Analysis of Alpha Band Decomposition in Different Level-k Scenarios with Semantic Processing

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Abstract. A coordination game is one in which two players are rewarded for making the same choice from the same set of alternatives. The ability of humans to tacitly coordinate effectively is based on the identification of pronounced solutions associated with salient features attracting the player's attention. These prominent solutions are referred to as focal points. Game theory fails to account for how people make decisions in tacit coordination games, and human behavior in these games cannot be explained by a single theory. One of the accepted theories for explaining human behavior is level-k theory. This theory assumes that each player has a different level of reasoning by which she assesses the behavior of other players in the game and makes strategic decisions based on that assessment. In Previous studies, we have found an association between the players' cognitive load as reflected by EEG power and the level-k during the coordination game. The goal of the current study was to examine the relationship between alpha frequency and its sub-bands and level-k during a tacit coordination game in the context of semantic processing.

Keywords: EEG · Tacit coordination games · Focal points · Alpha band

1 Introduction

A coordination game is one in which two players are rewarded for making the same choice from the same set of alternatives [1]. Research has shown that humans have the ability to successfully play coordination games even when communication is not possible (e.g. [1–4]). The ability of humans to tacitly coordinate effectively is based on the identification of pronounced solutions associated with salient features attracting the player's attention [1]. At present, no single consensus exists about how humans converge on the same focal point solution [5].One of the accepted theories of human behavior is level-k theory. This theory [6–8] assumes that humans make predictions about other players' actions based on their level k value, which reflects their depth of reasoning ability. That is, the level-k theory implies that each player believes that she is the most sophisticated person in the game and bases her actions on the assumption that everyone else is at one level below her. Previous studies that have examined the relationship between electrophysiological metrics in the framework of level-k theory have found that a linear relationship exists

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between the player's coordination ability and game difficulty with the that-beta ration (TBR) which reflects the cognitive load of the player [9, 10]. In addition the researches in [11] showed that the level-k of the player can be predicted based on the EEG signal using deep learning methods. In the current study we aimed to examine the power distribution of alpha frequency and its various components when performing tasks at different levels of reasoning based on level-k theory. To that end, an electrophysiological-behavioral experimental design was constructed. In this experiment, players were presented twice with the same set of 12 tasks. In the first presentation, the players performed a picking task in which each player had to freely select a word from a string of four words displayed on the screen. In the second presentation, the same 12 tasks were displayed again, but this time each player had to coordinate the choice of the specific word with an unknown player. According to level-k theory, it could be assumed that the picking task is level-k = 0 whereas the coordination task is level-k > 0. EEG was recorded from the scalp of each of the players while performing each of the tasks. Based on the electrophysiological results we examined the individual alpha frequency power distribution as a function of the level-k.

2 Materials and Methods

2.1 Measures

Level-K Theory. One main cognitive theory that tries to analyze and explain human behaviors in case of tacit coordination scenarios is the level-k theory which is derived from the cognitive hierarchy theory [13, 16, 17]. The level-k theory holds that players' reasoning depth relies on their subjective level of reasoning k. For example, players in which k = 0 (sometimes referred to as L_0 players) will act and choose randomly in their given space of solutions, while L_1 players assume that all other players are L_0 reasoners and will act according to this assumption, i.e., their strategy will assume all other players select a random solution. That is, L_0 players might utilize rules but will apply them randomly (picking), whereas $L_{k \geq 1}$ players will apply their strategy based on their beliefs regarding the actions the other players (coordination).

2.2 Experimental Design

Procedure. The study comprised the following stages. First, participants received an explanation regarding the overarching aim of the study and were given instructions about the experimental procedure and the interface of the application. Participants were offered a reward based on the total number of points they earned in both tasks (picking and coordination). The experiment consisted of two sets of 12 different trials each with a different set of words. For example, game board #1 displays a trial containing the set {"Water", "Beer", "Wine", "Whisky"} appearing in Hebrew, respectively. Each set of words was displayed between two short vertical lines following a slide containing only the lines without the word set so that participants will focus their gaze at the center of the screen (Fig. 1, A and B).

In the first experimental condition, the task presented to the players was a picking task, i.e., participants were only required to freely pick a word out of each set of four words presented to them in each of the 12 trials. Subsequently, participants were presented with the coordination task, comprising the same set of 12 different trials. However, in the coordination condition participants were instructed to coordinate their choice of a word with an unknown partner so that they would end up choosing the same word from the set. Each participant sat alone in front of the computer screen during the entire experimental session. It is important to note that no feedback was given between the games. That is, the participants were not informed whether they have coordinated successfully or not with their unknown co-player.

