EFFECTS OF PHYSICAL ACTIVITY ON NEURAL MARKERS OF ATTENTION IN CHILDREN

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ABSTRACT

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Low levels of physical activity among children have raised concerns over the effect of sedentary lifestyle on prerequisites of learning. Ample evidence has supported the protective effect of physical activity on wide range of cognitive functions. The role of attention disengagement in learning has steered the research towards further investigation of attention mechanisms. The studies investigating spatial attention have strengthened a functionally inhibitory role of alpha oscillations in attention. When attention is allocated to other hemifield, alpha activity increases in hemisphere ipsilateral to attended hemifield and decreases in hemisphere contralateral to attended hemifield. However, it remains unexplored whether physical activity induces adaptations in this alpha lateralization. The aim of this study was to characterize posterior alpha modulations in children with varying physical activity level in relation to allocation of attention. The subjects were divided into high fit (n=21) and moderate-to-low (mod-low) fit (n=26) groups according to their shuttle run test results. Posterior alpha activity was measured from 12–16 year old children using magnetoencephalography (MEG) while they performed a visuospatial attention task in which a cue was presented before the target-onset. In pre-target interval, the results showed increased alpha activity in the hemisphere ipsilateral to attended hemifield, whereas the alpha activity decreased relatively in the hemisphere contralateral to attended hemifield. Among all children (n=47), the modulation was significant at 300–1300 ms after cue-onset. In this study, the alpha modulation did not differ significantly between high fit and mod-low fit subjects. However, mod-low fit subjects showed a bias towards right visual hemifield in attention task within the first 500 ms after the cue-onset. In the time interval of 500–1000 ms after the cue-onset, the alpha modulation between the groups was similar in both hemispheres. In conclusion, the study showed that attention modulates alpha oscillations in 12–16 year old children. In addition, there was a trend for weaker rightward bias in high fit children, which might be utilized in the evaluation of the children's developmental level, since the rightward bias is typically observed from younger children and adults with attention deficits.

Keywords: attention, physical activity, alpha oscillation, magnetoencephalography

TIIVISTELMÄ

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Huoli passiivisen elämäntavan vaikutuksista oppimisen edellytyksiin on kasvanut, kun lasten fyysinen aktiivisuus on vähentynyt. Useat tutkimukset tukevat fyysisen aktiivisuuden suojaavaa vaikutusta erilaisiin kognitiivisiin toimintoihin. Tarkkaavaisuuden kohdistaminen relevantteihin ärsykkeisiin näyttää olevan merkittävä osa oppimista, minkä vuoksi mielenkiinto on kohdistettu nykytutkimuksessa tarkkaavaisuuden mekanismeihin. Alfa-oskillaatioiden inhibitorinen rooli tarkkaavaisuudessa on saanut vahvistusta spatiaalista tarkkaavaisuutta selvittäneistä tutkimuksista. Alfa-oskillaatioiden on havaittu lateralisoituvan siten, että alfa-aktiivisuus laskee näköärsykettä prosessoivalla aivokuorella ja samanaikaisesti nousee vastakkaisella näköaivokuorella. Ei kuitenkaan ole selvää, muokkaako fyysinen aktiivisuus suoraan lasten alfa-aktiivisuutta tarkkavaisuutta mittaavan tehtävän aikana. Tutkimuksen tavoitteena oli selvittää, miten aivojen takaosan alfa-oskillaatiot lateralisoituvat tarkkaavaisuustehtävän aikana lapsilla, jotka ovat kestävyyskunnoltaan erilaisia. Koehenkilöt jaettiin kahteen ryhmään kestävyyssukkulajuoksutuloksen perusteella. Hyväkuntoisten ryhmä koostui 21 lapsesta ja keskiverto- ja huonokuntoisten ryhmä 26 lapsesta. Aivojen takaosan alfa-aktiivisuutta mitattiin magnetoenkefalografian (MEG) avulla visuospatiaalisen tehtävän aikana. Tehtävässä koehenkilöille esitettiin vihje kohdeärsykkeen suunnasta hieman ennen varsinaisen kohdeärsykkeen esittämistä. Tuloksista havaittiin, että vihjeen esittämisen jälkeen alfa-aktiivisuus laski aktiivista näkökenttää vastaavalla aivopuoliskolla ja nousi samalla passiivisen näkökentän prosessoinnista vastaavalla aivopuoliskolla. Alfa-aktiivisuuden lateralisoituminen oli tilastollisesti merkitsevää 300–1300 ms:a vihjeen esittämisen jälkeen. Ryhmien välillä ei havaittu tilastollisesti merkitseviä eroja alfa-lateralisaatiossa. Kuitenkin keskiverto- ja huonokuntoisista lapsista koostuvassa ryhmässä havaittiin hieman voimakkaampaa oikeaan näkökenttään kohdistuvaa tarkkaavaisuutta 0–500 ms vihjeen esittämisen jälkeen. Tämä ero ei ollut havaittavissa enää 500–1000 ms vihjeen esittämisen jälkeen. Yhteenvetona voidaan todeta, että tarkkaavaisuus moduloi alfa-oskillaatioita 12–16 -vuotiailla lapsilla. Lisäksi havaittiin viitteitä parempikuntoisten lasten vähäisemmästä oikeaan näkökenttään kohdistuvasta vinoutuneesta tarkkaavaisuudesta, mikä saattaa olla hyödynnettävissä lasten yksilöllisen kehitystason arvioinnissa, sillä oikealle puolelle kohdistuvaa harhaa on aikaisemmin havaittu pienillä lapsilla ja aikuisilla, joilla on tarkkaavaisuusongelmia.

Avainsanat: tarkkaavaisuus, fyysinen aktiivisuus, alfa-oskillaatio, magnetoenkefalografia

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ABBREVIATIONS

ALI	Alpha lateralization index
CBF	Cerebral blood flow
CBV	Cerebral blood volume
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
ERD	Event-related desynchronization
ERS	Event-related synchronization
FFT	Fast Fourier Transformation
HPI	Head-position indicator
MEG	Magnetoencephalography
MI	Modulation index
MRI	Magnetic resonance imaging
SQUID	Superconducting quantum interference device
SSS	Signal Space Separation with temporal extension
TFR	Time-frequency representations
tSSS	Signal Space Separation
VO2max	Maximal voluntary oxygen uptake

CONTENTS

1 INTRODUCTION

The health benefits of physical exercise are known world-wide, but physical fitness is also associated with better cognitive performance. Hence, healthy lifestyle is not only an important factor in today's society, but it is also an investment in better future. Exercise might not only help to improve youngsters' physical health, but might also improve their academic performance. Regardless of the behavioral studies suggesting correlation between physical activity level and cognitive abilities, the mechanism is not yet understood.

In past decades, our lifestyle has become more passive with more hours of sedentary activities and fewer hours of physical activity. Low levels of physical activity have raised concerns whether the effects of sedentary lifestyle affect negatively on people's motor actions and cognitive functions. In general, physical activity has been linked to better cognitive performances and especially to better executive functions (Douw et al. 2014). Physical activity induced adaptations in cognitive function might play a big role even in academic achievements (Hillman et al. 2008). However, the factors contributing to better cognitive performance remain still unknown. Positive correlation between cognitive performance and physical activity might stem either from psychosocial and cognitive factors (motivation, cognitive capacity and social factors), or directly from the factors effecting on oxygen uptake.

In fact, growing evidence, especially from animal studies, suggests that physical activity might improve cognitive abilities via brain level modulations. Moreover, different brain rhythms have been related to neural prerequisites of learning. The results of Chaddock-Heyman et al. (2013) suggest that physical activity during childhood may enhance specific elements of prefrontal cortex function involved in cognitive control.

Selective attention is a crucial factor in all cognitive functions. Our brains receive a continuous flow of sensory information from which we have to be able to pick up the relevant information and ignore the disturbing or less relevant stimuli (Posner & Petersen 1990). The mechanism that enables filtering seems to be associated with regional specific modulation of 8–12 Hz oscillations. It has been suggested that these oscillations gate information flow through the brain network by means of functional inhibition (Klimesch et al. 2007), a process described by alpha inhibition hypothesis (Jensen & Mazaheri, 2010). A recent study has showed that children with more lateralized alpha modulation patterns have succeeded better in attention tasks that require attention allocation to one visual hemifield (Vollebregt et al. 2015).

When studying the mechanisms of different sensory regions, neural processing is usually measured via electrophysiological measurements. Event-related potentials (ERP) are typically used as a method when focus is set towards sensory regions. Brain rhythms, in turn, are measured when the goal is to get more information on the connectivity of the brain. In case the interest is in continuous brain activation, such as anticipation, different brain rhythms can give valuable information. Cortical rhythms can be studied in terms of memory, learning and attention but also in terms of motor action and cortex-motor coherence. Understanding the role of different rhythms enables one to analyze the data generated from different electrophysiological methods. Different brain areas are important in generating the rhythms, and different rhythms are important in multiple behavioral functions.

It has been argued in several studies that physical activity improves cognitive capabilities, in which attention-inhibition control is needed. In addition, there is evidence that lateralized alpha modulation pattern plays a crucial role in allocation of attention and improves cognitive performance. Regardless of that, there are no studies measuring cortical rhythms of children of varying physical activity level during attention task. Therefore, it is important to study whether the mechanism that enables better cognitive performance from physically active children is somehow related to lateralized alpha modulation pattern. There is a need for new studies to clarify the consequences of physical activity on wide range of cognitive functions.

In this Master’s thesis, the focus is set on the relationship between anticipatory alpha modulation and physical activity level of children. Changes in brain rhythms during cognitive tasks will be measured by magnetoencephalography (MEG). The literature review gives readers the basic knowledge that is needed to follow the research part.

First, previous studies that have measured a relationship between physical activity, cognitive function and brain are introduced. In next chapters, the focus is set more on brain rhythms and their role in cognitive tasks. In addition, the results from motor control studies are described to provide further information on brain oscillations in motor learning. Before the research section, the reader gets acquainted with MEG method and its data analysis. After the introduction of study protocol and methods, the results of the research are reported and these results are discussed with respect to previously published studies.

2 PHYSICAL ACTIVITY, COGNITIVE FUNCTION AND BRAIN

A growing body of evidence has strengthened a link between physical activity and cognition. With recent technical advancements, the focus in contemporary research has been on the mechanisms that explain the influence of exercise participation on cognition, especially on executive functions. Executive functions consist of higher order cognitive processes controlling goal-directed actions. Inhibitory control, working memory and mental flexibility are considered as core executive functions (Diamond 2013).

Several studies have shown either positive or neutral association between physical activity participation and academic performance (Ahamed et al. 2007; Castelli et al. 2007; Kim et al. 2003). In the meta-analytic study of Sibley and Etnier (2003), the significant overall positive association was found between physical activity and cognition in children. The study indicated a beneficial relationship between physical activity and perceptual skills, intelligence quotient, achievement, verbal tests, mathematic tests and academic readiness in school-age children (4–18 years). In terms of memory, no significant positive correlation was found. (Sibley & Etnier 2003.)

In previous studies, participation in physical activity has also affected positively on long-term memory (Ruscheweyh et al. 2011) and selective attention (Owsley & McGwin 2004; Roth et al. 2003) in older adults. These studies have given strong evidence on the protecting effect of physical activity programs on cognitive function of older adults.

Since the studies support promoting effect of physical activity on academic achievements and cognitive performance, the research focus has been set towards brain function from which the associations might be originated. In human neuroimaging studies, exercising has been observed to effect on brain structure and function, especially in regions that are involved in memory (Booth & Lees 2006). Animal research enables researchers to study the effects of physical activity more profoundly in molecular and cellular level. In animal studies, enriched environment has caused positive effects on neuronal growth and on neuronal systems involved in memory and learning (Vaynman & Gomez-Pinilla 2006). In the study of Wikgren et al. (2012), the rats with higher endurance capacity outperformed the low-capacity runner rats in cognitive tasks requiring plasticity of the brain structures. Moreover, in adult rats, physical exercise has promoted hippocampal neurogenesis when exercise has been aerobic and sustained (Nokia et al. 2016). The results support the importance of physical activity on cognitive function and even on brain structures.

The findings from a few magnetic resonance imaging (MRI) studies have shown correlations between structural brain volumes and physical activity level. In particular, higher physical activity level of children has been linked with larger brain volumes in hippocampus and dorsal striatum, which are the regions activated in memory and learning (Chaddock et al. 2010a; Chaddock et al. 2010b). However, genetic factors are still the ones explaining the differences the most (Sowell et al. 2004).

The data of Chaddock-Heyman et al. (2015) shows that aerobic fitness level correlates with childhood cortical gray matter structure that is important for scholastic success, particularly on mathematics tests. They found decreased gray matter thickness in superior frontal cortex, superior temporal areas and lateral occipital cortex from higher fit 9- and 10-year-old children compared to lower fit counterparts. In addition, they succeeded better in arithmetic test. Respectively, in the study of Sowell et al. (2004), cortical thinning in dorsal frontal and parietal regions was associated with improved performance on a test of verbal intellectual functioning.

According to Lee et al. (2016), longer duration of exercise (≥ 1 hr/day) was the only exercise-related variable having an effect on cortical thickness of adults. They found no correlation between cortical thickness and exercise intensity or frequency, when they studied 1 842 adult subjects. Lee et al. (2016) found duration of physical activity to be associated with increased cortical thickness in the bilateral dorsolateral prefrontal cortex.

In multiple brain imaging studies (Chaddock-Heyman et al. 2015; Sowell et al. 2004; Lee et al. 2016), brain activation has been measured from people with varying physical activity level. However, cognitive tests are not always included in the study, even though the direct correlation between physical activity and a certain brain function is occasionally reported. Differences in brain function in a certain brain structure do not necessarily contribute to differences in certain cognitive abilities. The brain areas participate in multiple cognitive functions and cooperate together meaning that cause-consequence -relationship is hard to prove valid. For that reason, it is better to conduct functional brain imaging during cognitive tasks to validate the correlation between physical activity and cognitive function.

Physical activity behavior seems to modulate brain activation also when measured with brain oscillations. Brain rhythms, in turn, might be linked to cognitive functions if measured functionally. Neurophysiological electroencephalography (EEG) studies have revealed increased activation in 4–8 Hz, 8–13 Hz and 13–20 Hz frequency bands in individuals with good aerobic fitness. In addition, mean frequency was higher in 0.25–4 Hz, 4–8 Hz and 13–20 Hz frequency bands in more active individuals. (Dustman et al. 1990; Dustman et al. 1985; Lardon & Polish 1996.)

The activation level of certain brain structures might be modulated already by light physical activity when performed regularly. Older adults, participating in a 6-month walking intervention, showed increased activation in middle frontal gyrus and superior parietal cortex, whereas the activation level decreased in anterior cingulate cortex (Colcombe et al. 2004). The fMRI study showed parallel improvements also in the performance of a selective-attention task. Compared to low fit peers, higher fit children have also shown more efficient brain activation patterns in fMRI- and ERP-measures during attentional tasks (Chaddock-Heyman et al. 2013; Voss et al. 2011).

Another measure of brain function has been cerebral blood flow (CBF). The results from CBF of hippocampus are particularly important, because the function of hippocampus is strongly related to learning and memory. Increases in cerebral blood volume (CBV) of the hippocampus were observed in middle aged participants in a 3-month fitness training study when compared to subjects in control and stretching group

(Pereira et al. 2007). The researchers found that CBV was positively associated with verbal learning, memory and cardiorespiratory fitness. From all the brain imaging methods, cerebral blood -related methods can be most logically linked to physical activity since the blood flow is modulated directly by physical activity.

As a summary of recent studies, static measurements, such as volumetric MRI-variables, have been measured widely from athletes and non-athletes. These studies have indicated connections between physical activity level and several brain structures. However, functional measurements are needed to investigate the brain function during cognitive processes. Static measurements provide information only on different brain structures, whereas the ultimate goal is to understand brain function more profoundly. The relevance of structural differences of brain regions can be confirmed only if the differences exist also in cognitive function.

3 OSCILLATORY ACTIVITY OF BRAIN

Different cortical rhythms characterize brain activity of sensory and motor areas during voluntary movements and somatosensory processing (Figure 1). Different regions of cortex are involved in the generation of brain rhythms. Higher-frequency EEG activity is originated from more restricted neuronal pools than low frequency EEG activity. Alpha activity of 8–12 Hz and theta activity of 4–7 Hz are widespread in anterior-posterior direction. Higher frequency beta activity (12–25 Hz) reflects activity between neighboring cortical sites and gamma frequency (25–100 Hz) reflects activity within localized areas. (Senior et al. 2009, 237–262.) Studies have shown that high-frequency beta and gamma oscillations are primarily generated in the cortex itself (Lopes da Silva 2010, 19–38).

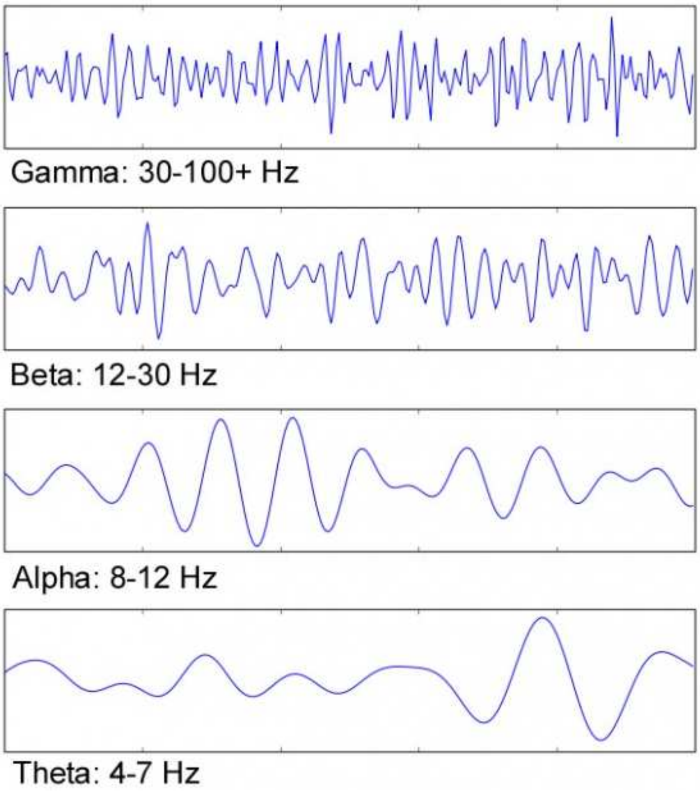

FIGURE 1. Examples of brainwaves in different frequency bands. (Adapted from http://psychedelic-information-theory.com/eeg-bands.)

