Deep Forest based Objective Auscultation in Traditional Chinese Medicine

Jianjun Yan[1], Rui Guo[2], Yiqin Wang[3]

[1] Center for Mechatronics Engineering, East China University of Science and Technology,
130 Meilong Road, Shanghai 200237, China
[2] Center for TCM Information Science and Technology, Shanghai University of Traditional Chinese Medicine,
1200 Cailun Road, Shanghai 201203, China
[3] School of Basic Medical Science, Shanghai University of Traditional Chinese Medicine,
1200 Cailun Road, Shanghai 201203, China

Abstract:
The goal of this study is to provide objective analysis and quantitative research for the auscultation in Traditional Chinese Medicine (TCM) by taking advantage of algorithm of wavelet packet and Deep Forest. Based on wavelet packet transform, the speech signals are decomposed into six-layer wavelet packet coefficients. Shannon entropy values are extracted as a useful acoustic parameter from wavelet packet coefficients, which are employed for feature analysis and recognition of healthy, Qi-deficiency and Yin-deficiency subjects. After the feature vector formed by the Shannon entropy values are inputted into Deep Forest to be trained and predicted. The results showed the methods proposed were effective and efficient to analyze and recognize auscultation signals. Although the number of subjects is limited, the classified results are satisfied in summary.

Keywords: Auscultation, Wavelet packet, Deep Forest, TCM.

1. Introduction

The auscultation is an important part in four-diagnosis of Traditional Chinese Medicine (TCM), which is the approach to collect information of examining patients for diagnosis by the physician's listening to the sound. In TCM, auscultation mainly depends on the auditory senses of the physician to accurately identify asthenia, sthenia, and visceral lesions in the patient. Therefore, auscultation is considered a qualitative method that produces unconvincing results.

Objective researches on auscultation have made some progress with the recent developments in pattern recognition and signal processing technologies [1]. Frequency spectrum analysis was made on the voice of cough patients making use of digital sonagraph [2]. The nonlinearity of the vowel /a:/ signals of healthy persons and patients with deficiency syndrome was investigated by using delay vector variance [3]. Four novel acoustic parameters were proposed to analyze and identify the characteristics among non-deficiency, Qi-deficiency and Yin-deficiency subjects [4]. The energy values of wavelet packet coefficients were calculated for the auscultation signals of healthy people and patients with five Zang-organs diseases[5, 6].

These researches provide a good basis for the objective research on its clinical use. However, objective auscultation is still in the initial stage: the experiments are usually carried out in limited conditions; the adopted auscultation signals are not typical and comprehensive enough; and the algorithms are unreliably conducted on a small sample database. Therefore, the creation of a reliable and accurate algorithm remains a challenge in auscultation research.

Considering the speech signal is usually non-stationary and time-varying, wavelet packet transform (WPT) can be used to analyze the speech signal based on time-frequency domain transform and the feature of the multi-scale and multi-resolution decomposition and reconstruction. It makes decomposition in both the low-frequency and high-frequency at the same time, and self-adaptively determines the signal resolution in different frequency bands [7]. Deep Forest is a novel decision tree ensemble approach with high performance in contrast to deep neural networks [8].

Therefore, this paper employs wavelet packet transform for analyzing speech signals of healthy, Qi-deficiency subjects, and Yin-deficiency subjects. Shannon entropy parameters are extracted for the quantitative analysis of auscultation signals based on six-layer wavelet packet coefficients. Statistical analysis is made to obtain the effective features, which are used as the input of the Deep Forest classifiers. Classification models are constructed to automatically identify the three groups of subjects. The classification results are discussed at the end of the study.

2. Material and Method

2.1 Material

A total of 181 subjects including 27 healthy subjects (Group H), 38 Yin-deficiency subjects (Group Y) and 116 Qi-deficiency (Group Q), were collected by TCM Syndrome Lab in Shanghai University of Traditional Chinese Medicine. The detailed information about the subjects is showed in Table 1. The speech signals of the three groups were recorded using a microphone and were digitized using a 24-bit A/D acquisitive card (Brand CME Xcorpio, with a frequency response range of 20 Hz to 20 kHz and a dynamic range of 100 dB) at a 16 KHz sampling rate with an anti-aliasing function. The speech signals were recorded at a maintained collecting distance and position. The vowel /a: / is easy for whether patients or health people to pronounce. In addition, the vocal organ is not abuttal and there is no obstacle in cavity when someone is sending out the vowel [9]. Thus, each patient was asked to utter the vowel /a: /. Each subject produced a sustained stable phonation of vowel /a: / that lasted about one second.

