The Finger Flexion Related Feature Extraction Method Based on Wavelet Time-Frequency Analysis in ECoG Signals

Haokun Shi
School of Information Science and Engineering, Yunnan University, Kunming P.R.China
1521864301@qq.com

Pengfei Yu*
School of Information Science and Engineering, Yunnan University, Kunming P.R.China
pfyu@ynu.edu.cn

Haiyan Li
School of Information Science and Engineering, Yunnan University, Kunming P.R.China
leehy@ynu.edu.cn

ABSTRACT

In the brain-computer interface system, the feature extraction of brain signals is a crucial procedure. Especially in the multi-channel brain signals such as Electroencephalogram (EEG), Electrocorticography (ECoG), the channel which has the most correlation with the goal human activity and intention is the priority concern. However, because of the complicated extraction to the feature of the human fine part movements, most of the previous studies are aiming at the imaginary or real activity of large body parts, and their features are usually used in classification tasks. Thus, in order to extract the feature which has a higher linear correlation with fine body part such as fingers, this paper proposes a method combining wavelet time-frequency analysis and principal component analysis (PCA) to extract finger flexion related feature. In the first step, the multi-channel signals will be pre-processed. Then the time-frequency spectrum of each channel's signal is calculated by continuous wavelet transform. After that the spectrum is optimized, and the first wavelet time-frequency spectrum principal component (Wtspc) is extracted by PCA. At last, the Wtspc, which has the highest correlation to the corresponding finger flexion, is chosen as the final feature. The experiment results indicate that the Wtspc feature which extracted by our method has a higher correlation than original signals and typical time-domain features in the previous studies. Particularly, in the local finger flexion period, the Wtspc feature highly demonstrates a linear correlation with corresponding finger flexion.

CCS CONCEPTS

• **Applied computing**; • **Life and medical sciences**; • **Bioinformatics**;

KEYWORDS

Brain computer interface, Electrocorticography, Wavelet transform, Principal component analysis, Feature extraction

*Corresponding author: Pengfei Yu, associate professor, Master's supervisor, research interest: Machine learning and image processing algorithm.

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1 INTRODUCTION

The goal of the brain-computer interface (BCI) is decoding or translating human intention and activity. For that purpose, various methods and appications have been proposed [1]. Some of them have been used in controlling robotic arm [2], character recognition and input [3], emotion recognition [4], and motor imagery recognition [5] et al.

For the large part of human beings, it has been well studied in previous research. Y. Gu [6] et al. use rebound of average movement-related cortical potentials (MRCPs) in EEG signals and the power in mu and beta band as features to discriminate two types of wrist movement. A. J. Doud [7] et al. decode the sensorimotor rhythms (SMRs) of upper limbs in EEG signals to control a virtual helicopter. Y. Hashimoto [8] et al. use beta rebound in EEG signals to classify left and right foot imagery movements at 81.6% accuracy in a single trial. For fine body structures like a finger, T. Hayashi [9] et al. decompose the EEG signal into alpha, beta, and gamma band as features and use the linear discriminate analysis (LDA) to classify finger movements. S. Bera [10] extract the feature from EEG signals by common spatial pattern (CSP) filter, and the extremely randomized tree binary classifier was applied to classify the motor imagery of thumb, index, and middle further. It achieves 74% accuracy at rest condition of finger and 60% average accuracy of all.

As mentioned above, most of the previous studies aim at classification tasks. Their features suit for classification tasks and may not work well at other tasks. But if the feature can discriminate the pattern of body activity at a high linear correlation, it will be helpful to establish a solid model to the BCI system [11]. Therefore, aiming at finger flexion, this paper proposes a method to extract the finger flexion related feature, which has a higher correlation with the corresponding finger flexion.

2 DATA COLLECTION

The dataset used in this paper is dataset 4 of BCI competition IV [12], which is an opening dataset. There are three subjects in the dataset, and each of them has epilepsy. In the dataset, subject 1, 2 and 3 have 62, 48 and 64 channels of ECoG signals, respectively. Meanwhile, each of the subjects has 5 channels of finger flexion data which represent thumb, index, middle, ring and little. The