3.1 Neuronal properties underlying cortical rhythms

Neurons generate time-varying electrical currents when activated. Scientists have identified some essential neuronal properties that play an important role in generating membrane potential oscillations. In the generation of action potentials, voltage-gated ion channels are the most important factors to induce periodic spiking. These ionic currents that are generated at the cellular level consist of transmembrane currents and are called as fast depolarization of neuronal membranes. (Hansen et al. 2010, 2–3.)

Another aspect for oscillatory activity is neuron network through which the neurons communicate with each other via synapses. The communication has a prolonged effect on the timing of spikes in the post-synaptic neurons. Several neurotransmitters mediate the membrane potential by means of synaptic activation. There are two different kinds of slow postsynaptic potentials, excitatory post-synaptic potentials (EPSPs) and inhibitory post-synaptic potentials (IPSPs), which depend on the type of receptor, neurotransmitter and their interaction. (Hansen et al. 2010, 2–3.)

As a result of both excitatory or inhibitory connections and coupling strength, the spike clusters may become synchronized. The neurotransmitter system regulates the wakefulness and arousal, for example, by affecting on amplitude of different brain waves, such as alpha activity. For instance, the projections that brainstem has within brain, influence the concentration levels of norepinephrine, acetylcholine and serotonin. (Muthukumaraswamy et al. 2009.) It is also known that network structures are specialized to promote oscillatory activity at specific frequencies (Hari et al. 2010).

It is also assumed that subthreshold membrane potential oscillations facilitate synchronous activity of neighboring neurons. Cortical cells function the same way as neurons in central pattern generators, since the neurons fire rhythmically at preferred frequencies. Scientists have consensus that the role of bursting neurons is most probably related to enhancement of neuronal resonance. Those neurons behave like pacemakers for synchronous network oscillations. (Malmivuo & Plonsey 1995, 33–43.)

In addition, different neural entities are connected through long-range connections to form a network of weakly coupled oscillators. The connection between thalamus and cortex is an example of long-range connection that can generate oscillatory activity. Feedback loops promote oscillatory activity since they are, in most cases, part of the reciprocal connections. Finally, large brain scale networks are formed from synchronized oscillations recorded from different cortical areas. Coherent activity in numerous brain regions enables the integration of diverged information. (Hari et al. 1997.)

3.2 Event-related synchronization (ERS) and desynchronization (ERD)

The changes in brain rhythms corresponds the changes in neuronal synchrony. Via the changes or modulations of different oscillations the brain codes and stores information it is receiving and transmitting (Senior et al. 2009, 237–262). Rhythmic activity can be utilized to unravel the connectivity between brain areas that work as functional networks. The transfer of information is bidirectional rather than sequential between these brain areas and varies in coupling strength. The function of distant brain areas can be coupled in different frequency bands. For example, cerebellum, motor cortex and premotor cortex are coherent at 8–12 Hz during slow finger movements. (Gross et al. 2001.)

Especially in alpha oscillations, the increase in power, termed event-related synchronization (ERS), is associated with a reduction in activation of a task-irrelevant area, possibly associated with inhibition. In turn, event-related neuronal desynchronization (ERD), i.e. the decrement of power, indicates cortical activity increment or the state of arousal. It has been proved in different motor and cognitive tasks that the more demanding the task is, the higher degree of cortical activation is detected, especially in alpha and beta band. In oscillations up to 25 Hz, the relationship between synchronization and cortical idling can be considered in a way that the more synchronization there is, the less brains have to be processing. As an opposite, when desynchronization increases, brain is required to function in a more inefficient way, which leads to cortical activation. (Senior et al. 2009, 237–262.)

In general, the frequency of brain oscillations is negatively correlated with their amplitude. As a result of this, the amplitude of fluctuations is smaller when the frequency increases. The reason for this relates to the amount of neurons in different cell assemblies: high frequency cell assemblies comprise fewer neurons than slow oscillation cells. Another principle is that the faster the rhythm gets, e.g. a certain rhythm is synchronized more frequently, the more excitable the cortex becomes. (Pfurtscheller et al. 1993.)

3.3 The properties of different brain oscillations

Alpha oscillations. Alpha activity is commonly defined as 8–12 Hz rhythmic brain activity. Until recent studies, the posterior alpha rhythm was related mainly exclusively to cortical idling (Adrian & Matthews 1934 in Pfurtscheller et al. 1996). However, latest electrophysical studies have indicated more active and important role for alpha oscillations in cognitive processing (Palva & Palva 2007). Alpha activity is related to memory function, since good memory performers consistently show 1 Hz higher alpha activity compared to bad performers (Klimesch 1997).

A body of evidence has indicated that allocation of spatial attention is associated with regionally specific changes in alpha oscillations. The function of these brain rhythms has been described by “alpha inhibition hypothesis” that assumes alpha oscillations to provide functional inhibitory system for brain. (Jensen & Mazaheri 2010.)

The alpha rhythm is generated at cortical layers IV and V of the visual cortex (Lopes da Silva 2010, 19–38). Opening of the eyes dampens parieto-occipital alpha rhythm in frequency of 10 Hz (Hari et al. 2010), whereas movement or motor imagery suppresses 10 Hz and 20 Hz frequency component that is measured from motor cortex (Hari et al. 1997). In turn, attention allocation either increases or decreases alpha activity in posterior hemispheres depending on the attended and ignored hemifields (Sauseng et al. 2005; Kelly et al. 2006). It has been proposed that oscillatory alpha activity (8-14 Hz) plays an important role in the activation and inhibition of sensory areas in different cognitive tasks (Haegens et al. 2011). Regardless of the role of alpha activity in active life, the strongest EEG brain signals are still occipital alpha waves that are measured when the eyes are closed (Palva & Palva 2007.)

Beta oscillations. Event-related desynchronization in alpha and beta band is generally related to fine cognitive-motor performance (Klimesch et al. 1997). Beta activity occurs in situations of specific task demand. The distribution of 12-25 Hz activity is less widespread than alpha and the activity patterns are more localized. There is a common consensus that neural networks in the primary motor areas are responsible for the generation of oscillatory beta bursts. Beta activity is responsible for longer-distance synchronization, associated with the activity of long axons of excitatory neurons with high conduction velocities. (Senior et al. 2009, 237–262.)

Higher beta activity is associated with increased alertness in thalamo-cortical systems. Senior et al. (2009, 237–262) observed increases in beta activity with increased precision of motor task. During constant muscle activation, spinal level oscillations become synchronized with beta oscillations of motor cortex. In addition, Senior et al. (2009, 237–262) demonstrated that a change in movement is associated with temporal decreament in beta oscillations. However, the beta oscillations return to initial level if the position is hold again as an isotonic contraction. For this reason, beta activity is associated with a more efficient processing of peripheral feedback.

The range of frequencies in beta is wide and, therefore beta waves are generally grouped into low and high amplitude beta waves. Kühn et al. (2004) observed low amplitude beta activity especially in frontal areas when people practice active thinking, problem solving or are engaged in their work. Higher amplitude beta waves are typically considered to arise from the motor cortex. Its peak frequency of 20 Hz becomes less rhythmic during motor action and planning, whereas the rhythmicity increases following motor actions (Kühn et al. 2004).

In the EEG study of complex motor movement, the group of subjects that practiced the movement with action observation performed better than the control group and the group trained with motor imagery (Gonzalez-Rosa et al. 2015). The action observation group had also the strongest beta synchronization during task performance. As a conclusion, it seems that decrement of cortical activity, that is increment of synchronization, enhances motor performance. In the study, the comparison groups made more errors in the task while the beta synchronization rate was lower. Researchers observed bilateral parietal beta activations to be the strongest predictor for movement execution. In general, it is assumed that increasing cognitive task difficulty leads to increased beta desynchronization. This would mean that the ones with higher beta desynchronization have to process the information the most. Probably these subjects have also a weaker performance in cognitive task, since the task is more difficult for them. The results from motor control study have also indicated enhanced beta band synchronization for better performed subjects, hence the researchers found higher beta band synchronization following a successful movement (Kühn et al. 2004).

Gamma oscillations. High frequency gamma waves (25–100 Hz) are related to neural consciousness via attention mechanism. Magnetoencephalography studies have lately indicated links between gamma activity and sensory processing, especially in the visual cortex. (Engel et al. 2001.) Even though gamma-band activity occurs within localized areas, it also provides a link between functionally discrete areas across the brain. This enables the necessary spatial and temporal connections that bind together different processes within different brain regions. As a result of the integration, coherent perception is finally produced. (Senior et al. 2009, 237–262.)

Theta oscillations. Low frequency theta rhythms can be separated to hippocampal theta rhythm and cortical theta rhythm. Strong hippocampal 4–7 Hz activity has mainly been observed from animals from all the areas that interact strongly with the hippocampus. Low frequency oscillations in animals are associated with REM sleep and active motor behavior. The faster the animal runs, the higher the theta frequency. In animals, it has been suggested that theta rhythm functions as an online state of hippocampus, which enables the animal to prepare for incoming signals. (Buzsáki, 2002.)

In humans, the cortical theta rhythm is more related to meditative or sleeping states. Especially in children’s studies, the cortical rhythm has been observed more clearly. According to Lopes da Silva (1992), the theta rhythm functions as a “fingerprint of all limbic structures”. Since the memory task results seems to relate on the frontal theta wave power, the rhythm is possibly an index of hippocampal activity also in humans. A large body of evidence implies that 4–7 Hz activity is somehow related to spatial learning and navigation. (Buzsáki, 2005.)

4 ALPHA OSCILLATIONS IN COGNITIVE TASKS

Alpha activity over parieto-occipital cortex is supposed to be modulated by visual attention (Foxe et al. 1998). Pfurtscheller (2001) demonstrated increment in visual cortex alpha power during cortical deactivation, whereas decrement in alpha power was linked to cortical activation and enhanced cortical excitability. In previous studies, the activation pattern has been lateralized in visual spatial attention tasks since the posterior alpha activity has decreased contralateral to attended hemifield and increased contralateral to ignored hemifield (Huurne et al. 2013; Kelly et al. 2006; Sauseng et al. 2005). Hence, high alpha power over task-irrelevant areas seems to be crucial for optimal attentional performance (Händel et al. 2011).

The effects of lateralized alpha activity seem to be directly related to succeeding in attention tasks since positive correlation has been found between lateralized alpha activity and visual detection performance (Thut et al. 2006). In support of this, the function of alpha oscillations might be to allocate resources to relevant regions and direct focal attention (Jensen & Mazaheri 2010).

4.1 Attention related cognitive tasks

Several cognitive tasks have been used in brain research to measure the changes in cortical oscillations during different attentional conditions. In general, the tasks used in cognitive brain imaging studies, include competitive stimuli from which the subject has to ignore the distractive stimulus and pay attention to the more relevant one. When attentional processes are under evaluation, a cue is usually presented before the target. A cue directs attention to the left or right visual hemifield, which allows the investigation of alpha power in hemispheres processing attended and unattended visual hemifields (Vollebregt et al. 2015).

Vollebregt et al. (2015) used an adjusted version of Posner's cueing paradigm to study spatial orienting of attention (Posner 1980). They studied how posterior alpha oscillations differ between the hemispheres during anticipation interval in the attention task. The goal in the task was to save a fish from being eaten by a shark. Trial included 500 ms pre-cue periods in which a fish was presented at the center and sharks were presented at each side of the screen. During an attentional 200 ms cue, the fish shifted gaze towards the left or the right shark, which was either valid or invalid cue of the upcoming target side. In the following period (1000–1500 ms), a child was assumed to prepare for the target. After the preparation period, both sharks opened their mouths for 100 ms but the target shark had a mouth clearly wider than the other shark. The child chose the correct side by pressing the button with either index or middle finger within 1400 ms depending on the target side. The cue was valid only in 75 % of the trials. (Vollebregt et al. 2015.)

Attentional network involves two main systems that play an important role in directing attention and controlling goal-directed behavior. Bilaterally functioning dorsal fronto-parietal system is specialized in stimulus-response selection that is essential in intentional activities. The ventral system, lateralized to the right side, detects unexpected stimuli and then activates the dorsal system. Hereby the ventral system is thought to work as an alerting mechanism. (Corbetta & Shulman, 2002.) In Posner's cueing paradigm, the role of dorsal system is to enable early orienting towards a cued location, whereas the ventral system participates in shifting attention towards targets (Vollebregt et al. 2015). According to the alpha inhibition hypothesis, lateralized alpha modulation can be measured during the preparation interval, when goal-directed allocation of attention is expected.

Huurne et al. (2013) used similar cognitive task to study allocation of attention (Figure 2). Each subject had a 45 min session, in which 864 visuospatial attention tasks were presented. During 600 ms of baseline measurements, subject fixated at a cross presented at the center of the screen. Next, two random kinematograms were displayed on both hemifields while the cross was replaced by either arrow or question mark. The direction of the arrow functioned as a cue in 5 of 6 trials, whereas a question mark offered a neutral cue condition. After the preparation interval of 600–1100 ms, the other half of the dots moved horizontally while the dots in the other hemifield moved vertically. Subjects tried to ignore vertical movements and detect the horizontal ones. The direction of the horizontal movement was reported by pressing one of the two buttons.

The cue was invalid in 20 % of the trials. In the study, the results from the task (the reaction times and accuracy for validly vs invalidly cued targets) were studied in relation to posterior hemispheric alpha lateralization of the subjects. (Huurne et al. 2013.)

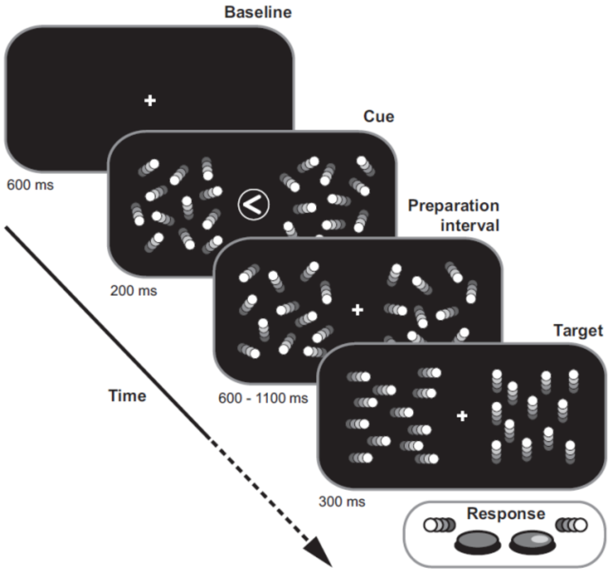

FIGURE 2. Spatial orienting of attention has been studied also with cognitive task, in which two random kinematograms functioned as cues and targets. (Adapted from Huurne et al. 2013.)

In attention related cognitive tasks, the alpha oscillations have been analyzed with several variables. In general, the power of oscillations is represented with time-frequency representations (TFR). Moreover, the TFR is typically compared between the hemispheres or between the different cue conditions (cues presented either on right or left hemifield). Previous studies (Vollebregt et al. 2015; Huurne et at. 2013) have calculated TFR values for both hemispheres to measure whether the alpha power differs in one hemisphere in left versus right cued trials. Hemispheric TFR values indicate the subtraction of alpha power in left versus right cued trials, which has been termed modulation index (MI) (Vollebregt et al. 2015; Huurne et at. 2013), albeit the normalization value has differed between the studies. In addition, Vollebregt et al. (2015) also compared TFRs between the hemispheres by comparing left versus right modulation indices as a combined MI. This comparison provides information from the overall alpha lateralization. In addition to MI values, Huurne et al. (2013) calculated also alpha lateralization index (ALI) for both left and right cue conditions by contrasting the left and right alpha power. The values of ALI_{left} cue and $\text{ALI}_{\text{right}}$ measured whether the alpha band activity differed between the hemispheres in left or right cue conditions. These variables (hemispheric MIs, combined MI, ALI_{left} and $\text{ALI}_{\text{right}}$) have been correlated with several values from behavioral data, such as reaction times and accuracy for invalid cues, to show whether the alpha power variables are related to performance level.

4.2 Alpha oscillations and attention

Attention is often studied with anticipatory tasks that include a cue by which the subject can make decisions based on predictions. In anticipatory visual-spatial attention tasks, subjects demonstrated the alpha band (8–14 Hz) preparatory oscillatory signals that were evident especially for sustained, spatially selective, occipito-parietal cortex modulations of ongoing activity (Grent-‘t-Jong et al. 2011). During pre-target interval, studies have reported either more desynchronization or more synchronization effects in oscillatory alpha power over occipital and parietal sites. For example, the studies of Sauseng et al. (2005) and Kelly et al. (2009) supported the dominance of desynchronization since the oscillatory alpha power decreased contralateral to the direction of attention. In turn, Worden et al. (2000) and Kelly et al. (2006) showed predominantly increased alpha power over ipsilateral sites. This ipsilateral synchronization, seen during visual-spatial cueing, might have a role as an inhibition mechanism that suppresses the distracting task-irrelevant visual input (Kelly et al. 2006).

Vollebregt et al. (2015) studied the posterior alpha band activity (8–12 Hz) of children in spatial cueing task. They found that the children that were less induced by spatial cueing were also the ones whose posterior alpha power was modulated the strongest. Hence, the response times on invalid trials were negatively related to posterior alpha modulation. The alpha power decreased in the hemisphere contralateral to the attended hemifield, whereas relative increment was reported in the ipsilateral hemisphere. It was suggested that high posterior alpha activity could enable the subject to change target of attention more easily. (Vollebregt et al. 2015.)

Balance in amplitude of alpha oscillation across hemispheres provides information from hemispheric alpha oscillations of unattended and attended hemifield, whereby those allow the study of attentional bias. In children, attentional bias towards right visual hemifield has been reported in the studies of Takio et al. (2013) and Vollebregt et al. (2015). However, the adults seem to display a bias towards the left visual hemifield (Manly et al. 2005). Adults with ADHD have demonstrated attentional bias towards right hemifield (Huurne et al. 2013). This has also been present in typically developed subjects with decreased levels of attention (Manly et al. 2005; Dufour et al. 2007; Poynter et al. 2010). Hence, posterior alpha oscillations might give information about individual development level.

