Investigation of Methodologies for Extracting Individual Brain Oscillations: Comparisons & Insights

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***Abstract*— There is increasing evidence that the effects of non-invasive brain stimulation can be maximized when the applied intervention matches internal brain oscillations. Extracting individual brain oscillations is thus a necessary step for implementing personalized brain stimulation. In this context, different methods have been proposed for obtaining subject-specific spectral peaks from electrophysiological recordings. However, comparing the results obtained using different approaches is still lacking. Therefore, in the present work, we examined the following methodologies in terms of obtaining individual motor-related EEG spectral peaks: fast Fourier Transform analysis, power spectrum density analysis, wavelet analysis, and a principal component based time-frequency analysis. We used EEG data obtained when performing two different motor tasks – a hand grip task and a hand opening-and-closing task. Our results showed that both the motor task type and the specific method for performing the analysis had considerable impact on the extraction of subject-specific oscillation spectral peaks.**

***Clinical Relevance*— This exploratory study provides insights into the potential effects of using different methods to extract individual brain oscillations, which is important for designing personalized brain-machine-interfaces.**

I. Introduction

Electroencephalography (EEG) is a non-invasive method for monitoring brain activity. Based on the underlying oscillatory frequencies, the EEG signal can be categorized into different bands, e.g, the mu (8 – 12Hz), beta (15 – 30Hz) and gamma frequency band (30 – 90Hz) [1]. During motor task execution, decreases in the EEG signal spectral power within the mu and beta frequency band, along with an increase in the gamma band power, have been observed [2]. These phenomena are termed event-related desynchronization (ERD) and event-related synchronization (ERS) respectively. Abnormal ERD and ERS patterns have been reported in patients with motor deficits such as stroke and Parkinson's disease [3], [4]. Therefore, an association seems to exist between oscillatory brain patterns (e.g, ERD and ERS) and motor performance.

Transcranial alternating current stimulation (tACS) is a non-invasive brain stimulation (NIBS) technique that modulates the excitability of neurons and affects brain activity, which can, in turn, be used to improve motor performance [5]. It has been reported that beta-band tACS impairs motor function, while gamma-band tACS enhances visuomotor performance [6], [7]. Previous studies aiming to modulate motor performance using open-loop tACS protocols have applied empirically pre-determined parameters (e.g., frequency & intensity of the current), which remained constant during stimulation. However, due to inter-individual variability (e.g., neuro-anatomical characteristics), the "one set to all" tACS protocols used so far have yielded highly subject-specific outcomes, which have, in turn, prevented their widespread clinical applications [8].

In this context, personalized tACS protocols matching individual brainwaves yield promise for achieving better intervention effects, e.g, better motor performance. To this end, several approaches have been applied previously. For instance, Nowak and colleagues utilized the Fast Fourier transform (FFT) on magnetoencephalography (MEG) data and pinpointed the peak frequency by detecting zero-crossings in the spectrum's differential [9]. Espenhahn et al. detected the beta peak frequency in EEG data by observing the most substantial power shift during movement compared to the resting state [10]. Bin Dawood and team used a wavelet-based time-frequency analysis on EEG data to identify peaks in the resulting time-frequency graphs [11]. Up to date, no comparison exists regarding the results obtained using different techniques. Therefore, in the present study, we compared different methodologies for analyzing subject-specific brain oscillations with the following methods: power spectrum density (PSD) analysis based on the Welch and autocorrelation methods, fast Fourier Transform (FFT) analysis, wavelet-based time-frequency (TF) analysis, as well as a principal component analysis (PCA) approach to decompose the EEG TF matrix. Our results showed that subjects demonstrated motor-evoked brain activities with distinct brain oscillatory frequencies while performing different motor tasks. This suggests that using different methodologies may have a considerable impact on the extraction of individual motor-related electrophysiological spectral peaks.

II. Methods

A. Data Acquisition and Pre-processing

Four healthy, young and right-handed subjects participated in data collection. The experimental protocol was approved by the McGill Faculty of Medicine Institutional Review Board. All subjects were asked to give written informed consent and received monetary compensation for their participation.