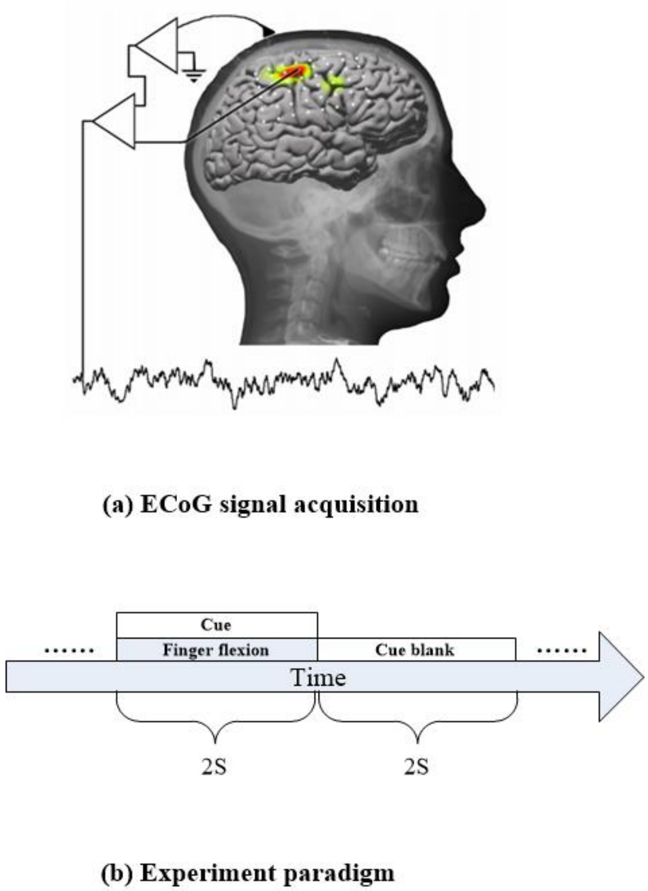

Figure 1: The ECoG Signal Acquisition Method and Paradigm of Dataset.

ECoG signals are collected by the electrode array that implant on the cerebral cortex, and the finger flexion data are gathered by data glove. The sample rate of the ECoG signals is 1000Hz, and the finger flexion data are super-sampled to 1000Hz. In the experiment, each subject should look at a screen that displays the finger name or blank. If the screen shows a finger name, the subject should move the corresponding finger simultaneously. Each cue of the finger takes 2s and follows 2s blank. Finally, the first 2/3 (about 400000ms) of ECoG signals and finger flexion data are taken as the training sets, and the 1/3 (about 200000ms) remained are test sets. The ECoG signals acquisition method and paradigm are shown in Figure 1. The data samples of subject 1 are presented in Figure 2

3 METHOD

3.1 Data Pre-Processing

The common average reference filter (CAR) [13] is applied to pre-process the ECoG signal in each subject. The CAR is a spatial filter that can increase the signal-to-noise ratio (SNR). Thus, it is widely used in EEG, ECoG, or other brain signal processes [14-16]. The

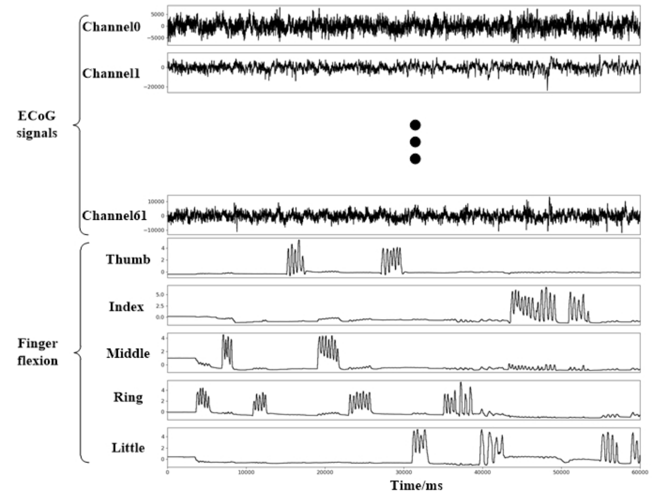

Figure 2: The Data Samples in Dataset of Subject 1.

CAR takes the form of formula (1):

$$S_h^{'}(t) = S_h(t) - \frac{1}{H}\sum\nolimits_{i=0}^{H-1} S_i(t) \tag{1}$$

Where H is the total number of ECoG signal channels, $S_h(t)$ and $S_h^{'}(t)$ are the signals before and after CAR pre-processing at time t on channel h.

3.2 Continuous Wavelet Transformation

After CAR pre-processing, the ECoG signals of each channel are used in the calculation of the time-frequency spectrum by the continuous wavelet transformation (CWT) [17]. The CWT is a time-frequency analysis theory that usually uses in non-linear and non-stationary random signals such as brain signals. The CWT is defined as below:

$$W_f\ (a,\ b) = s(t), \psi_{a,\ b}(t) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\psi^*(\frac{t-b}{a})dt \tag{2}$$

Where $\psi_{a,\ b}(t) = |a|^{-\frac{1}{2}}\psi(\frac{t-b}{a})$ is the mother wavelet function which satisfy the admissibility condition, a is the scale factor, and b is the time shift factor which denotes the time location. $s(t), \psi_{a,\ b}(t)$ is the inner product of signal s(t) and $\psi_{a,\ b}(t)$, f is the frequency point that corresponds with a.

