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Alpha Down-Regulation Neurofeedback: Its Effects on Short Term Memory and Learning Predictors

by

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Final Year Project Report submitted in partial fulfillment
of the requirements for the Degree of

Bachelor of Science in Electrical and Computer Engineering

2015



**Faculty of Science and Technology
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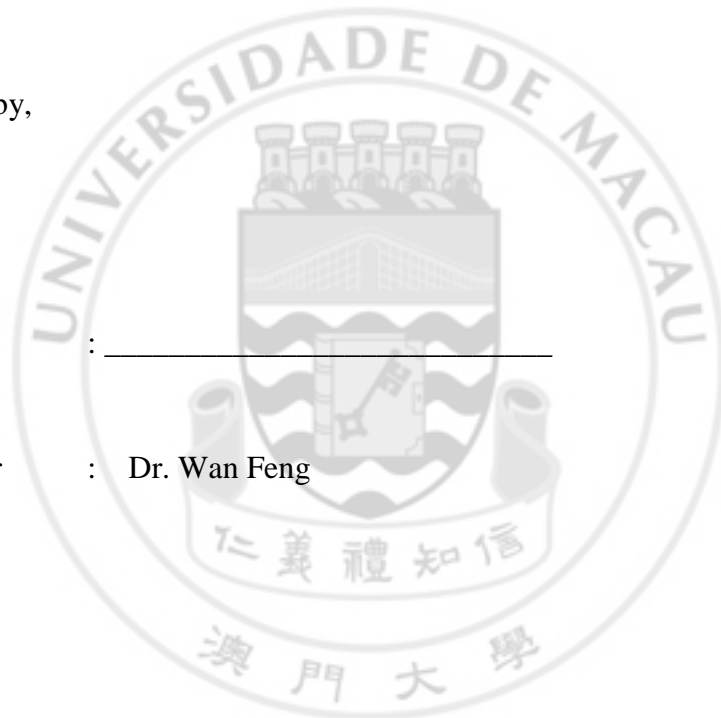
APPROVAL FOR SUBMISSION

This project report entitled “**Alpha Down-Regulation Neurofeedback: Its Effects on Short Term Memory and Learning Predictors**” was prepared by Tang Qi (DB) in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Computer Engineering at the University of Macau.

Endorsed by,

Signature : _____

Supervisor : Dr. Wan Feng



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ABSTRACT

Regulation of brain activity by neurofeedback training has been widely applied in treatment of human psychological disorders, improvement of human cognitive performance and recently enhancement of brain-computer interfaces (BCIs) performance. Nevertheless, different people possess different ability in learning how to regulate the brain activity by neurofeedback. On the other hand, no study has investigated whether the same EEG feature but with different training direction has the reverse effects on some performance. Regarding alpha neurofeedback, it has been demonstrated that *up-regulation* alpha neurofeedback has positive effects on short term memory enhancement and more interestingly that resting alpha activity can predict learning ability in up-regulation alpha neurofeedback. However, it is unknown whether *down-regulation* alpha neurofeedback has side effects on short term memory and whether the learning ability in this neurofeedback can be predicted by resting alpha activity. Thus, this project was concentrated on the investigation on: 1) whether multi-session neurofeedback training can decrease alpha activity and its effects on other EEG bands; 2) whether resting alpha (or other frequency bands) can predict the learning ability in alpha down-regulation neurofeedback training; 3) Whether this neurofeedback training has side effects in cognitive test of short term memory.

A total of 19 subjects performed 10 sessions of individualized alpha down-regulation neurofeedback training and real-time EEG indices in baseline tests and training sessions were recorded. 14 out of total 19 subjects could decrease the training parameter, their individual alpha band (IAB), over training sessions. The learning ability was assessed by four indices. It was found that five EEG indices (IAB, HIAB, alpha, beta and individual theta) from initial baseline before neurofeedback training (BL1) can predict the learning ability in alpha down-regulation neurofeedback training. The finding of predictors would be beneficial in looking for crux of and preventing frustration from non-learners. Moreover, it would help to improve the efficiency in further neurofeedback studies and enhance the performance for learners. In terms of the

cognitive performance, no significant change in short term memory was observed before and after the alpha down-regulation neurofeedback training, indicating that this type of training has no side effects in short term memory.



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CHAPTER 1 INTRODUCTION

1.1 HUMAN BRAIN

Human brain is located in the head of a human being and protected by the skull. As the central organ of the nervous system of mammals, the structure of human brain is the same as other mammals'. However, human brain has a more developed cerebral cortex. If we measure the size of the brain using encephalization quotient, which is a measure considering the compensations for body size, the encephalization quotient is almost twice as large as that of a dolphin and even three times as large as that of a chimpanzee (Parent, 1995; Cosgrove, 2007; Gur, 1999). The existence of the cerebral cortex explains this phenomenon. The frontal lobes which are associated with self-control, abstract thought and other executive functions, makes great contributions to this expansion (Azevedo, 2009). Part of the cerebral cortex devoted to vision, so the visual cortex of human brain is also greatly larger than other mammals (Kandel, 2000). The human cerebral cortex is a thick layer of neural tissue whose coverage is almost the whole brain. This layer is folded by more and more surface until it can fit into the volume available (Cosgrove, 2007). Except some small variations, the pattern of the folds is similar among individuals (Gur, 1999). Generally, the cortex can be divided into four parts, including frontal lobe which we have mentioned above, temporal lobe, parietal lobe and occipital lobe which are shown in Fig. 1. There are a large number of cortical areas within each lobe and each area is associated with certain particular function such as motor, language and control. The left side of the cortex is similar to the right side in shape and most cortical areas are replicated on both sides. However, some cortical areas show very strong lateralization, especially those areas involved in language (Jones, 2012; Fisch, 1999).

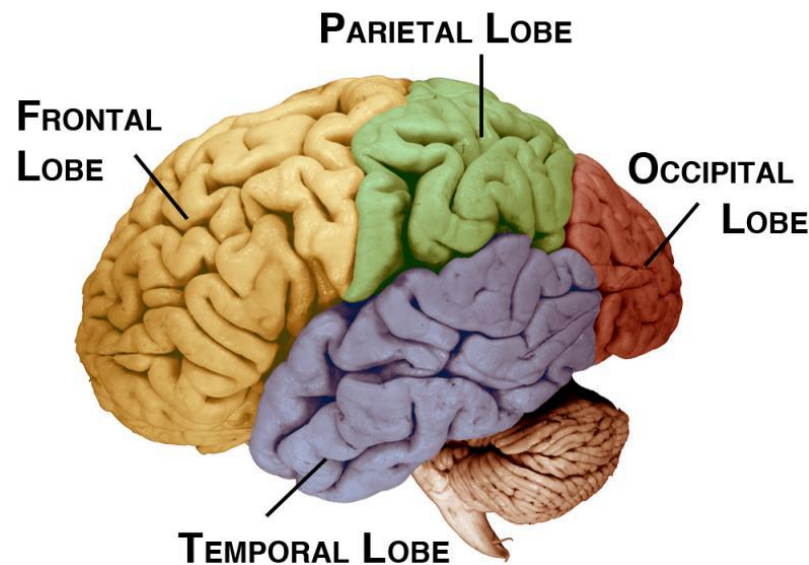


Fig. 1 Four cortex regions.

In spite of protected by the skull and isolated from the bloodstream, the human brain is still susceptible to damage and disease. Parkinson's disease, Alzheimer's disease and multiple sclerosis is common degenerative disorders of the brain (Jones, 2012). There are also still a number of psychiatric conditions thought to link with brain dysfunctions (Fisch, 1999), but the nature of those brain anomalies is not well understood and need to be investigated. Thus, to attain more knowledge about human brain is vital.

1.2 ELECTROENCEPHALOGRAPH (EEG)

Scientifically, the techniques used to study the human brain differ from those used to study other mammals' brains. It means that invasive techniques used with non-human species like inserting electrodes into the brain, or disabling parts of the brain in order to examine the effect on behavior, are generally not performed with humans for ethical reasons. Furthermore, humans are the only subjects who are able to respond to some complex verbal instructions. So it is possible to use non-invasive techniques such as electroencephalograph (EEG) recording or functional neuroimaging more productively with humans compared to that with non-humans. Moreover, some important topics, just like language, can only be studied in humans. To a certain extent, human and non-human studies form essential complements to each other in many cases (Niedermeyer, 2004).

EEG is a non-invasive method to record the summed electrical activity of the cortex by placing the electrodes on the scalp. EEG records average neuronal activity from the cerebral cortex and it can also detect changes in activity over large areas (Abou-Khalil, 2006). The voltage fluctuations EEG measured are resulting from ionic current flows within the neurons of the brain (Niedermeyer, 2004). EEG recordings are sensitive enough to detect tiny electrical impulses lasting only a few milliseconds. Most EEG devices have good temporal resolution, but low spatial resolution. In conventional scalp EEG, the recording is obtained by placing electrodes on the scalp as mentioned above with a conductive gel or paste. And to reduce impedance due to dead skin cells, usually it is necessary to prepare the scalp area by light abrasion before smearing the gel. Some systems use electrodes attached to an individual wire each while some systems use caps or nets into which electrodes are already embedded in advance particularly common when high-density arrays of electrodes are needed.

Electrode locations and their names are (ground and system reference) are used in most clinical applications (American Clinical Neurophysiology Society, 2006). One electrode is connected to one input of a differential amplifier (one amplifier per pair of electrodes) while a common system reference electrode is connected to the other input of each differential amplifier. These amplifiers will amplify the voltage between the active electrode and the reference electrode. In analog EEG, the signal is then filtered, and the EEG signals are the outputs as the deflection of pens as paper passes underneath. However, most EEG systems in recent years are digital, and right after being filtered by an anti-aliasing filter, the amplified signal is always digitized via an analog-to-digital converter. Analog-to-digital sampling typically occurs at 256–512 Hz in clinical scalp EEG. During the recording, a series of activation procedures which may induce normal or abnormal EEG activity that might not otherwise be seen such as neurofeedback training may be used.

