EEG-Based Physiological Feature Analysis of Expert Operators in Grinding Process

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Abstract

Complex industrial process is often inseparable from human behavior factors. It is helpful to improve intelligence, if we find the physiological feature regularity of the operators and assess their influence factors objectively in the complex industrial process. In this paper, the wavelet entropy (WE) and wavelet time-frequency analysis were used to find the eLectroencephalogram (EEG) features of the operators in a complex industrial process (i. e. the grinding process). We also proposed the wavelet entropy algorithm based on B-spline curve for real-time analysis to find the physiological feature regularity and assess their influence factors objectively.

1. Introduction

Complex industrial processes such as steel making, mineral processing and paper making use operational knowledge of on-site human operators together with various control systems to operate and optimize the productions for guaranteed product quality, production quantity and costs reduction. In general the operational knowledge of on-site operators can be realized by artificial intelligence (AI) and expert systems [1]. The complexity of the behavior of the operators and the subjectivity of the operation of the production make the dynamicity, uncertainty and randomness of the complex industrial processes increase dramatically. Therefore, in order to achieve further optimization control and intelligence of the complex industrial process, human behavior factors cannot be ignored.

Electroencephalographic (EEG) signal may be one of the most predictive and reliable measurements to measure the influence of the human behavior factors as it reflects directly human brain activity [2]. EEG is a record of electric potential from the human scalp, which is generated by inhibitory and excitatory postsynaptic potentials of cell bodies and dendrites of pyramidal neurons [3]. As the spontaneous electric physiological activity of the brain, the recorded EEG signals are non-linear, non-stationary and random in nature [4]. One approach to the nonlinear estimation of dynamical EEG activity is complexity analysis. Among complexity analysis approaches, entropy-based algorithms have been used to obtain robust estimators for evaluating EEG regularity or predictability [5, 6]. Shannon Entropy (SE) is a disorder quantifier and is a measure of flatness of energy spectrum in the wavelet domain [7, 8]. In this study, we use the energy sequence distribution to replace the distribution of the probability distribution of SE to calculate Wavelet Entropy (WE). Wavelet transform (WT) developed in the 1980s is a useful tool for time frequency analysis for neurophysiological signals [7, 9]. Wavelet time-frequency analysis integrates the WT and the short-time Fourier transform (STFT) to extract the time-frequency spectrum information of the signals. It has the advantages of the two transforms.

In this paper, the wavelet entropy and wavelet time-frequency analysis were used to find the EEG features of the operators in a complex industrial process (i. e. the grinding process). We also proposed the wavelet entropy algorithm based on B-spline curve for real-time analysis to find the physiological feature regularity and assess their influence factors objectively.

2. Experiments and Data

2.1 Experiment Design

24 healthy subjects (16 males and 8 females) between ages 20 and 35 were included in the study. The EEG signals of the subjects were collected when the subjects operated the simulated control system of the grinding process in the laboratory (Fig. 1). The subjects were divided into the following two groups. Group 1 consisted of 12 subjects including 8 males and 4 females. They are experienced in the control of the grinding process. They are the experts for the grinding process. Group 2 consisted of 12 subjects including 8 males and 4 females. They did not operate the system before this experiment. They are classified as non-experts for the grinding process.

Subjects need to control the ore and the water supply of the grinding system to make the final grinding particle size reach a pre-given standard within 5 minutes. The subjects cannot see the changes of the grind size. They can only empirically adjust based on the relationship among the ore supply, the water supply and the grind size. In the actual production process, the grind size is also difficult to measure online. It is gotten through the tests at regular intervals.

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The brain activity was conducted with 40 channels mounted on a cap (NuAmps, Neuroscan). Electrodes (Ag/AgCl) were attached to the scalp according to the International 10-20 System. The EEG data used in this paper were continuously recorded from 4 electrodes (the parietal P3, P4 and the occipital O1, O2) at a sampling rate of 200Hz. Recordings were performed with the linked ears electrode as the common reference.

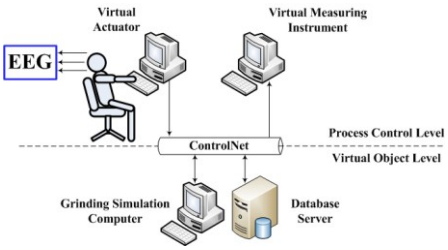

Fig. 1. Experimental setting [10].

2.2 Data Preprocessing

Since the collected signals are disturbed by noise in the experiments, we use WT to achieve EEG signal filtering to make further analysis. WT is particularly effective for representing various aspects of signals, such as trends, discontinuities, and repeated patterns, where other signal processing approaches fail or are not as effective. It is especially powerful for non-stationary signal analysis [11].

WT decomposes a signal into a set of basic functions called wavelets. These basic functions are obtained by dilations, contractions and shifts of a unique function called wavelet prototype. WT is divided into the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT).

DWT analyses the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detailed information. DWT employs the sets of scaling functions and wavelet functions, which are associated with the lowpass filter g[n] and the highpass filter h[n], respectively. After filtering, half of the samples will be eliminated according to the Nyquist' rule, and the coarse approximation and detailed information can be distinguished. The procedure forms one level of wavelet decomposition.