The time-frequency spectrum can be evaluated by formula (3):

$$|W_f\ (a,\ b)|^2 = \left| \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\psi^*(\frac{t-b}{a})dt \right|^2 \tag{3}$$

In this paper, the mother wavelet function used is the complex morlet function which takes the form of formula(4) [18]:

$$\psi(t) = \frac{1}{\sqrt{\pi B}} e^{-\frac{t^2}{B}} e^{\,j2\pi Ct} \tag{4}$$

Where B is the bandwidth and C is the central frequency. In the calculation of this paper, the value of B is 3Hz and C is 3Hz too.

In order to reduce the calculation time, the time-frequency spectrum is calculated section-by-section in 400ms time windows. Each section of signals will be extended symmetrically on both sides,

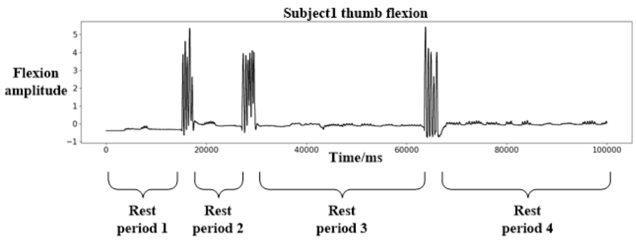

Figure 3: Example of the Rest Period in Dataset Subject 1.

which can erase the distortion of the spectrum in the calculation. Finally, the time-frequency spectrum is obtained by combining all sections of the spectrum.

3.3 Time-Frequency Spectrum Optimization

The power density distribution (PSD) of EEG or ECoG signals is obeyed the power law ($P \sim A/f^{\,b}$, where P is the power, f is the frequency, and A, b is constant parameter respectively) [19], which means that most of the power concentrate in the low-frequency band. But previous studies [20] show that the movements of the fine parts, which like the finger flexion, can cause the time-domain waveform or power changing not only in the low-frequency band but also in the high-frequency band. Therefore, the time-frequency spectrum shall be optimized to suit the different frequency bands.

First, the time frequency spectrum is recalculated as formula (5) shown:

$$\left|W_f{}^h(a,\ b)\right|_r = \left|W_f{}^h\ (a\ ,b)\right| / stv_{finger} \tag{5}$$

Where $|W_f{}^h(a,\ b)|_r$is the value of recalculated spectrum, h is the channel number, stv_{finger} is the standard value of spectrum to the rest condition of finger flexion, and finger represents which finger is researched. The stv_{finger} can be calculated as below:

$$stv_{finger} = \frac{1}{N_r} \sum_{i=0}^{N_r-1} \left|W_f{}^h(a\ ,b_i)\right| \tag{6}$$

Where b_i ($i = 0, 1 \ldots\ldots, N_r - 1$) is the time point in all rest periods of the finger flexion, and N_r is the total number of rest time points. The rest period for calculation is shown in Figure 3

After recalculation, the time-frequency spectrum can describe the signal changing that caused by finger flexion in each Hz.

Besides, to erase the outlier value of recalculated spectrum, a threshold is applied to filter the outlier value as formula (7):

$$\left|W_f{}^h(a\ ,b)\right|_r' = \begin{cases} \left|W_f{}^h(a,\ b)\right|_r, & \left|W_f{}^h(a,\ b)\right|_r \le g \\ 0, & \left|W_f{}^h(a,\ b)\right|_r > g \end{cases} \tag{7}$$

Where g is the threshold, whose value is 30 in this paper, $|W_f{}^h(a,\ b)|_r'$ is the final optimized time-frequency spectrum.

3.4 Wtspc Extraction

The PCA is applied to extract the Wtspc from the optimized time-frequency spectrum. The steps of the Wtspc extraction are shown as follows:

Suppose the optimized time-frequency spectrum as an f×t matrix that like formula (8) shows:

$$W = \begin{bmatrix} \left|W_{f_i}{}^h(a_i, 0)\right|_r' & \cdot s & \left|W_{f_i}{}^h(a_i, b_j)\right|_r' \\ \vdots & \ddots & \vdots \\ \left|W_{f_0}{}^h(0, 0)\right|_r' & \cdot s & \left|W_{f_0}{}^h(0, b_j)\right|_r' \end{bmatrix} \tag{8}$$
$$(i = 0, 1, \ldots, f-1,\ j = 0, 1, \ldots, t-1)$$

- Step1: Transpose the W to W^T.
- Step2: Each column of the W^T is zero-centered and normalized to get W_s^T.
- Step3: Compute the covariance matrix C of W_s^T by column.
- Step4: Compute the eigenvalueλ_i of the matrix C:$\lambda_1 > \lambda_2 > \lambda_3 \ldots\ldots > \lambda_N$, $N < f$.
- Step5: Compute the eigenvector of C:$u_1, u_2, u_3, \ldots\ldots, u_N$.
- Step6: The principal component of the optimized time-frequency spectrum is obtained as follows:

$$(y_1, y_2, y_3, \ldots\ldots, y_N) = (u_1, u_2, u_3, \ldots\ldots, u_N)^T W_s^T \tag{9}$$

- Step7: The first component y_1 is smoothed by a low-pass filter and then the filtered component y_1 is chosen as the Wtspc.

