EXPERIMENTAL AND SIMULATION-BASED EFFORTS TO ADVANCE UNDERSTANDING OF COGNITIVE, MOTOR, AND NEURAL PREDICTORS OF DUAL-TASK PERFORMANCE

by

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ABSTRACT

Dual tasks are characterized by the splitting of attention between tasks and are common in everyday life as well as sports scenarios. These scenarios reflect real-world challenges for populations such as those with injuries, older adults, or athletes. While attention control's role in multitasking is well studied, its relevance in physically demanding dual tasks remains unclear. Alongside attention control ability, neural activation could give insights into the ability to divide attention during these cognitive-motor dual tasks. Understanding what allows some individuals to multitask better than others could inform training, rehabilitation, and performance optimization. Attention control (AC) was assessed through a short test battery and dorsolateral prefrontal cortex (DLPFC) activation was measured during this task. Cognitive-motor multitasking abilities were tested through a challenging dual-task. High DLPFC activation and performance in AC testing correlated with fewer dual-task deficits. The low correlation between AC scores and DLPFC activation shows that they each account for some of the variability in dual-task ability. This suggests that AC performance and neural engagement may be independently important in predicting dual-task function.

fNIRS measurements in dynamic settings often shows motion-related artifacts that can obscure neural signals if not addressed. Short-separation channels have been validated as a regression method to remove physiological artifacts such as those related to heartbeat, blood pressure changes, and respiration rate in the scalp, skull, and cerebrospinal fluid. Though effective in stationary settings, their role in reducing motion artifacts from fluid inertia remains unclear. Thus, the ability to reduce motion artifacts through short-separation channel regression remains a critical gap in knowledge. Failure to address this fundamental unknown of fNIRS signal quality limits our confidence in neural activity measurements under dynamic conditions, such as dual tasks. In this study, motion artifacts were simulated at varying frequencies and neural activation strengths. In settings with low contrast-to-noise (i.e. neural signal obscured by motion artifact), short-separation channels showed improved accuracy in identifying true neural signals.

Overall, the findings provide new insights into the relationship between attention control, neural activation, and performance in physically challenging dual-task scenarios and expand on the use of short-separation channels during dynamic movements.

CHAPTER ONE

INTRODUCTION

Attention control, dorsolateral prefrontal cortex activation, and dual-task performance

1.1 Dual-task demands in everyday life and sport

Dual-task scenarios are present in many facets of everyday life. Whether driving a car in rush hour or walking while talking on the phone, the ability to control attention effectively is essential for many everyday tasks. In sport, athletes are subject to even higher demands as they, for example, attempt to score a goal amidst defenders or execute a game plan while reacting to in game stimuli [1]. The cognitive and motor demands of modern sport play a key role in athletic abilities and sport prowess, influencing performance, adaptability, and decision-making in competitive environments. As more tasks are performed concurrently and mental load increases, performance on each individual task typically declines [2,3]. While some scenarios exist where performance is enhanced in a dual task, for many individuals and situations, this is not the case [4,5]. Investigation into dual tasks provides information about individual performance in sport and everyday life scenarios. Decrements in either the cognitive or motor task could present as slower decision making or movements that may contribute to injury risk in sport (reviewed by [6]). Those who exhibit increased performance in a laboratory dual task may be more likely to show better performance in a real sport environment. Although dual tasks are just one way to measure performance during concurrent tasks (e.g. task-switching tasks), they provide a measure of cognitive-motor interference and neuromuscular control in movement patterns similar to those seen in sports.

1.2 Dual-task cognitive resource allocation

When attending to a dual task, the brain must first process the stimuli, select a response to the stimuli, and then execute the chosen response (Figure 1). Several theories on the cognitive mechanisms and resource allocation underlying dual-task performance have been proposed [5]. The capacity sharing model is the most widely accepted model for explaining dual-task deficits. This theory states that when multiple tasks are performed, there is less capacity for each individual task, leading to decreased performance on the individual tasks. When task difficulty increases past an individualized threshold, the ability to perform concurrent tasks well decreases. Previous works have suggested that this capacity can be unequally divided between tasks and thus, individuals appear to have some control over the mental resources they give to each individual task [7,8]. For example, in a dual task where decreased performance of a task could result in more dangerous consequences, we are generally able to prioritize that task.