4.3 Alpha modulation index

In the study of shark paradigm, the researches aimed to observe a potential task-based modulation (8–12 Hz) from the alpha modulation index (MI) of cue-locked data (Vollebregt et al. 2015). The EEG-data from the study was bandpass filtered at 2–30 Hz, and calculated to time-frequency representations of power by FFT. The time interval used in analyses was 250 ms before to 1500 ms after the cue-onset. The difference in alpha power of right-cued trials from left-cued trials for each electrode was divided by half of the sum of these values to generate the MI. The results from individual electrodes were combined by averaging left and right parietal and occipital electrodes separately (left MI, right MI). Finally, a combined MI was generated as a difference of left and right MI. (Vollebregt et al. 2015.)

In the study (Vollebregt et al. 2015), lateralized alpha modulation was presented with pictures of left and right MI separately (Figure 3). Positive values demonstrated stronger alpha power for left cued trials and negative values demonstrated stronger alpha power for right cued trials. The results showed positive alpha MIs in left hemisphere and negative alpha MIs in right hemisphere especially at 500–1050 ms after cue-onset. Hence, the alpha power was strongly lateralized, such that alpha power was stronger for ipsilateral cues and weaker for contralateral cues. The researchers correlated combined MI values with reaction times for validly and invalidly cued trials and found combined MI to be associated only with invalidly cued trials. (Vollebregt et al. 2015.)

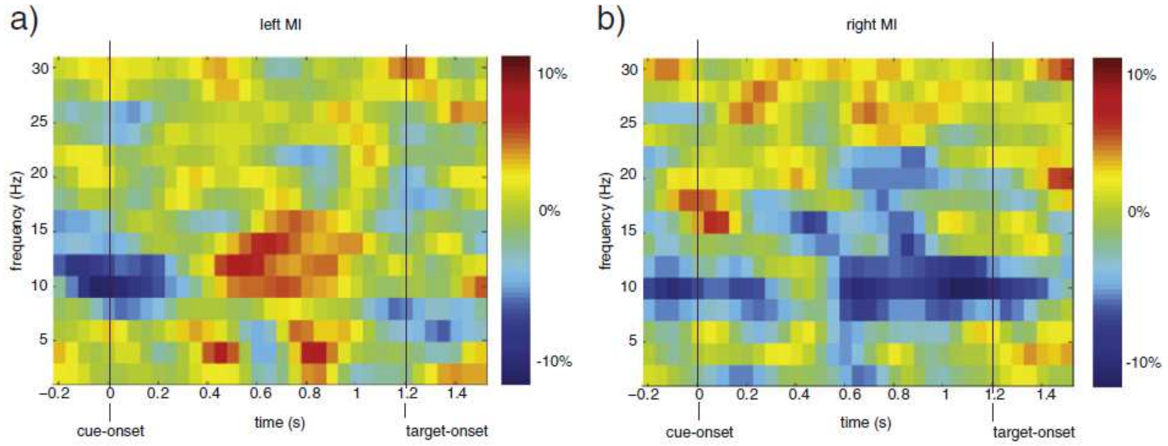

FIGURE 3. The modulation of alpha band power in response to the spatial cue. The alpha power was stronger for ipsilateral compared to contralateral cues in left (a) and right (b) hemisphere. (Vollebregt et al. 2015.)

In the MEG-study, where visuospatial attention task was investigated, the modulation index (MI) was determined to characterize the modulation in oscillatory activity with respect to the direction of attention. The Fast Fourier transformation (FFT) was used to transform the data to time-frequency representations of power (5–30 Hz). Time window for the analyses was 600 ms before to 1400 ms after cue onset. The difference in alpha power in left- and right-cued trials was normalized by the sum of the values, which generated the MI in the study. In addition, eight adjacent sensors with the strongest modulation in the preparation interval were selected from both hemispheres to define a left and a right region of interest. Finally, the alpha lateralization index (ALI) was calculated to demonstrate the alpha power in left versus right hemispheres (normalized by the sum of the values) separately for left ($ALI_{left\ cues}$) and right cues ($ALI_{right\ cues}$). (Huurne at al. 2013.)

The results from both control group and attention-deficit hyperactivity disorder (ADHD) group indicated strongest modulation in 9 Hz to 12 Hz band within pre-target period. The modulation indices of both groups demonstrated a clear modulation in left and right occipital sensors during the preparation interval. However, the groups did not differ significantly in the modulation in either of the hemispheres. Even though the ADHD subjects were capable of modulating posterior alpha oscillations, the differences compared to control group existed in attentional maintenance. The equal alpha lateralization was observed between the groups in attention shifting period, but the lateralization declined in ADHD subjects at the end of maintenance period when the cue was presented to the left visual hemifield (Figure 4). In ADHD group, these results indicated an attentional bias toward right visual hemifield when cued to the left. (Huurne et al. 2013.)

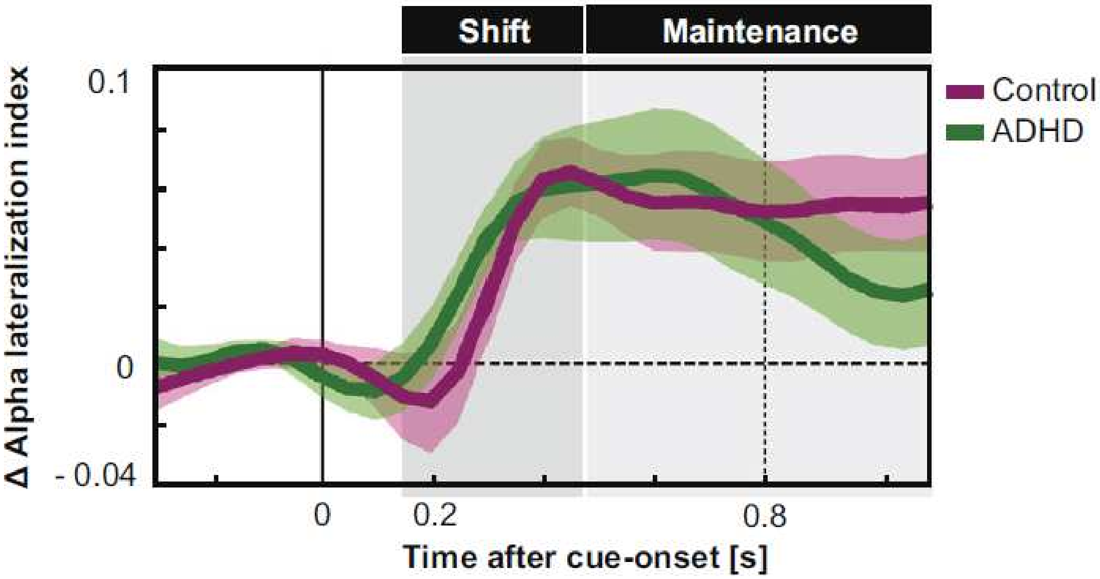

FIGURE 4. Mean Δ alpha lateralization index (ΔALI) over time (mean in dark color, SEM in light color). Both groups showed a shift in lateralization, but the ADHD group showed an inability to sustain the lateralization in the maintenance period. (Huurne et al. 2013.)

5 EFFECTS OF PHYSICAL ACTIVITY ON ALPHA RHYTHM

The rhythmic signals in nervous system function as a connection mechanism within different brain areas as well as between brain and muscles (Senior et al. 2009, 237–262). Hence, the rhythms provide a channel for information signaling between muscles and brain. 8–12 Hz rhythm can be measured from both motor control and cognitive tasks. However, in motor control studies, 8–12 Hz activity is called rolandic mu-rhythm and it is measured from sensorimotor cortex (Pfurtscheller & Lopes da Silva 1999). The mu-rhythm over the rolandic areas consists of signals at about 10 Hz and 20 Hz. Lower frequency signals appears to be true somatosensory rhythm, whereas the higher frequency rhythm reflects activity from pre-central motor cortex. (Hari et al. 1997.) In spite of the difference to visual alpha rhythm, the term alpha activity is often used also in motor control studies even though the rhythm is measured from the sensorimotor regions instead of the visual cortex. Taking into account the signaling function of the rhythms, 8–12 Hz oscillations have most likely similar functions in brain, even though the visual alpha rhythm and motor alpha rhythm can be measured from different brain areas.

The physiological function of rolandic mu-rhythm is still unknown (Phurtscheller & Lopes da Silva 1999). Regardless of that, rolandic mu-rhythm is a relevant factor in motor control studies as it seems to be attenuated by voluntary movement (Babiloni et al., 1999). The sensorimotor areas, where 8–12 Hz activity exists, are assumed not to be in function in certain time. For that reason, rolandic mu-rhythm is considered to be inhibitory. Similarly to visual cortex occipital alpha waves, rolandic mu-rhythm has been considered as an idling rhythm that is related to sensorimotor cortex. (Pfurtscheller et al., 1996.) The rhythm appears when the subject is at rest and blocked by movement (Lopes da Silva 2010, 26). In addition, the rhythm can be observed basically from all the subjects after the movement (Hari et al. 1997). Nevertheless, contemporary research has suggested more active role also for mu-rhythm since the enhancement of mu-rhythm has been observed during the tasks involving working memory (Klimesch et al., 1999). In addition, mu-rhythm might facilitate the information processing, since it reflects functions from separate thalamocortical loops (Hari et al. 1997).

The results from previous studies indicate an important role for 8–12 Hz activity in both cognitive (Thut et al. 2006; Vollebregt et al. 2015) and motor performances (Deeny et al. 2003; Babiloni et al. 2008; Cooke et al. 2015), but it is unclear how much the adaptations in one rhythm effect on the other. In general, physical activity studies have showed significant differences between elite athletes and non-athletes in alpha band mu-rhythm when measured in rest and during motor execution (Douw et al. 2014; Völgyi et al. 2015).

5.1 Adaptations of cortical rhythms to long-term physical activity

Resting state MEG and physical activity level were measured from 4-5 years old children in the study of Völgyi et al. (2015). The activity level was measured objectively with accelometer that subjects used for two days. The average total step count was 7870 steps daily. Body composition was evaluated with Dual-energy X-ray to assess fat mass and lean mass as accurately as possible. FFT was completed for delta (0–4 Hz), theta (4–7 Hz), alpha (8–12 Hz) and beta (12–20 Hz) frequencies. The results showed statistically significant correlation between moderate-level physical activity and alpha activity in the central region. In addition, left hemisphere alpha activation in central region correlated positively with time spent performing sport. Concluded from the results, body composition is not necessarily as strong predictor of resting state alpha activity as the level of physical activity. (Völgyi et al. 2015.) According to the study, higher levels of physical activity seem to be related to oscillatory activity that is assumed to be crucial in higher cognitive functions.

The hypothesis of neural efficiency of athletes was tested in the study comparing the modulation of alpha rhythm in non-athletes and athletes (Percio et al. 2010). Ten karate athletes and 12 non-athletes participated in the study where voluntary wrist extensions were measured during EEG recordings. Cortical activation (ERD) was determined by power decrement of high-frequency alpha (10–12 Hz) during the motor preparation and execution. In the results, athletes were observed to have lower alpha ERD in primary motor area and premotor areas during both preparation and execution of dominant right hand movements. With left hand movements, 10–12 Hz ERD decreased only during movement execution. Lower amplitude of bilateral frontal and central alpha ERD in elite athletes might underlie the role of alpha rhythms in spatially selective cortical action of frontal motor system. (Percio et al. 2010.) The results support the hypothesis of diminished cortical activation in elite athletes during simple movements. According to the results, it can be concluded that motor cortex activity is strongly related to previous exercise background. Furthermore, lower activation of motor cortex seems to be beneficial for the performance since fewer amounts of resources are used for motor planning and execution.

In the study of Douw et al. (2014), resting state MEG was conducted for 41–44 -year old women to test whether neural network organization is related to cardio respiratory fitness and cognitive functioning. The analysis was done for six frequency bands from delta to gamma frequencies. The results of physical activity level were based on subjects' six years old maximal voluntary oxygen uptake ($VO2_{max}$) results that were measured in previous longitudinal study with the same subjects. The $VO2_{max}$ correlated well between subject's adulthood and childhood $VO2_{max}$ values. Positive association between intelligence quotient and $VO2_{max}$ was observed, whereas negative correlation was found between $VO2_{max}$ and upper alpha and beta band modularity. In the study, modularity referred to the amount of coherent subsystems in brain. The researchers concluded that not only physical fitness and cognitive functioning are related, but also their association has a relation to topology of the functional brain network in resting-state condition (Douw et al. 2014). These results support the hypothesis that physical activity induces brain modulations that are crucial in cognitive functions.

5.2 The effect of cortical rhythms in motor control tasks

Alpha activity is also involved in learning of a complex coordination movement during action observation. In fact, desynchronization in alpha band seems to be related to neural efficiency in sport experts. The smaller amount of alpha power is observed, the better prediction the subject has for succeeding in demanding motor task. In the study of complex motor task, alpha-related power decreased the most in the group of action observation subjects during training period. Later this group also performed with the fewest mistakes in the motor task. As a conclusion, cortical activation in the alpha band, which is equal to event-related desynchronization in this context, seemed to promote learning in complex motor task. The changes in alpha activity during training were more evident in posterior brain areas. (Gonzalez-Rosa et al. 2015.)

In a motor control study (Douw et al. 2014), pre-movement high-alpha power was negatively correlated with movement accuracy. Ten expert and ten novice golfers performed 120 putts in a row while alpha activity was measured with EEG. Especially in experts, pre-movement alpha power was lower following error putt. The researchers assumed that after errors the subjects allocated more resources on motor programming. Hence, the amount of resources allocated in motor response could be predicted from pre-movement high-alpha power level. Particularly, decreased high-alpha power in frontal and central areas were associated with succeeded movements (e.g., holed golf puts) (Cooke et al. 2015). Admittedly, lower alpha power is not only indicator of higher task difficulty (Percio et al. 2010), but it might also suggest subject's higher effort for the task, for example after error. For that reason, some of the alpha power changes might remain unclear if the performance is not tracked during the measurement of brain oscillations.

Similar findings have been observed also from the study of Babiloni et al. (2008), where the interest was set towards cerebral rhythms and fine motor control of elite golfers. The study protocol included use of EEG and stabilometric recordings in 12 subjects. While the subjects performed 100 golf putts at a golf green, the changes in alpha and beta power were recorded during each pre-movement period. The putts were analyzed as successful or unsuccessful movements according to the distance from the hole. The results represented a strong correlation between the reduction of high-alpha power in right sensorimotor area and decreased distance from the hole. (Babiloni et al. 2008.) As a conclusion, the role of high-frequency alpha rhythms in premotor, associative and non-dominant primary motor areas seem to be related to motor control and golfers' performance. Like in Douw's et al. (2014) study, higher effort that was seen by lower alpha power indicated better performance in golf putts. Seemingly, lower alpha power might indicated better performance in simple motor tasks, but in more complex ones, higher alpha power is needed for better performances.

A study of cortico-cortical communication has also revealed interesting connections of alpha and beta frequency bands and motor control. When expert marksmen and skilled shooters performed four seconds aiming period prior to trigger pull, cortico-cortical coherences differed significantly between the groups. The EEG data revealed that the better performed experts engaged in less cortico-cortical communication compared to skilled shooters. The coherence was significantly lower between left temporal association and motor control areas in experts. As a conclusion, researchers assumed that the experts did not use cognitive processes with motor function as much as less skilled shooters. (Deeny et al. 2003.) In turn, these results could suggest that in fine motor actions the result is better if cognitive processing does not consume too much resource that is needed for simple but extremely accurate motor function.

6 MAGNETOENCEPHALOGRAPHY

In human, all the cognitive processes, motor actions and percepts rely on accurate neuronal timing ranging from milliseconds to seconds. Such temporal activities can be tracked with electrophysiological methods, such as electroencephalography (EEG) and magnetoencephalography (MEG). The brain activity, measured with EEG or MEG, contains both rhythmic and irregular components that can be studied in both time and frequency domains. Typically, the frequencies concentrate below 30 Hz and are affected by subjects's vigilance, task or disease (Hari et al. 2010).

MEG is a direct measurement of neural activity. The brain imaging method uses sensors that are extremely sensitive to changes in magnetic fields produced by changes in the electrical activity within the brain. (Hämäläinen et al. 1993.) The detected signal reflects real-time information transfer between neurons, which is the strength of both MEG and EEG method (Hansen et al. 2010, viii). Main power of EEG and MEG brain rhythms are in a frequency band of 4–40 Hz. The most prominent spontaneous brain rhythms occur around 10–20 Hz and react strongly to external stimuli and subject's state. (Hari et al. 2010.)

In brain imaging, electrophysiological measurements utilize changes in postsynaptic potentials. Even though EEG and MEG are based on the same physical principles, different sensors are used for detecting the signals. The advantage in MEG over EEG is that the magnetic field recorded outside the head is the same as the one recorded on the brain surface. This allows more accurate monitoring of cortical activation sequences and improves reconstruction of the signal during the analysis process. In EEG, electrical fields are strongly influenced by changes of electric conductivity between different tissue types, such as brain, membranes and cerebrospinal fluid. Changing conductivity causes distortion of the EEG signal while the signal travels from deeper brain structures towards the surface of the brain. In MEG, there is markedly less distortion in the signal since the magnetic field is not affected strongly by conductive properties. (Hari et al. 2010.)

Multiple methods are used to study changes in the activity of cortex. The strength of the field depends on the strength, distance and geometry of the current distribution (Hari et al. 2010). Each method has its own pros and cons and, in some cases, part of the data cannot be observed with certain method. Cortical rhythms are based on timing, and that is why the temporal resolution of the method needs to be high enough.