3.5 Feature Selection

For N channels of ECoG signals, there are N Wtspcs that can be obtained. But not all of them will represent the correlation with corresponding finger flexion. In order to determine which is the most correlation channel with the corresponding finger, the correlation coefficient is computed between the Wtspc on each channel and the finger flexion data. Finally, the Wtspc which has the highest correlation coefficient, is chosen as the feature to the corresponding finger flexion.

In summary, the procedure of the finger flexion-related feature extraction method is shown in Figure 4

4 THE EXPERIMENT RESULTS

4.1 The Optimized Wavelet Time-Frequency Spectrum Feature Selection

By using the feature extraction method of this paper, the example of the optimized wavelet time-frequency spectrum in the subject 1 training set is shown in Figure 5

In Figure 5, there is a spectrum value enhancement phenomenon in the dashed and rounded rectangle area. This phenomenon appears when the thumb flexion begins and disappears at the flexion end. It is the event-related synchronization and event-related desynchronization (ERS/ERD) [21] phenomenon of corresponding finger flexion. This ERS/ERD phenomenon can help us confirm which channel correlates with the corresponding finger, and extract the Wtspc further.

4.2 Wtspc Extraction and Feature Selection

In order to identify the most related channel to the finger flexion in each subject, the Wtspc of all channels is extracted, and the correlation coefficient between the Wtspc and corresponding finger flexion data is computed. For instance, Figure 6 demostrates the

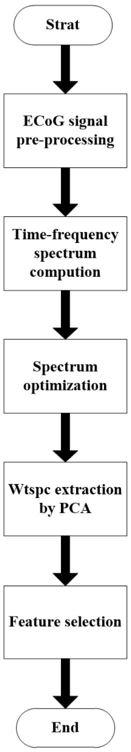

Figure 4: The Flowchart of Feature Extraction Method.

Wtspc extraction process in the training set, and the correlation coefficient between the thumb flexion and the Wtspc of all channels in the subject 1 training set is shown in Figure 7

As is illustrated in Figure 7, the channel whose Wtspc has the highest correlation coefficient with thumb flexion is 42 in the subject 1 training set. That means among all channels of subject 1, channel 42 has a direct correlation with thumb flexion, and its Wtspc can be the related feature of the thumb flexion. By normalizing the Wtspc

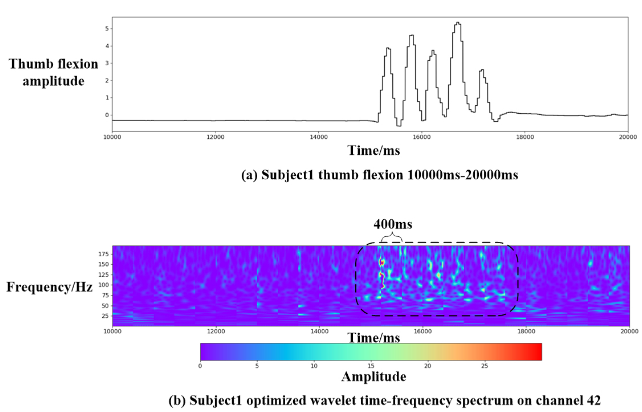

Figure 5: The Thumb Finger Flexion and Optimized Wavelet Time-Frequency Spectrum of Subject 1 on Channel 42.

Table 1: The Selected Channel and Correlation Coefficient r between Its Wtspc and Finger Flexion

Subject	Finger	Selected channel	r
Subject 1	Thumb	42	0.405
	Index	0	0.615
	Middle	0	0.136
	Ring	38	0.395
	Little	16	0.294
Subject 2	Thumb	23	0.517
	Index	23	0.258
	Middle	2	0.177
	Ring	14	0.363
	Little	14	0.199
Subject 3	Thumb	48	0.430
	Index	17	0.425
	Middle	53	0.450
	Ring	40	0.401
	Little	40	0.490

and corresponding thumb flexion at the same time, Figure 8 shows the comparison between the Wtspc and finger flexion.

Moreover, the selected channels which have the highest correlation coefficient r with corresponding finger flexion in each subject training set are listed in table 1

4.3 Results and Comparison in the Test Set

Based on the channel selection and the value of stv from the training set, in the test set, the correlation coefficients between the finger flexion and the Wtspc, original ECoG signals and typical time-domain feature are computed. The results are listed in table 2. (Keep two significant digits, Tips: The α band:8-15Hz, β band:16-31Hz and γ band:32-128Hz of ECoG signals are all obtained by Finite Impose Response (FIR) filter.)