The bottleneck model states that for some mental operations, such as response selection, parallel processing could be impossible (Figure 1) [9]. A bottleneck occurs when multiple tasks require a mental operation at the same time leading to delay and/or impairment of one or more tasks. The bottleneck theory has been connected to the psychological refractory period (PRP) paradigm which describes how responses to stimuli happen in order of stimulus presentation, when presented asynchronously, and must occur serially [9]. Determining the response to stimulus presentation has been described as an operation where parallel processing is impossible, leading to a bottleneck – decreased performance in the second of the presented tasks. PRP study designs have manipulated response types (vocal, oculomotor, pedal, manual) and determined a prioritization scheme of oculomotor over pedal, over vocal, over manual response types at the

bottleneck [10]. This indicates the order of task performance prioritization, in the instance of a bottleneck, during a dual task. This becomes important when considering dual tasks involving both cognitive and motor subtasks, as seen in sport, and subsequent dual-task study designs.

The third of the most relevant theories of dual-task processing is the crosstalk model. This theory argues that the degree of dual-task performance deficits is dependent on the context of the information being processed, rather than the appropriate response to the information. It is generally accepted that more dual-task performance decrements are seen if the two tasks involve similar processing information [8]. These theories are not always mutually exclusive as strategic bottlenecks could be introduced to a dual-task scenario if the crosstalk between subtasks was deemed too great [5]. Another bottleneck could occur if resource capacity was allocated sequentially due to task difficulty. Many dual-task studies have relied on one or more of these theories of resource allocation as explanation for cognitive and behavioral responses in dual-task scenarios.

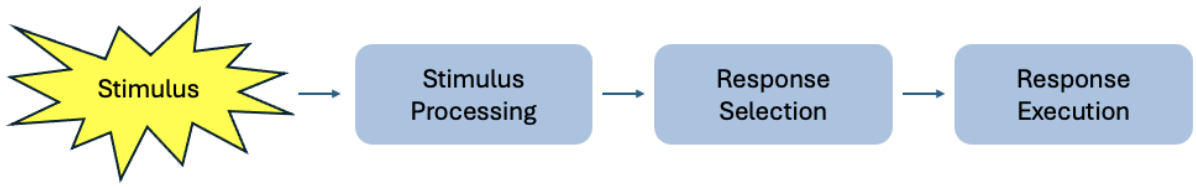

Figure 1: Stimulus processing stages according to Pashler et al. [9]. Bottleneck effects are seen in the response selection stage of this sequence.

1.3 Relevance and variety of cognitive-motor dual tasks

Designing interfaces for investigation into dual-task performance provides opportunities to understand the limits of human multitasking. Decrements in subtask performance during a dual task, coined ‘interference’ in the literature, is a common occurrence when an individual is

faced with a multitasking scenario. Within the cognitive-motor dual task, four outcomes (and the interactions of these outcomes) are possible – cognitive task facilitation, cognitive task interference, motor task facilitation, and motor task interference [11]. Decrements in performance are typically linked to limited brain processing capacity and one of the three previously described theories of cognitive resource allocation. Performance is decreased if one or more tasks demand more cognitive resources than are available. Cognitive-motor dual tasks have been studied extensively across populations and with various cognitive and motor tasks.

Walking while performing a concurrent cognitive task is a common study design. The magnitude of dual-task walking decrements have been found to depend on the type of cognitive task and how difficult the task is perceived to be [12]. These various relationship strengths between cognitive task type (visuomotor reaction time, word list generation, serial subtraction, and Stroop) and walking variables show that dual-task interference varies both by individual and by task, with some cognitive tasks causing more severe decrements. Another study investigating gait variables during walking alone and with a subtraction task found decreases in gait speed, stride length, stride time, and number of subtractions during the dual task condition [13]. It appears that overground and treadmill walking have different effects on cognitive-motor performance during a dual task. In a study of healthy adults, dual-task effects were evident as slower and more variable gait during both overground and treadmill walking [14]. A positive dual-task effect was seen in the treadmill dual-task condition while no dual-task effect on cognitive performance was seen in the overground walking condition. Other studies have found no differences in step times [15,16], variability in step time [15,16], or cognitive task accuracy between single- and dual-task conditions in young and older adults [16]. These authors noted that

their results could have been influenced by a learning effect on the cognitive tasks [16]. Walking dual-task investigations are well represented in the literature and give insights into multitasking during a common everyday movement across populations.