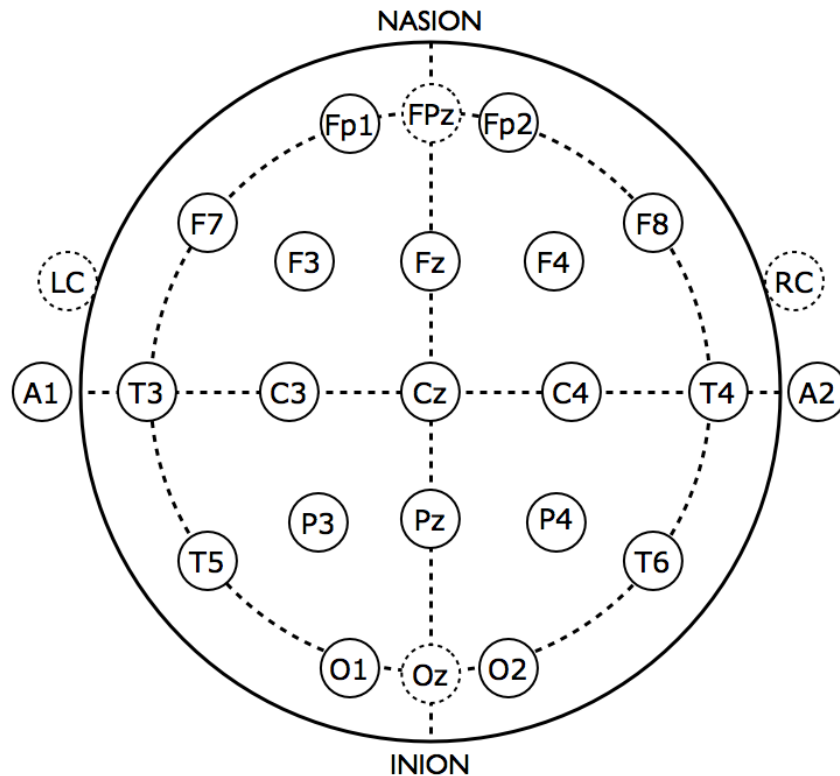


Fig. 2 Electrode locations of International 10-20 system for EEG (electroencephalography) recording.

1.3 EEG FREQUENCY BAND

The EEG is described in terms of rhythmic activity and transients. The rhythmic activity is described by frequency. Most cerebral signal in the scalp falls in the range of 1–20 Hz. EEG are subdivided into bandwidths known as delta, theta, alpha, beta, and gamma. Delta is a slow-speed & high- amplitude wave ranging from 0.5 Hz to 4 Hz. It is related to the third and fourth stage of slow wave sleep. Its amplitude is highest compared to other band amplitude whereas it is the slowest waves. It can be observed in adults while sleeping and is quite normal in babies. It is usually most prominent frontally in adults and posteriorly in children. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions.

Theta is the frequency of neural oscillation ranging from about 4 Hz to 8 Hz, related to sub-consciousness. Theta is observed normally in young children. Yet it is also

observed to appear in older children and adults during their drowsiness, arousal state or meditation.

Alpha is frequency of neural oscillation ranging from 8 Hz to 12 Hz named after Hans Berger named as the first rhythmic EEG activity. This was the "posterior basic rhythm" (also named the "posterior dominant rhythm" or the "posterior alpha rhythm"), because it appears in the posterior regions of the head on both sides, higher in amplitude on the dominant side. It emerges from the state when eyes closed & relaxed, and attenuates when eyes are open or in mental exertion. As a matter of fact, the posterior basic rhythm is usually slower than 8 Hz in young children.

In addition to the posterior basic rhythm, there are other normal alpha rhythms such as the mu rhythm (alpha activity in the contralateral sensory and motor cortical areas) that appears when the hands and arms are idle; and the "third rhythm" (alpha activity in the temporal or frontal lobes). When individuals are in coma, alpha would become abnormal and it is not responsive to external stimuli. This phenomenon is called "alpha coma".

Beta is the frequency of neural oscillation ranging from 15 Hz to about 30 Hz. It usually appears on both sides in symmetrical distribution and is most evident frontally. Beta activity has close link with motor behavior and it attenuates during active movements. Low amplitude beta is usually associated with busy, active, or active concentration and anxious thinking. Rhythmic beta with a dominant set of frequencies is associated with various pathologies and drug effects, especially benzodiazepines. It may be absent or reduced in cortical damage. It is the dominant activity in patients with alertness or anxiety or eyes opening.

Gamma is the frequency of neural oscillation ranging from around 30 to 100 Hz. Gamma waves is likely to have some relationships with the creation conscious unit. Thus, it is mostly observed in state of meditation.

Mu is the frequency of neural oscillation ranging from around 8 to 13 Hz, and is partly overlaps with other frequency bands. It is speculated that the Mu suppression could reflect motor mirror neuron systems. For the simple reason that when an action is observed, the pattern extinguishes.

1.4 SHORT TERM MEMORY

Short term memory is the capacity to hold a small amount of information in mind for a short period of time (usually less than 60 seconds). Previous study reports that capacity is 7 ± 2 items. For visual short-term memory, previous research has reported that it has a fixed capacity of about four objects. However, Alvarez and Cavanagh (2004) found that capacity varied substantially across the stimulus classes, and there is also an upper bound on capacity of approximately four or five objects. Thus, visual short-term memory is limited by both the visual information load and number of objects.

The capacity of short-term memory is named as memory span. In a memory span test, lists of items (e.g. digits or words) with increasing length are presented to the user. A user's memory span is determined as the longest list length that he /she can recall correctly in the given order on at least half of all trials. Memory span varies widely with the tested populations and with material used. For instance, the ability of recalling words in order depends on the characteristics of these words: the word-length effect and the phonological similarity effect. When all of the words in a list are taken from a single semantic category than from same categories, recall performance is better. For short term memory capacity, the digit span is usually adopted to measure it.

On the other hand, Jensen et al. (2002) studied the role of alpha oscillations in working memory. EEG was recorded from the scalp during the retention interval of a modified Sternberg task. It was found a clear peak of spectral at 9–12 Hz during the retention interval. Moreover, the PAF systematically increased with the number of items held in working memory. The increase was prominent over the posterior and bilateral central

regions. The results provide strong evidence that the alpha generating system is directly or indirectly linked to the circuits responsible for working memory. Moreover, Klimesch (1999) reported that high resting alpha but small test alpha is related to good memory performance. Thus, we can see that memory performance has close relation with alpha frequency.

1.5 NEUROFEEDBACK

Neurofeedback (NF) is a type of brain training via real-time feedback. Subjects are stimulated and taught to self-modify their cortical activities, in other words, to reduce or to increase the activities of brain waves through certain reinforcement. NF can offer noninvasive intervention to brain by means of extracting relevant message with positive feedback for desired brain activity and negative one for the undesired. And Electroencephalography (EEG) is most frequently used for the immediate displays of brain activity. Hence, EEG-based NF is widely applied to build a causal joint between rhythmic cortical activities and computers.

Ordinarily, people cannot reliably regulate their brain activity because they lack awareness of them. However, when they can see their brainwaves on a computer screen or hear the brainwaves by a tone real time, it gives them the ability to influence and gradually change them. The mechanism of action is operant conditioning. At the beginning, the changes are short-lived, but the changes gradually become more enduring. With continuing feedback, coaching, and practice, healthier brainwave patterns can usually be retrained in most people.

As shown in Fig. 3, the subject is equipped with several sensors on scalp to detect brain activities. EEG amplifier and other external devices for signal recording and processing are needed. Brainwaves are detected, recorded and feedback to the training subject by visual or audio format. If the brain activity meets the training goals, subjects will get positive feedback set by default, informing the achievements, therefore reinforcing the

behavior. When subjects keep taking more training sessions, their brain will have to work harder in the expected trend to get rewarded.

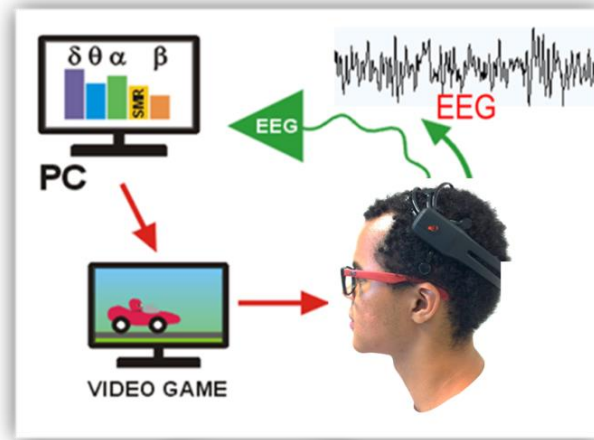


Fig. 3 NF example with visual feedback.

NF training may be an estimable and certificated solution for improving cognitive and affective outcome in healthy participants (e.g. creative music performance) as well as treatment of neurological disorders (e.g. learning disabilities, depression, epilepsy, autism etc.). What is more, EEG-based NF could induce structurally and functionally brain changes as well as vastly decrease detrimental effects. And these NF effects could be utilized immediately after individual training session(s) to promote behavioral performance. In addition, neuro-plastic changes were proved to occur after the NF training and the increase of neuro plasticity can have broad prospects, such as improvement of memory limit, and treatment of amnesia.

On the other hand, NF training is indispensable in respect of Brain-Computer Interaction (BCI). The techniques of BCI provide a direct communication pathway between the brain and controllable devices. Signals recorded in non-invasive BCI have been used to power muscle implants and restore partial movement. Yet, the “BCI illiteracy” problem had not been a rare case. The term of “BCI illiteracy” problem refers the phenomenon that subject could not figure out proper activities in brain to control the external devices. Among all approaches to alleviate this problem so far, it is the NF TRAINING that help subjects aware of and decrease their “noisy” spontaneous brain

waves to be the most efficient way, instead of other approaches related to signal processing, classification algorithms, etc.

In summary, EEG-NF applications are increasing in fields of clinic treatment, optimal performance, as well as SSVEP-based BCI.

1.6 ALPHA NF

Growing NF protocols have been proposed such as theta, PAF, upper alpha, SMR and gamma training protocols. Previous studies found that theta enhancement by NF have positive effects on creative insights. Enhancement of PAF can improve cognitive performance in elderly. SMR and beta1 neurofeedback protocols have been widely used in treatment of Attention Deficit Hyperactivity Disorder (ADHD). Moreover, they have positive effects on the sustained attention, selective attention and memory performance of healthy subjects (Gruzelier, 2014a). Regarding alpha NF protocol, enhancement of alpha by NF have shown positive effects on mental rotation ability and short term memory, whereas suppression alpha by NF can decrease response time and facilitation of implicit learning. In the following parts, we mainly focus on alpha suppression neurofeedback since most papers focus on alpha enhancement effects in NF and few studies reported alpha suppression neurofeedback.

