Brain Networks based on EEG between High and Low-Proficiency Operators by controlling of mineral grinding process

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Abstract

This paper presents the difference in brain networks between the high-proficiency operators and low-proficiency operators while they did the controlling of mineral grinding process. The brain functional connectivity during the controlling task was investigated by means of Granger causality, like partial direct coherence (PDC) based on EEG. In the experiment, the ocular artifacts were removed using Independent Component Analysis (ICA) and sample entropy. The results show that the brain networks of high-proficiency operators (Hps) are more complex and complete than low-proficiency operators' (Lps) ($p<0.05$). The brain networks could be a useful method to describe the operators' proficiency.

1. Introduction

In recent years, considerable analysis of structure of the brain functional connectivity has been carried out to study the cognitive activity compared with resting state, and the method of structural analysis in the frequency domain was named as PDC [1]. PDC can provide direct structural information for multivariate auto-regressive (MVAR) models. The MVAR models can be obtained from multivariate channel EEG signal. In this analysis PDC is employed to reveal whether and how two structures under study are functionally connected, so that the difference in cognitive compared higher with lower proficiency is implied [2]. We contrasted two groups of 20 different proficiency subjects. 10 of them are Hps while the rest of them are Lps by the controlling of mineral grinding process. In this paper, brain network is used to study the changes in the brain function of the operators while they are in the work, in order to reveal the inside information of the operators' brain, which is conducive to understand the brain thinking and cognitive status of operator in the process of grinding controlling [3].

2. Methods

2.1 Experiments

The EEG data was recorded from 20 healthy subjects (3 females, 17 males) during they were controlling the value of the three variables to achieve the best grinding particle size (GPS) on a distributed simulation platform for optimizing control of mineral grinding process. The three variables are feeding capacity, feedwater quantity and revolving speed of underflow pump. The 10 Hps practiced to operate GPS for about a weed to improve the operation skills, and 10 Lps were told what to do half an hour before tests. Every subject's EEG was recorded by Emotiv EPOC, a wireless neuroheadset, which is convenient for operators' behavior. The Emotiv EPOC has 16 electrodes, of which the P3 and P4 are reference electrodes. The 14 channels EEG data can be obtained by 14 wet electrodes with the conducting solution on them. But only 8 channels of them would be used, and the electrode position of the EEG signals is: AF3, F7, F3, O1, O2, F4, F8 and AF4, because these position was for behavioral controlling, problem solve planning and vision. All signals were sampled at a rate of 128 Hz and were low-pass filtered (cut off frequency 32 Hz). Each subject was seated in a comfortable chair located about 1 m in front of the computer screen. Each run of experiment lasted 5 minutes and collected about 38400 data points. Because there are several segments were influenced by operators' behavior in the long data. And the long data needs high order of MVAR, which will increase the calculation difficulty. Only 5 short segments of each person's EEG data was used in the analysis, and the length of each segments is 10s. In this paper, these EEG data would be pre-processed to remove artifacts, and then used to estimate MVAR models to get the MVAR coefficients. PDC would be computed from the MVAR coefficients. Finally the difference of connection among these structures between Hps and Lps can be found.

2.2 Data processing

Contamination of EEG recordings with different kinds of artifacts is the main obstacle to the analysis of EEG data. ICA is now a widely accepted tool for detection of artifacts in EEG data [4]. One major challenge of artifact removal via ICA is the identification of the artifact components, especially in processing EEG data without an EOG reference channel. Wang kui etc, provide an approach based on sample entropy to identify EOG artifact components, it needs shorter data and has less data loss [5]. Ocular artifacts in EEG data are below 5 Hz. In this paper, extraction of EEG data in the

wavelet coefficient below 5 Hz via wavelet decomposition should be for ICA directly. Not only because signal below 5 Hz is necessary, but also the super gaussian of the wavelet coefficient is stronger than the original signal, and kurtosis is bigger. In wavelet domain ICA in the convergence rate of the iterative algorithm and antinoise ability has significant advantages [6]. ICA is supposed that $S_{M\times l}=[s_1 s_2 \ldots s_M]^T$ is the original unknown multivariate signal, but in this paper it is original unknown multivariate wavelet coefficient, so $X_{N\times l}=[x_1 x_2 \ldots x_N]^T$ is the observed wavelet coefficient and is transformed through the unknown linear unmixing matrix $W_{M\times N}$ such that:

$$S_{M\times l}=W_{M\times N}\times X_{N\times l} \tag{1}$$

The ocular artifacts in these components would be identified by sample entropy. The output of sample entropy-based method was used to divide the independent components into two categories: EEG and ocular artifacts, because the sample entropy of ocular artifacts is smaller than EEG. Then the artifacts components were replaced by the zero, and the equation:

$$X_{N\times l}=A_{N\times M}\times S_{M\times l} \tag{2}$$

was used to reconstruct the wavelet coefficient, and the $A_{N\times M}$ is mixing matrix. Then the EEG signal without EOG artifacts would be obtained by wavelet inverse transformation of treated low frequency coefficient and high frequency coefficient together. In this manner, the EOG artifacts were corrected from the EEG recordings without unnecessary loss of EEG information.