In the experiment, the subjects were asked to perform two motor tasks using their dominant hand. The first motor task (Task 1) consisted of 50 handgrips at a level of force corresponding to 15% of each participant's maximum

This study is partially funded by a scholarship from the Fonds de Recherche du Québec Nature et technologies (B2X - 312765).

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voluntary contraction (MVC). The second task (Task 2) involved 50 times of continuous hand opening and closing (Figure 1). Each trial lasted 4s and was followed by a random resting interval of a duration between 8 and 10s. The EEG signal was recorded during motor task execution using a 64-channel ActiCap (Brain Vision, Munich, Germany). Signals were collected at a sampling rate of 2.5KHz and all electrodes were referenced to FCz. Electrode impedances were kept below 10kΩ.

The EEG recordings were processed using the open-source toolbox Brainstorm [12]. Raw EEG data were filtered (0.1-100 Hz bandpass and 60Hz notch), down-sample to 250Hz, and re-referenced to an average reference. We removed noisy epochs and channels (e.g., muscle, head and jaw movement artifacts) by visual inspection. Independent component analysis was applied to identify and remove eye movement artifacts.

Figure 1. Demonstration of motor tasks used in the experiment. Task 1: 50 times of hand grips at a level of force corresponding to 15% of each participant's MVC. Task 2: 50 times of continuous hand opening and closing.

B. *Extraction of Individual Brain Oscillations*

We applied four methods to extract individual brain frequencies using EEG data from electrode C3: PSD analysis with the Welch and autocorrelation methods, FFT, wavelet-based TF analysis and PCA decomposition on the TF matrix.

1) *Power spectrum density (PSD) analysis*

We defined several time intervals during different stages of motor task execution. Specifically, based on the visual cue that denotes the movement onset, we defined the time interval [-1,0]s prior to the visual cue as the *pre-mov* period and [0.5,3.5]s post visual cue as the *move* period. The PSD was calculated using the Welch method within each separate movement phase and the frequency that exhibited the largest power change during the *move* period as compared to *pre-mov* period was selected as the corresponding individual brain oscillatory frequency. For instance, the frequency that decreased the most within the Beta frequency band was considered as the individual beta frequency (IBF).

We also obtained the signal PSD based on its autocorrelation function. This is achieved by first calculating separately the autocorrelation of the EEG signals during the *pre-mov* and *moving* period, then calculating the FFT of the resulting autocorrelation estimates. The autocorrelation function was estimated as follows:

$$\hat{\varphi}_{xx}[m] = \frac{1}{N-|m|} \sum_{n=1}^{N-|m|} x[n+m]x[n] \qquad (1)$$

In which N is the signal length, m is the lag selected for calculating autocorrelation. In our case, we used a time lag of 1s. Considering the limited data length, we computed the autocorrelation on the entire data length without applying windows.