6.1 Overview of the method

MEG is a method that provides spatially and temporally accurate signal with reliable localization of active brain areas. The theoretical difference between biomagnetic and bioelectric signals is in the differences of their sensitivity distributions. Because of this, the results differ from each other when exactly the same measurements are conducted with either MEG or EEG. MEG senses accurately tangential currents, because the sensitivity of the magnetic leads is orientated tangentially. An advantage in MEG is its sensitivity to fissural cortex activation, where currents flow tangentially to the skull. The activation of fissural cortex cannot be reached with any other electrophysiological means, including intracranial recordings. In case of MEG, poor conductivity of the skull does not have an effect on the lead field. (Hari et al. 2010.) In EEG, skull suppresses strongly the signal and effects on the observed electrical currents. In turn, currents from deeper layers can be measured well with EEG if the orientation is appropriate, whereas MEG measures principally only currents in the cortex. (Hämäläinen et al. 1993.)

For optimal summation, the contributing structures need to be in proximity and oriented in parallel. Thus, the MEG signal is mainly produced by postsynaptic tangential currents in apical dendrites of pyramidal neurons in the neocortex. Coherent magnetic fields are generated in pyramidal neurons when those are activated synchronously. Moreover, postsynaptic potentials last longer than action potentials, and they are thus more likely to overlap in time. Pyramidal neurons, that are primary intracellular current, behave as current dipoles since their activity can be measured by sensors placed over the skull. (Hari et al. 2010.) The magnitude of source strength is presented in Figure 5.

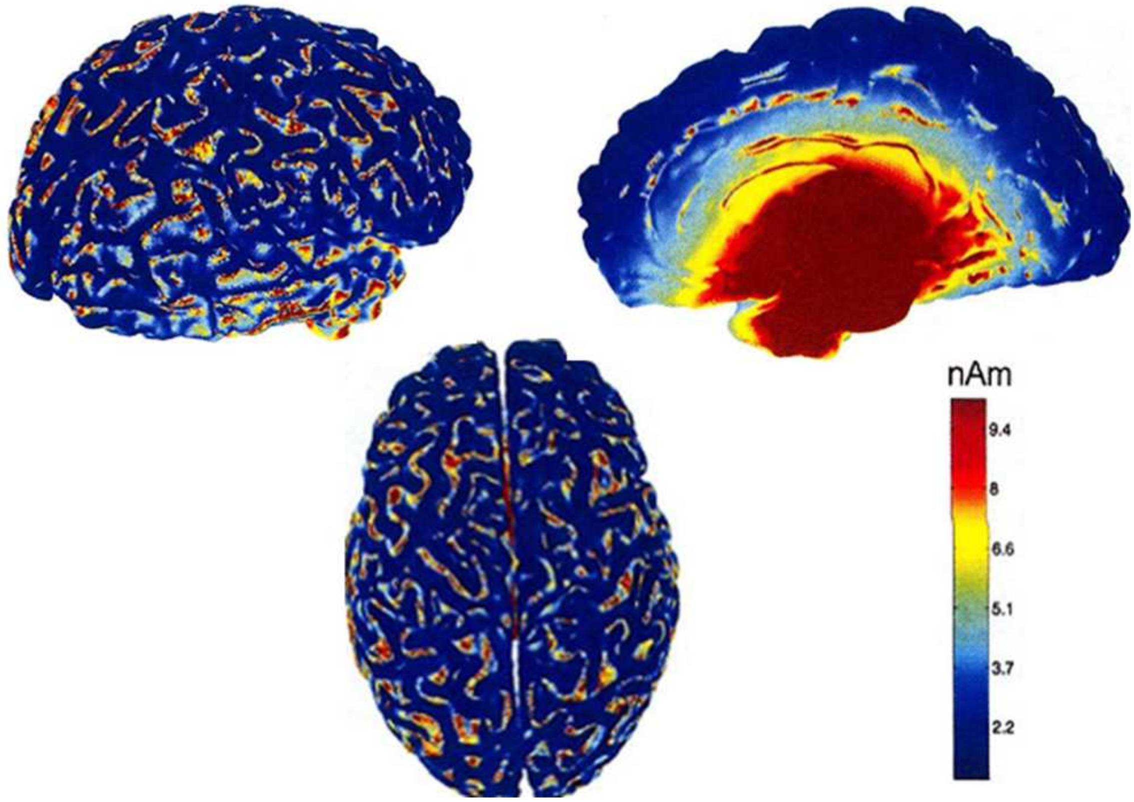

FIGURE 5. Maps of the source strength needed to obtain a detection probability of 70 % in MEG. In deep sources, the strength of the source has to be at least 10 nAm in order to be detected. (Adapted from Hillebrand & Barnes 2002.)

MEG is based on magnetism phenomenon, in which the electrical current produces magnetic field. The direction of magnetic field can be determined according to the right-hand rule (Figure 6). It is assumed that 50 000 active neurons are needed to cause a detectable signal (Okada 1983 as cited in Williamson et al., 399–408.) The challenge with MEG and EEG is to define the location of electric activity within the brain, since the measurements are done from outside the skull. The variables to be taken into account in MEG imaging are the electric origin of the magnetic signal and the sensitivity distribution of magnetic measurement. The electrical signals within brain are weak and therefore detectable only with the superconducting quantum interference device (SQUID) that is sensitive enough for high-quality biomagnetic measurements. In contrast to EEG, MEG is reference-free in the sense that the measured signal need not to be compared with signal from another location. (Hari et al. 2010.)

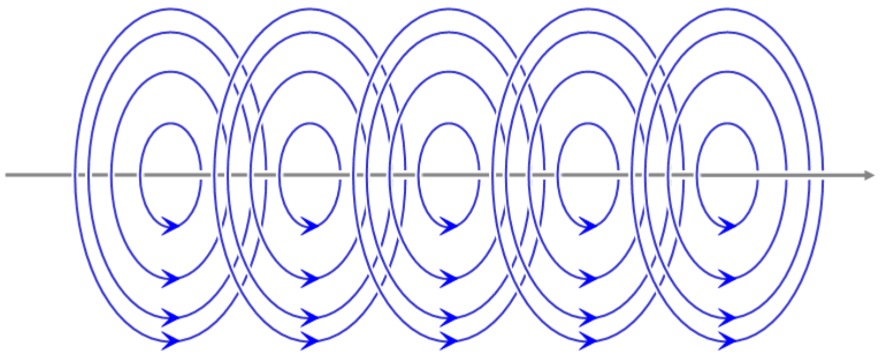

FIGURE 6. The grey line presents the current and the circles present the direction of magnetic field induced. The magnitude of the magnetic field is proportional to the distance from the symmetry axis. With right-hand rule the direction of magnetic flux is easy to determine: if a thumb of right hand is oriented with the current, then other fingers point out the direction of magnetic flux. (Adapted from Malmivuo & Plonsey 1995, 232.)

In MEG, the detector coils are constructed from two different coil types, named magnetometers and gradiometers (Figure 7). The options for gradiometers are first- or second order gradiometers and planar gradiometers. In the first mentioned coils, two or three gradiometer coils are arranged in a row, one on top of the other. Planar gradiometers, in turn, have two adjoining circular detector coils that are connected together to form the shape of figure 8. The planar gradiometer detects the signal if positive magnetic flow passes the one loop and negative flow the other one, at which the magnetic fields are to the opposite directions. This means that the current must pass through the symmetric axis of 8-shape coil. Hence, the most probable location of the signal source is in the middle of figure 8, since the sensitivity is the highest under the spot. (Malmivuo & Plonsey 1995, 260–274.)

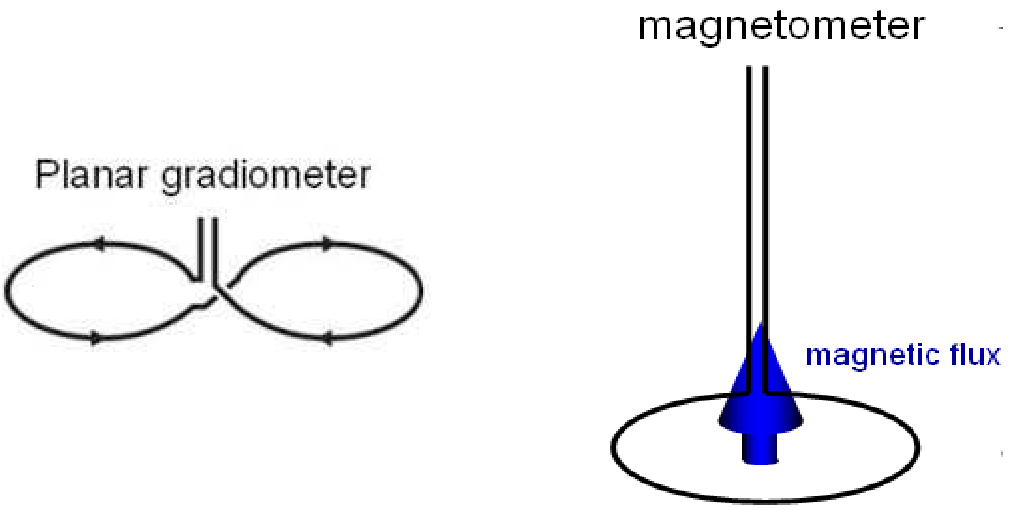

FIGURE 7. The layouts of planar gradiometer and magnetometer. To detect the signal in gradiometer, the magnetic fluxes need to pass the loops to opposite directions. In magnetometer, magnetic flux needs to pass the loop perpendicularly in order to be detected. (Adapted from http://meg.aalip.jp/scilab/CoilType.html.)

Usually in MEG devices (e.g. Elekta Neuromag) the single loop coils, called magnetometers, are added to the design so that each measurement point includes two gradiometers and one magnetometer. The electric signal source has to pass outside the loop to be detectable with a magnetometer, because magnetometer senses only the magnetic flux that passes through the loop. Therefore, the detected signal originates from sources located mainly in the region closest to the detector. The distance between the coil and the signal source has a more powerful effect on planar gradiometer's sensitivity distribution than magnetometers (Figure 8, Figure 9). All the coils are assumed to be located in the same plane and the orientation of the detector coil is parallel to the surface of the skull. (Malmivuo & Plonsey 1995, 260–274.)

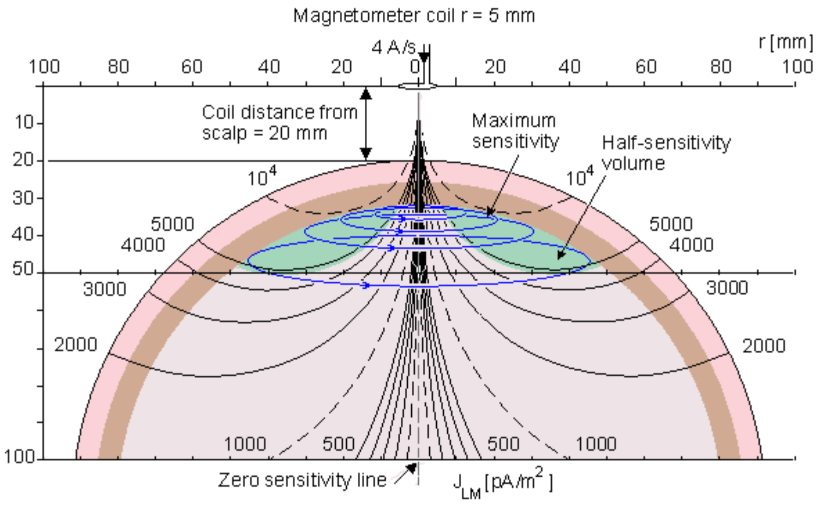

FIGURE 8. Isosensitivity lines in MEG measurement are presented with a single coil magnetometer. The sensitivity is everywhere oriented tangential to the symmetry axis which is the line of zero sensitivity. Within the brain area the maximum sensitivity is located at the surface of the brain. (Adapted from Malmivuo & Plonsey 1995, 267.)

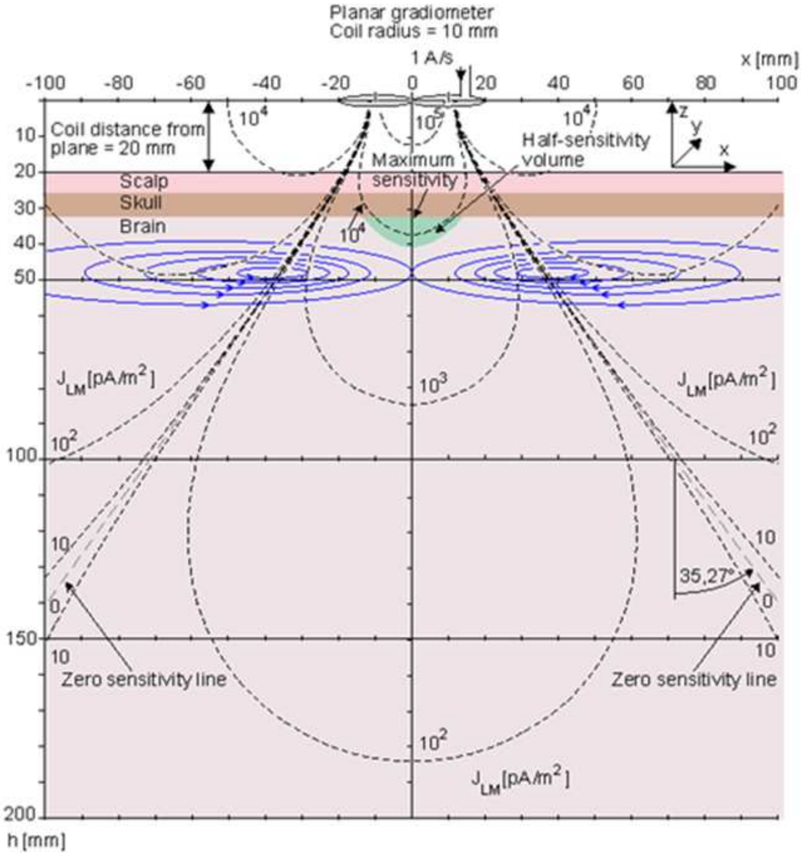

FIGURE 9. Isosensitivity lines are presented with dashed lines in planar gradiometer model. Lead field current flow lines are drawn with thin solid lines. Maximum sensitivity is induced in the middle of the coil. (Adapted from Malmivuo & Plonsey 1995, 269.)

An efficient way to protect MEG sensors from far-away interference sources is to use gradiometers instead of magnetometers since the gradiometer's response to a source falls off faster with distance than magnetometer's. However, magnetometers are still important, when the interfering signal of helmet needs to be extrapolated from the measurements at the reference sensors. For this reason, the sensor array usually includes both magnetometers and gradiometers. (Hansen et al. 2010, 48.) A whole-head MEG system includes 100–300 MEG channels from which the data is sampled in parallel (Hansen et al. 2010, 44).

6.2 The analysis of MEG signal

The output of MEG is a signal detected from the surface of the skull. Part of the MEG analysis is to localize the neural sources of electric current within the brain. The detector coils record the time-course of the changes in magnetic fields by which the analysis can be done. Hence, the estimation of MEG sources requires computational models of the biophysical sources and of the volume conductor. (Hansen et al. 2010, 14.)

A head as a volume conductor is composed of different particles (scalp, skull, cerebrospinal fluid layer and brain) and each of those has different conductive properties. When EEG is used, different conductive properties effect on the signal much more than with MEG. The simplicity in modeling is a significant advantage in MEG over EEG. (Lopes da Silva 2010, 19–38.)

In contemporary research, the MEG data is recorded in continuous mode, in which the time windows are not determined beforehand. Hence, the raw signal is measured during the entire task and later on it can be used either with time-locked tricers or as a continuous data (Hansen et al. 2010, 45).

In addition to MEG measurement, usually anatomical MRIs are also taken. Then the results can be visualized on anatomical MRIs, which enable more reliable localization of the source currents (Hansen et al. 2010, 24). Complete MEG systems also include head-position tracking coils that can be utilized in the analysis stage (Hansen et al. 2010, 39).

Preprocessing of MEG signal includes noise reduction and artifact detection and removal. At the end, the MEG signal is usually averaged and filtered in time and space to improve signal-to-noise ratio. The sampling rates of MEG signal range between 300 HZ and 4 kHz resulting from MEG signal frequencies and Nyquist condition. (Hansen et al. 2010, 41.)

Limitations of MEG. The problems of source modeling and poor spatial resolution of EEG have been overcome with MEG. However, it is important to remember that even though MEG data allow estimation of the center of an active brain area, it does not model its shape (Hansen et al. 2010, ix). Regardless of all the advantages in MEG, the sensitivity might be reduced due to its insensitivity to radial sources. Another limitation might be the artefact that metallic objects cause in extremely sensitive SQUIDs if the objects move in the body. (Senior et al. 2009, 237-262.) However, in most cases the subjects with metallic implants can be measured with MEG since the artefact can be removed if the artefact originates from outside the brain area. For example, Signal Space Separation (SSS) can be utilized in the analysis if the subject has dental braces (Taulu et al. 2005).

7 PURPOSE OF THE STUDY

Since the recent studies have demonstrated a relationship between structural brain variables and physical activity level (Booth & Lees 2006; Vaynman & Gomez-Pinilla 2006; Chaddock et al. 2010a; Chaddock et al. 2010b; Lee et al. 2016), there is a need to study if these physical activity induced differences can be observed also from functional brain measurements that are conducted during cognitive processing. The differences that have been observed from numerous brain structures become relevant only if the differences exist also in cognitive function and, hence, really effect on cognitive performance. In this study, the brain oscillations are measured during cognitive task to see whether the differences can be observed during visuospatial anticipation task. However, the analysis of cognitive performance will be based on previously conducted similar studies.

Previous studies have indicated a relationship between posterior alpha oscillations and attention-related cognitive performance (Thut et al. 2006; Kelly et al. 2009; Händel et al. 2011). On the other hand, these oscillations have been studies from children (Takio et al. 2013; Vollebregt et al. 2015) and adults (Manly et al. 2005), but also from adults with ADHD (Huurne et al. 2013). Comparisons of these oscillations have shown that children and adults differ in their alpha lateralization since attentional bias seems to be more towards right hemifield in children and more towards left hemifield in adults. In addition, ADHD subjects have demonstrated more children-like alpha lateralization. These differences could indicate a development-related role for alpha oscillation. However, the evaluation of the role of physical activity on attention-related alpha lateralization has not been conducted before.