1.6.1 ALPHA FREQUENCY

Alpha is the dominant frequency in the human scalp EEG of adults. Usually, alpha frequency is defined in terms of peak within the traditional alpha frequency range about 7.5-12.5 Hz. Peak alpha frequency (PAF) is that spectral component which shows the largest power estimate, and it has inter-individual difference. Previous studies have reported that individual alpha frequency band (IAB) ranges from PAF-4 Hz to PAF+2 Hz. Individual higher alpha band (HIAB) is from PAF to PAF+2 Hz and individual lower alpha band (LIAB) is between PAF-4 Hz and PAF (Klimesch, 1999).

PAF changes with age. From early childhood up to puberty alpha frequency increases, but then starts to decline with age (Klimesch, 1999). A few studies have also shown that hormonal changes can influence alpha frequency. For example, there is an increase in PAF concurrent with enhanced progesterone activity during the menstrual cycle and in conditions when cortisol blood level increases. PAF also vary with personal cognitive involvement in task performance. Increased PAF is associated with good performance, but decrease in PAF is related to a drop in performance and fatigue (Bazanov and Vernon, 2013).

1.6.2 ALPHA DOWN-REGULATION NF

Prior studies have proved an inverse relation between initiative alpha synchronization and MEP amplitude (Romei et al. 2008; Sauseng et al. 2009). It is found that intrinsic decrease of alpha amplitude can bring about sturdy raise in corticospinal excitability and drop in intracortical inhibition of up to 150% for at least 20 min. In addition, it can also motivate a plastic reinforcement of dACC connectivity within the salience network, and the improvement in salience network connectivity was in negative correlation with changes in “on task” mind-wandering as well as resting state alpha rhythm (Ros, 2013). In brief, alpha down-regulation could be beneficial for the therapies of brain disorders associated with abnormal cortical rhythms (Ros, 2013) as well as reduction of mind-wandering (Ros, 2013).

Alpha down-regulation NF can bring better cognitive performance. Impermanent promotion of original motor cortex excitability by alpha down-regulation NF can engender better cognitive performance, such as a faster response time. One single session of this NF could help to encourage the early acquisition of a procedural perceptual-motor task (Ros, 2013).

It is worthy to notice that alpha down-regulation is usually followed by a significant increase (“rebound”) back to resting alpha. This rebound was found linked to increased

calmness, greater salience network connectivity with the right insula, and enhanced default mode network connectivity with bilateral posterior cingulate, right middle frontal gyrus, and left medial prefrontal cortex (Kluetsch, 2013).

1.7 NF QUESTIONS

1.7.1 NF LEARNING AND ITS PREDICTION

Although NF training has shown positive effects on many aspects, there are still some questions not solved yet. One important question is non-learner phenomenon: many participants fail to gain control their brain signals during NF training. Non-learner phenomenon is very common, no matter what the training protocol is and how long the training is. Non-learners in some studies have been shown to comprise up to 50% of the participants (e.g. Enriquez-Geppert et al, 2013a; Zoefel et al, 2011; Hanslmayr et al, 2005).

The NF learning is very important because it has a close link with NF training outcome (Gruzelier, 2013a). For instance, Egner and Gruzelier (2003) reported that the improvement of musical performance had high correlation with the learning ability to progressively increase theta over alpha band amplitudes. Take another example, Nan et al. (2012) found that short term memory improvement was positively correlated with the upper alpha increase between the first session and last session. Some studies have further reported that only the successful NF learning to regulate the brain activity can achieve behavior improvement. In Kouijzer et al. (2013), the authors conducted NF training for autism spectrum disorders. It was reported that only the subjects who significantly reduced the training feature during NF sessions revealed significant enhancement in cognitive flexibility. Similarly, in Hanslmayr et al. (2005), only the learners showed enhanced performance in a mental rotation task after upper alpha neurofeedback training.

It is necessary to find out the non-learner reason and predict the learning ability as early as possible. However, few studies reported the prediction of NF learning. Regarding the theta NF, the motivation or commitment has no influence on the learning ability (Enriquez-Geppert et al. 2013a), but the volume of the mid cingulate cortex as well as the volume and concentration of the underlying white matter structures of the subjects can be the predictor of NF learning in theta training (Enriquez-Geppert et al. 2013b). For SMR NF, control beliefs and mental strategies affected the SMR NF results (Kober et al. 2013; Witte et al. 2013). In alpha NF, Wan et al. (2014) has reported that resting alpha activity can predict NF learning in alpha up-regulation NF. However, it is unknown the predictor of alpha down-regulation NF.

1.7.2 UP-REGULATION VS DOWN-REGULATION

For the same training parameter, it could have two training direction: up-regulation and down-regulation. For instance, enhancement of theta activity by NF can enhance creativity in music performance whereas decrease of theta activity by NF has benefits on treatment of ADHD. However, no study has examined whether training the same EEG feature in different direction can also have the opposite effects on the same behavioral performance.

CHAPTER 2 MOTIVATION AND CONTRIBUTION

2.1 MOTIVATION

First of all, based on prior alpha down-regulation studies, there were only one-day session investigation of alpha down-regulation NF and no direct evidence on whether multi-session NF can decrease alpha or not and whether NF has influence on other EEG bands.

Second, individuals have different ability to learn how to regulate the brain activity by neurofeedback. Making predictions for the outcome of learning ability would not only help to enhance the efficiency in further neurofeedback studies, but also find out the reasons for non-learners as well as enhance the performance for learners. Although resting alpha activity can be predictor of NF learning in alpha up-regulation NF, it is unknown whether the NF learning in alpha down-regulation NF also can be predicted by resting alpha activity.

Third, it had been proved that the improvement of short term memory was in positive correlation with the amplitude of HIAB in alpha up-regulation NFT (Nan et al. 2012). In this project, a negative hypothesis, whether short term memory can be decreased by down-regulation of alpha NF, is investigated.

2.2 OBJECTIVES

Based on the motivations, this project is mainly concentrated on investigating the predictors for the learning ability of alpha down-regulation NF. Although no evidence was provided for multi-session neurofeedback to decrease alpha activity, there was a proved effect between the related single session of neurofeedback and decreased alpha amplitude. Additionally, this project evaluates whether short term memory can be affected by the alpha down-regulation NF. In summary, the objectives of this project are to investigate:

- a) Whether multi-session NF training can decrease alpha activity and whether it has effects on other EEG bands.
- b) Whether resting alpha (or other frequency bands) is the predictor of learning ability in alpha down-regulation NF training.
- c) If alpha amplitude is reduced following the training, whether it have an influence on short term memory.

2.3 STUDY HYPOTHESIS

Prior study on alpha down-regulation neurofeedback demonstrated that alpha showed decreased during one single session but its resting baseline rebounded after training (Ros et al. 2013). In this study, our hypothesis is that alpha will show decrease during multi-session training and it will have no significant difference in resting baseline between before and after training.

For the influences on short term memory, changes in initial baseline (BL1) and post-training baseline (BL4) should be taken into account at the first place. If there is no significant difference in baseline between before and after training, the short term memory should remain the same. If the training parameter, individual alpha amplitude, became significantly lower in BL4 than in BL1, it would be reasonable to speculate that short term memory regressed after the alpha down-regulation NFT since memory performance is positively related to resting alpha amplitude (Klimesch, 1999).

2.4 STUDY CONTRIBUTION

This is the first study to investigate:

- a) The learning prediction in down-regulation alpha NF. The results can help understand the mechanism of NF, optimize the training protocol, avoid the

frustrated mood of non-learners, and save energy on non-learners.

- b) The down-regulation alpha NF effects on short term memory. The results can provide confidence to the researchers that down-regulation alpha NF do not have side effects on short term memory.



CHAPTER 3 MATERIALS AND METHODS

3.1 PARTICIPANTS

A total of 19 healthy and qualified students aged from 20 to 30 years volunteered to participate in the NF training experiment which consisted of 4 resting baseline recording and 10 alpha down-regulation training sessions. Moreover, 9 out of the total 19 participants were performed short term memory test before and after the NF training. Criteria are that participants disavowed any current or previous psychiatric or neurological disorders, no psychotropic medications or addiction drugs, and with normal or corrected-to normal vision. Prior to the experiment, all participants signed an informed consent form after the experimental nature and procedure were explained and their questions were answered. The protocol was in accordance with the Declaration of Helsinki and approved by the Research Ethics Committee (University of Macau).

3.2 NF TRAINING

3.2.1 EEG RECORDINGS



Fig. 4 EEG Cap

During the NF training experiment, the participants sat in a quiet room. The feedback signal was recorded from Oz channel (according to the international 10-20 system). Besides the feedback signal, we also recorded other 15 channels including O1, O2, P3, PZ, P4, C3, CZ, C4, F3, FZ, F4, T3, T4, T5 and T6. The participants wear an EEG cap with 16 electrodes to record the above EEG signals (Fig. 4). The conduction between the EEG cap and participant's scalp was realized by the injection of electro-gel in all 16 electrodes. To minimize the impedance of sub-circuits of reference at left mastoid and ground at forehead, before the stickup of electrode button, mastoid and the forehead should be scrubbed with skin prep gel (NuPrep, WEAVER and company) to wipe off an excess of cutin, enhancing bioelectrical conduction.

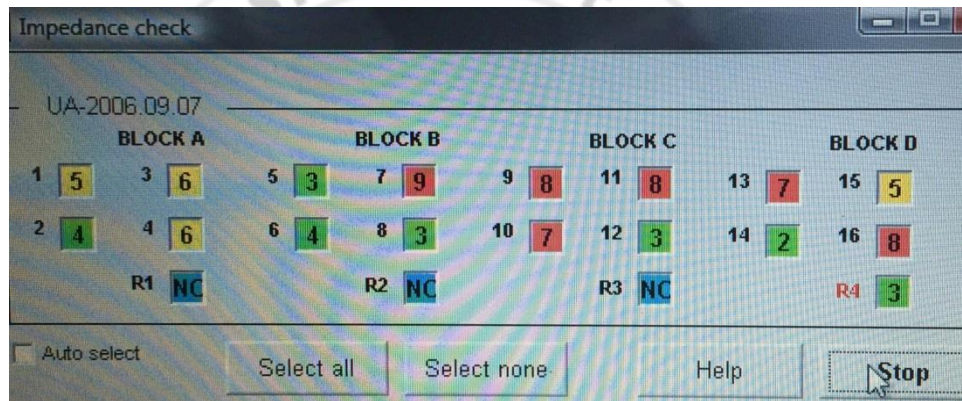


Fig. 5 Impedance check.