In table 2, compare with the original ECoG signals and their time domain features, the Wtspc shows a higher linear correlation with the corresponding finger flexion. That means the Wtspc could be an efficiency and related feature which can demonstrate the pattern of finger flexion. Figure 9 illustrates the Wtspc and corresponding finger flexion in the subject 1 test set.

5 DISCUSSION

In the experiment above, the Wtspc has been confirmed that it is a related feature of finger flexion. However, as shown in table 1, there exists a phenomenon in which some finger flexion corresponds the same channel, especially in subject 2. This phenomenon may confuse the matching relationship between the Wtspc feature and the finger flexion, and the effectiveness of the Wtspc feature will decrease. The possible factors which lead to this problem may be complex, such as the location of electrode is both related to one or more fingers, the finger like middle and ring can influence each other when flexion appears et al. Despite the fact that this phenomenon can affect our research of finger flexion, on the channel which related multiple fingers, the Wtspc still represent the correlation

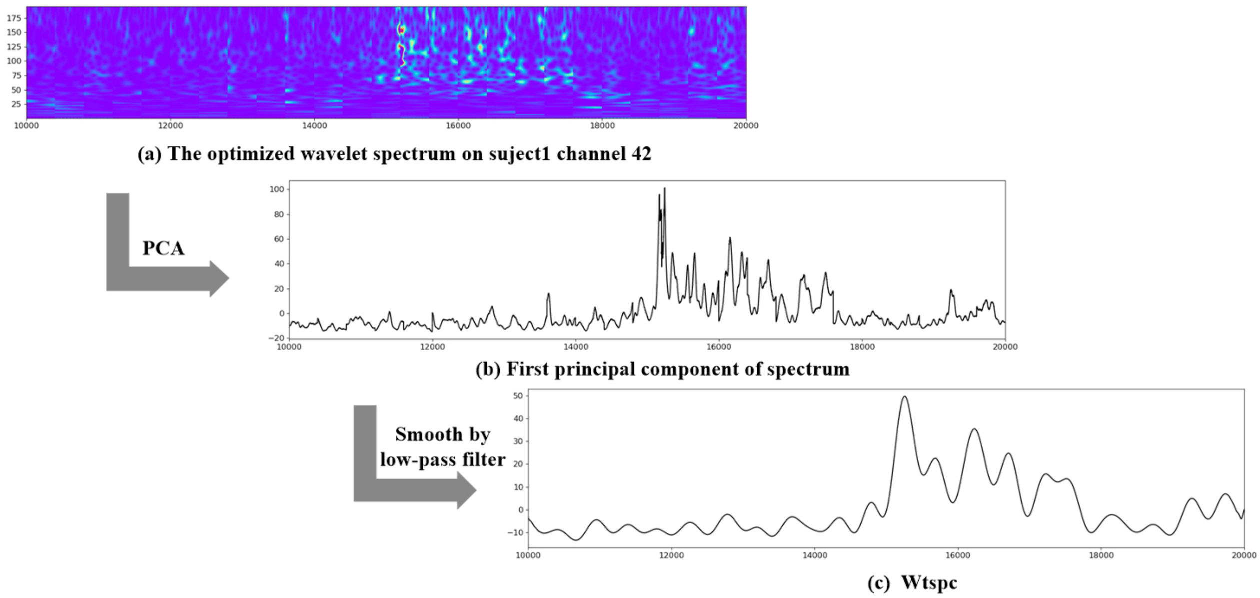

Figure 6: The Wtspc Extraction Process in Subject 1.

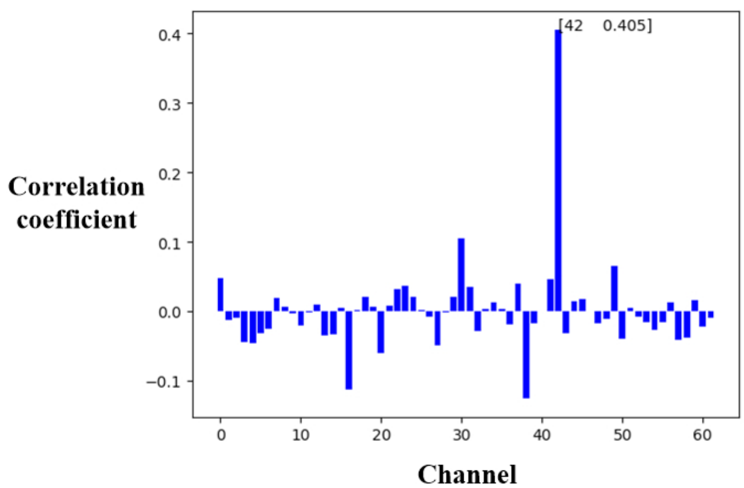

Figure 7: The Correlation Coefficient between the Thumb Flexion Data and Wtspc of All Channels in Subject 1.