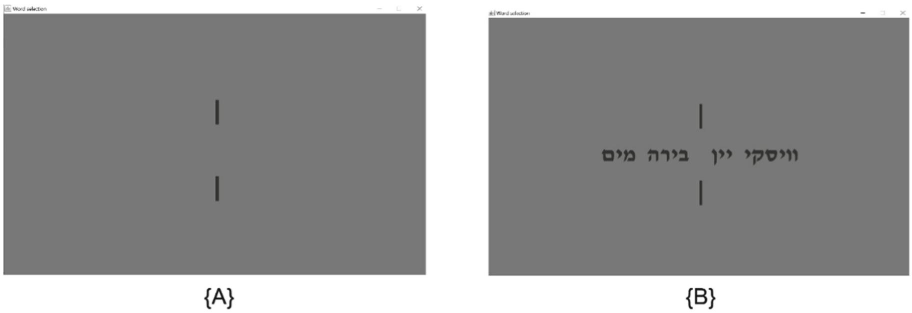

Fig. 1. (A) Stand by screen (B) Game #1 {"Water", "Beer", "Wine", "Whisky"}

Figure 2 portrays the outline of the experiment. Each slide containing the set of words (task trials) was preceded by a slide containing only the vertical lines without the word set (stand-by slides) to keep the gaze of participants in the middle of the screen throughout the experiment. Each of the stand-by slides was presented for *U(2,2.5)* sec., while each slide containing the set of words was presented for a maximal duration of 8 s. Following a task trial, participants could move to the next slide with a button press. The sequence of the task trials was randomized in each session.

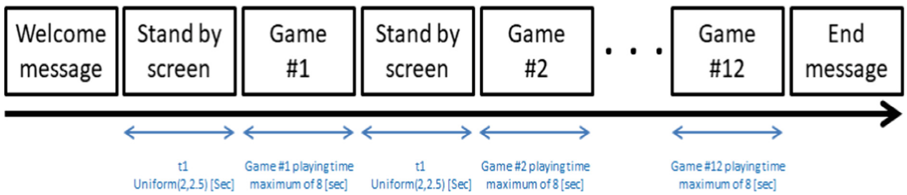

Fig. 2. Experimental paradigm with timeline

Participants. The experiment involved 10 university students that were enrolled in one of the courses on campus (right-handed, mean age = ~26 [years], SD = 4). The study was approved by the IRB committee of the University. All participants provided written informed consent for the experiment.

EEG Recordings. EEG was recorded from participants while they were performing the tasks. The EEG was recorded by a 16-channel g.USBAMP biosignal amplifier (g.tec, Austria) at a sampling frequency of 512 Hz. 16 active electrodes were used for collecting EEG signals from the scalp based on the international 10–20 system. The recording was done by the OpenVibe [12] recording software. The impedance of all electrodes was kept below the threshold of 5K [ohm] during all recording sessions. Before performing the actual experiment, participants underwent a training session while wearing the EEG cap, to get them familiar with the application and task.

3 Results and Discussion

3.1 EEG Preprocessing Scheme

Based on the literature (e.g. [13–17]), we have focused on the following cluster of frontal and prefrontal electrodes (Fp1, F7, Fp2, F8, F3, and F4). The preprocessing pipeline consisted of finite impulse response (FIR) band-pass filtering (BPF) [1, 32] Hz and artifact removal following ICA. The data was re-referenced to the average reference and down sampled from 512 Hz to 64 Hz following baseline correction (see Fig. 3). Data was analyzed on 1-s epoch windows from game onset which resulted in a total of 12 decision points (i.e., EEG epochs) per participant.