Impedance check were performed and all impedance shown be kept below 10 (k Ω) before the baseline test and NF training, as show in Fig. 5. Blocks of No.1 to No.16 represented the corresponding impedance in 16 electrodes on electrode cap while R4 represented the co-impedance from ground and reference. The ground was located at forehead while the reference was at the left mastoids. Circuit impedance was kept below 10 k Ω for all electrodes (Fig1). Blocks of No.1 to No.16 represented the corresponding impedance in 16 electrodes on electrode cap while R4 represented the impedance of reference. The signals were amplified by an amplifier of g.USBamp (Guger Technologies, Graz, Austria) with a sampling rate of 256 Hz and filtered by a 0.5 Hz to 30 Hz band-pass filter and a 50 Hz notch filter to avoid the high frequency noise, baseline drift and powerline interference, as shown in Fig. 6.

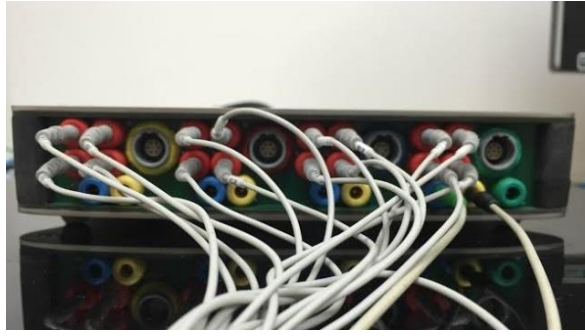


Fig. 6 G. tec amplifier.

After EEG recorded and amplified, signals would be imported into computer for signal processing and would later on be used for the real-time feedback of brain activity. These functions of importation, signal processing and real-time display of certain brain activity was achieved by Simulink in Matlab 2006a. The internal distribution is as shown in Fig. 7.

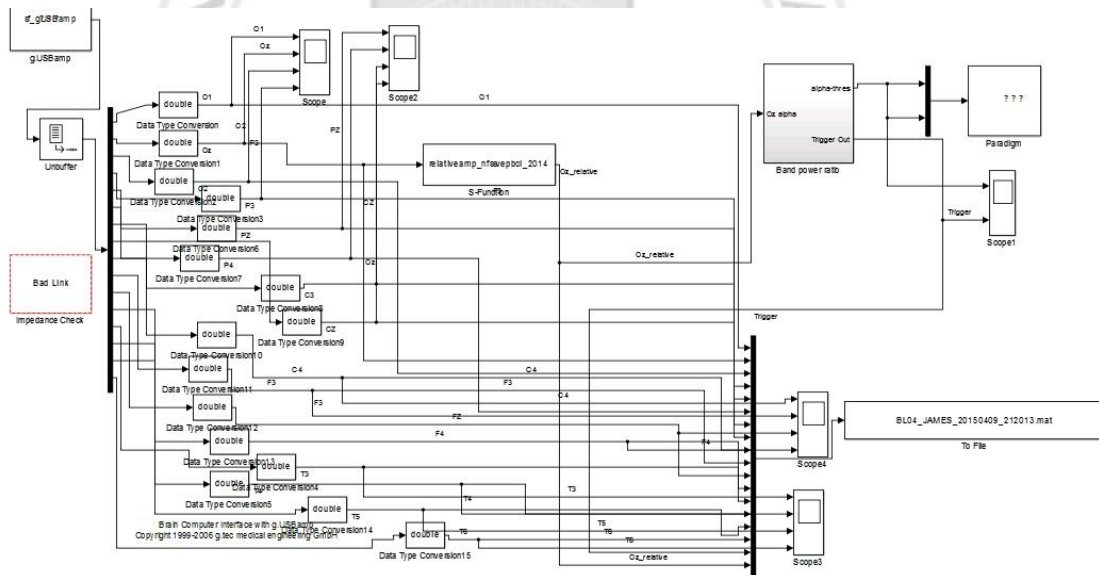


Fig. 7 Signal processing in Matlab Simulink.

3.2.2 TRAINING PARAMETER

Participants were trained to modify their individual alpha band (IAB) which was determined by the corresponding PAF in the initial resting baseline. In this NF training experiment, IAB is defined as band ranges from PAF+2 Hz to PAF-4 Hz. Thus, the training parameter is relative IAB amplitude (relative to 0.5-30 Hz) and this NF training

aimed to inhibit the IAB amplitude. Fast Fourier transformation (FFT) was applied to calculate the amplitudes every 0.125 s using the last 512 samples. Thus, the Frequency resolution was $256/512=0.5$ Hz.

3.2.3 TRAINING PROTOCOL

The flow chart of the experiment procedures are shown in Fig. 8.

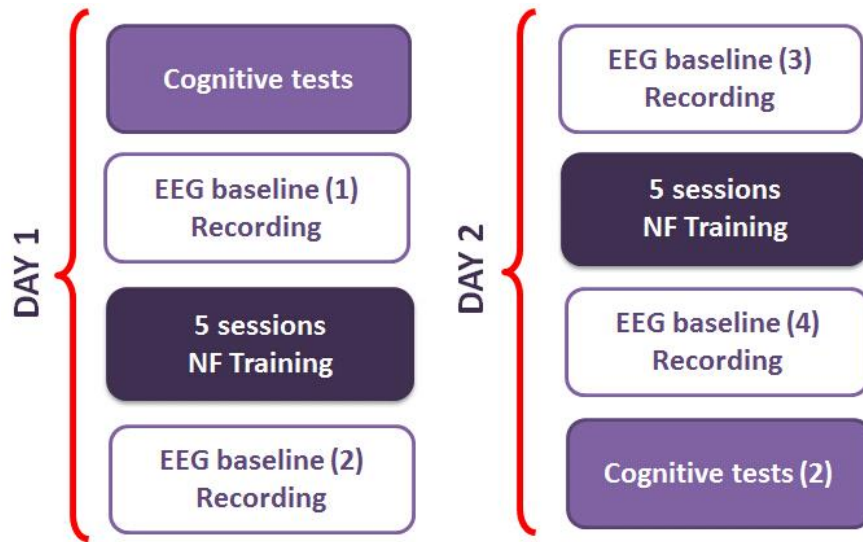


Fig. 8 Experiment procedure

During the NF training, participants were asked to perform individualized efficient thoughts in order to decrease their IAB amplitude. The whole NF training lasted for 2 consecutive days. Each participant completed 5 sessions per day for a total of 10 sessions in 2 days. Each session has three 1min trials with an interval of 5s between two consecutive trials. Before and after the 5 sessions of NF training in each day, the resting baselines were recorded, thus there were 4 resting baseline recording totally in the whole 2 days NF training. And the resting baseline recording consisted of three 30s eyes open and three 30s eyes closed epochs with 10 s intervals between every switchover.

In the process of resting baseline recording and NF training, subjects were supposed to stay quiet and fixed, trying to avoid the eye twinkling. Otherwise, the data collected would be of too much noise considering the subtleness and weakness of brain signals from scalp. For resting baseline recording, subjects were required to have three “30s

eye-open trial followed 30s eye-closed trial” with 10s interval, being relaxed and idle. Whereas for the training sessions, subjects should firstly apply various mental strategies to find out the most efficient one (or more) that could modify certain brain activities. Later on, the efficient mental strategy (or strategies) should be kept applied in order to get positive real-time feedback from screen.

3.2.4 NF DISPLAY

During training sessions, all participants received a real-time feedback of IAB amplitude displayed on the monitor. The feedback from the computer contained two visual episodes (Fig. 9 and Fig. 10), ball and square, reflecting the feedback parameter in real time. If the training parameter (IAB amplitude) below the threshold we set in advance (Goal 1), the color of the ball would gradually turn to purple and the radius of the ball would increase. If Goal 1 was continually achieved over a period of 2 s, which was Goal 2, the cube would rise towards the top (as shown in Fig. 9). Otherwise, the ball color would gradually turn to white and it would shrink to a small point while the cube would drop to or remain at the bottom (as shown in Fig. 10). Hence, participants were instructed to adjust their mental strategies to purple and maximize the ball as well as raise the cube, reinforcing the down-regulation of IAB.

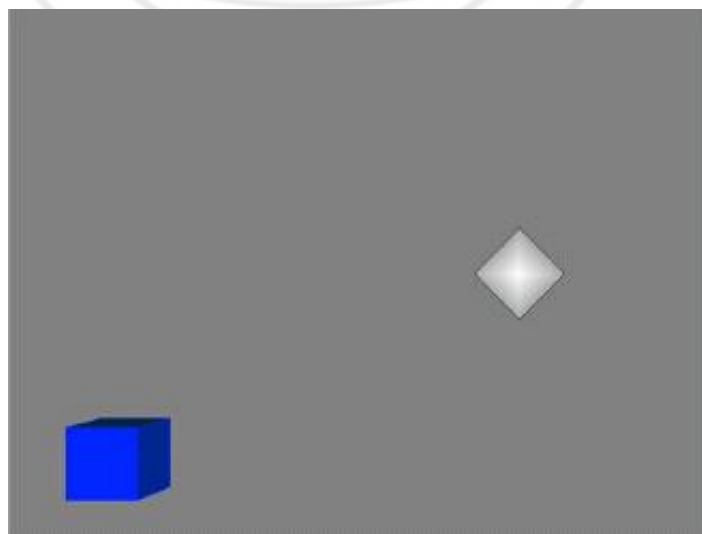


Fig. 9 Goal 1 and Goal 2 not achieved.