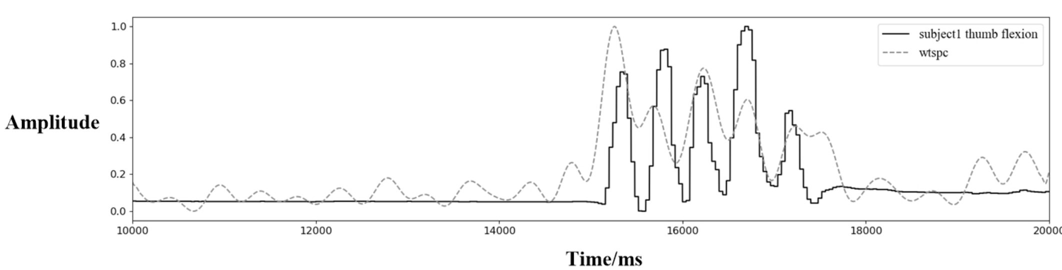

Figure 8: The Comparison between the Thumb Flexion and Wtspc in Subject 1.

Table 2: The Correlation Coefficient between the Finger Flexion and Wtspc or Other Features in Test Set

Subject	Feature on same channel	Thumb	Index	Middle	Ring	Little	Mean
Subject1	Wtspc	0.49	0.59	0.12	0.48	0.29	0.39
	Original ECoG	0.03	-0.01	-0.01	-0.02	0.02	0.01
	α band of ECoG [8]	0.00	0.00	0.00	0.00	0.00	0.00
	β band of ECoG [8]	0.00	0.00	0.00	0.00	0.00	0.00
	γ band of ECoG [8]	0.00	0.00	0.00	0.00	0.00	0.00
Subject2	Wtspc	0.38	0.23	0.09	0.39	0.19	0.26
	Original ECoG	0.00	-0.03	-0.08	0.01	0.03	-0.01
	α band of ECoG	0.00	0.00	0.00	0.00	0.00	0.00
	β band of ECoG	0.00	0.00	0.00	0.00	0.00	0.00
	γ band of ECoG	0.00	0.00	0.00	0.00	0.00	0.00
Subject3	Wtspc	0.46	0.42	0.57	0.53	0.54	0.50
	Original ECoG	-0.18	-0.13	-0.08	-0.01	-0.01	-0.08
	α band of ECoG	0.00	0.00	0.00	0.00	0.00	0.00
	β band of ECoG	0.00	0.00	0.00	0.00	0.00	0.00
	γ band of ECoG	0.00	0.00	0.00	0.00	0.00	0.00
Total mean	Wtspc	0.38					
	Original ECoG	-0.03					
	α band of ECoG	0.00					
	β band of ECoG	0.00					
	γ band of ECoG	0.00					

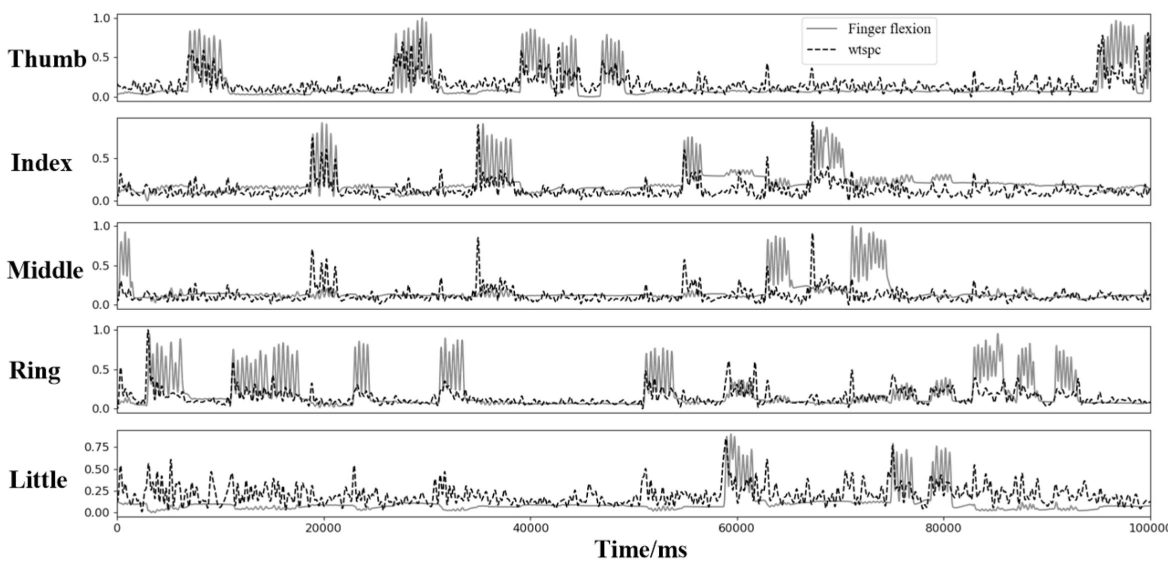

Figure 9: The Comparison between Finger Flexion and Wtspc in Subject 1 Test Set.

with finger flexion in the local flexion period. By taking subject 2 as an example, the Figure 10 shows the comparison between the Wtspc and finger flexion in the local period of subject 2 test set.