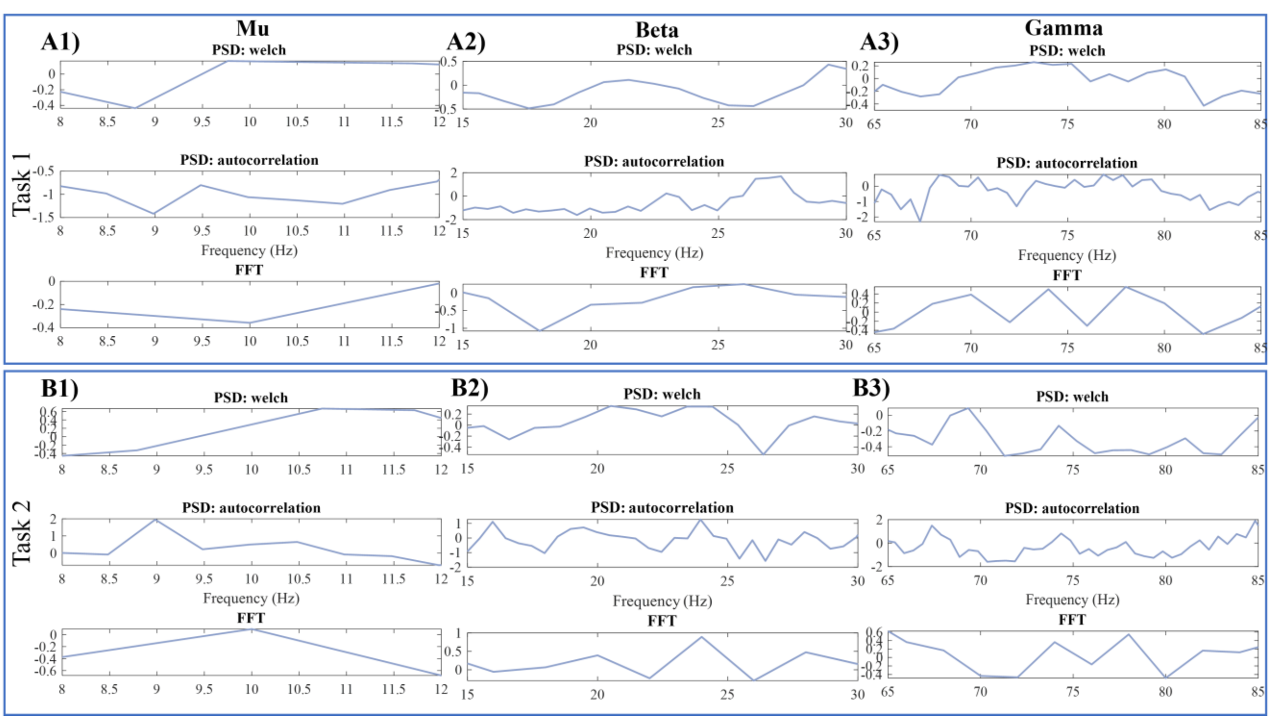

Figure 2. Power changes in the *move* period compared to the *pre-mov* period within different frequency bands using different methods. (A) Power changes while performing task 1 (the hand grip task) in the Mu (A1), Beta (A2) and Gamma (A3) frequency bands. (B) Power changes while performing task 2 (the opening-and-closing hand task) in the Mu (B1), Beta (B2) and Gamma (B3) frequency bands. In general, PSD analysis using the Welch and auto-correlation methods demonstrated similar wave morphology. It can be clearly observed that individual peaks are located at different frequencies for different approaches, and the type of motor task performed also has an impact on the obtained spectral patterns.