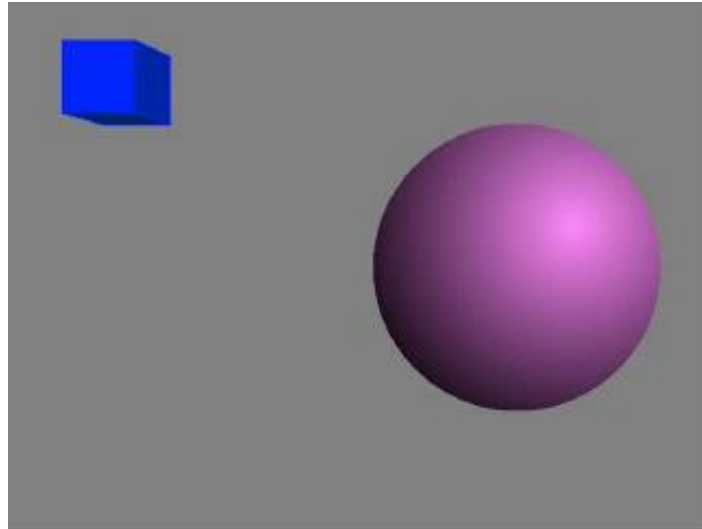


Fig. 10 Goal 1 and Goal 2 achieved.

3.2.5 THRESHOLD SETTING

Due to brain activities varying from individuals and even in sessions to varying degree, the threshold for the training parameter (IAB amplitude) should not be uniformly set. Timely adjustment should be made. Moreover, making adjustment of threshold setting based on an earlier session was reliable. As to the first session of each day, the threshold was set to be the mean IAB amplitude in resting baseline of that day. The percentage of time for the IAB amplitude being below the threshold was calculated by MATLAB. If the time proportion was above 60%, the threshold value would be reduced by 0.05 in the coming session. On the other hand, if the time proportion was less than 20%, the threshold value would increase by 0.05 in the coming session. This strategy would allow the participant to have a sense of achievement, aside from the possibility that an asymptote may be attained after four or five sessions.

3.3 SHORT TERM MEMORY TEST

Right before and after the whole NF training, the cognitive tests were performed to evaluate the change of short term memory and only 9 out of total 19 participants took part in the cognitive tests. The cognitive test was the forward and backward digit span test (via Somnium software platform, Cognitron, SP, Brazil) which was a good measure to assess the short term memory capacity. Random digits displayed at the rate of one

digit per second in a series of trials in each test. In each trial participants attempted to remember as many digits as possible and typed them on textbox and the number of the digits would increase by 1 until the participant failed twice to recollect every digit. The maximum number of the digits recollected correctly was regarded as the score of the participant's cognitive test. In forward digit span test, participants should type the digits with the same order as displayed while in backward digit span test, the digits were typed reversely.

3.4 DATA ANALYSIS

For the offline analyses, besides the IAB, other EEG bands including delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), sigma (12–16 Hz), beta1 (16–20Hz), and beta2 (20–28 Hz) were also calculated in each training sessions and resting baselines.

In order to examine whether the training parameter, IAB amplitude, decreased in multi-session NF and whether other EEG bands showed change trend over sessions, Pearson correlation analysis was applied between the above EEG bands during each session and session number.

In order to find out the predictors of NF learning, Pearson correlation test was performed between learning indices and EEG indices in initial resting baseline (BL1).

To investigate whether there were significant difference in IAB between BL4 and BL1 as well as in short term memory between pre and post training, paired *t* test was applied. This helped to clarify that whether IAB amplitude was reduced after training, and would it have an influence on short term memory.

All the statistical analyses were performed via IBM SPSS software. The *p* value in Pearson correlation is an index to represent reliability of the sample variables and if the sample data is more reliable, the *p* value will be smaller. For instance, if $p=0.05$, we regard 5% of the relative correlation is caused by contingency. To judge whether it has

statistical validity, 5% will be estimated as acceptable error. From practical statistics, If $0.05 \geq p \geq 0.01$, the sample is valid. And if $0.01 \geq p \geq 0.001$, the sample will be of high statistical significance.

Pearson correlation is a measure of the linear correlation between two variables. The correlation coefficient is between +1 and -1. When the correlation coefficient is 1, it means total positive correlation. 0 is no correlation, and -1 is total negative correlation. The calculation is shown as equation (1) where cov is the covariance and σ_X is the standard deviation of X.

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} \quad (1)$$

The formula for ρ can be also expressed by mean and expectation. Because

$$\text{cov}(X,Y) = E[(X - \mu_X)(Y - \mu_Y)], \quad (2)$$

then equation (1) can also be expressed by

$$\rho_{X,Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y}. \quad (3)$$

A paired t test is employed to compare two population means, where observations in one sample can be paired with observations in the other sample. One example which need paired t test: Pre and post observations on the same subjects (e.g. medication treatment on the same patient group before and after treatment).

The steps to carry out a paired t test are shown as follows:

To test the null hypothesis that the true mean difference is zero, the procedure is as followings:

Step 1. The difference is calculated between the two observations on each pair, making sure that the distinguish between positive and negative differences.

Step 2. The mean difference is calculated.

Step 3. The standard deviation of the differences is calculate, and use this to calculate the standard error of the mean difference

Step 4. Calculate the t statistic. Under the null hypothesis, this statistic follows a t distribution with $n - 1$ degrees of freedom.

Step 5. Use the t distribution tables to compare your value in Step 4 for T to the t_{n-1} distribution. We will get the p value for the paired t test.



CHAPTER 4 RESULTS AND ANALYSIS

4.1 EEG INDICES CHANGES OVER TRAINING SESSIONS

Subjects were following the training protocol and attempted to decrease their individual alpha amplitude via trials of mental strategies over 10 training sessions. Data analysis was performed in three steps to clarify how EEG indices changes over training sessions.

In the first step, we plotted the trends of changes (maximum, mean and minimum value) of all subjects' IAB during training sessions. According to Fig. 11, the IAB decreased with sessions, especially sessions of the same day.

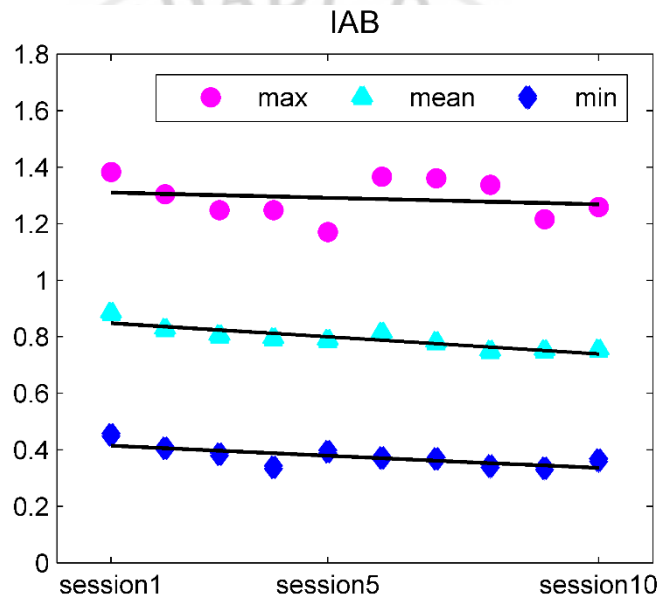


Fig. 11 Max,mean & min of 19 subjects' IAB over 10 sessions.

Nevertheless, according to Fig. 11, IAB was not in a linear decrease over training sessions. Instead, it rebounded slightly in session 06. This phenomenon was appeared and explained in the Kluetsch et al. (2013) that the amplitude of training parameter would rebound back to baseline to varying degrees after a period time of break. Here in this two-day experiment, subjects were required to perform the experiment of the same time in both days with five training sessions in each day. Hence, there was around 24-hour period of break between session 05 and session 06, leading to a “rebound back to

baseline” in the amplitude of IAB.

In the second step, the average amplitudes of all subjects’ EEG indices in 10 training sessions were calculated, as shown in Table 1. Based on the data, the relationship of amplitudes and session number was more aligned with the power function trend within one single day. However, considering the “rebound” effect, linear function would best describe the total trend. And this was approved to be feasible by curve approximation and statistics of total 19 subjects. Later on, linear trend lines would be applied to match the changing trend of all EEG indices, as shown in Fig. 7.

Table 1 Average amplitudes of all EEG indices over sessions

	IAB	LIAB	HIAB	Delta	Theta
Session 01	0.884	0.918	0.823	2.39	1.08
Session 02	0.826	0.872	0.740	2.29	1.05
Session 03	0.803	0.846	0.729	2.30	1.04
Session 04	0.793	0.831	0.729	2.25	1.04
Session 05	0.788	0.830	0.715	2.40	1.07
Session 06	0.813	0.836	0.771	2.43	1.06
Session 07	0.780	0.820	0.704	2.350	1.04
Session 08	0.749	0.798	0.654	2.44	1.02
Session 09	0.751	0.796	0.667	2.56	1.02
Session 10	0.753	0.797	0.671	2.28	1.06
	Alpha	Beta	Sigma	Beta1	Beta2
Session 01	0.863	0.669	0.835	0.726	0.611
Session 02	0.798	0.689	0.855	0.725	0.638
Session 03	0.784	0.709	0.859	0.740	0.662
Session 04	0.755	0.698	0.845	0.738	0.653
Session 05	0.743	0.685	0.840	0.716	0.640
Session 06	0.782	0.669	0.823	0.704	0.621

Session 07	0.748	0.679	0.807	0.703	0.645
Session 08	0.711	0.678	0.780	0.710	0.646
Session 09	0.707	0.671	0.804	0.690	0.643
Session 10	0.718	0.690	0.824	0.714	0.659