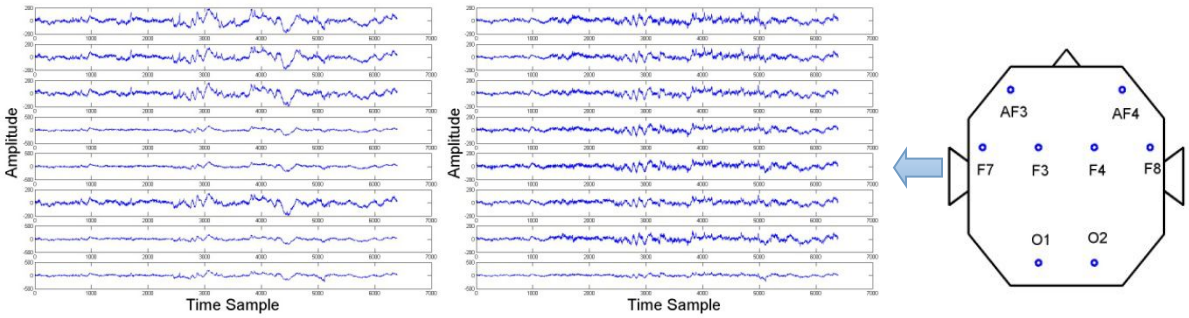

Fig.1. The far left of the figure above is the original EEG recording, and the EEG recording after EOG artifact correction is on the right of it. Most the right side is figure of electrode position, only eight of which had been used.

2.3 MVAR model and PDC

The approach was named as PDC by Luiz A. Baccala and Koichi Sameshima. It was computed from parameters of the MVAR models that model the EEG recording. The MVAR models are able to represent interactions between EEG signals in the form of linear difference equations. The ability of the brain to conduct high level sensory and cognitive functions depends strongly on underlying interactions between two different brain functional structures.

The optimum model order for the time-varying MVAR model is computed by AR_{FIT} algorithm. AR_{FIT} package estimates both the time-invariant parameters of the MVAR model and its optimum order p [7]. A time-varying N-variate AR process of order p can be represented as:

$$\begin{bmatrix} x_1(n) \\ \vdots \\ x_N(n) \end{bmatrix} = \sum_{r=1}^{p} A_r \begin{bmatrix} x_1(n-r) \\ \vdots \\ x_N(n-r) \end{bmatrix} + \begin{bmatrix} w_1(n) \\ \vdots \\ w_N(n) \end{bmatrix} \tag{3}$$

where w is a vector white noise, the matrices A_r are given by:

$$A_r = \begin{bmatrix} a_{11}(r) & \cdots & a_{1N}(r) \\ \vdots & \ddots & \vdots \\ a_{N1}(r) & \cdots & a_{NN}(r) \end{bmatrix} \tag{4}$$

for $r=1,\ldots,p$ and their elements are estimated using the Yule-Walker equation. A number of connectivity measures like PDC can be defined based on the following transformation of the MVAR parameters ($A_r(n)$) to the frequency domain:

$$A(f)=I-\sum_{r=1}^{p} A_r e^{-i2\pi rf} \tag{5}$$

and PDC be computed as:

$$\pi_{ij}(f)=\frac{A_{ij}(f)}{\sqrt{a_j^H(f)a_j(f)}} \tag{6}$$

where $a_j(f)$ is the j' th column of the matrix $A(f)$. PDC take values between 0 and 1 where high values in a certain frequency band reflect a directionally linear influence from channel j to channel i in that band ($CH_i \leftarrow CH_j$).

3. Results

After the calculation of PDC of every Hps and Lps comes out, brain networks, being shown as diagram, can be built up. What can be saw visually out in which is that the brain networks of Hps are more complex and integrated than network of Lps in the α_1-band, α_2-band, β_1-band and β_2-band (see Fig.2), especially in the β_1-band, β_2-band. In the brain networks, there are two lines to link two electrode positions and one of them is red and another is blue. The red one and the blue one are different in direction and the width of directed line is equal to the value of PDC in the same direction, and this value of PDC is the average of all of Hps and Lps respectively. Throng the brain network the flow direction and flow rate of information can be saw [8].