This study will contribute to enhanced understanding of anticipatory alpha oscillations and its adaptations to physical activity in children. The research questions for this study:

1. Are alpha oscillations lateralized in general in 12–16 year old children during anticipation period?

2. Is alpha lateralization different in children with high and low endurance abilities in anticipation period?

The first research hypothesis is that posterior alpha (8–12 Hz) power is lateralized in attention task when measured from 12–16 years old children by MEG. This could be assumed from previous studies indicating posterior alpha band lateralization in attention task (Thut et al. 2006; Kelly et al. 2009; Händel et al. 2011; Huurne et al. 2013; Vollebregt et al. 2015). Additionally, the focus is set towards the time interval in which the lateralization is most pronounced. Another research hypothesis is that posterior alpha band activity is different in children with high and low endurance abilities. This can be hypothesized since the children with higher physical activity have performed better in numerous cognitive tasks (Sibley & Etnier 2003; Castelli et al. 2007; Kim et al. 2003), and moreover, better performance seems to be related to higher posterior alpha lateralization.

To the best knowledge of the author, there are no published studies evaluating posterior alpha band lateralization between high and low fit subjects when measured during attention task.

8 METHODS

8.1 Participants

During autumn 2015 and spring 2016, 47 voluntary seventh, eighth and ninth graders (27 girls, 20 boys) participated in the study. The subjects were selected from two databases obtained from previous studies (Young Finns Study (n = 2060) and Finnish Schools on the Move Study (n = 900)). The children originated from two different municipalities in Jyväskylä area and from Helsinki area. The average age of the subjects was 14.25 ± 0.94 years. The subjects were divided into two different groups according to their physical activity level. High fit group included 21 subjects, whereas remaining 26 subjects formed a group of moderate-to-low (mod-low) fit. The handedness of each subject was measured by the Edinburgh Handedness Inventory (Oldfield, 1971), which resulted 45 of 47 right handed subjects.

Prior to the study, the subjects fulfilled a questionnaire with their parents to ensure that they were not suffering from any neurodevelopmental or psychiatric illness or they did not have contraindications to MEG measurements, such as metallic implants in their body. In the laboratory, the subjects filled an Informed Consent with their guardian. All the subjects were informed about the content of the study and their right to withdraw at any time. Each subject had to participate in endurance running test and monitor their daily activity for a certain time to be approved as a subject in the study. MEG measurements were carried out in Advanced Magnetic Imaging (AMI) Centre in Aalto University and MEG laboratory in the Centre for Interdisciplinary Brain Research in University of Jyväskylä. The study was approved by Helsinki and Uusimaa Ethics Committee.

The children were grouped into high fit and mod-low fit groups according to their endurance running test results. Physical activity and sedentary time were measured from each child during school day and leisure-time. ActiGraph accelerometer was used as an objective measurement to record the physical activity of children for seven days. During the monitoring period, subjective measurements were also used since the children self-reported their physical activity and sedentary time. Maximal endurance running capacity was measured by shuttle run test in Move! test battery.

High-fit group resulted with 61.66 ± 21.46 min daily physical activity on average whereas mod-low fit group resulted with 44.71 ± 14.23 min respectively. The average shuttle run test score was 8.02 ± 1.57 min for high fit group and 4.26 ± 1.58 min for mod-low fit group. The national average score of secondary school pupils in shuttle run test was 5.6 min.

8.2 Study procedure

The study protocol was first introduced to the child and guardian. The handedness of the child was tested before the actual measurements by Edinburgh Handedness Inventory (Oldfield, 1971). In the test children had to use their preferred hand in daily chores, such as paper cutting, handwriting and eating with a spoon.

To avoid magnetic artifacts, all the metallic objects were removed from the subject. For the preparation, subject was asked to sit in a digitizing chair. To record the eye movements, five electrodes were placed on the head. The skin was prepared with alcohol, and electrode paste was applied to each electrode before attaching them to the skin. An electrode was placed above the right eye and another below the right eye. Two electrodes were placed at the temples, one to the left and one to the right of the eyes. The ground electrode was placed on the subject’s neck.

The machine used in the MEG-measurements was Elekta Neuromag Triux System, which includes head-position indicator (HPI) system and three-dimensional digitizers. The system enables one to determine the position of the head with respect to the sensory array. In the study, five HPI coils were used. One of the HPI coils was placed frontally up in the middle near the hairline. Two HPI coils were placed near the hairline to both sides of forehead. Remaining two marker coils were placed near the head behind the ears as high as possible. The HPI coils were attached using skin tape. Three landmark points (nasion and two pre-auricular points) were marked using a three-dimensional digitizer attached to the acquisition computer. After that, the digitizer was used for drawing the circumference of the subject's head, which enabled the ultimate modelling of the head.

Before entering to the magnetically shielded room, the subjects were asked to wear non-magnetic goggles in case they were wearing glasses. The task was then introduced to the subjects with standardized guidelines.

In magnetically shielded room, the subject was placed to the chair. The chair was elevated until the coils on the head were well inside the helmet. The distance from the stimulus screen was 1.0 meter and the fixation point in the middle of the screen was set in the middle of the subject's visual field. The response device was set on a table located over the subject's legs connected to the chair. The child was instructed to sit in the chair as still as possible. Finally, the researchers ensured that the subject felt comfortable in the chair and saw the screen accurately enough. Before closing the door of the room, the subject practiced the task for a couple of minutes by theirself and researchers make sure that they understand the task correctly. The audio connection to the room was also checked before the actual measurements.

8.3 Attention task

In the study, Vollebregt's et al. (2015) attention task was used for studying spatial orienting of attention. In the task, originally adapted from Posner (1980), the goal was to save fish from being eaten by a shark. Each subject performed four blocks with 100 trials per block. Between blocks the subjects were allowed to rest during some minutes until they expressed being ready for the next block.

In each task, the fish was presented in the middle of the screen as the fixation point, whereas the sharks were presented on both sides of the screen (Figure 10). This pre-cue period lasted for 500 ms. While the subject was fixating at the fish, the cue was presented when the fish gazed towards either left or right shark quickly (200 ms). The left and right cue occurred with equal probability. In the following 1000–1500 ms, the child prepared for the target. After the preparation period, both sharks opened their mouths (100 ms). The assignment was to choose the shark that opens the mouth wider than the other. The child had to press a button in the response device as quickly as possible within 1400 ms, when the target shark was chosen. Only in 75 % of the trials the cue was valid, meaning that the gaze of the fish was to the same direction as the target shark. The child got positive or negative feedback (500 ms) right after each button press.

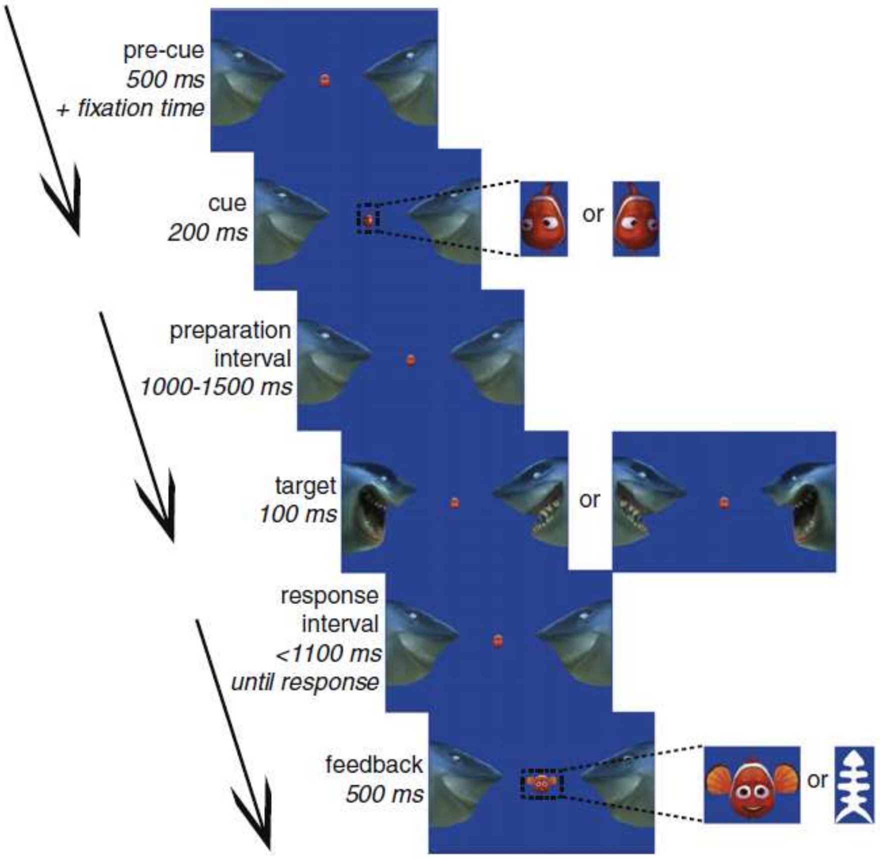

FIGURE 10. The attention task. A cue (gaze of the fish) was presented either on left or right visual hemifield. After the preparation interval, the target (a shark with a wider mouth) was presented either on validly or invalidly cued hemifield. (Adapted from Vollebregt et al. 2015.)

8.4 Magnetoencephalography data acquisition

MEG signals were recorded using a Vectorview™ system (Magnetom Skyra, Siemens and Elekta Neuromag TRIUX). The devices comprises of 306 sensors arranged in triplets (two planar gradiometers and one magnetometer).

At the beginning of the measurement, the location of the head with respect to the sensors was defined with five HPI coils. After 0.03–330 Hz band-pass filtering, the signals were sampled at 1000 Hz. Eye movements and blinks were monitored with vertical and horizontal electrooculography (EOG).

8.5 Analysis of MEG data

Movement correction of the data using Signal Space Separation (SSS) (Taulu et al. 2005) included in Maxfilter 2.2 software was completed for all the subjects. For the recordings from subjects wearing dental braces, Signal Space Separation with temporal extension (tSSS) was used. The rest of data preprocessing was performed using Meggie software (Leppäkangas, 2015), such as heart beat corrections with electrocardiogram (ECG) and eyes movement corrections with electrooculogram (EOG). Segments of data showing other kind of artifacts were visually inspected and removed from the recordings. The segments of data where saccades were identified (showing that the subject was not looking at the fixation point) were also removed. Further analysis of MEG data was performed using MNE-Python software (Gramfort et al. 2013).

The data was decomposed in frequency bands using FFT (Fast Fourier Transform). The time-frequency representations (TFRs) of power in a frequency range of 2–30 Hz were calculated after FFT. The TFRs were calculated for a time period of 0.2 sec before to 1.4 sec after cue-onset with frequency resolution of 2 Hz. The length of the time window was determined to be fixed in relation to frequency, meaning decreased length with increased frequency ($\Delta T = 5/f$). Only trials in which the child fixated were used for further analysis. To reduce the spectral leakage and control the frequency smoothing, a Hanning taper was used in TFR calculations.

The alpha modulation index (MI) was used to evaluate a task-based modulation in alpha band (8–12 Hz). The MI was determined to each parietal and occipital sensors with following equation:

$$MI = \frac{alpha_{\,left\ cued\ trials} - alpha_{\,right\ cued\ trials}}{\frac{1}{2} * (alpha_{\,left\ cued\ trials} + alpha_{right\ cued\ trials})}$$

The MI was averaged over parietal and occipital sensors separately on right (right MI) and left (left MI) hemispheres. The time windows of 100 ms were used in MI calculations. Combined MIs were calculated by subtracting right MI from left MI. The method was adapted from Vollebregt's et al. (2015) EEG study, where averaged parietal and occipital electrodes were used to determine MIs.

8.6 Statistical analysis

Non-parametric tests were applied for the analysis of MI results, since the MI data (left MI, right MI, combined MI) were not normally distributed and consisted of outliers. For statistical analysis, the hemispheric TFRs were averaged in 100 ms time intervals (-200–1400 ms) before the calculation of MIs. Hence, the MI values used in the analysis were averaged alpha power values from 100 ms intervals.

Non-parametric Mann-Whitney U test was utilized for the group comparisons of left and right MIs. The analysis was used to investigate whether the groups differed in hemispheric alpha power in contralaterally and ipsilaterally cued trials. Combined MIs were analyzed to evaluate whether the alpha modulation differed between the groups. Mann-Whitney U test was used for group mean comparisons in combined MIs for each 100 ms time interval. In addition, left versus right MIs were also analyzed by Wilcoxon signed-rank test.

Correlations were calculated between the MIs and shuttle run test results and between the MIs and physical activity. In correlations, the results of left MI, right MI and combined MI were considered separately. Spearman correlations were used to study whether the alpha MI correlated significantly with daily physical activity or maximal endurance test result.

To test the assumption of normality, Kolmogorov-Smirnov test was applied for physical activity and shuttle run results. The results of physical activity included three missing values that were replaced by the group means. Since the assumptions for parametric tests were valid, physical activity was correlated with shuttle run test results by Pearson correlation. The group means of physical activity were analyzed with independent t-test.

Equal variances were not assumed between the groups in physical activity, since mod-low fit group included a wider range of subjects. Inequality of variances was also seen from Levene's test, in which the groups differed significantly in physical activity. The criterion for significance was set at * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$. Statistical analysis was completed with R software (version 3.1.3).

9 RESULTS

9.1 Group differences in physical activity

The groups differed significantly from each other in the time of daily physical activity ($p < 0.01$) (Figure 11). The average daily physical activity for high fit group was 61.62 ± 21.1 min when measured with accelerometer. Mod-low fit group, respectively, resulted with 44.69 ± 14.05 min of physical activity. Especially the standard deviation is 1.5 times greater in high fit group compared to mod-low fit group.

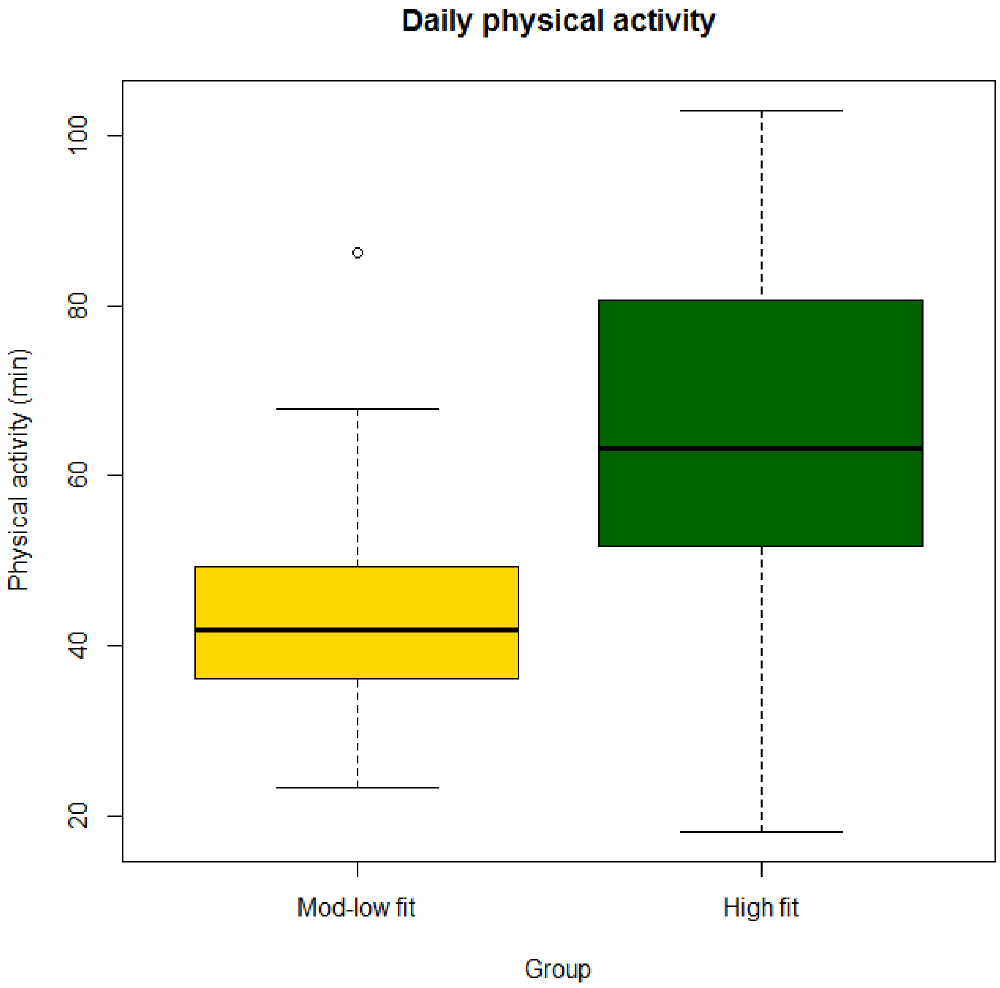

FIGURE 11. The results from daily physical activity separately for both groups. The boxplot presents the median values, 25 % and 75 % quartiles and the extreme values. Mod-low fit group had also an outlier result.

Since the subjects were classified to either high or mod-low fit groups according to their shuttle run test results, the actual results of daily physical activity needed to be analyzed as well. The correlation between physical activity and shuttle run test result was significant, indicating better shuttle run result for physically more active subjects (r = 0.51, p < 0.001) (Figure 12).