Table 1: Information of the whole samples

	Healthy	*Qi-deficiency*	*Yin-deficiency*	*Total*
Samples	27	116	38	181
Males	9	39	11	59
Females	18	77	27	122

2.2 Wavelet packet

Wavelet transform is a sort of time-frequency analysis, which uses different scales to obtain the best resolution of time-domain and frequency-domain in different parts of the signal. But the resolution analysis only produces further decomposition in the low-frequency part so that the high-frequency part is not subdivided. Wavelet packet transform provide a more precise decomposition for signal analysis. It can produce further decomposition in the high-frequency part, so frequency bands are subdivided synchronously in the low-frequency and high-frequency part. In addition, wavelet packet can select self-adaptively the signal resolution in different frequency bands. Thus wavelet packet improves the time-frequency resolution. Through compared with the analysis results of db, coif, sym wavelet functions, db4 wavelet function with high energy concentration [10] is ultimately chosen for the analysis of the voice signals of healthy, Qi-deficiency and Yin-deficiency subjects.

2.3 Extraction of speech parameters

In order to effectively analyze the subjects' speech signals, the analysis programs were developed under the MATLAB environment. Entropy is mainly used to measure the regularity of the information. The smaller the entropy, the stronger the regularity of information. So Shannon entropy is selected to be extracted as feature parameter from wavelet packet coefficients of six layers. The Shannon entropy parameter E is defined as follows:

$$E = \sum_i E(s_i) = -\sum_i s_i^2 \log(s_i^2) \quad (1)$$

where the signal S is a group of orthogonal basis on the coefficient, and s_i is the i coefficients of S in an orthogonal basis, while the entropy E is the value stack up by a certain transform of the coefficients of per orthogonal basis. In addition, because of different pronunciation time and sound intensity of different subjects, the parameter values cannot be used directly. So the ratio of the entropy of every decomposed node and the entropy of the root node is taken as feature parameter for the further analysis in this paper.

3. Deep Forest

We utilize Deep Forest to classify the small-scale data of auscultation.

Inspired by representation learning in deep neural networks, Deep Forest (multi-Grained Cascade forest, gcForest) [7] is a novel decision tree ensemble approach with performance highly competitive to deep neural networks. This algorithm constructs a deep forest ensemble with a cascade structure (Shown in Figure 1) which is able to do representation learning. Multi-grained scanning can further improve the representational learning ability of the algorithm in the case of the high dimension of inputs. Due to the number of cascade levels can be automatically computed, the model complexity can be controllable. The gcForest has much fewer hyper-parameters than deep neural networks. For different data across different domains, excellent performance can be obtained by almost same settings of hyper-parameters.

gcForest is easier to train. Furthermore, compared with deep neural networks which require large-scale training data, gcForest can run well even on small-scale data set.

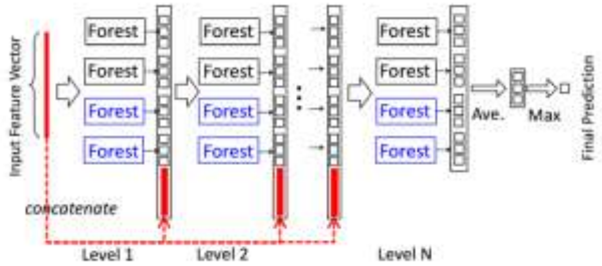

Figure 1: Illustration of the cascade forest structure. Suppose each level of the cascade consists of two completely-random tree forests (blue) and two random forests (black). If there are three classes to be predicted, a three-dimensional class vector concatenated for re-representation of the original input will be output by each forest,.