Although well represented in the literature, dual-task paradigms are not limited to gait analysis. Neuromuscular control has been investigated during jump landing dual tasks, as the task is more closely related to those seen in sport environments [17]. Drop landings provide an opportunity to investigate body movements that may increase future injury risk such as anterior cruciate ligament (ACL) tear. A study investigating dual task drop jump landings with healthy controls found decreased knee flexion angle and increased vertical ground reaction force values during the dual-task condition, indicative of stiff landings and increased risk of future ACL injury [17]. A similar investigation with anterior cruciate ligament reconstruction (ACLR) individuals showed altered trunk, hip, knee, and ankle mechanics during a dual task drop jump landing [18]. This population has also shown greater dual-task effects during single- and double-limb stance paradigms [19]. Besides drop jump landings, hop distance tests have been used in conjunction with a cognitive task to test dual-task abilities. Previous work has shown decreased hop distance and preserved cognitive performance under dual-task conditions, although results have varied by type of hop and cognitive test performed [20]. Dual-task paradigms which involve a jumping motor task provide an opportunity to uncover dual-task effects under conditions more similar to a sport scenario.

Other populations such as older adults show increased dual-task interference in a cognitive-motor scenario. In situations involving walking (treadmill or in place) and a cognitive task, results on step metrics have been varied but generally show motor task prioritization. One

study showed a higher proportion of correct serial 3 subtractions under single-task over dual-task conditions while no differences in step time variability were noted between conditions [21]. Older adults have also shown a decrease in the number of steps taken under dual-task conditions in stationary stepping and serial subtraction task [21]. Another study investigating the effects of treadmill walking and two difficulties of working memory task show that older adults were less accurate than younger adults regardless of cognitive task difficulty during the dual-task condition [16]. It was noted that the more difficult working memory task showed greater age differences with older adults showing greater differences between single- and dual-task performance during this condition. Although these studies highlight various gait metrics and cognitive tasks, older adults consistently show postural control prioritization over secondary task performance in dual-task conditions.

Many applications of dual-task study design are represented in the literature. These scenarios highlight the breadth of dual-task paradigms in both everyday life and sport environments and provide insights into performance decrements seen in these scenarios.

1.4 The role of attention control in cognitive performance

Attention control underpins goal-directed behavior in everyday life and sport scenarios. Regardless of the task, managing attention requires an amount of mental resources unique to each individual [7]. Previous works have suggested that attention control may be the modulator between working memory and fluid intelligence, maintaining goals and relevant information while inhibiting distractions and irrelevant responses [22]. Attention control complements working memory's storage and processing functions and fluid intelligence's reasoning ability by maintaining goal-directed focus on relevant information and stimuli [23]. Top-down attention

abilities, where an individual is thought to be in control of their attention and willfully directs attention based on previous goals, plans, and knowledge, help to explain variations in performance during tests of working memory and fluid intelligence [23,24]. For instance, when attention control scores are added as a mediator, correlations between fluid intelligence and working memory are not statistically significant [25]. This suggests that attention control accounts for the shared variance between working memory and fluid intelligence and acts as a mediator between the two cognitive constructs.

1.5 Attention control in multitasking and dual-task performance

Given attention control's relevance in working memory and fluid intelligence, its connection to many other cognitive processes is expected. Attention control displays a strong relationship with domain-general cognitive ability – cognitive operations that can apply to a wide variety of tasks [26]. Domain-general cognitive abilities can include association, problem-solving, learning and memory, among other functions. Aside from these general cognitive abilities, previous research has aligned attention control abilities with more specific functions including processing speed, multitasking abilities, and sensory discrimination ability, among others [25–27]. These connections underscore the critical role of attention control in multitasking scenarios (i.e. dual tasks). Generally, multitasking can be categorized into multiple cognitive tasks or cognitive-motor tasks, especially when physical demands are more pronounced. Previous work has found tests of attention control to account for 75% of the variance in cognitive multitasking abilities [25]. The authors conclude a relationship between balancing multiple tasks and overall attention control capacity. Working memory and fluid intelligence have also been connected to general multitasking abilities [27]. The known relationship between these two

cognitive processes and attention control provides more evidence towards the link between attention control and multitasking.

Although insightful, the connections between attention control and multitasking have generally been limited to investigations during simultaneous cognitive tasks. Investigation into attention control and other cognitive resource allocation in physically demanding cognitive-motor dual tasks is essential to our understanding of performance in these situations. Effective dual-task performance relies on the ability to direct attention towards subtasks and the integrity of executive functions [28]. In dual tasks with relatively larger physical demands (e.g. walking rather than standing), attention control costs increase [29]. However, the effect of dual-task interference in these cognitive-motor dual-task scenarios cannot be extrapolated from cognitive multitasking performance. Performance in cognitive-motor scenarios may differ from cognitive-only multitasking due to the demands of each individual subtask and the interference between them [5]. While dual-task performance is viewed as a measure of cognitive-motor integration abilities, attention control may be contributing factor to the distribution of mental resources to the dual-task components.