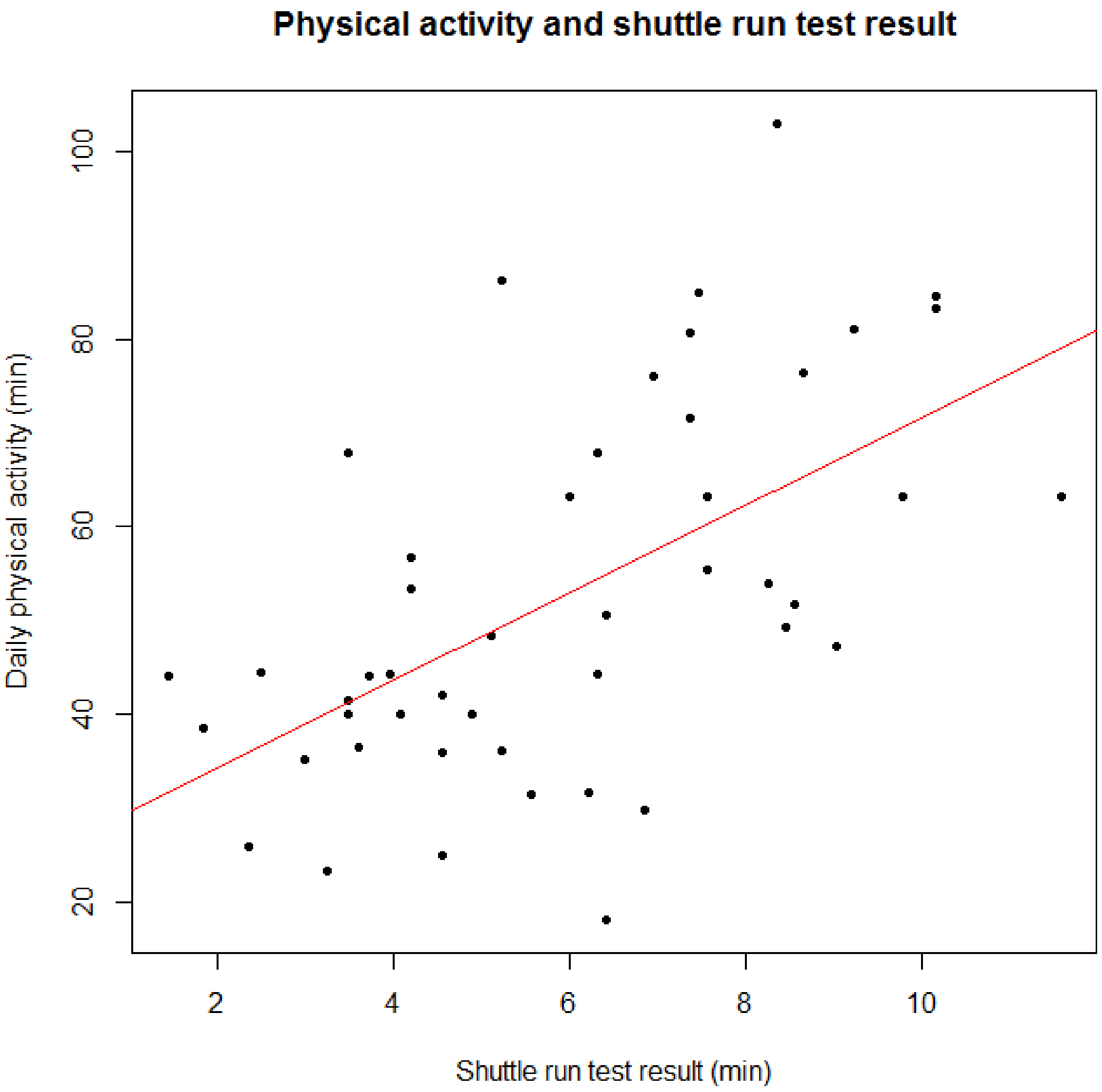

FIGURE 12. A scatter plot reveals a relationship between shuttle run test result and physical activity (r = 0.51, p < 0.001).

9.2 Lateralized alpha modulation

The calculation of the MI enabled the study of hemispheric modulation of oscillations following the cue initiated allocation of attention. TFRs of power for left cued minus right cued trials, normalized by their mean, represented a modulation in high fit and mod-low fit groups (Figure 13). The MIs were calculated separately for left and right hemispheres.

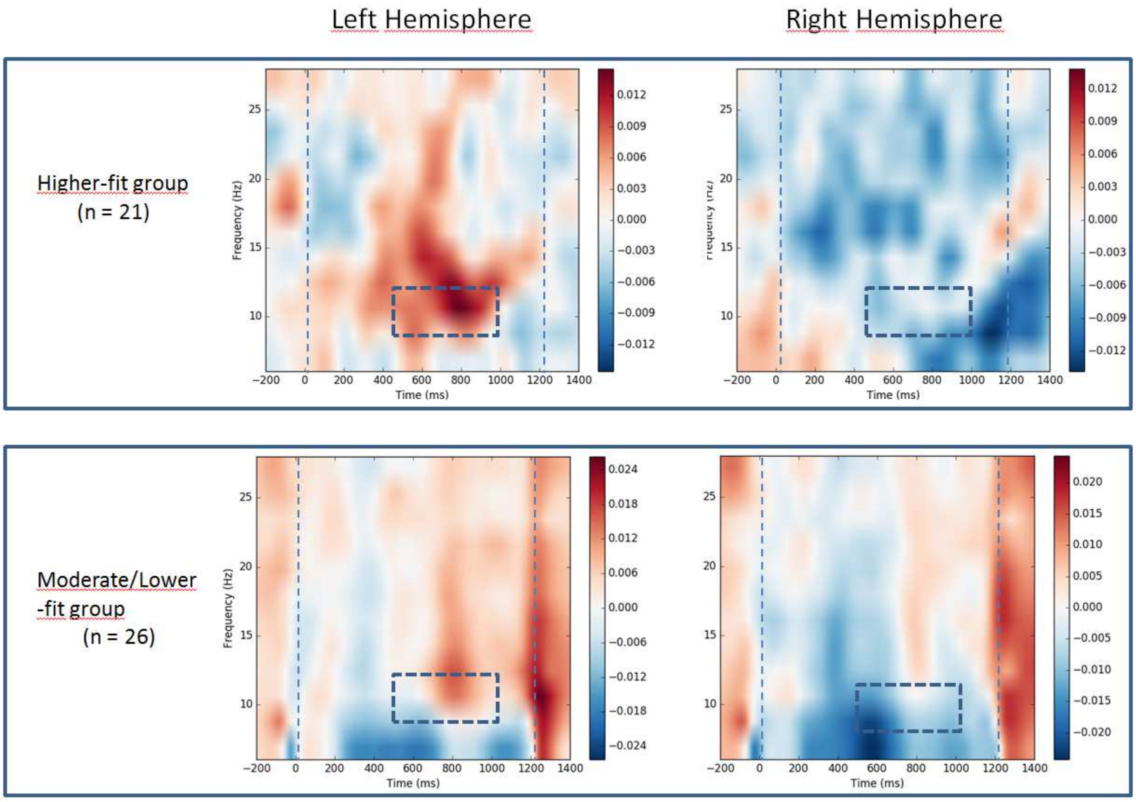

FIGURE 13. The modulation of 2–30 Hz frequency band in response to a spatial cue presented with time-frequency representation (TFR) of the MI. The results of high fit and mod-low fit group are presented on the top of the other. The results indicate stronger alpha power for ipsilateral compared to contralateral cues (squared area). The first possible target-onset is presented at t=1200 ms, and vertical line at zero represents the cue onset.

In high fit and mod-low fit groups, the alpha power was stronger for ipsilateral cues and weaker for contralateral cues in both hemispheres. Hence, in left hemisphere the alpha power was stronger for left cues and weaker for right cues. In right hemisphere, the alpha power was weaker for left cues and stronger for right cues. Based on visual analysis, the data averaged from occipital and parietal electrodes demonstrated a strong modulation in alpha band especially in left hemisphere in high fit group (Figure 13). However, the groups did not differ significantly in left or right MIs in pre-target period.

In the alpha band (8–12 Hz), significant group differences were evident in 1100–1400 ms interval after cue-onset, in which the mod-low fit subjects had stronger alpha power for left cues compared to right cues in both hemispheres. Since the first possible target-onset was at t=1200 ms, the time period of 1100–1400 ms after cue-onset included also information from the time of target presentation. In the left hemisphere, the alpha MI differed significantly at t = 1100–1200 ms ($W = 395$, $p < 0.01$), t=1200–1300 ms ($W = 420$, $p < 0.01$) and t=1300–1400 ms ($W=362$, $p < 0.05$). In the right hemisphere, the differences were observed at t=1200–1300 ms ($W=369$, $p < 0.05$) and t=1300–1400 ms ($W=373$, $p < 0.05$)

9.3 Comparison of left and right MI

Modulation index values were calculated separately for both hemispheres, which allowed the analysis of left MI versus right MI. Lateralized alpha modulation during pre-target interval was also confirmed when left and right hemisphere MIs were compared together in Wilcoxon signed-rank test. The hemispheric modulation was significant in time intervals of 300–1300 ms ($p < 0.001$), when high and mod-low fit subjects were grouped together (Figure 14, Table 1).

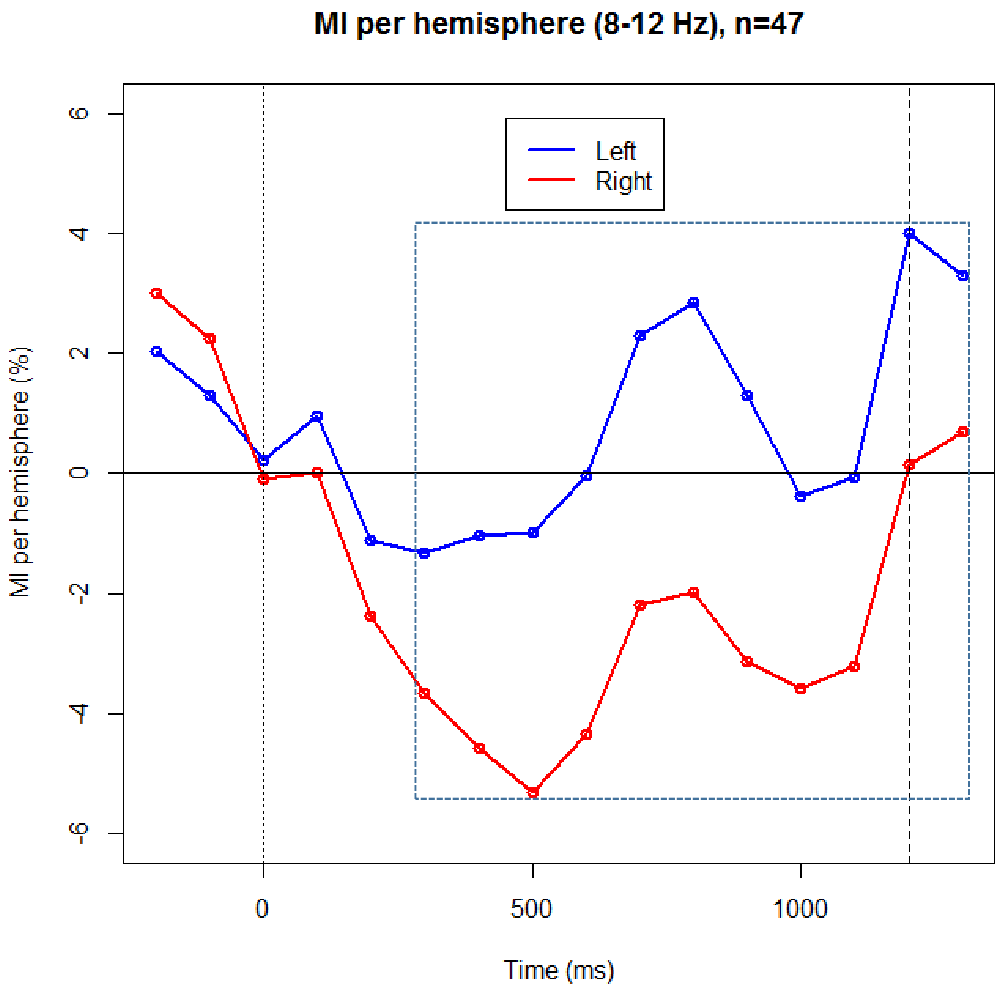

FIGURE 14. A comparison of the right hemisphere MI (red) and left hemisphere MI (blue) in a function of time when the data was gathered from both groups. Dashed square represents the time interval in which the hemispheric MIs differed significantly ($p < 0.01$).

TABLE 1. The results from Wilcoxon signed-rank test of right and left MIs (n=47).

Time (ms)	**Mean of right MI**	**Mean of left MI**	**V-value**	***p*-value**
300-400	-3.66	-1.33	833	< 0.01*
400-500	-4.59	-1.05	939	< 0.001*
500-600	-5.32	-0.99	945	< 0.001*
600-700	-4.33	-0.04	933	< 0.001*
700-800	-2.18	2.29	983	< 0.001*
800-900	-1.97	2.84	989	< 0.001*
900-1000	-3.13	1.30	1016	< 0.001*
1000-1100	-3.59	-0.38	911	< 0.001*
1100-1200	-3.20	-0.06	944	< 0.001*
1200-1300	0.15	4.00	949	< 0.001*
1300-1400	0.69	3.28	817	< 0.01*

*Denotes for statistically significant difference between right MI and left MI.

In combined MI values (left MI subtracted by right MI), the deflection from zero line indicated the modulation at 300–1300 ms after cue-onset (Figure 15). Figure 15 shows the time-course of combined MI when the groups were analyzed together (n=47). Positive values in combined MI indicate stronger alpha power for ipsilaterally presented cues and weaker alpha power for contralaterally presented cues.

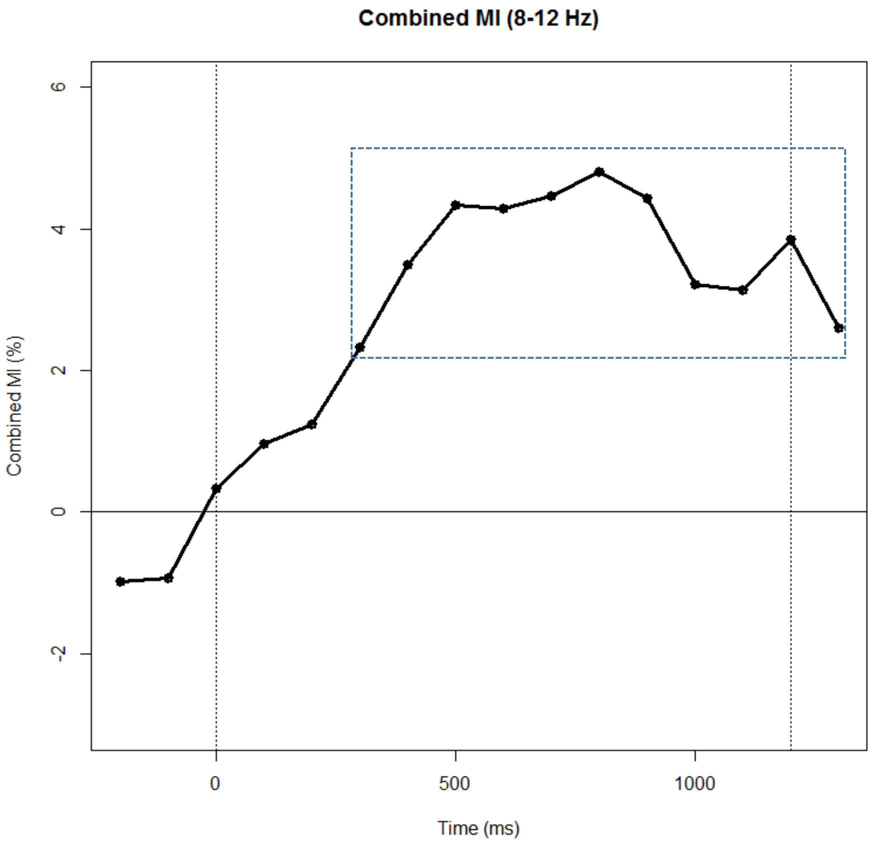

FIGURE 15. Time-course of the combined MI averaged in the 8–12 Hz alpha band. The dashed square represents the time intervals in which the alpha power differed significantly in right hemisphere and left hemisphere (n=47) ($p < 0.01$).

The combined MI values were utilized to the evaluation of group differences in left and right MI. Within the pre-target interval, no significant differences were found in Mann-Whitney U test, when combined MIs were compared between the groups in 100 ms time interval (Figure 16). Only in frequency band of 10–12 Hz, the groups differed nearly significantly in the time period of 1000–1100 ms (W=360, p=0.06). A trend for significant group differences was also evident in a frequency band of 10–12 Hz at 900-1000 ms (W=349, p=0.10). Table 2 shows the results from combined MI values separately for both groups and also for the entire sample (n=47). As can be concluded from Table 2, the standard deviations of combined MI values were large in both groups.

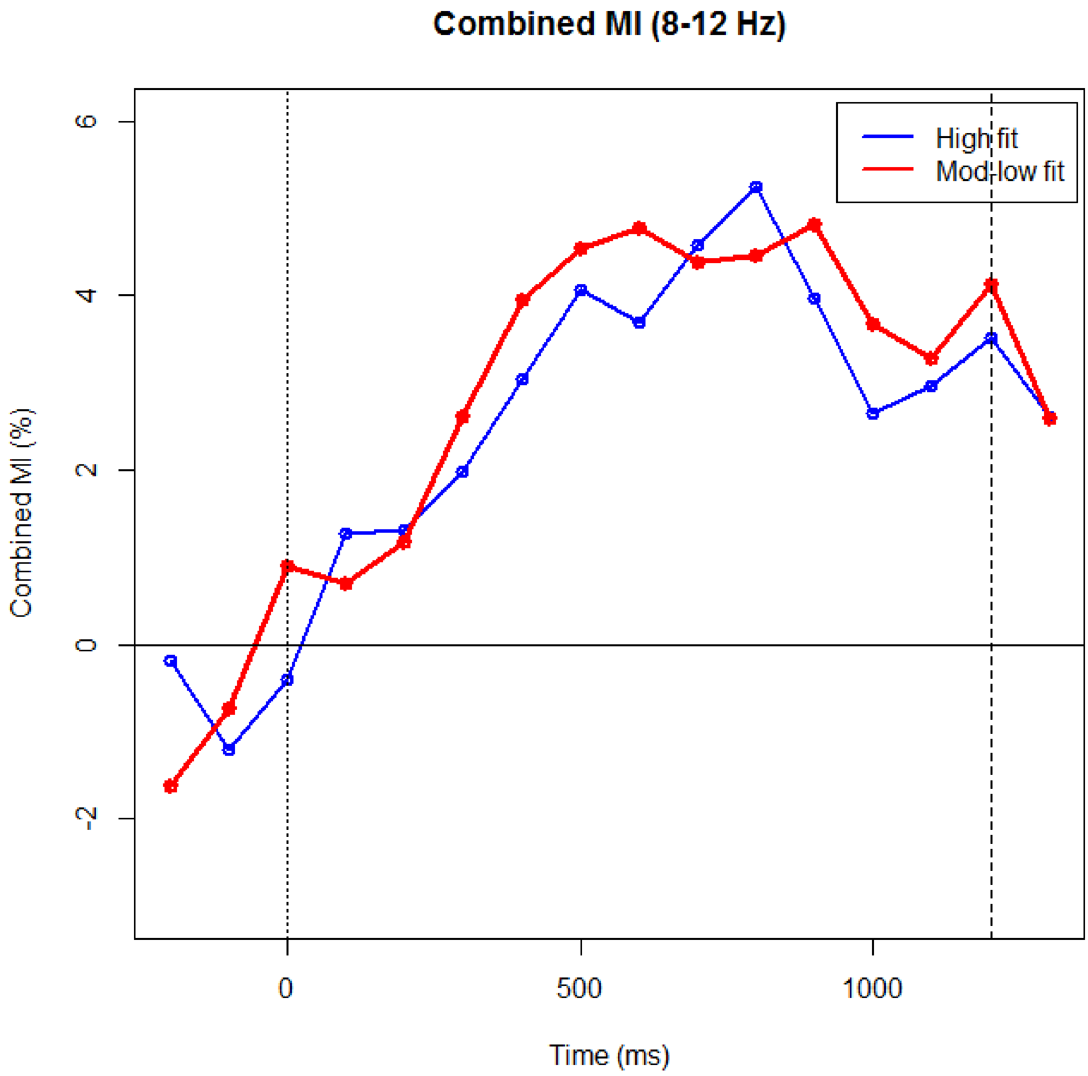

FIGURE 16. Combined MI (left MI subtracted by right MI) presented in a function of time by groups (blue=high fit, red=mod-low fit). No significant group differences were found.