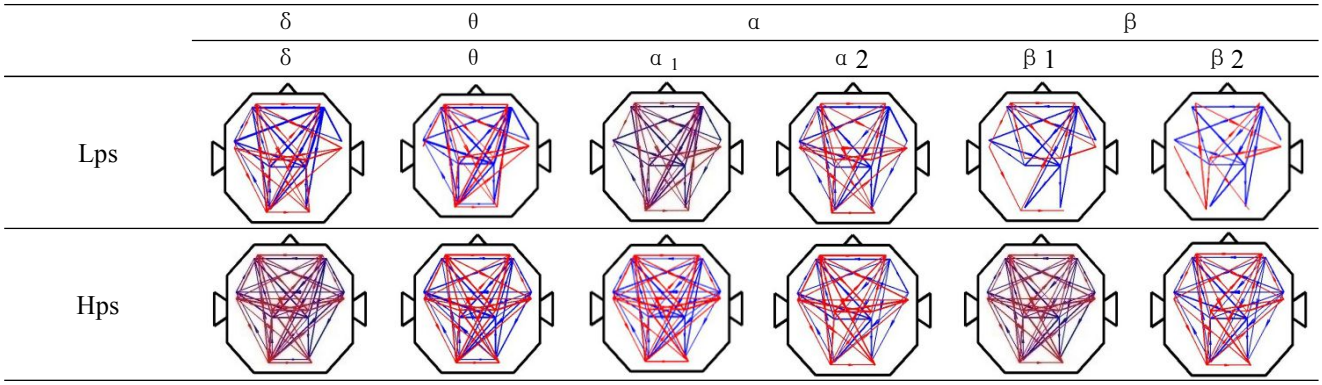

Fig.2. The brain networks in Hps versus Lps based on DTF in the δ :(0.5-4Hz), θ :(4-7Hz), α_1 :(8.0-10.0Hz), α_2 :(10.5-12.5Hz), β_1 :(13.0-18.0Hz), β_2 :(18.5-31.5Hz).