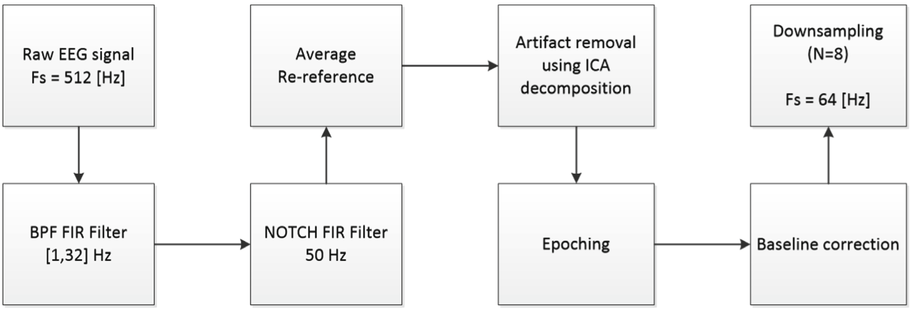

Fig. 3. Preprocess pipeline

3.2 Alpha Band Decomposing Analysis in Coordination Process

The oscillations in the alpha band can be divided into two main sub-bands, lower-alpha (8–10 [Hz]) and upper-alpha (10–13 [Hz]) [18–20]. Previous research has already shown that coordination necessitates the exertion of additional resources compared to picking as reflected by the modulation of the alpha frequency band (see for example [9–11, 17]). Here, based on previous findings, we assumed that as the complexity of the task increases, i.e., the progression form picking (level-k = 0) to coordination (level-k > 0), alpha frequency should decrease more in the upper-alpha than in the lower-alpha, especially in the context of semantic processing [18–22].

The statistical comparison was performed as follows. For each EEG epoch which was recorded during the picking and coordination tasks we calculated the relative energy of the lower-alpha and upper-alpha frequency bands (see Fig. A.1 in Appendix A). Then, we divided the relative energy values between the corresponding picking and coordination games in order to estimate the change in energy that occurred in the different alpha bands. That is, for each two corresponding epochs we estimated the energy changes within the alpha band according to the ratio $\frac{E_{lower-Alpha}|coordination}{E_{lower-Alpha}|picking}$ and $\frac{E_{upper-Alpha}|coordination}{E_{upper-Alpha}|picking}$, for the lower- and upper-alpha band, respectively.

Analysis of the results of all 12 games showed that the decrease in upper-alpha between coordination and picking was significantly more pronounced compared to the decrease in lower-alpha ($t(1438) = 3.9937$, $p < 0.001$). In order to estimate the dynamic changes in the power distribution of the alpha frequency band throughout the course of the experiment, we split the set of 12 games into thirds. The first third included games 1 through 4, the middle third, games 5 through 8, and the final third, games 9 through 12. Table 1 displays the average values of the relative changes in upper- and lower-alpha together with the p-value associated with each of the paired t-tests.

It is evident form Table 1 that the same trend appeared at the first (games 1–4) and middle (games 5–8) thirds of the experiment ($t\,(478) = 5.7788$, $p < 0.001$; $t(478) = 3.5248$, $p < 0.001$, respectively). Regarding the final third (games 91–2), it can be seen that the average change in upper-alpha was lower than in lower-alpha, but the difference was not significant. Figure 4 resents graphically the distribution of the data by box plots. The three upper panels present the boxplots for upper- and lower-alpha according to the split of the data by thirds. The lower panel displays the boxplot corresponding to each sub-band for the entire dataset of 12 games.

Table 1. Relative power change between coordination and picking in alpha sub-band (lower and upper) – t-test results.

	All games	Games 1- 4	Games 5- 8	Games 9- 12
Mean ($\frac{E_{lower-Alpha}|coordination}{E_{lower-Alpha}|picking}$)	0.9084	0.8812	0.9052	0.9389
Mean ($\frac{E_{upper-Alpha}|coordination}{E_{upper-Alpha}|picking}$)	0.8740	0.8284	0.8550	0.9385
t-test p-value	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p > 0.05$

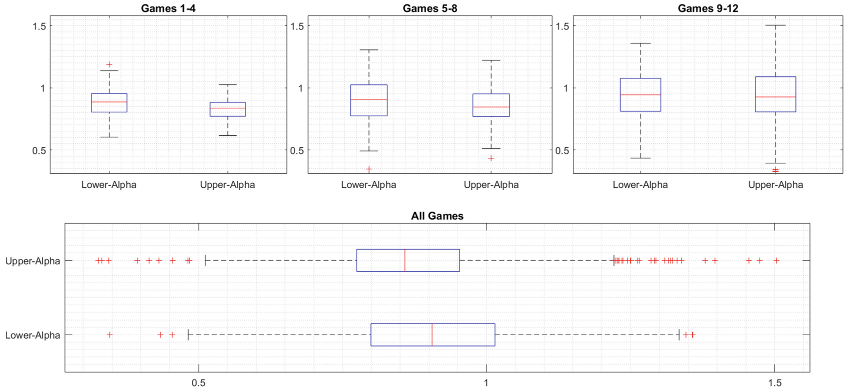

Fig. 4. Relative power change between coordination and picking in alpha sub-band (lower and upper) – boxplot scheme