1.6 Neurocognitive risk factors and attention control associated with injury risk

Understanding the intertwined nature of attention control and dual-task performance has the potential to provide insights into sport performance, injury prevention, and rehabilitation strategies. Although attention control has not been directly related to biomechanical risk factors of injury, its association with other cognitive processes (e.g. reaction time, working memory, processing speed, etc.) and the connection between these factors and acute injury risk suggests

the need to explore their potential connection. Neurocognitive deficits may be linked to increased risk of acute injury in the ACLR, CAI, and post-concussion populations.

1.6.1 Anterior cruciate ligament injuries

Seminal work in neurocognitive function and ACL injury risk found increased reaction times and processing speeds in addition to decreased visual and verbal memory scores for those who had sustained a noncontact ACL injury, when compared to non-injured athletes [30]. In sport, athletes are faced with scenarios that demand complex cognitive-motor interactions and must rapidly make decisions in response to stimuli. The increase in acute injury incidence during cognitively challenging sport-related tasks could be explained by deficits in neurocognitive function in these individuals [31].

Dual-task conditions facilitate investigation into movement patterns during these cognitively challenging situations. Previous work exploring postural regularity with the addition of a visual-cognitive task in individuals post anterior cruciate ligament reconstruction (ACLR) found that these individuals prioritized balance over the cognitive task [32]. This effect was not seen in their healthy control counterparts. In another study, visual attention scores were negatively associated with knee proprioception error in the ACLR population suggesting a different neural strategy compared to healthy controls [33]. These results have been seen across neurocognitive assessments in the post ACL reconstruction population and have consequences for future injury risk.

1.6.2 Chronic ankle instability

Individuals with chronic ankle instability (CAI) show decreased neurocognitive function compared to healthy controls. These deficits are especially apparent in tests of attention and

memory [34]. Further investigation has shown a connection between attention control abilities and decreased postural regularity in center of pressure measures in this population [35]. Although the mechanisms of neurocognitive impairment in those with CAI are not fully understood, this link to attention control and diminished performance under dual-task conditions shows deficits in cognitive resource allocation. These findings have been corroborated in other studies showing that attentional demands are higher during a dual-task scenario for those with CAI [36]. This decrease in postural control compared to healthy controls in a dual-task scenario points towards impaired balance regulation and could be indicative of future injury risk.

1.6.3 Concussion management and return-to-play

Concussions are accompanied with neurocognitive function deficits that persists past asymptomatic return to sport or other activities. Previous research has connected these decrements in cognitive function with lower limb injury risk [37]. In this study, each previous concussion impacting cognitive scores increased the risk of time-loss lower limb injury by 34 percent, likely due to impaired neuromuscular control following concussion. In another study, individuals who were asymptomatic following a concussion showed decreased walking speed and center of mass displacement and velocity in a dual-task walking paradigm [38].

1.7 Neural activation in attention control and dual-task performance

While task-performance provides insight into the mental resource allocation at play during a task, neural activation measurement can highlight inefficiencies and provide a clearer picture of resource allocation in various scenarios. In response to a task, either decreased or increased neural activation is typically noted. Neural efficiency frameworks support decreased

activation while strategic engagement frameworks are associated with increased neural activation [39]. In response to a sustained attention task, previous work has found increased activation, consistent with the latter, strategic engagement framework [40]. Prefrontal lobe activation is associated with many different cognitive demands especially executive function where increased activation is seen during cognitive control tasks [41]. The prefrontal lobe's role in complex tasks (i.e. tasks involving attention control) demonstrates its importance in supporting overall task performance.

Increased dorsolateral prefrontal cortex (DLPFC) and anterior cingulate cortex (ACC) activation, within the prefrontal lobe, has been noted routinely in tasks that require complex cognitive control, such as novel tasks and those that involve working memory [42]. In a previous study, all participants showed increased DLPFC (BA46 and BA9) activation under dual-task conditions which the authors attributed to this area's management and distribution of attentional resources to each subtask [43]. Generally, DLPFC activation is associated with strategic control of executive functions while the ACC implements this control. The dynamic interactions between these two brain regions is supported by the top-down processing of the DLPFC and the evaluation and planning processes of the ACC [44]. An investigation into the temporal resolution of these areas show an effect of load, but not time on the DLPFC (BA46 and BA9), potentially due to a sustained hemodynamic response to the given working memory task [42]. These findings suggest that a clean separation between maintenance and executive processes may not be supported and associates the DLPFC with both which could be supported by the goal maintenance functionality of this region. In tasks involving executive function, such as attention control or dual-task scenarios, increased activation in the DLPFC and specifically BA46 and

BA9 is likely to be seen as this area distributes cognitive resources. As the longevity of the task increases, monitoring of resource allocation is increased, leading to higher ACC activation. Overall, these findings highlight the important roles of DLPFC and ACC activation in managing complex tasks requiring sustained attention and working memory.