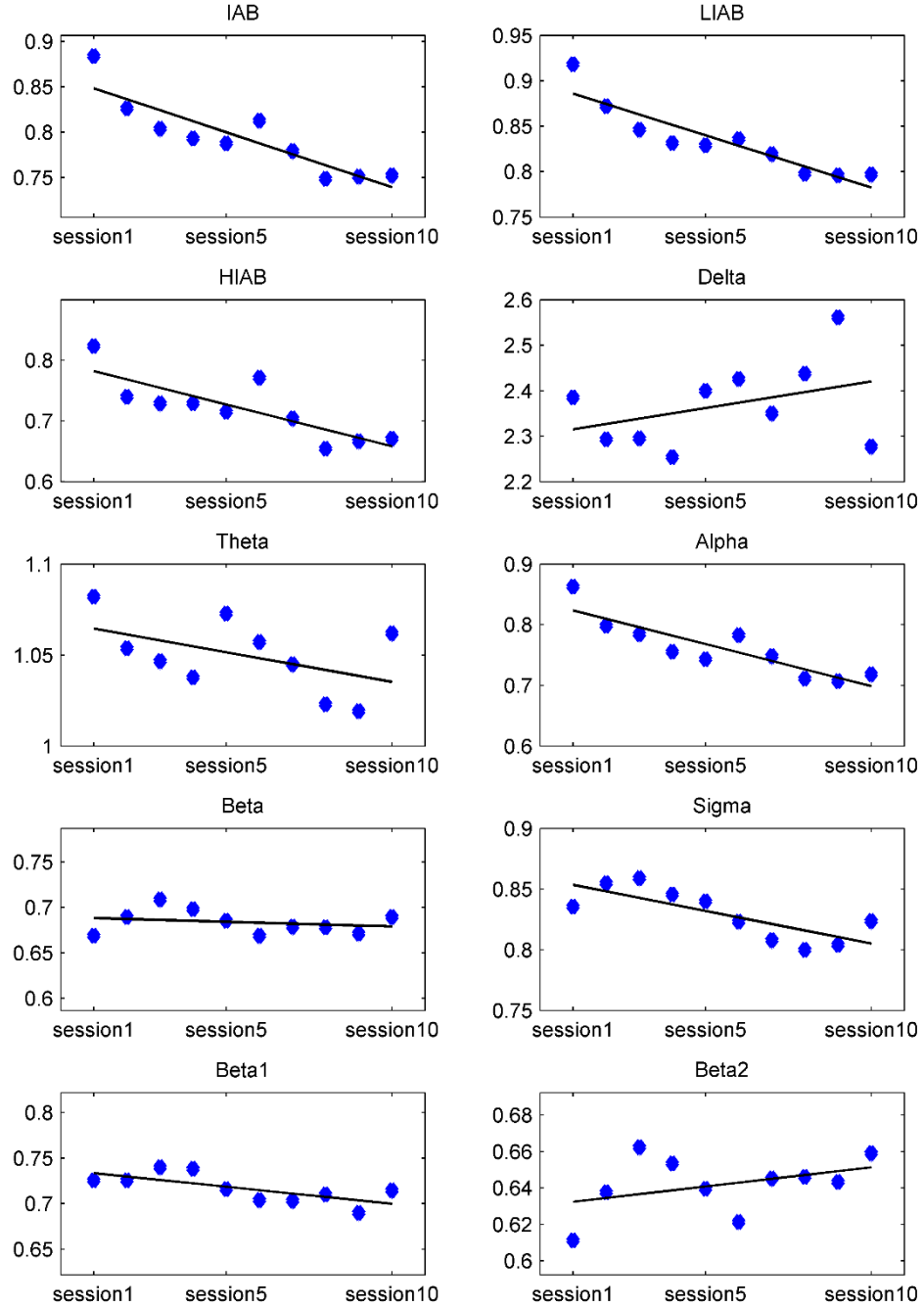


Fig. 12 EEG bands changes over sessions.

From Fig. 12, we could better observe the “rebound” effect in session 06. Amplitudes of the all alpha-related EEG indices (IAB, LIAB, HIAB, alpha) increased in session06

compared to session 05. Moreover, slopes of the 10 trend lines were calculated and their absolute values were compared. Bands that have the top five absolute slope are alpha (slope=-0.0139), HIAB (slope =-0.0138), IAB (slope = -0.0121), delta (slope= 0.0117) and LIAB (slope =-0.0115). The four alpha-related bands (IAB, HIAB, LIAB, alpha) were all have the absolute slope in top 5. It was worthy to notice that the changes over delta were also great. It is reasonable to speculate that the down-regulation of alpha may lead to the up-regulation of delta.

In the third step, 2-tailed Pearson Correlation was applied on all EEG bands and session number. Results shown in Table 3 indicated that there were significant negative correlation between IAB amplitude and session number ($r = -0.886$, $p < 0.001$), meaning the IAB did decrease over the alpha down-regulation NF training.

Table 2 2-tailed Pearson Correlation results of bands & session number

	<i>r</i>	<i>p</i>
IAB	-0.886	0.000637
LIAB	-0.913	0.000228
HIAB	-0.813	0.00424
Delta	0.378	0.282
Theta	-0.490	0.150
Alpha	-0.879	0.000817
Beta	-0.236	0.512
Sigma	-0.774	0.00856
Beta1	-0.711	0.0211
Beta2	0.400	0.252

Besides the IAB, other bands were correlated to session number as well. IAB ($p < 0.001$), LIAB ($p < 0.001$), HIAB ($p < 0.005$), alpha ($p < 0.001$), sigma ($p < 0.05$) were all in significantly negative correlation to session number, which indicated that subjects could decrease their amplitudes of these five EEG bands by means of NF training. As in this

NF training experiment, it was the amplitude of alpha that trained as parameter, thus, it would not be hard to understand the amplitude reduction of LIAB, HIAB and alpha. Nevertheless, the sigma band was also down-regulated and was in significant correlation to session number while there was no significant effect on delta, theta, beta and beta2 bands. It would be reasonable to speculate that the down-regulation of IAB may somehow cause the decrease of sigma band.

4.2 PREDICTORS FINDING

Predictors for the learning ability in NF training should firstly require learning indices to quantify the ability of subjects in learning to regulate their brain activity in NF training. Four learning indices have been applied to do the quantification of learning ability. Here in this project, they are named after as L1, L2a, L2b and L3 and definitions are that:

L1: the amplitude of IAB changes between the first (session 01) and last session (session 10);

L2a: the mean within training day changes of IAB amplitude in each session relative to the first session of the corresponding training day;

L2b: the regression slope between differences in corresponding sessions of two training days and session number;

L3: the regression slope between changes across whole training and session number.

The learning indices of total 19 subjects were calculated. The characteristic value of range, mean and standard deviations are as shown.

From the above table, we could observe that L2a ($\sigma = 0.21889723$) had the greatest value of standard deviation while L3 ($\sigma = 0.014101845$) had the smallest value of standard deviation.

Table 3 Characteristic values of L1, L2a, L2b, L3

	L1	L2a	L2b	L3
max	0.128	0.297	0.0219	0.0135
aver	-0.131	-0.271	-0.0187	-0.0121
min	-0.490	-0.781	-0.0726	-0.0467
Standard deviation	0.136	0.219	0.0196	0.0141

Table 4 Correlation of learning indices and EEG indices in *a)* initial baseline¹

		IAB	LIAB	HIAB	Delta	Theta	Alpha
L1	<i>r</i>	-0.278	0.0137	-0.458*	0.228	0.487*	-0.421
	<i>p</i>	0.249	0.955	0.0487	0.347	0.0346	0.0729
L2a	<i>r</i>	-0.185	0.0869	-0.403	0.283	0.443	-0.318
	<i>p</i>	0.449	0.723	0.0871	0.241	0.0575	0.185
L2b	<i>r</i>	-0.0777	0.0726	-0.219	0.140	0.392	-0.164
	<i>p</i>	0.752	0.768	0.368	0.567	0.0965	0.503
L3	<i>r</i>	-0.490*	-0.186	-0.543*	0.167	0.265	-0.530*
	<i>p</i>	0.033	0.446	0.0162	0.494	0.272	0.0196
		Beta	Individual Theta	Individual Beta	Sigma	Beta1	Beta2
L1	<i>r</i>	-0.235	0.464*	-0.191	-0.312	-0.107	-0.160
	<i>p</i>	0.333	0.0451	0.435	0.193	0.663	0.512
L2a	<i>r</i>	-0.295	0.331	-0.278	-0.383	-0.205	-0.202
	<i>p</i>	0.220	0.166	0.249	0.105	0.401	0.407
L2b	<i>r</i>	-0.205	0.285	-0.179	-0.360	-0.164	-0.119
	<i>p</i>	0.401	0.236	0.464	0.130	0.501	0.626
L3	<i>r</i>	-0.08107	0.274	-0.0434	-0.330	0.0264	-0.000750
	<i>p</i>	0.741	0.257	0.860	0.167	0.915	0.998

¹ *: Corresponding *p* is less than 0.05.

In the next step, we attempted to find predictors for the learning ability through correlations between learning indices (L1, L2a, L2b, and L3) and EEG indices from:

- a) initial baseline;
- b) first session;
- c) the subduction of EEG indices in baseline and first session.

Later on, Pearson Correlation was performed, r and p value of learning indices and EEG indices in a) b) & c) were showed respectively in Table 4, Table 5 and Table 6.

Table. 5 Correlation of learning indices and EEG indices in *b*) first session

		IAB	LIAB	HIAB	Delta	Theta
L1	<i>r</i>	-0.0544	-0.0819	-0.00651	-0.0278	0.125
	<i>p</i>	0.825	0.739	0.979	0.910	0.611
L2a	<i>r</i>	-0.213	-0.226	-0.156	-0.0798	0.0880
	<i>p</i>	0.381	0.353	0.523	0.746	0.720
L2b	<i>r</i>	-0.147	-0.202	-0.0262	-0.0737	0.280
	<i>p</i>	0.547	0.406	0.915	0.764	0.245
L3	<i>r</i>	-0.0253	-0.0554	0.0166	-0.0670	-0.0255
	<i>p</i>	0.918	0.822	0.946	0.785	0.917
		Alpha	Beta	Sigma	Beta1	Beta2
L1	<i>r</i>	-0.0402	0.0769	-0.0526	0.0907	0.104
	<i>p</i>	0.870	0.754	0.831	0.712	0.672
L2a	<i>r</i>	-0.177	0.106	-0.0458	0.0765	0.155
	<i>p</i>	0.470	0.665	0.853	0.755	0.525
L2b	<i>r</i>	-0.122	-0.0307	-0.0282	-0.0287	-0.0335
	<i>p</i>	0.620	0.901	0.909	0.907	0.892
L3	<i>r</i>	0.00946	0.168	-0.135	0.171	0.252
	<i>p</i>	0.969	0.491	0.582	0.482	0.298

According to the above tables, only in Table 4 had the p value less than 0.05, (for simplicity and intuitive, asterisk “*” was applied). In other words, there were correlations between learning indices and EEG indices in initial baseline whereas there were no correlations between the four learning indices and any EEG indices in b) & c).

In terms of Table 4, the learning index of L1 was correlated with HIAB, Theta and Individual Theta amplitude in eye open state of initial baseline while L3 was negatively correlated with IAB, HIAB and alpha amplitude in eye open state of initial baseline. Thus, HIAB, Theta and Individual Theta, IAB, HIAB and alpha from eye open state of initial baseline could be the predictors for the learning ability in alpha down-regulation NF training.