4 Conclusions and Future Work

The alpha frequency band has been previously shown to be modulated by mental workload [23, 24], and alertness [25]. The overarching goal of the current study was to examine the susceptibility of the lower- and higher-alpha frequency bands to varying levels of mental effort corresponding to different level-k. In this study we employed two cognitive tasks, i.e., picking and coordination, each associated with a different level-k (level-k = 0 and level-k > 0, respectively).

Our results indicate that the differential effect of level-k on the alpha sub-bands was modulated as a function of task progression. Specifically, in the first and middle thirds of the dataset (games 1–4 and games 5–8, respectively) the difference in relative energy in the alpha band was significant, whereas, in the case of the last third of the dataset (games 9–12) there was no difference in the relative energy in the alpha band indicating that the alpha sub-bands were less sensitive to the differential effect of level-k in the final section of the experiment. The decrease in the upper alpha frequency band in the coordination task (level-k > 0) was more pronounced compared to the lower-alpha sub-band (see Table 1). The more pronounced decrease in upper alpha is further confirmation of the effect of performing the semantic task which known as alpha desynchronization [26]. These results are consistent with previous studies [26–28] that showed that there is connection between intensity and fluctuations in alpha frequency band to abilities such as language, imagination, perception, and planning abilities that can be termed brain cognition.

There are a number of possible directions for future research. Behavioral experiments have shown that players in coordination games are influenced by a variety of factors such as loss-aversion [29], social value orientation [30–32] revenue distribution [30] and culture [31, 33]. The effect of these factors and the possible interaction effects should be examined in the context of level-k and since they may contribute to the variability in the individual coordination ability of players [34, 35] and therefore modulate the associated electrophysiological patterns. Moreover, extracting the brain sources associated with different level-k may improve models that aim to simulate the behavior of autonomous agents [36–39] as well as brain-computer interfaces.

Appendix A: Alpha Band Decomposition and Relative Power Estimation

Following the pre-processing step, we have estimated the relative power in the alpha sub-bands (lower and upper alpha) for each picking and coordination epoch. The full process of alpha band power estimation is presented in Fig. A.1. we have used the Discrete Wavelet Transform (DWT) [40, 41] (black rectangles). The DWT is based on a multiscale feature representation. Every scale represents a unique thickness of the EEG signal [42]. Each filtering step contains two digital filters, a high pass filter, $g(n)$, and a low pass filter $h(n)$. After applying each filter, a down sampler with factor 2 is used in order to adjust time resolution. In our case, we used a 3-level DWT, with the input signal having a sampling rate of 64 Hz (left red rectangle). As can be seen in Fig. A.1, this specific DWT scheme resulted in the coefficients of the four EEG main frequency bands (green rectangles). Next, we use two band pass filters to split the alpha band into the upper-alpha ([8–10] Hz) and lower-alpha (10–13 [Hz]) sub bands. Finally, to calculate the relative energy (right red rectangle), we divided the energy of each band by the sum of all the different bands (delta, theta, alpha, beta).

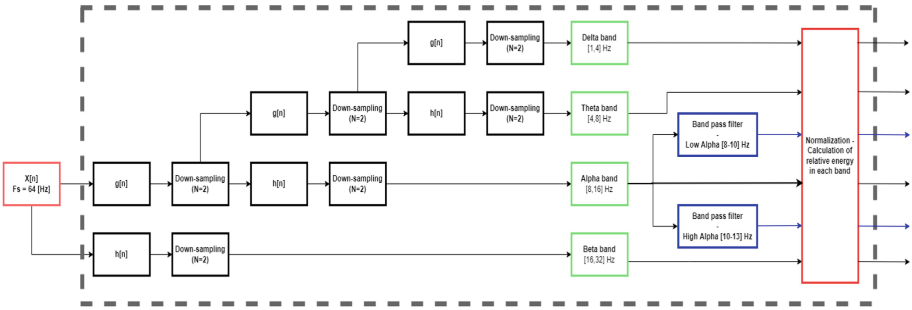

Figure A.1. EEG Alpha band power estimation and decomposition to lower and upper sub bands using 3 level DWT scheme

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