In this work, we used the Daubechies wavelet of order 6 (db6) because of its efficiency. The number of decomposition levels was chosen to be five. The EEG signals were decomposed into the details D1-D5 and approximations A1-A5. A5 decomposition is roughly within the δ range (0-3Hz). D5 decomposition is roughly within the θ range (4-7Hz). D4 decomposition is roughly within the α range (8-13Hz). D3 decomposition is roughly within the β range (14-30Hz).

3. Feature Extraction

3.1 Wavelet Entropy

If we decompose a signal at m levels using WT. Assume the wavelet coefficient vector at jth level is $w_j=(w_{j1}, w_{j2})$. 1 represents approximation information. 2 represents detail information. The energy of the wavelet coefficient vector is defined as:

$$E_{jk} = \left|w_{jk}\right|^2 \quad (j = 1, 2, \cdots, m \;\; k = 1, 2) \tag{1}$$

The energy sequence distribution is defined as the normalized energy of every wavelet coefficient vector.

$$p_i = E_{jk} / E \quad (i = 1, 2, \cdots, 2m) \tag{2}$$

where E is the total energy.

$$E = \sum_{j=1}^{m} \sum_{k=1}^{2} E_{jk} \tag{3}$$

Combined with the definition of entropy, replace the distribution of the probability distribution with the energy sequence distribution p_i. The entropy based on the energy distribution is defined as Wavelet Entropy [6].

$$WE = -\sum_{i=1}^{2m} p_i \log_2 p_i \tag{4}$$

3.2 Wavelet Time-frequency Analysis

Time-frequency analysis aims to construct a joint density function of time and frequency to reveal the signal frequency components and their evolution characteristics. Wavelet time-frequency analysis is an effective tool for the non-stationary signals with time-varying statistics. The principle of wavelet time-frequency analysis is as follows. First use orthogonal wavelet to decompose the signals into orthogonal wavelet components at different scales. Then analyze the components by using STFT with the window function based on the corresponding wavelet basis function to obtain the time-frequency spectrum information. Overall the wavelet time-frequency analysis can play both the multi-scale and multi-resolution advantages of WT and the frequency identification advantage of STFT [12].

3.3 Wavelet Entropy Real-time Analysis Based on B-spline Curve

There is larger difference between the WE values of the occipital regions of the expert and the nonexpert brains (see Table 1). In addition, the occipital fast waves (i. e. α and β) of the expert brain increased (see Fig. 2). Therefore we proposed the wavelet entropy real-time analysis based on B-spline curve to analyze the EEG signals of the occipital region. The algorithm is as follows:

1) we employ the sliding window with the length to be 200 points (1s) to analyze experimental data. The window moves along the data points step by step.

2) Every time when the window moves, decompose the data in the window into five levels using DWT and calculate the WE of $(\alpha+\beta)/(\delta+\theta+\alpha+\beta)$. Namely replace the distribution of the probability distribution in Equation (4) with the energy distribution $E(\alpha+\beta)/E(\delta+\theta+\alpha+\beta)$ to calculate the WE in one second.

3) Average the WE values of the experimental data of each group in the window respectively. When the window moves to the end of the data, we obtain the wavelet entropy changes of the EEG signals in five minutes. the wavelet entropy versus time curves of the experts and the nonexperts are the blue lines in Fig. 3a and Fig. 3b respectively. The abscissa represents the time. The ordinate represents the corresponding average wavelet entropy.

4) Use B-spline curve to fit the wavelet entropy versus time curves to get the change trend.

4. Results and Discussion

In this paper, we selected the parietal and occipital EEG signals for physiological feature analysis. First of all, the WE of the expert and nonexpert EEG which was calculated as a mean value ± standard deviation (SD) is presented in Table I. There is larger difference between the WE values of the two parts of the expert brains. When people concentrate, EEG becomes more complex and the WE has bigger value [2]. The occipital electrodes are included in the visual area. This indicates that the experts can concentrate more easily on finding the target and know where to watch using their eyes. The parietal electrodes are included in the somatosensory area. This indicates that the experts had better plan on the operation and the operation was more robust.

Table 1: The Values of Wavelet Entropy

	Parietal EEG WE (mean ±SD)	Occipital EEG WE (mean ±SD)
Experts	2.4093±0.0223	2.8690±0.0114
Nonexperts	2.5602±0.0152	2.5374±0.0108

To obtain the time-frequency features, the expert EEG wavelet time-frequency spectrums of the natural state before the experiments and the work state in the experiments were calculated. As shown in Fig. 2, the parietal fast waves α (8-13Hz) and β (14-30Hz) of the expert brain generally reduced in the experiments and the occipital α and β generally increased over time. This indicates that the parietal fast waves spread to the occipital region. This also explains why the WE value of the occipital region of the experts in Table I is significantly bigger than the WE value of the parietal region at the physiological level.