Yet, of all, HIAB from eye open initial baseline may best predict the learning ability best.

Table 6 Correlation of learning indices and EEG indices in c) the subduction of EEG indices in baseline and first session.

		IAB	LIAB	HIAB	Delta	Theta
L1	<i>r</i>	0.011	-0.089	0.143	-0.173	-0.226
	<i>p</i>	0.963	0.716	0.559	0.479	0.353
L2a	<i>r</i>	-0.164	-0.261	-0.001	-0.266	-0.236
	<i>p</i>	0.503	0.281	0.998	0.271	0.330
L2b	<i>r</i>	-0.125	-0.232	0.049	-0.171	0.037
	<i>p</i>	0.610	0.339	0.842	0.483	0.880
L3	<i>r</i>	0.089	-0.004	0.190	-0.180	-0.237
	<i>p</i>	0.718	.986	0.435	.461	.328
		Alpha	Beta	Sigma	Beta1	Beta2
L1	<i>r</i>	0.063	0.226	0.086	0.192	0.230
	<i>p</i>	0.799	0.352	0.725	0.432	0.344

L2a	<i>r</i>	-0.101	0.294	0.129	0.234	0.315
	<i>p</i>	0.682	0.221	0.598	0.334	0.190
L2b	<i>r</i>	-0.083	0.092	0.140	0.065	0.056
	<i>p</i>	0.736	0.707	0.568	0.792	0.819
L3	<i>r</i>	0.140	0.229	-0.006	0.218	0.261
	<i>p</i>	0.568	0.345	0.979	0.370	0.280

4.3 CHANGES OF SHORT TERM MEMORY

9 out of total 19 subjects participated in the cognitive test of short term memory before and after the NF training. For the sake of observation and simplicity, histograms were made for the results of forward digit span and backward digit span test respectively.

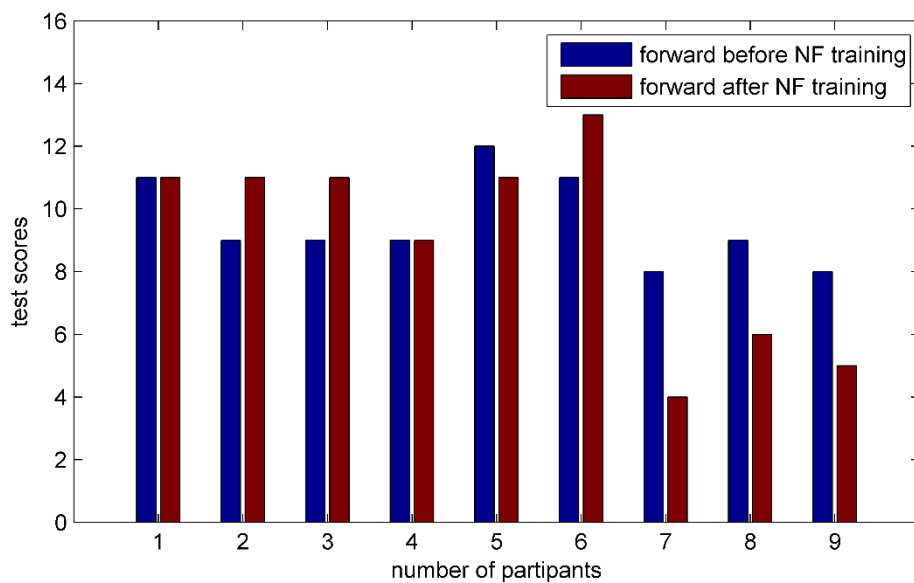


Fig. 13 Results of forward digit span test before and after the NF training.

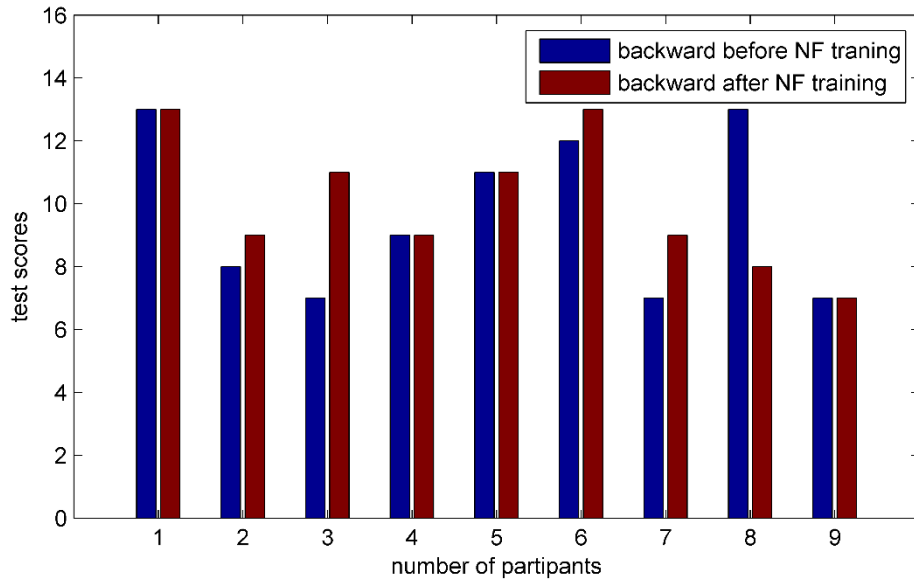


Fig. 14 Results of backward digit span test before and after the NF training.

From Fig. 13 and Fig. 14, there were increases as well as decreases in results of forward digit span test before and after the NF training, and so did in results of backward digit span test before and after the NF training.

Hence Paired- t test was applied to find whether there was significant difference between the cognitive test before and after NF training, as shown in Table 7

Table 7 Paired- t test of digit span before and after the NF training

	t	p
forward_before_NF training - forward_after_NF training	0.709	0.499
backward_before_NF training - backward_after_NF training	-0.417	0.688

NF training was consistently performed for clinic treatment or better cognitive performance. Yet it remains to be explored whether the NF would give rise to a bad effect or worse cognitive performance.

Based on previous studies, the short term memory improved with the increase of IAB amplitude. Here in this alpha down-regulation NF training, the short term memory should be improved if the IAB amplitude was higher in BL4 than in BL1, according to

prior studies. And it would remain to be explored that would the short term memory be improved, retrogressed or maintain unchanged when the IAB amplitude were lower in BL4 than in BL1 or of the same.

The IAB amplitudes of 9 participants in eye-open state over the four baselines are shown in Table 8.

Table 8 IAB amplitudes of 9 participants in eye-open state over the four baselines

Participants No.	BL1	BL2	BL3	BL4
11	0.940	1.05	1.21	1.23
12	1.34	1.31	1.26	1.26
13	1.10	0.920	0.956	0.856
14	0.934	0.934	0.989	0.955
15	0.952	1.175	0.885	1.11
16	1.18	0.966	0.915	1.14
17	1.15	1.0704	1.144	1.22
18	1.26	1.16	1.02	1.06
19	1.03	1.03	1.19	1.13

Paired-*t* test on the three pairs, IAB amplitude in BL4 and BL1, forward digit span before and after the NF TRAINING, backward digit span before and after the NF TRAINING were performed, as shown in Table 9.

Table 9 Paired-*t* test on IAB amplitude in BL4 and BL1, forward digit span and backward digit span before and after the NF training

	<i>t</i>	<i>p</i>
BL1 - BL4	-0.204	0.843
Forward_before_NF training - Forward_after_NF training	0.709	0.499
Backward_before_NF training - Backward_after_NF training	-0.417	0.688

As all p value were far larger than 0.05, there were no significant differences between the amplitude of IAB in BL4 and that in BL1. And either did the results of the forward (or backward) digit span before and after the NF training. Thus, in short, bad effects or worse cognitive performances in previous assumption were not occurred.

Admittedly, we could not just conclude that NF training would not lead to any bad effects on individuals. First of all, not enough (only 9) subjects participated into the cognitive test and it sure contained randomness. Moreover, only the cognitive performance of short term memory was measured, yet changes in other performances were still uncertain.



CHAPTER 5 DISCUSSION AND CONCLUSION

In the present study, we investigated whether multi-session NF training could decrease alpha activity and its effects on other EEG bands. From descriptive analysis, 14 out of total 19 subjects could decrease the activity of IAB over sessions (evaluated by L3). After applying Pearson correlation between the mean amplitude all subjects and session number, we could say amplitude of IAB, LIAB, HIAB, alpha and sigma decreases significantly over training sessions. As sigma is not related to training parameter, it remains to be investigated that whether the alpha down-regulation would lead to the decrease of sigma activity.

As shown in the results, the learning ability evaluated by L1, L2a, L2b, and L3 differed among individuals. We can see that participant 17 showed the best training performance since this participant had the largest decreased in all learning indices compared to other participants. The training goal was to decrease IAB amplitude, but some participants even showed increase in IAB. In particular, the participant 18 showed increased IAB in all four learning indices. The non-learner phenomenon also has been reported by previous studies (Kotchoubey et al. 1999; Hanslmayr et al. 2005; Kropotov et al. 2005; Doehnert et al., 2008; deBeus and Kaiser, 2011; Escolano et al., 2011; Weber et al., 2011; Zoefel et al. 2011; Enriquez-Geppert et al. 2013a; Kouijzer et al. 2013). It is quite important to make prediction of learning ability before training in order to save money, time and energy on the non-learners.

For the learning prediction, several EEG indices are found to be able to predict the learning ability in alpha down-regulation NF. And among all potential predictors, HIAB in eye-open baseline appears to be the most practical implication, not only because it was correlated learning indices of both of L1 and L3, but also because the smallest p value is between L3 and eye-open resting HIAB. Consistent with our objective, we found resting EEG as a predictor of NF learning in down-regulation alpha NF. Similarly,

Nan et al. (2012) also found resting alpha activity predicted NF learning in up-regulation alpha NF where the participant performed 20 training session in two weeks. Thus, we can conclude that resting alpha activity can predict alpha NF learning whatever the training direction is and the training schedule is.