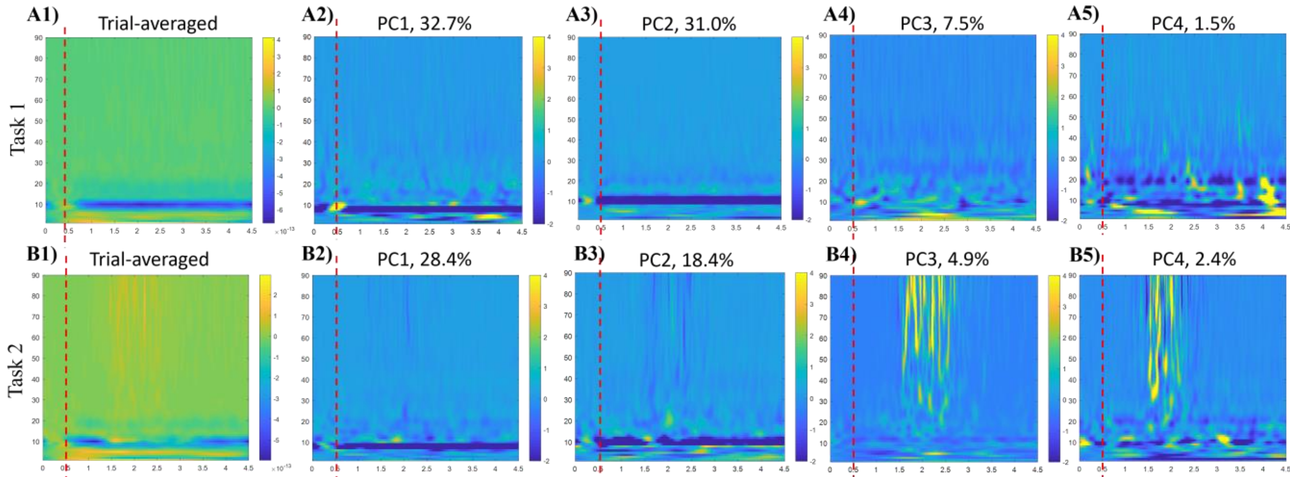

Figure 3. Time-frequency plots obtained by the wavelet method and PCA decomposed principal components while subject was performing the two types of motor task. The movement onset was at 0.5s. (A) Time-frequency plots while performing task 1 (hand-grip motor task): A1) Trial-averaged time-frequency plot. A2) – A5) the first 4 components obtained from PCA decomposition. (B) Time-frequency plots while performing task 2 (opening-and-closing hand task): B1) Trial-averaged time-frequency plot. B2) – B5) the first 4 components obtained from PCA decomposition.

2) *Fast Fourier Transform (FFT)*

The use of FFT for extracting individual frequencies is similar to the PSD analysis. The squared magnitude of FFT during different phases of the motor task was calculated, and the individual Mu (IMF), Beta and Gamma frequencies (IGF) were determined accordingly.

3) *Wavelet-based time-frequency (TF) analysis*

The Morlet wavelet was used to decompose the EEG signals of interest into the time-frequency domain with a frequency resolution of 1Hz and time resolution of 50ms. Subsequently, the magnitude of the wavelet coefficients was averaged over separate time windows according to the phases of motor task execution. The frequency with the largest change during the *move* period as compared to *pre-mov* period was selected as the individual brain oscillatory frequency.

TABLE I.
IMF, IBF AND IGF OBTAINED USING DIFFERENT METHODS FROM SUBJECT 1 WHILE PERFORMING 2 TYPES OF MOTOR TASKS

	IMF (Hz)		**IBF (Hz)**		**IGF (Hz)**	
	Task 1	Task 2	Task 1	Task 2	Task 1	Task 2
PSD: welch	10	12	18	26	78	78
PSD: autocorrelation	9.0	8.5	19.5	26.4	76.8	67.4
FFT	8.8	8	17.6	26.4	73.2	69.3
Wavelets	10	9	16	18	79	81
PCA TF analysis	8	8	16	17	68	82

4) *PCA analysis*

We implemented a PCA algorithm with Varimax rotation on the wavelet-derived TF map to separate movement-elicited ERD/ERS and obtain enhanced event-related power changes at different frequency bands [13]. This method was previously used for estimating time-frequency electrophysiological responses and a detailed description can be found in Hu et al., 2015 [13]. In this study, the PCA algorithm with Varimax rotation was applied on the trial-averaged TF maps.

5) *The correction of 1/frequency power distribution*

It is commonly observed in EEG data that signal power decreases with increased frequency, resulting in a 1/f power distribution pattern. The existence of 1/f may interfere with the precise estimation of EEG spectral peaks. Therefore, we implemented the algorithm proposed by Donoghue et al. to detrend the signal power used in methods 1), 2) and 3) for estimating a corrected power estimation in the *pre-mov* period and the *move* period [14]. Since the application of 1/f detrending may affect the convergence of PCA algorithm and we would like to compare between TF plots before as well as after PCA, in the present study we did not perform 1/f detrending on the TF plots.