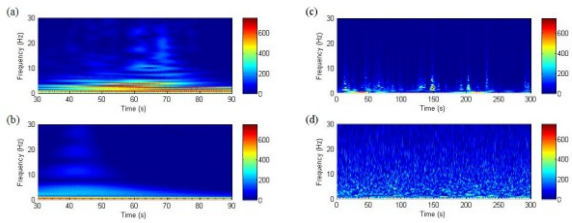

Fig. 2. Wavelet time-frequency spectrums of the expert EEG. (a) Parietal region under nature state; (b) Occipital region under nature state; (c) Parietal region under work state; (d) Occipital region under work state.

In the wavelet entropy real-time analysis, the occipital EEG with the significant features was used to calculate WE to acquire the B-spline curves. The results are shown in Fig. 3 (the red lines with asterisks). The curve of the experts increased. This indicates the brains were under vigilance states and more attention had been focused on the problem of the operational decisions of the grinding process. They had better plan on the operation and the operation was more robust. The curve of the nonexperts decreased. They were under the learning state. This indicates the efficiency of operational decisions was low.

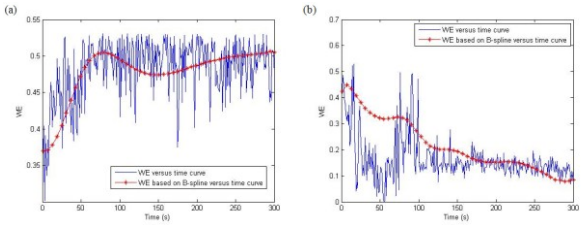

Fig. 3. Occipital WE versus time curves in the experiments. (a) Experts; (b) Nonexperts.

5. Conclusion

The EEG signals of the nonexperts and the experts of the grinding process were collected in the laboratory. We used the WE, the wavelet time-frequency analysis and the wavelet entropy real-time analysis based on B-spline curve to extract the EEG features and the following regularity is obtained. In the complex industrial process, the parietal fast waves (i. e. α and β) of the expert brain reduced and the occipital fast waves increased. Compared to the nonexperts, the occipital curves of the experts show an upward trend. This indicates that the brains of the experts were under vigilance states and more attention had been focused on the problem of the operational decisions. The results show that we can assess their influence factors objectively by using these methods.

6. Acknowledgments

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7. References

1. C. Zhang, H. Wang, H. Wang, and M. H. Wu, “EEG-based expert system using complexity measures and probability density function control in alpha sub-band,” *Integrated Computer-Aided Engineering*, vol. 20, September, 2013, pp. 391-405.
2. A. Yildiz, M. Akin, M. Poyraz, and G. Kirbas, “Application of adaptive neuro-fuzzy inference system for vigilance level estimation by using wavelet-entropy feature extraction,” *Expert Systems with Applications*, vol. 36, May 2009, pp. 7390-7399.
3. S. K. L. Lal and A. Craig, “A critical review of the psychophysiology of driver fatigue,” *Biological Psychology*, vol. 55, February 2001, pp. 173-194.
4. U. R. Acharya, F. Molinari, S. V. Sree, S. Chattopadhyay, K. H. Nge, and J. S. Suri, “Automated diagnosis of epileptic EEG using entropies,” *Biomedical Signal Processing and Control*, vol. 7, July 2012, pp. 401-408.
5. T. Takahashi, R. Y. Cho, T. Mizuno, M. Kikuchi, T. Murata, K. Takahashi, and Y. Wada, “Antipsychotics reverse abnormal EEG complexity in drug-naive schizophrenia: A multiscale entropy analysis,” *NeuroImage*, vol. 51, May 2010, pp. 173-182.
6. C. Zhang, H. Wang, and R. Fu, “Automated Detection of Driver Fatigue Based on Entropy and Complexity Measures,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, February 2014, pp. 168-177.
7. S. Kar, M. Bhagat, and A. Routray. “EEG signal analysis for the assessment and quantification of driver’s fatigue,” *Transportation Research Part F*, vol. 13, September 2010, pp. 297-306.
8. C. E. Shannon, “A Mathematical Theory of Communication,” *Bell System Technical Journal*, vol. 27, July/ October 1948, pp. 379-423.
9. J. Morlet, G. Arens, E. Fourgeau, and D. Giard, “Wave propagation and sampling theory-Part II: sampling theory and complex waves,” *Geophysics*, vol. 47, February 1982, pp. 222-236.
10. M. Tie, Y. S. Fan, and T. Y. Cai, “Distributed Simulation Platform for Optimizing Control of Mineral Grinding Process,” *Journal of System Simulation*, vol. 20, August 2008, pp. 4000-4005.
11. A. Yildiz, M. Akin, M. Poyraz, and G. Kirbas, “Application of adaptive neuro-fuzzy inference system for vigilance level estimation by using wavelet-entropy feature extraction,” *Expert Systems with Applications*, vol. 36, May 2009, pp. 7390-7399.
12. J. Luo and Y. M. Zhong, “Research and application of wavelet packet time-frequency analysis,” *Journal of Chongqing University of Posts and Telecommunications (Natural Science Edition)*, vol. 21, June 2009, pp. 379-387.