4. Experimental Results

3.1 Statistical analysis

SPSS 20.0 is used for statistical analysis of the extracted features. The non-parametric tests are made for Shannon entropy parameters of wavelet coefficients in every layer of the speech signals of Group H, Group Q, and Group Y. By paired analysis for Group H, Group Q, and Group Y, Shannon entropy parameters with significant differences are selected and shown in Table 2, 3, and 4.

Table 2: Shannon entropy parameters with significant differences for Group H and Group Q

Frequency band (Hz)	*Group H*	*Group Q*
1500-2000	1.52E-01±0.00513	1.88E-01±0.00622
4000-4500	1.86E-05±7.98E-10	7.83E-06±4.11E-11
4250-4500	1.45E-05±4.96E-10	6.00E-06±2.38E-11
4250-4375	9.29E-06±1.91E-10	3.93E-06±1.25E-11
4375-4500	5.38E-06±7.47E-11	2.12E-06±2.62E-12

Table 3: Shannon entropy parameters with significant differences for Group Q and Group Y

Frequency band (Hz)	*Group Q*	*Group Y*
0-4000	9.00E-01±0.00042	8.95E-01±0.00030
4000-5000	6.67E-05±1.17E-09	1.05E-04±1.22E-08
4500-5000	5.74E-05±8.68E-10	8.85E-05±7.02E-09
5500-6000	2.20E-04±1.97E-08	2.79E-04±2.43E-08
4500-4750	3.86E-05±3.82E-10	5.83E-05±2.41E-09
4750-5000	1.92E-05±1.55E-10	3.08E-05±1.38E-09
5500-5750	6.80E-05±1.42E-09	9.70E-05±4.23E-09
4500-4625	2.16E-05±1.33E-10	3.07E-05±5.91E-10
4625-4750	1.75E-05±1.05E-10	2.81E-05±7.13E-10
4750-4875	6.36E-06±2.86E-11	1.08E-05±2.05E-10
4875-5000	1.28E-05±6.89E-11	2.00E-05±5.43E-10
5625-5750	4.22E-05±7.77E-10	6.21E-05±2.02E-09
5875-6000	6.89E-05±3.27E-09	8.24E-05±2.65E-09

Table 4: Shannon entropy parameters with significant differences for Group H and Group Y

Frequency band (Hz)	*Group H*	*Group Y*
1000-2000	2.00E-01±0.00783	2.50E-01±0.01074
1500-2000	1.52E-01±0.00513	2.00E-01±0.00663
250-500	1.28E-01±0.00395	9.43E-02±0.00199
1750-2000	5.56E-02±0.00104	7.55E-02±0.00184
5750-6000	1.42E-04±1.40E-08	1.84E-04±1.12E-08
375-500	9.28E-02±0.00300	6.28E-02±0.00140
1625-1750	4.70E-02±0.00050	6.21E-02±0.00108
1875-2000	3.29E-02±0.00041	4.60E-02±0.00084
5875-6000	6.36E-05±3.71E-09	8.24E-05±2.65E-09

As can be seen from Table 2, 3, and 4, there are many Shannon entropy parameters with significant differences in different frequency bands between pairwise groups, which will be inputted into gcForest for classification.

3.2 Classification analysis

In gcForest there are two random forests and two completely random tree forests, and the number of the trees is set to 100 for each forest. In order to avoid the random of one-time training and prediction, 70% of samples are randomized as the training set and the remaining 30% are used for testing in the auscultation data. The classification analysis for auscultation signals is repeated for 20 times and the mean value of accuracy was recorded.

Table 5: Average accuracies using gcForest

Group Name	Accuracy
Group H Group Q	89.34%
Group Q Group Y	80.62%
Group H Group Y	71.18%
Group H Group Q Group Y	70.79%

As can be seen from Table 5:

(1) The classification accuracy of Group H and Group Q reaches 89.34%, which is highest in the above four categories, and the average accuracy; but the classification accuracy of Group H and Group Y is only 71.18%.

(2) The classification accuracy is 70.79% for Group H, Group Q, and Group Y.