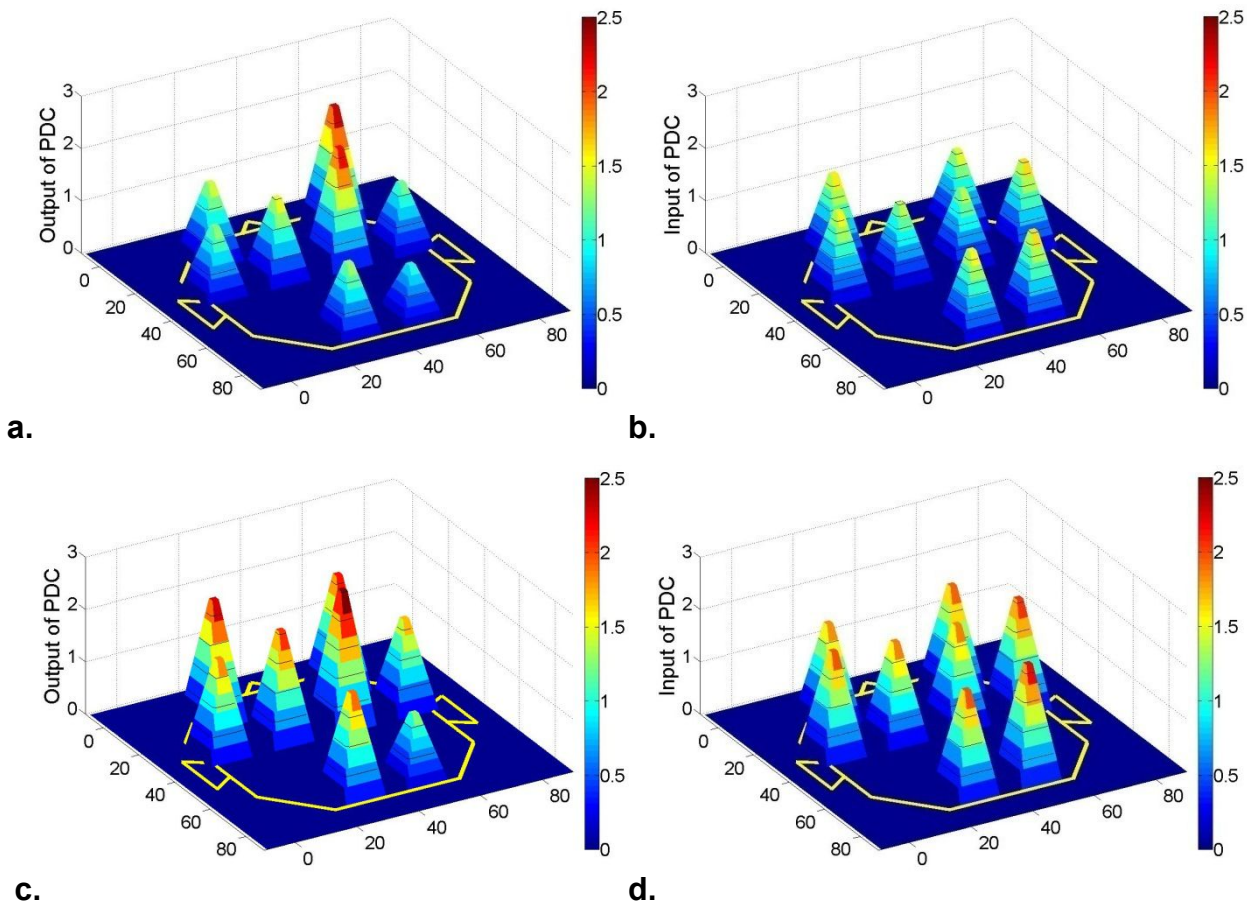

Fig.3. Input and output of every channel in the β-band: (13.0-31.5Hz). (a) the output of Lps; (b) the input of Lps; (c) the output of Hps; (d) the input of Hps.

The cortical cooperation in this frequency range, however, may not reflect an inactive brain state, but internal mental activity. In this study, PDC of Hps in α_1 -band, α_2 -band, β_1 -band and β_2 -band is higher than them of Lps. This feature can also be found from all of electrodes' input and output quantity, which the input of CH_j and output of CH_i is the value of PDC in $CH_i \rightarrow CH_j$ direction (see Fig.3). Then the sum of the input of all channels can be obtained and the sum of Hps is higher than that of Lps (see Fig.4). The error bar in the Fig.4 represented the standard deviation of input of all segments of the all Hps or the all Lps. This different is obvious in the higher frequency bands, such as α_1 -band, α_2 -band, β_1 -band and β_2 -band.

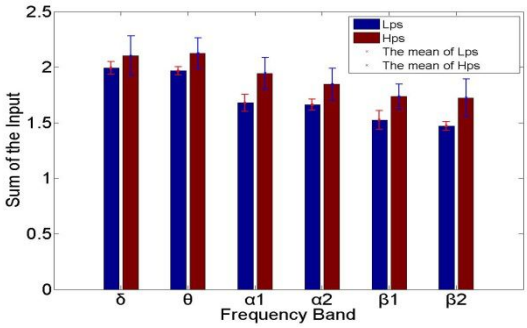

Fig.4. PDC based on the EEG of all channels in the δ :(0.5-4Hz), θ :(4-7Hz), α_1 :(8.0-10.0Hz), α_2 :(10.5-12.5Hz), β_1 :(13.0-18.0Hz), β_2 :(18.5-31.5Hz).

4. Conclusion

In this paper, a new approach was introduced to present the brain networks of high versus low-proficiency operators while they did the controlling of mineral grinding process. The results show that the brain networks of Hps are more complex and complete than Lps' ($p<0.05$). The brain networks could be a useful method to describe the operators' proficiency. It means that according to the brain networks, man could identify who is high-proficiency operator and who is low-proficiency operator based on EEG recording.

5. Acknowledgments

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6. References

1. Luiz A. Baccalá,Koichi Sameshima, "Partial directed coherence: a new concept in neural structure determination," Biological Cybernetics,2001, pp.846.
2. Katarzyna J. Blinowska, Maciej Kamiński, Aneta Brzezicka, Jan Kamiński, "Application of directed transfer function and network formalism for the assessment of functional connectivity in working memory task," Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2013, 3711997.
3. Chi Zhang, Hong Wang*, Hong Wang, and Mian-Hong Wu. "EEG-based expert system using complexity measures and probability density function control in alpha sub-band. Integrated Computer-Aided Engineering," 2013, 20(4): pp. 391-405.
4. Weidong Zhou, Jean Gotman, "Automatic removal of eye movement artifacts from the EEG using ICA and the dipole model," Progress in Natural Science, 2009, pp. 19.
5. Zhu Danhua, Tong Jijun, Chen Yuquan, "An ICA-based Method for Automatic Eye Blink Artifact Correction in Multi-channel EEG", 2008.
6. Hosna Ghandeharion, Abbas Erfanian, "A fully automatic ocular artifact suppression from EEG data using higher order statistics: Improved performance by wavelet analysis," Medical Engineering and Physics, 2010, pp. 327.
7. A. Omidvarnia, M. Mesbah, J.M.O'Toole, P. Colditz, B. Boashash, "Analysis of the time-varying cortical neural connectivity in the newborn EEG: A time-frequency approach," Systems, Signal Processing and their Applications (WOSSPA), 2011 7th International Workshop on , vol., no., pp. 179, 182, 9-11 May 2011.
8. Susanne Reiterer, Claudia Hemmelmann, Peter Rappelsberger, Michael L. Berger, "Characteristic functional networks in high- versus low-proficiency second language speakers detected also during native language processing: An explorative EEG coherence study in 6 frequency bands," Cognitive Brain Research, 2005, pp. 252.