TABLE 2. Combined MI values presented for both high and mod-low fit groups and for all the subjects (n=47) (mean % ± standard deviation %).

Time (ms)	**Combined MI (%)**		
	n=47	**High fit (n=26)**	**Mod-low fit (n=21)**
300-400	2.33 ± 5.01	1.98 ± 4.09	2.61 ± 5.54
400-500	3.50 ± 5.43	3.04 ± 5.23	3.95 ± 5.46
500-600	4.33 ± 6.67	4.07 ± 7.38	4.54 ± 5.89
600-700	4.29 ± 7.16	3.69 ± 7.91	4.78 ± 6.29
700-800	4.47 ± 7.18	4.58 ± 8.42	4.38 ± 5.83
800-900	4.81 ± 7.26	5.24 ± 8.55	4.46 ± 5.82
900-1000	4.43 ± 6.49	3.97 ± 7.89	4.81 ± 4.89
1000-1100	3.21 ± 5.72	2.64 ± 7.02	3.67 ± 4.21
1100-1200	3.14 ± 5.04	2.97 ± 5.90	3.28 ± 4.10
1200-1300	3.85 ± 6.03	3.52 ± 5.10	4.11 ± 6.56
1300-1400	2.60 ± 6.45	2.61 ± 5.25	2.59 ± 7.16

In addition to combined MI comparisons, right and left MI values were also compared one by one between the groups. In the high fit group, the mean values of the left MIs resulted mainly with positive values, whereas the mean values of the right MIs resulted with negative values (Figure 17a). The results from high fit group demonstrate stronger alpha power for ipsilateral cues compared to contralateral cues in both hemispheres. In mod-low fit group, the time-course of left MI includes both positive and negative values in pre-target interval (Figure 17b). On the contrary to high fit group, the alpha power is stronger for contralateral cues for the first 600 ms after the cue-onset. However, after the first 500 ms the alpha power becomes stronger for ipsilateral cues also in mod-low fit group. The right MIs, in turn, demonstrate stronger alpha power for ipsilateral cues immediately after the cue-onset, similarly to high fit group (Figure 17b). Regardless of the group differences in MI time series (Figure 17), no statistically significant group differences were found in the hemispheric MI analysis when the MI data was analyzed in three frequency bands (8–10 Hz, 10–12 Hz, 8-12 Hz) in 100 ms time intervals.

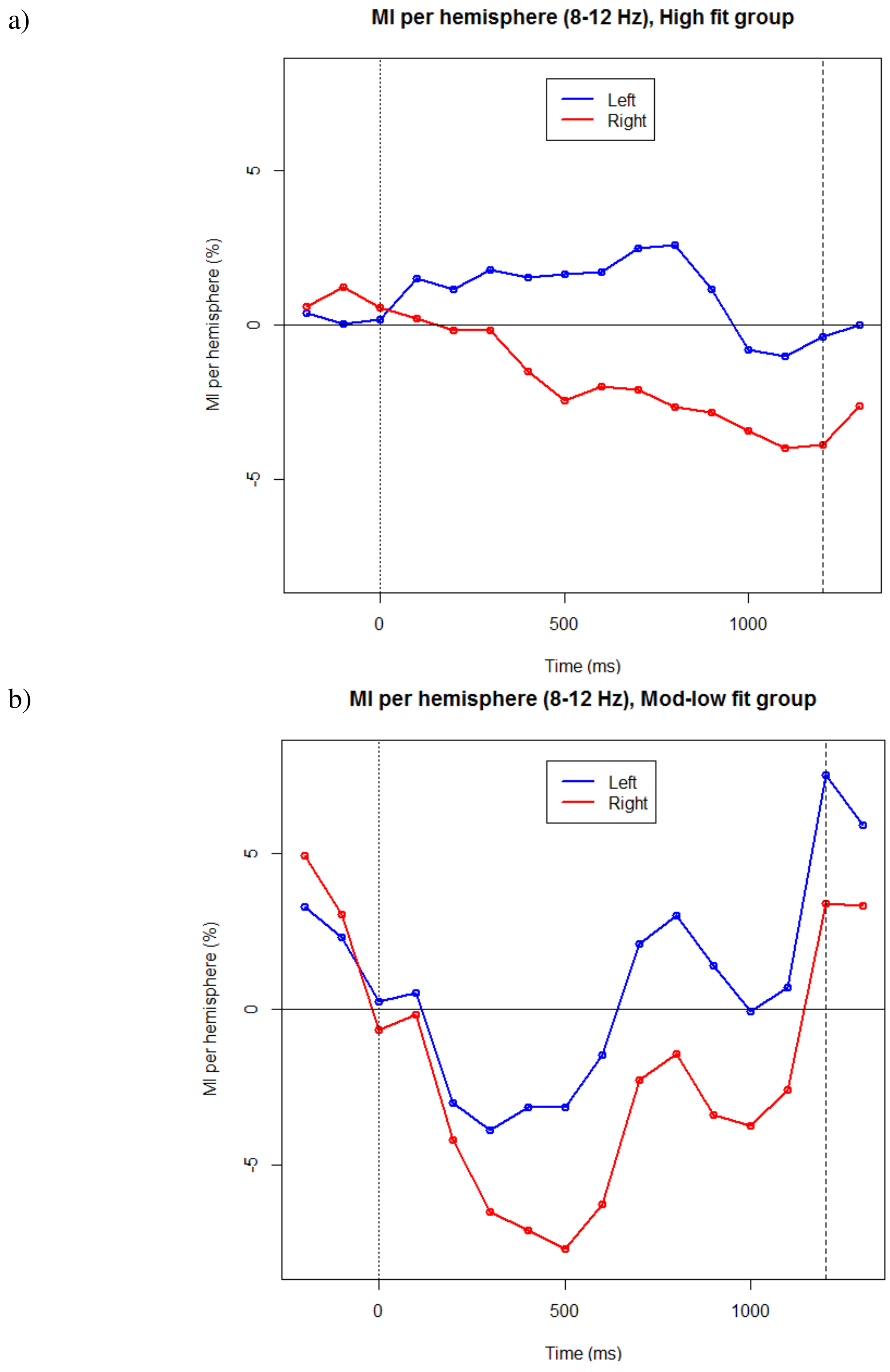

FIGURE 17. Right (red) and left (blue) alpha modulation indices presented separately for both groups. a) High fit group demonstrates stronger alpha power for ipsilateral cues compared to contralateral cues. b) Mod-low fit group has stronger alpha power for right cues in both hemispheres for the first 600 ms after cue-onset. After 600 ms, the alpha modulation becomes more similar to high fit group.

9.4 Correlation between combined MI and physical activity

The correlation was calculated between the amount of daily physical activity and the MI values (right MI, left MI, combined MI) in 8–10 Hz, 10–12 Hz and 8-12 Hz frequency bands. However, no significant correlations were found between physical activity and alpha modulation indices. Approaching significance was found from the Spearman correlation between physical activity and combined MI values in 900–1000 ms interval in 10–12 Hz frequency band ($r_s = -0.25$, $p = 0.09$).

9.5 Correlation between combined MI and shuttle run test

Another correlation evaluated whether the shuttle run test results were significantly related to MI values. Since no significant differences were found from the hemispheric MIs, the correlation between combined MI and shuttle run result was analyzed more accurately. Approaching significance appeared at 400–500 ms after the cue-onset in 8–12 Hz frequency band ($r_s = -0.24$, $p = 0.11$). The result indicated stronger lateralized alpha modulation for weaker shuttle run test performers, since the correlation is negative between the variables (Figure 18).

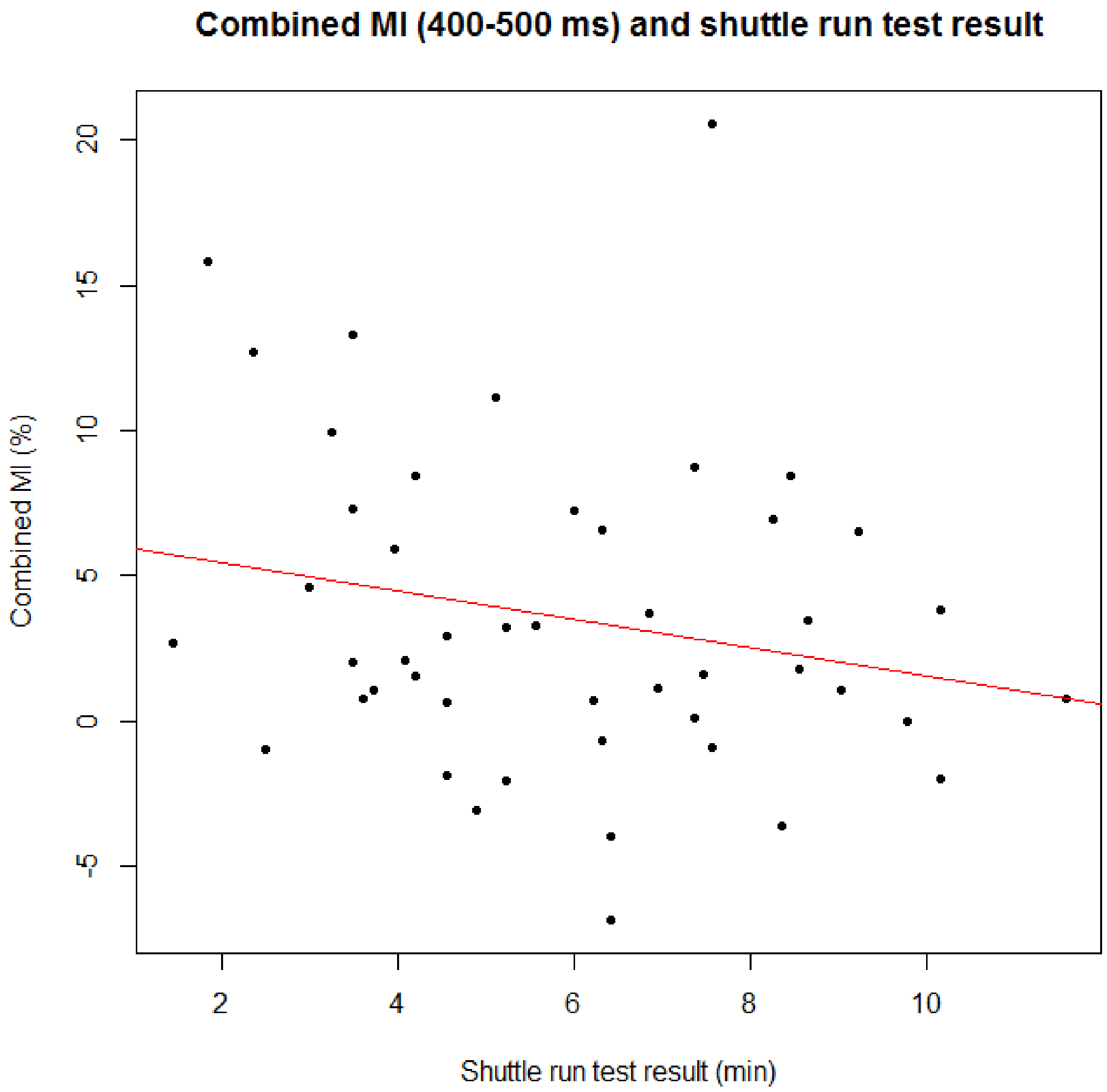

FIGURE 18. A scatter plot for shuttle run test results and combined MI in 8–12 Hz at 400–500 ms after cue-onset ($r_s = -0.24$, $p = 0.11$).

10 DISCUSSION

The current study investigated the modulation of alpha band activity in 12-16 year old children with varying physical activity level. The alpha modulation was studied by MEG when the children were performing an anticipatory visuospatial attention task. In anticipatory period, the results showed decreased alpha power in the hemisphere contralateral to the attended hemifield, whereas the increments in alpha power were observed in the hemisphere ipsilateral to the attended hemifield. These results were in accordance with several previous studies (Kelly et al. 2006; Thut et al. 2006; Huurne et al. 2013; Vollebergt et al. 2015). Increases in visual cortex alpha power have been observed during cortical deactivation, whereas decreases have been linked to cortical activation (Pfurtscheller 2001). Hence, the alpha power increases in hemisphere ipsilateral to attended hemifield would be related to cortical deactivation, whereas the decreases would we related to cortical activation, respectively. Regardless of clear posterior alpha band modulation in anticipation period, significant differences between the groups were not observed in MI values.

When the groups were combined together (n=47), significant overall alpha lateralization was observed from left and right MI comparisons at 300–1300 ms after cue-onset. As can be concluded from combined MI result, the alpha modulation was strongest from 500 ms to 900 ms after cue-onset when there were no significant changes in values. In Vollebregt's et al. (2015) study, the modulation with attention was most pronounced in children at 600 ms after cue-onset (Figure 19). In turn, Huurne et al. (2013) found significant differences between left and right alpha lateralization from early (500–700 ms) and late (900–1100 ms) maintenance period from healthy adults. Hence, the results of this study are well in line with previous findings. The results of lateralized alpha modulation support also the suggestion of Jensen and Mazaheri (2010), whereby the function of alpha oscillations might be to allocate resources to relevant regions and direct focal attention.

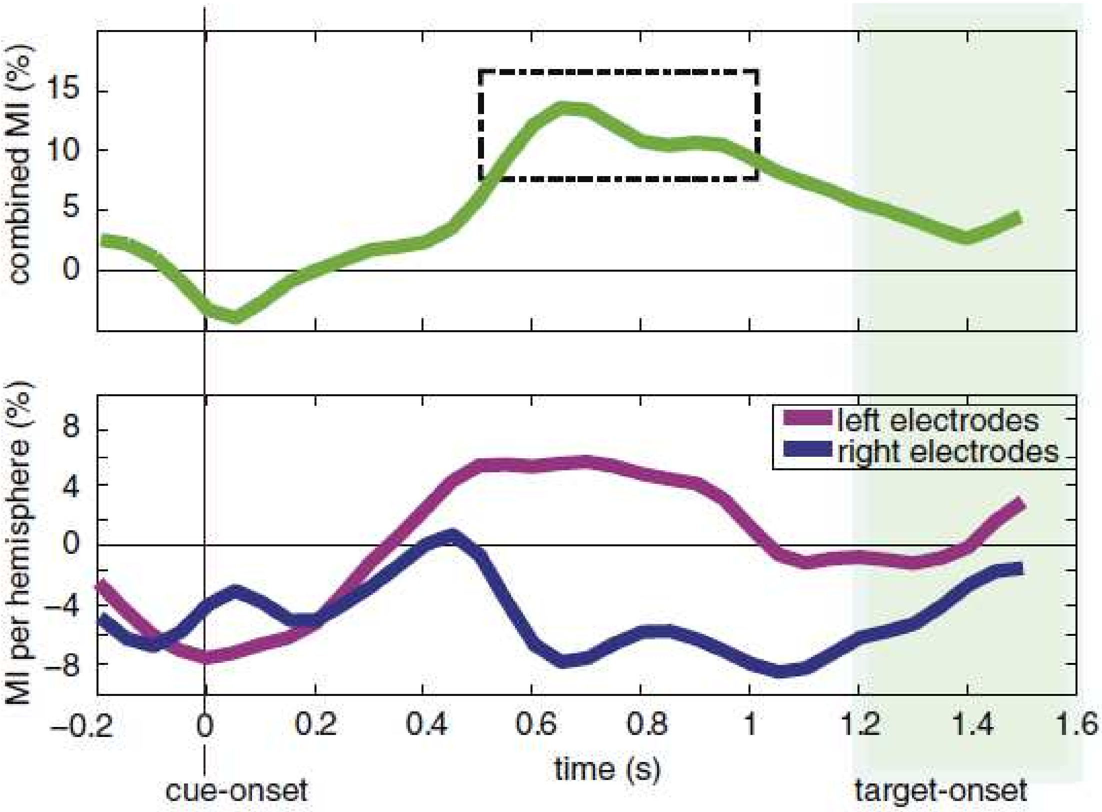

FIGURE 19. The modulation of alpha band power in response to the spatial cue. (Top panel) Time-course of the combined alpha MI averaged over children (occipital and parietal electrodes). The combined MI values differed significantly between right and left electrodes in time interval of 0.5–1.05 s after cue-onset ($p < 0.05$). (Bottom panel) Combined MI values are presented separately. (Vollebregt et al. 2015.)