As is shown in Figure 10, the waveform of the Wtspc on channel 23 of subject 2 and the index flexion is similar in the local index flexion period, even though the correlation coefficient is low in the whole period. The correlation coefficient in the local period, which Figure 10 shows, is 0.74. Furthermore, the results of the local period in subject 2 test set are listed in table 3 (Keep two significant digits). In consideration of the limited space to this paper, other subjects will not be discussed in this paper, but they have similar results like subject 2 in their local flexion period.

6 CONCLUSION

In this paper, a finger flexion-related feature extraction method based on time-frequency analysis is proposed. The experimental results indicate that the Wtspc feature has a higher correlation to

Table 3: The Correlation Coefficient between Wtspc and Finger Flexion in Local Period of Subject 2 Test Set

Subject	Finger	Local flexion period	Correlation coefficient	Mean
Subject2	Thumb	33500ms-38000ms	0.65	0.43
		90700ms-98000ms	0.72	
		109600ms-115000ms	0.57	
		129600ms-143000ms	0.30	
		146000ms-150000ms	-0.01	
		153800ms-159000ms	-0.01	
		173800ms-177500ms	0.79	
	Index	0ms-2000ms	0.94	0.59
		2000ms-6000ms	0.74	
		21800ms-25500ms	0.75	
		29800ms-34500ms	0.69	
		97800ms-102000ms	0.55	
		113700ms-118000ms	0.42	
		162400ms-166000ms	0.38	
		181500ms-194000ms	0.27	
	Middle	5700ms-10000ms	0.73	0.52
		25900ms-29500ms	0.07	
		103000ms-106500ms	0.68	
		117900ms-121500ms	0.68	
		169600ms-174000ms	0.46	
	Ring	13800ms-18000ms	0.82	0.73
		26000ms-30500ms	0.65	
		42000ms-46000ms	0.87	
		53600ms-61500ms	0.75	
		69800ms-73500ms	0.81	
		73500ms-77500ms	0.87	
		77800ms-83000ms	0.56	
		85900ms-90000ms	0.73	
		142000ms-146700ms	0.79	
		158000ms-163000ms	0.43	
		177800ms-181500ms	0.66	
		194000ms-200000ms	0.78	
	Little	9600ms-15000ms	0.48	0.48
		17800ms-22000ms	0.52	
		37700ms-42000ms	0.69	
		45700ms-53500ms	0.65	
		62000ms-69500ms	0.05	
		78000ms-87000ms	0.48	
		105800ms-109500ms	0.59	
		121600ms-125500ms	0.72	
		125500ms-130000ms	0.36	
		165800ms-169500ms	0.26	

corresponding finger flexion, and it can demonstrate the pattern of finger flexion in the whole or local period. The Wtspc feature could be used in other BCI-related studies or applications. In later work, more algorithms like machine learning will apply to enhance the real-time and efficiency of the Wtspc feature, and we will continue the research of the matching relationship between the body activity and ECoG signals on cerebral cortex area. We believe that the Wtspc feature will be helpful to the research or application of the relationship between the brain signals and human physical activity such as controlling robotic arm by brain signals, tactile sensation recognition and diagnosis of neuro system disease et al.

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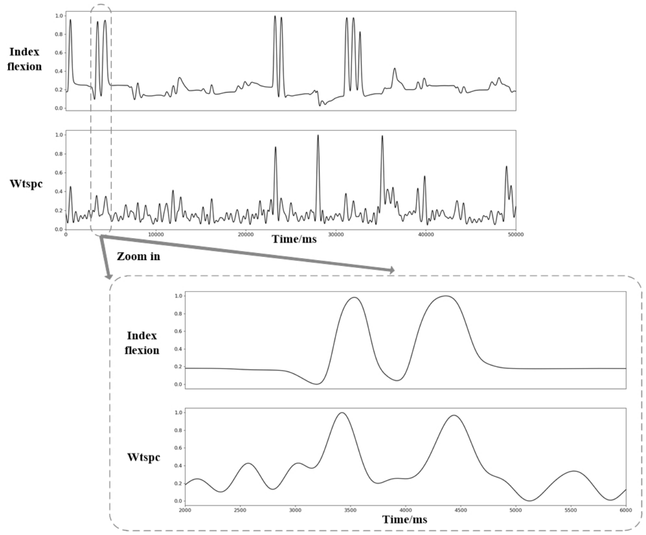

Figure 10: The Wtspc of Channel 23 and Corresponding Index Finger Flexion in Local Period of Subject 2 Test Set.