Furthermore, we attempted to find if resting IAB amplitude was reduced following the training. The results showed no significant difference of IAB amplitude between BL1 and BL4, which is in line with literature (Ros et al. 2013). In Ros et al. (2013), 17 participants performed a 30-min session of down-regulation alpha NF. After NF, an increase of connectivity within regions of the salience network involved in intrinsic alertness (dorsal anterior cingulate) was found. The increase in salience network (default-mode network) connectivity was negatively (positively) correlated with changes in ‘on task’ mind-wandering as well as resting state alpha rhythm. However, no significant difference was found in resting alpha activity. Thus, we can see that alpha activity have decrease during NF but no change in resting period. It also indicate that the resting baseline is difficult to change.

Nan et al. (2012) found short term memory improvement by enhancement alpha NF. Thus, we are interested in whether down-regulating alpha by NF have side effects on short term memory and would this alpha down-regulation have an influence on short term memory. The result indicates that this type of training has no side effects on short term memory. This is a positive results, providing evidence to the researchers that it is not necessary to worry about the short term memory performance when using down-regulating alpha NF to improve some specific performance such as implicit motor learning and reaction time.

In conclusion, this study found that resting alpha activity can predict NF learning in down-regulation alpha NF. Further, down-regulation alpha NF does not have side effects on short term memory.

REFERENCES

Abou-Khalil, B. and Misulis, K. E., 2005. Atlas of EEG & Seizure Semiology: Text with DVD. Butterworth-Heinemann.

Alvarez, G. A. and Cavanagh, P., 2004. "The capacity of visual short-term memory is set both by visual information load and by number of objects". Psychological Science, Vol. 15, pp. 106-111.

American Clinical Neurophysiology Society, 2006. "Guideline 6: a proposal for standard montages to be used in clinical EEG". American Journal of Electroneurodiagnostic Technology, Vol. 46, pp. 226.

Azevedo, F. A. C., Carvalho, L. R. B., Grinberg, L. T., Farfel, J. M., Ferretti, R. E. L., Leite, R. E. P., Filho, W. J., Lent, R. and Herculano-Houzel, S., 2009. "Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain". Journal of Comparative Neurology, Vol. 513, pp. 532–541.

Bazanov, O. M. and Vernon, D., 2014. "Interpreting EEG alpha activity". Neuroscience & Biobehavioral Reviews, Vol. 44, pp. 94-110.

Cosgrove, K. P., Mazure, C. M., Staley, J. K., 2007. "Evolving knowledge of sex differences in brain structure, function, and chemistry". Biological Psychiatry, Vol. 62, pp. 847–855.

deBeus, R., & Kaiser, D. A., 2011. "Neurofeedback with children with attention-deficit hyperactivity disorder: A randomized double-blind placebo-controlled study". In Neurofeedback And Neuromodulation Techniques And Applications, pp. 127-152.

Doehnert, M., Brandeis, D., Straub, M., Steinhausen, H. C., and Drechsler, R., 2008. "Slow cortical potential neurofeedback in attention deficit hyperactivity disorder: is there neurophysiological evidence for specific effects?" Journal of Neural Transmission, Vol. 115, pp. 1445-1456.

Enriquez-Geppert, S., Huster, R. J., Scharfenort, R., Mokom, Z. N., Vosskuhl, J., Figge, C., Zimmermann, J., and Herrmann, C. S., 2013a. "The morphology of midcingulate cortex predicts frontal-midline theta neurofeedback success". Frontiers in human neuroscience, Vol. 7, pp. 453.

Enriquez-Geppert, S., Huster, R. J., Scharfenort, R., Mokom, Z. N., Zimmermann, J., and Herrmann, C. S., 2013b. "Modulation of frontal-midline theta by neurofeedback". Biological Psychology, Vol. 95, pp. 59-69.

Escolano, C., Aguilar, M., and Minguez, J., 2011. "EEG-based upper alpha neurofeedback training improves working memory performance". In Engineering in medicine and biology society, EMBC, 2011 Annual International Conference of the IEEE, pp. 2327-2330.

Feng, W., Nan, W., Vai, M., and Rosa, A., 2014. "Resting alpha activity predicts learning ability in alpha neurofeedback". Frontiers in Human Neuroscience, Vol. 8, pp. 500.

Fisch, B. J. and Spehlmann, R., 1999. Fisch and Spehlmann's EEG Primer: Basic Principles of Digital and Analog EEG. Elsevier Health Sciences.

Jones, R., 2012. "Neurogenetics: What makes a human brain?" Nature Reviews Neuroscience, Vol. 13, pp. 655.

Hanslmayr, S., Sauseng, P., Doppelmayr, M., Schabus, M., and Klimesch, W., 2005.

“Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects”. Applied psychophysiology and biofeedback, Vol. 30, pp. 1–10.

Kandel, E. R., Schwartz, J. H. and Jessel, T. M., 2000. Principles of Neural Science. McGraw-Hill Professional.

Klimesch, W., 1999. “EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis”. Brain research reviews, Vol. 29, pp. 169–195.

Kober, S. E., Witte, M., Ninaus, M., Neuper, C., and Wood, G., 2013. “Learning to modulate one's own brain activity: the effect of spontaneous mental strategies”. Frontiers in human neuroscience, Vol. 7, pp. 695.

Kouijzer, M. E., van Schie, H. T., Gerrits, B. J., Buitelaar, J. K., and de Moor, J. M., 2013. “Is EEG-biofeedback an effective treatment in autism spectrum disorders? A randomized controlled trial”. Applied Psychophysiology Biofeedback, Vol. 38, pp. 17-28.

Kotchoubey, B., Strehl, U., Holzapfel, S., Blankenhorn, V., Froscher, W., and Birbaumer, N., 1999. “Negative potential shifts and the prediction of the outcome of neurofeedback therapy in epilepsy”. Clinical Neurophysiology, Vol. 110, pp. 683-686.

Kropotov, J. D., Grin-Yatsenko, V. A., Ponomarev, V. A., Chutko, L. S., Yakovenko, E. A., and Nikishena, I. S., 2005. “ERPs correlates of EEG relative beta training in ADHD children”, International Journal of Psychophysiology. Vol. 55, pp. 23-34.

Nan, W., Wan, F., Lou, C., Vai, M. and Rosa, A., 2013. “Peripheral visual performance enhancement by neurofeedback training”. Applied Psychophysiology Biofeedback, 38, 285-291.

Nan, W., Rodrigues, J. P., Ma, J., Qu, X., Wan, F., Mak, P. and Rosa, A., 2012. "Individual alpha neurofeedback training effect on short term memory". International Journal of Psychophysiology, Vol. 86, pp. 83-87.

Niedermeyer, E. and da Silva, F. L., 2004. Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. Lippincot Williams & Wilkins.

Niv, S., 2013. "Clinical efficacy and potential mechanisms of neurofeedback". Personality and Individual Differences, Vol. 54, pp. 676-686.

Jensen, O., Gelfand, J., Kounios, J. and Lisman, J. E., 2002. "Oscillations in the alpha band (9–12 Hz) increase with memory load during retention in a short-term memory task". Cerebral Cortex, Vol. 12, pp. 877-882.

Parent, A., 1996. Carpenter's Human Neuroanatomy, Williams & Wilkins.

Ros, T., Munneke, M. A. M., Parkinson, L. A. and Gruzeliizer, J. H., 2014. "Neurofeedback facilitation of implicit motor learning". Biological Psychology, Vol. 95, pp. 54-58.

Gruzeliizer, J. H., 2014a. "EEG-neurofeedback for optimising performance. I: A review of cognitive and affective outcome in healthy participants". Neuroscience & Biobehavioral Reviews, Vol. 44, pp. 124-141.

Gruzeliizer, J. H., 2014b. "EEG-neurofeedback for optimising performance. II: Creativity, the performing arts and ecological validity". Neuroscience & Biobehavioral Reviews, Vol. 44, pp. 142-158.

Gruzeliizer, J. H., 2014c. "EEG-neurofeedback for optimising performance. III: A review

of methodological and theoretical considerations”. Neuroscience & Biobehavioral Reviews, Vol. 44, pp. 159-182.

Gur, R. C., Turetsky, B. I., Matsui, M., Yan, M., Bilker, W., Hughett, P. and Gur, R. E., 1999. “Sex differences in brain gray and white matter in healthy young adults: correlations with cognitive performance”. The Journal of Neuroscience, Vol. 19, pp. 4065–4072.

Ring, C., Cooke, A. Kavussanu, M., McIntyre, D. and Masters, R., 2015. “Investigating the efficacy of neurofeedback training for expediting expertise and excellence in sport”. Psychology of Sport And Exercise, Vol. 16, pp. 118-127.

Ros, T., Munneke, M. A., Ruge, D., Gruzelier, J. H., and Rothwell, J. C., 2010. “Endogenous control of waking brain rhythms induces neuroplasticity in humans”. European Journal of Neuroscience, Vol. 31, pp. 770-778.

Ros, T., Theberge, J., Frewen, P. A., Kluetsch, R., Densmore, M., Calhoun, V. D., and Lanius, R. A., 2013. “Mind over chatter: Plastic up-regulation of the fMRI salience network directly after EEG neurofeedback”. Neuroimage, Vol. 65, pp. 324-335.

Weber, E., Koberl, A., Frank, S., and Doppelmayr, M., 2011. “Predicting successful learning of SMR neurofeedback in healthy participants: methodological considerations”. Applied Psychophysiology Biofeedback, Vol. 36, pp. 37-45

Witte, M., Kober, S. E., Ninaus, M., Neuper, C., and Wood, G., 2013. “Control beliefs can predict the ability to up-regulate sensorimotor rhythm during neurofeedback training”. Frontiers in Human Neuroscience, Vol. 7, pp. 478.

Zoefel, B., Huster, R. J., and Herrmann, C. S., 2011. “Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance”. Neuroimage,

Vol. 54, pp. 1427-1431.



APPENDIX: RELATED PUBLICATIONS

Qu, X. T., **Tang, Q.**, Yang, L. M., Nan, W. Y., da Cruz, J. N., Wan, F., Mou, P. A., Mak, P. I., Mak, P. U., Vai, M. I., Hu, Y. and Rosa, A. C. "How mental strategy affects beta/theta neurofeedback training". In *IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA 2015)*, accepted.

Wong, C. M., **Tang Q.**, da Cruz, J. N. and Wan, F., "A multi-channel SSVEP-based BCI for computer games with analogue control". In *IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA 2015)*, accepted.