The group specific data from hemispheric MI values indicated strong alpha lateralization especially for high fit group in left hemisphere. Even though the difference between the groups was not statistically significant in left MI, the time-course of mean left MI was clearly different for high and mod-low fit subjects. For high fit group, the left MI sustained positive during the entire pre-target interval. This means that their alpha power in left hemisphere was stronger for left-cued trials compared to right cued trials during the entire anticipation time (0–1200 ms). Higher left hemisphere alpha power, that is higher left hemisphere synchronization, might have a role as an inhibition mechanism that suppresses the distracting task-irrelevant input (Kelly et al. 2006). Mod-low fit group, in turn, had a similar amount of modulation in left hemisphere but starting not before 600 ms after cue-onset. Before that, the left alpha power was stronger for contralaterally (right) cued trials. Hence, mod-low fit subjects seem to have stronger alpha power for right hemifield 0–500 ms after cue-onset in both hemispheres regardless of the cue location. Since the previous studies show stronger alpha power for hemisphere ipsilateral to attended hemifield (Kelly et al. 2006; Thut et al. 2006; Huurne et al. 2013; Vollebergt et al. 2015), mod-low fit subjects seem to have a slight attentional bias toward the right visual hemifield. However, this attentional bias is evident only right after cue-onset. According to the suggestions of Kelly et al. (2006), mod-low fit group might not have as efficient inhibition mechanism that suppresses the task-irrelevant right hemifield visual information. Concluded from the results, both groups were capable of modulating their posterior alpha oscillations but the modulation occurred later for mod-low fit subjects in left hemisphere.

When left hemisphere alpha power of high fit children is compared to Vollebregt's et al. (2015) respective time-course (Figure 19), differences can be observed at the onset of lateralization. The subjects of Vollebregt's et al. (2015) study demonstrated lateralization for the first time at 400 ms after cue-onset. In this study, the lateralization occurred right after the cue-onset in the high fit group. In mod-low fit group, the lateralization in left hemisphere occurred even later than in Vollebregt's et al. (2015) study. Since Vollebregt's et al. (2015) study included probably subjects with varying physical activity level, the results from this study might indicate better inhibition mechanism for right hemifield visual information for high fit children.

In previous studies, an attentional bias toward the right visual hemifield has been related to attention problems in normally developed subjects (Manly et al. 2005; Dufour et al. 2007; Poynter et. al. 2010). Also Huurne et al. (2013) have reported attentional bias toward right hemifield for subjects with ADHD. However, this attentional bias was observed during late maintenance of attention at 900–1100 ms after cue-onset (Figure 20). Compared to healthy adult subjects, the subjects with ADHD showed a significantly higher accuracy for invalidly cued right targets compared with invalidly cued left targets (Huurne et al. 2013). Another study has linked an increased ability to modulate alpha activity with smaller cueing effect and diminished rightward visual bias (Vollebregt et al. 2015). In the current study, behavioral performance was not evaluated, which prevents the interpretation of rightward bias as a part of cognitive performance. Anyway, it could have been interesting to evaluate if the subjects with stronger rightward attentional bias would had shown differences in their attentional performance. This could be assumed according to Manly et al. (2005), Dufour et al. (2007) and Poynter et al. (2010), since they found decreased levels of attention from subjects with rightward attentional bias.

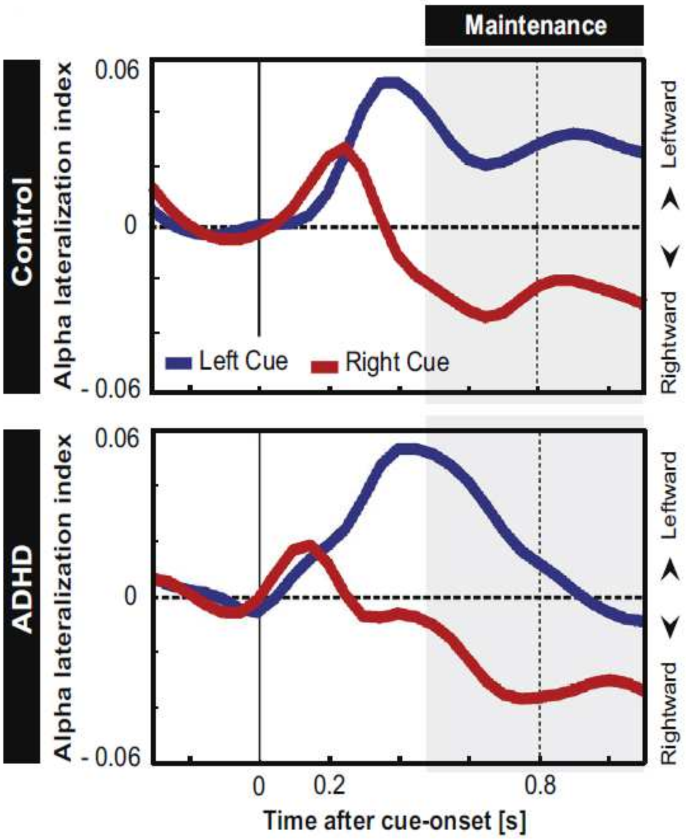

FIGURE 20. Mean alpha lateralization indeces (ALI) of the left and right cue condition. The time-courses of ALI in ADHD and control groups showed positive values, when alpha power was stronger for left hemisphere and negative values for right hemisphere, respectively. In ADHD group, the rightward bias was evident at the end of the maintenance period. (Huurne et al. 2013.)

In the current study, the only significant group differences in left and right MI were observed at 1100–1400 ms after cue-onset. Within the time interval, high fit group resulted with equal alpha power for left and right cued trials in left hemisphere, whereas the alpha power was slightly higher for right cues in right hemisphere. Mod-low fit group, instead, had significantly higher alpha power for left cued trials in both hemispheres at 1200–1400 ms intervals. It was possible to observe the tendency for leftward alpha modulation already right before the first possible target onset at 1100–1200 ms interval, although the hemispheric MI values were rather equal to left- and right-cued trials. The results of mod-low fit group are opposite to Huurne's et al. (2013) study, where ADHD group had a stronger right hemisphere alpha before the target presentation. This study might indicate stronger rightward bias for low-mod fit group at the beginning of anticipation period, but within maintenance period the shift was rather toward left hemifield.

It is interesting to speculate wherefrom the group differences in MI values in 1100–1400 ms interval were originated. One possible explanation could be related to the greater need of target processing in mod-low fit subjects since the modulation is larger for that group. This could be assumed, since higher modulation, i.e. stronger inhibition for one hemifield and stronger activation for another hemifield, relates to increased cortical activation (Senior et al. 2009, 237–262). This would mean that if high fit subjects were better inhibiting irrelevant information during the cue time, then they would have less information to process during the target period. In mod-low fit group, higher alpha modulation at target-onset would mean more information processing and inhibition.

Regardless of the detected group differences, further research is needed to conclude, whether the physical activity level really effects on the alpha modulation right before the target-onset. Because of the cue-locked data and varying times in target presentation (1200–1700 ms after cue-onset), for this part the only rational time interval to be interpreted was 1100–1200 ms after cue-onset. In 1200–1700 ms interval, some of the targets were already presented and some were not. Thus, it cannot be said whether those differences were related to either alpha power changes induced by target presentation or alpha power changes induced by different cue processing.

The comparison of combined MI values enabled the investigation of group differences in lateralized alpha modulation. Figure 16 showed fairly well the similarity of alpha band lateralization between the groups. Physical activity induced adaptations in lateralized alpha band activity did not get support from this study when left and right hemisphere alpha powers were compared. Surprisingly, there was a slight trend for higher upper alpha modulation (10–12 Hz) in mod-low fit group in 900–1100 ms time interval (900–100 ms: p = 0.10; 1000–1200 ms: p = 0.06). However, the group differences were relatively small even at 900-1000 ms interval when regarding the group standard deviations that were larger than the actual combined MI values. It was interesting to notice that the group differences that were distinguishable in hemispheric MI comparisons (0–500 ms) were not present in combined MI values. The reason that covered the group differences in combined MI was strongly negative right MI, which compensated the weaker alpha lateralization of left MI in mod-low fit group. Hence, the hemispheric MI values varied more between the groups than overall posterior alpha lateralization (combined MI). Which one of these alpha lateralization values – hemispheric alpha power or overall alpha lateralization – is more valid when regarding attention mechanism, needs to be studied more closely.

When correlation was studied between alpha modulation and physical activity indicators, it was important to notice the significant correlation between daily physical activity and shuttle run test result. The correlation between two independent indicators validated the physical activity level of the children as the children with higher amount of daily physical activity resulted also with higher shuttle run scores. However, neither of these physical activity indicators correlated significantly with any of the MI values. Hence, the study did not give strong evidence for a clear relationship between lateralized alpha power and physical activity level of a child. Nevertheless, combined MI values indicated a slight trend for stronger alpha lateralization from weaker shuttle run performers in the halfway of anticipation period (400–500 ms). When combined MI values are interpreted by means of hemispheric MI values, it can be concluded that the correlation related to 400–500 ms time period is induced by exceptionally strong negative alpha power in right hemisphere in mod-low fit group. This could be related to highlighted rightward bias of mod-low fit group. For example, the mean of right hemisphere MI in high fit group resulted with -2.42 % from baseline, whereas mod-low fit had more than twice the value (-7.67 %) at 500–600 ms after cue-onset. In mod-low fit group, this could be related to stronger right hemisphere inhibition for right cues or stronger right hemisphere activation for left cues when compared to high fit counterparts (Pfurtscheller 2001). To prove these distinguishable group differences statistically significant, larger sample sizes would have been needed.

Even though the behavioral performance was not evaluated in this study, previous studies have indicated the relationship between posterior alpha lateralization and visual detection performance (Thut et al. 2006; Kelly et al. 2009; Händel et al. 2011). For example, Huurne et al. (2013) found that modulation of alpha activation over visual cortex gave a rise to individual differences in performance in control group, though the correlation was absent in ADHD group. In the study of Huurne et al. (2013), strong alpha lateralization was associated with strong spatial focus, which improved the response accuracy but slowed reaction times. In turn, Vollebregt et al. (2015) concluded that the children having least difficulty with an unexpected switch of attention would most likely be the ones who are least induced by spatial cueing. Then high posterior alpha activity could enable the subject to change the target of attention more easily. In addition, Vollebregt et al. (2015) demonstrated that children who were least induced by spatial cueing (response times were less effected by invalid cues) were also the ones whose posterior alpha activity was modulated the strongest. If this was the case also with the subjects of the current study, then no significant differences in cueing effect could have been observed between the groups since the groups did not differ significantly in combined MI values. This could be an indication of equal development of the children, as it has been suggested that cueing effect might increase with development (Vollebregt et al. 2015). Then the groups would also succeed equally in the tasks including unexpected switch of attention.

Motor control studies have demonstrated different alpha modulation in motor cortex also after error in motor task (Cooke et al. 2015). Since the attention task provided positive or negative feedback for the children after each trial, it would have be interesting to evaluate whether this phenomenon could have been observed also in cognitive task. Another aspect would be to analyze whether the error induced alpha modulation differed in physically active and inactive children.

Even though the significant differences between high fit and mod-low fit subjects were minor in this study, it is still worth evaluating wherefrom the divergences between the groups in hemispheric MI values could be originated. The differences at the target-onset and right before the target presentation could be related to the same phenomenon that has been observed in motor-control studies. Namely, Deeny et al. (2003) have observed that the experts used less cognitive processes with motor function when comparing to less skilled shooters (Deeny et al. 2003). In this study, mod-low fit subjects seemed to have higher alpha modulation right before the target or at the target-onset, which refers to higher brain activation (Senior et al. 2009, 237–262).

Another motor control studies (Gonzalez-Rosa et al. 2015; Cooke et al. 2015; Babiloni et al. 2008) have linked alpha band desynchronization to neural efficiency so that smaller amount of alpha power predicts better performance in sports. However, in this study, that kind of connections could not be derived straightforward since the behavioral performances were not evaluated at all and alpha band values were not used as such. Regardless of that, those results can be linked to this study if the alpha MI values are analyzed more closely. Higher desynchronization refers to lower alpha band activity in task-relevant area, whereupon alpha power should be low in the hemisphere contralateral to attended hemifield if the theory would fit also for cognitive abilities. Since the alpha activity was stronger for ipsilateral cues and weaker for contralateral cues, it can be concluded that same kind of mechanisms are utilized in motor and cognitive performances even though the 8–12 Hz activity would be measured from different cortexes.

Another interesting factor to be considered is whether the high and mod-low fit subjects differed in cerebral blood volume (CBV). Since previous studies have shown connections between CBV and verbal learning, memory and cardiorespiratory fitness (Pereira et al. 2007), the relationship between CBV and functional alpha rhythm could provide information about the mechanism that causes the associations between physical fitness and cognitive functioning.

In this study, three different frequency bands (8–10 Hz, 10–12 Hz and 8–12 Hz) were analyzed to see whether the alpha power differed in any of these frequency bands between the groups. Even though higher and lower alpha band activity seemed to be similar between the groups in pre-target interval, one possibility could have been to study if the mean alpha frequency differed between the groups. Frequency resolution of 2 Hz was used in this study, which did not allow the study of minor mean frequency differences. According to Klimesch (1997), differences could have been observed since the memory task results have indicated 1 Hz higher alpha activity to good performers compared to bad performers. However, the mean frequencies could not have been compared between good and bad performers since behavioral performances were not measured in this study. Nonetheless, the comparison could have been made between high and moderate-to-low fit subjects. The mean frequency differences could have indicated performance differences in high and mod-low fit subjects if the same mechanism could be observed in attention and memory tasks.

The current study has limitations that need to be considered in interpreting the results. The groups were not similar since the high fit group included only better than average shuttle run performers, whereas the other group included subjects with moderate and low shuttle run results. However, the variances between the groups were equal in shuttle run tests and 1.5 times larger for high fit group in physical activity variable. Plausible group differences could have been more clearly seen if the groups would have consisted only on the extremities when it comes to endurance running abilities. However, considerable part of the subjects were counted as moderate fit children, whereupon the sample size would have decreased in number if those subjects had been excluded from the study. Regardless of reasonable group sizes, a higher amount of subject could have brought forth significant group differences, since the variances were remarkably large in both groups. In posterior alpha oscillations, individual variation seems to be large in general.

Behavioral performances in shark test were not analyzed in this study. Therefore, the cause-consequence –relationship between MIs and behavioral performance must be interpreted with caution. However, the same testing pattern was used as in Vollebregt's et al. (2015), which makes it possible to assume the relationship between MIs and behavioral performance to be fairly similar. In addition, several other studies have supported Vollebregt's et al. (2015) results when they have used similar kind of attention related cognitive test (Huurne et al. 2013, Kelly et al. 2006, Thut et al. 2006).

Another factor to be considered is the attention task that was used. Even though the paradigm has been utilized identically in Vollebregt's et al (2015) study, and similarly in other studies (Huurne et al. 2013), the shark paradigm does not necessarily reveal all the neuronal factors that are important in cognitive performance related attentional abilities. However, the task performance has correlated significantly with hemispheric alpha modulation (Vollebregt et al. 2015; Huurne et al. 2013), which implies that these kind of attentional tasks measure at least some part of attentional abilities reliably and validly.

The shuttle run test scores were chosen as a grouping variable, since those enabled the comparisons of individual scores to gender- and age -specific standardized values. The shuttle run result indicates cardiorespiratory fitness, which can be considered relevant factor when studying the effects of physical activity. For example, CBF has been associated with both cardiorespiratory fitness and cognitive abilities (Pereira et al. 2007), which would imply a relevant role for shuttle run scores in both brain function and cognitive abilities. However, other physical activity indicators, such as force production abilities, could have been also measured. On the other hand, resting-state alpha power has correlated positively, in particular, with endurance abilities (Völgyi et al. 2015). Hence, similar connections between endurance fitness and visual cortex alpha power could be assumed also during cognitive tests.

11 CONCLUSION

The results of the current study showed decreased alpha power in the hemisphere contralateral to the attended hemifield and increased alpha power in the hemisphere ipsilateral to attended hemifield. When 47 subjects were studied, the modulation of hemispheric alpha power was significant at 300–1300 ms after cue-onset. These results showed that pattern of alpha oscillations modulated by attention is present in 12–16 year old children.

However, the relationship between childhood physical activity and posterior alpha band activity during attentional task did not get strong support from the study. Although previous results have supported correlation between both physical activity and cognitive performance, and visual cortex alpha band modulation and cognitive performance, the connection between physical activity and alpha band activity seems not to be that simple. Nonetheless, a trend for rightward bias was observed in mod-low fit group right after the cue-onset, which might indicate differences in developmental level within the children. According to previous literature (Vollebregt et al. 2015; Huurne et al. 2013), the rightward bias that is observed especially from reduced alpha MI in left hemisphere might lead to weaker attentional performance. Hence, the evaluation of alpha modulation is an important factor when studying neural prerequisites of learning.

For further research, larger sample sizes are needed to bring forth the connection between physical activity and lateralized alpha band activity more clearly. Evaluation of behavioral achievement would provide additional information that could be taken into account in the analysis. Especially, behavioral performance would have given information which is the more important indicator of alpha lateralization: hemispheric alpha power (left MI, right MI) or overall alpha power (combined MI). If overall alpha power predicts better attention performance, then no group differences could be assumed according to this study. But if hemispheric lateralization is more crucial, then some group differences could be concluded from the study. In addition to cue-locked data, target-locked data should be used to provide reliable information from the time intervals right before the target-onset. Physical activity induced differences in posterior alpha modulation might not be easily seen and hence comparing subjects with exceptionally high or exceptionally low fitness could be an approach worth trying.

In conclusion, the results of the current study suggest that alpha band modulation is related to inhibition in task-irrelevant area and activation in task-relevant area. Given that the development of attention disengagement is in great importance in cognitive performance, there is certainly need for further research related to filtering mechanism. This study showed that good endurance abilities might be related to children's developmental level, since the rightward bias was present only within mod-low fit children. Especially, alpha band modulation is related to inhibition in task-irrelevant area and activation in task-relevant area. However, the connection was weak in this study and needs to be supported with statistically significant results in order to be validated. The mechanism for physical activity induced cognitive improvements remains still unclear, even though the promoting effect of physical activity on academic achievements (Ahamed et al. 2007; Castelli et al. 2007; Kim et al. 2003) and cognitive functions (Sibley & Etnier 2003) has been shown widely. It is still probable that alpha rhythm has somehow important role in explaining the cognitive performance differences between physically active and inactive children, but further evidence is needed. The fact that alpha modulation varies not only between children with varying physical activity but also with adults and ADHD-subjects, opens up the possibility of using lateralized alpha modulation as an indicator of individual development.

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