III. RESULTS

A. *Relative power changes based on the welch-based PSD analysis, autocorrelation-based PSD analysis, and FFT*

As we removed the effect of the 1/f power distribution, the calculation of relative power changes was achieved by directly subtracting the mean power during the *pre-mov* period from the mean power during the *move* period. Results obtained using the Welch-based PSD analysis, autocorrelation-based PSD analysis and the FFT from one representative subject are shown in Figure 2. In general, relative power changes obtained using the FFT and autocorrelation methods demonstrated similar patterns. Additionally, within the Mu frequency band, this subject exhibited clearer ERD patterns while performing the hand-grip task (Figure 2, A1) compared to the opening-and-closing hand task (Figure 2, B1). Moreover, the subjects generally yielded different IMF, IBF and IGF when executing the two different motor tasks (Figure 2 A2), A3), B2), B3) & Table I). This is not surprising, because motor tasks involving different movements will generally affect the precise locations of activated brain regions and the resulting neural firing patterns. For instance, forced and self-paced hand movement have been shown to be related to different active regions in the brain [15]. In turn, the internal brain oscillatory frequencies may be affected.

B. *Wavelet-based TF analysis and PCA decomposition*

Results regarding the trial-averaged TF plots and the PCA decomposed components are shown in Figure 3, in which different event-related responses can be observed by comparing Figure 3 A1) and B1), whereby the movement-evoked mu-ERD is the most dominant pattern. It can also be observed that this subject exhibited clearer gamma ERS patterns when executing task 2 (hand opening-and-closing task) as compared to task 1 (hand-grip task). We further plotted the first 4 PCA components that explained the largest percentage of variance in the trial-averaged TF maps. The results are shown in Figure 3 A2), A3), A4 and A5), as well in Figure 3 B2, B3), B4 and B5), where the mu-ERD is the most obvious pattern in the first one or two components with the largest variances. This is because in EEG data, the mu wave is the dominant one with the largest power, thus the mu power change is subsequently the most obvious pattern, which can also be seen in Figure 3 A1) & B1). The TF patterns of the higher-order decomposed components were more dominated by the beta and gamma activity (e.g, Figure 3 A5) and Figure 3 B4)). Meanwhile, by comparing between Figure 3 B1) and Figure 3 B4), we can see that TF decomposition with PCA resulted in clearer ERS gamma patterns. As the EEG signal power generally decreases with increased frequency, making it difficult to analyze high-frequency EEG oscillations, the TF decomposition approach with PCA is promising for localizing higher-frequency EEG peaks.

TABLE II.

INDIVIDUAL BRAIN OSCILLATIONS OBTAINED USING PCA DECOMPOSED TF ANALYSIS FOR SUBJECTS 1 TO 4 WHILE PERFORMING 2 TYPES OF MOTOR TASKS

	IMF (Hz)		IBF (Hz)		IGF (Hz)	
	Task 1	Task 2	Task 1	Task 2	Task 1	Task 2
Subject 1	8	8	16	17	68	82
Subject 2	12	8	17	19	70	/
Subject 3	10	8	17	20	/	75
Subject 4	12	12	22	30	71	68

C. *Comparison among different motor tasks and subjects*

Since the PCA decomposed TF approach yielded better results in localizing high-frequency peaks, we subsequently analyzed individual brain oscillations using this approach and summarized results in Table II, where the IMF, IBF and IGF were listed while subjects conducted different motor tasks. In some cases, the subjects did not exhibit a clear gamma ERS pattern. Thus, the individual gamma frequency is missing for subject 2/ task 2 and for subject 3/ task 1. As seen in this table, the extraction of individual frequencies is subject-specific, with each subject exhibiting distinct brain oscillatory frequencies. Moreover, even the same subject exhibited different brain frequencies while performing different motor tasks.

IV. DISCUSSION

In the present study, we applied different approaches to extract subject-specific brain frequencies most sensitive to motor task execution. We showed that the type of motor task and the methodology used for analysis may have a considerable impact on the final results. Furthermore, the PCA-based TF analysis yielded clearer Gamma-ERS pattern, suggesting that the PCA decomposition of TF patterns may be advantageous for high-frequency EEG analysis. As the extraction of reliable subject-specific biomarkers in the brain has a critical role in personalized brain-machine-interface or closed-loop neurofeedback system applications, the results obtained in the present study provide insights into their design. In the future, we plan to conduct a more comparative and detailed investigation to identify an optimal approach in terms of extracting individual brain oscillations in a larger subject cohort.

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