REFERENCES

[1] V. Chamola, A. Vineet, A. Nayyar, E. Hossain (2020). Brian-computer Interface-Based Humanoid Control: A Review, Sensors, 20(13), 3620.

[2] R. Roy, M. Mahadevappa, and C. S. Kumar (2016). Trajectory Path Planning of EEG Controlled Robotic Arm Using GA, Procedia Computer Science, 84, 147-151.

[3] T. Fukami, T. Shimada, E. Forney (2012). EEG character identification using stimulus sequences designed to maximize mimimal hamming distance, in Proceedings of Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, 1782-1785, January.

[4] T. Chen, S. Ju, F. Ren (2020). EEG emotion recognition model based on the LIBSVM classifier. Measurement, 164, 164:108047.

[5] H. Namazi, T. S. Ala (2019). Decoding of simple and compound limb motor imagery movements by fractal analysis of Electroencephalogram (EEG) signal, Fractals, 27(03).

[6] Y. Gu, K. Dremstrup, D. Farina (2009). Single-trial discrimination of type and speed of wrist movements from EEG recordings, Clinical Neurophysiology, 120.8, 1596-1600.

[7] A. J. Doud, J.P. Lucas, M.T. Pisansky, B. He (2011). Continuous three-dimensional control of a virtual helicopter using a motor imagery based brain-computer interface, PLoS ONE, 6,.

[8] Y. Hashimoto, J. Ushiba (2013). EEG-based classification of imaginary left and right foot movements using beta rebound, Clinical Neurophysiology Official Journal of the International Federation of Clinical Neurophysiology, 124.11, 2153-2160.

[9] T. Hayashi, H. Yokoyama, I. Nambu (2017). Prediction of individual finger movements for motor execution and imagery: An EEG study, in Proceedings of IEEE International Conference on Systems, Man and Cybernetics, October.

[10] S. Bera, R. Roy, D. Sikdar, M. Mahadevappa (2019). An Ensemble Lea rning Based Classification of Individual Finger Movement from EEG.

[11] G. Schalk, J. Kubanek, K.J. Miller, N.R. Anderson *et al* (2007). Decoding Two-Dimensional Movement Trajectories Using Electrocorticographic Signals in Humans, J.Neural.Eng, 4, 264-275,.

[12] K.J. Miller, G. Schalk. Prediction of finger flexion :4th brain-computer interface data competition, BCI Competition IV, Cite : http://www.bbci.de/competition/iv/#dataset4.

[13] K.A. Ludwing, R.M Miriani, N.B. Langhals, M.D. Joseph *et al* (2009). Using a common average reference to improve cortical neuron recordings from microelectrode arrays, Journal of Neurophysiology, 101(3), 1679-1689.

[14] S. Tsuchimoto , S. Shibusawa, S. Lwama, M. Hayashi *et al* (2021). Use of common average reference and large-laplacian spatial-filters enhances eeg signal-to-noise ratios in intrinsic sensorimotor activity, Journal of Neuroscience Methods, 353 , 109089.

[15] X. Liu, W. Hong, L. Shan , C. Yan *et al*(2017). Adaptive common average reference for in vivo multichannel local field potentials, Biomedical Engineering Letters, 7(1), 7-15.

[16] B. Binias, H. Palus (2016). Windowed local area average reference filter for increasing the spatial resolution of EEG signals, in Proceedings of 21st International Conference on Methods & Models in Automation & Robotics, MMAR, September 26.

[17] H. Sirait, K. Sebayang, S. Humaidi, T. Sembiring *et al* (2020). Time frequency signal classification using continuous wavelet transformation, in Proceedings of IOP Conference Series Materials Science and Engineering, IOPMSE, 851, 012045.

[18] H. Ping, L. Pan, H. Sun (2011). Feature extraction of acoustic signals based on complex morlet wavelet, Procedia Engineering, 15, 464-468.

[19] K.J. Miller, D. Nm, J.G. Ojemann, L. Sorensen (2007). EcoG observations of power-law scaling in the human cortex, quantitative biology.

[20] J. Kubanek, K.J. Miller, J.G. Ojemann, J.R. Wolpaw et a l(2009). Decoding flexion of individual fingers using electrocorticographic signals in humans, Journal of Neural Engineering, 6(6) ,066001.

[21] H. Nagai, T. Tanaka (2019). Action observation of own hand movement enhances event-related desynchronization, IEEE transactions on neural systems and rehabilitation engineering, 27(7), 1407-1415.