It seems that the feature parameters with significant difference guarantee a satisfied classification. Moreover, gcForest performs well in spite of few subjects. This is a first step to employ deep forest for classification for the auscultation signals in TCM.

5. Conclusion

This paper selected the vowel /a:/ to be pronounced by each subject to decrease the interference, complexity, and uncertainty of the auscultation signal analysis. Shannon entropy parameters of were extracted for wavelet packet coefficient of the auscultation signals based on wavelet packet transform. The Shannon entropy parameters of WPT coefficients of were analyzed to identify the significant differences between any two groups of subjects, which were inputted into gcForest classifier to identify the three groups of subjects. The results showed integrating WPT with gcForest provided a novel way for objective auscultation.

The clinical subject size must be extended for future studies to verify our research. Our future research aims to develop an automatic auscultation system to assist in clinical diagnosis.

References

1. X. M. Mo, Y. S. Zhang, J. L. Zhang, “Current situation and prospect of auscultation research in TCM,” Chinese Journal of Basic Medicine in Traditional Chinese Medicine, 4(1), pp. 54-56, 1998.
2. X. M. Mo, “Preliminary study on making use of sound ring instrument for the diagnosis of deficiency syndrome of the lung with cough,” Journal of Traditional Chinese Medicine Research, (3), pp. 43, 1987.
3. C.C. Chiu, H. H. Chang, and C. H. Yang, “Objective auscultation for traditional Chinese medical diagnosis using novel acoustic parameters,” Computer Methods and Programs in Biomedicine, 62(2), pp. 99-107, 2000.
4. J.J. Yan, Y.Q. Wang, H. J. Wang et al., “Nonlinear analysis in TCM acoustic diagnosis using delay vector variance,” in Proceedings of the 2nd International Conference on Bioinformatics and Biomedical Engineering (iCBBE '08), pp. 2099-2102, 2006.
5. J.J. Yan, S.Y. Mao, Y.Q. Wang, F.F. Li, R. Guo, C. F. Chen, C. M. Xia, H. X. Yan, C. Wang, “Analysis of Sound Signal of Five Internal Organs Based on Wavelet Packet,” in Proceedings of IEEE International Conference on Bioinformatics & Biomedicine 2010 (BIBMW 2010), pp. 707-711, 2010.
6. J. J. Yan, S. Y. Mao, Y. Q. Wang, F. F. Li, R. Guo, C. F. Chen, C. M. Xia, Q. W. Shen, H. X. Yan, “Wavelet Packet Based Analysis of Sound of Five Internal Organs in TCM,” in Proceedings of the 3rd International Conference on Biomedical Engineering and Informatics (BMEI 2010), pp. 1084-1088, 2010.
7. A.H. Tewfik, D. Sinha, P. Jorgensen, “On the Optimal Choice of a Wavelet for Signal Representation, ” IEEE Trans on Information Theory, 38(2), pp. 747-765, 1992
8. Z.H. Zhou, J. Feng, “Deep Forest: Towards An Alternative to Deep Neural Networks,” Twenty-sixth International Joint Conference on Artificial Intelligence, pp. 3553-3559, 2017.
9. L.Z. Hou, D.M. Han, “Selection of the vowel sound in the throat sound detection,” Journal of Audiology and speech Diseases, (10), pp. 16, 2002.
10. S.H. Liang, I. Hartimo, “A feature extraction algorithm based on wavelet packet decomposition for heart sound signals, ” Proc of IEEE-SP Intre. Symp, USA, IEEE, pp. 93-96, 1998

Author Profile

Jianjun Yan is an Associate Professor at Huadong University of Science and technology. He received his PhD from Huazhong University of Science and technology in 2003. His research focus is in machine learning and biological signal processing.

Rui Guo is a Research Associate at Shanghai University of Traditional Chinese Medicine. She received her PhD from Shanghai University of Traditional Chinese Medicine in 2016. Her research focus is in machine learning and objectification of pulse diagnosis.

Yiqin Wang is a Professor at Shanghai University of Traditional Chinese Medicine. She received her PhD from Shanghai University of Traditional Chinese Medicine. Her research focus is in standardization and objectification of TCM diagnosis.