Addressing fluid-induced motion artifact in functional near-infrared spectroscopy

2.1 Functional near-infrared spectroscopy (fNIRS) for neural activation measurement

In settings where individuals engage in movement activities, portable and non-invasive options for functional neuroimaging, such as functional near-infrared spectroscopy (fNIRS), are commonly employed to measure neural activation [45]. fNIRS traditionally relies on block design data collection paradigms where a task is performed following a stationary period and repeated for multiple blocks [45]. It is worth noting that discreet event stimuli [46] and single trial designs [47] have been effectively demonstrated but are far less represented in the literature. Block designs can be implemented seamlessly into biomechanics studies, especially those investigating dual-task performance. fNIRS has been previously validated against the gold standard, functional magnetic resonance imaging (fMRI), and the two techniques have proven to be highly correlated in concurrent measurements [48,49]. Due to the light-based nature of this neural activation measurement technique, limited depth of measurement is seen compared to the gold-standard, fMRI. Although fNIRS shows improved spatial resolution compared to electroencephalography (EEG), its lack of temporal resolution has been criticized in the literature [50]. fNIRS measurements have been validated in adult, infant, and child populations and have demonstrated reproducibility across assessments [51].

2.2 Other modalities of functional neuroimaging

Quantification of neural activation provides an additional perspective on neuromuscular control and function that contribute to task performance. Other modalities have previously been used to measure functional neural activation. Each technique relies on either electrophysiological or metabolic and hemodynamic processes to measure brain activity [52]. Besides fNIRS, fMRI and EEG, among others, are commonly employed techniques to measure functional neural activation in biomechanics studies. As many modalities of neuroimaging are available, advantages and disadvantages exist for each mode of measurement.

2.2.1 Functional magnetic resonance imaging (fMRI)

fMRI is regarded as the gold standard measurement of functional neuroimaging due to its spatial precision. It relies on hemodynamic changes in cortical tissues following neural activity and provides spatiotemporal measurements of the blood-oxygen-level-dependent (BOLD) response [53]. Despite its measurement capabilities, fMRI recordings require participants to perform tasks that allow their head to remain completely still in a supine position. Previous works have relied on fMRI measurements to assess neural activation during stationary cognitive tasks and simple motor movements (e.g. finger tapping, leg kicking). Due to movement constraints, force matching and motor imagery paradigms have provided insights into neural activation during more complex movements. An fMRI force matching study aimed to assess neural processes associated with knee extension and flexion [54]. Connections to cerebellar, sensorimotor, and visual processing brain areas were noted. Another force matching paradigm investigated the impact of knee osteoarthritis on motor cortex modification [55]. The results show differences between affected individual and healthy controls in performance during knee

and ankle motor task and motor cortex activation. Due to the constraints of fMRI movements, neural activation during motor imagery, where participants are asked to mentally simulate movements, has been investigated to gain insights into physical movements. A recent publication noted similarities between neural activation during walking (measured with EEG) and motor imagery of walking (measured with fMRI) [56]. These findings support the use of motor imagery to supplement movement tasks but other work has revealed more brain areas associated with imagery than the actual task, especially those involved in movement planning such as the parietal and occipital regions [57]. Although these studies have provided insights into neural activation during movement tasks, they lack the ability to measure participants in a more ecologically valid environment (i.e. during sitting, standing, or other relevant movements). fMRI is regarded as the most reliable and robust functional neuroimaging modality, however, constraints during movement paradigm measurements limit its use in biomechanics studies.

2.2.2 Electroencephalography (EEG)

For movement paradigms, EEG is a commonly employed for its portability and improved temporal resolution compared to other neuroimaging techniques [58]. As neuronal tissues activate, electromagnetic signals are recorded [52]. The rapid propagation of electric potential from neural signals provides neuronal time scale resolution and precision [59]. Although exhibiting improved temporal resolution, EEG provides only moderate spatial resolution, which is often desired in functional neuroimaging research questions [60]. In EEG measurements, spatial resolution improves with greater electrode coverage. For measurements with 19 electrodes, the spatial resolution is between 22-37 cm^3 while measurements with 129 electrodes improve this value to 6-8 cm^3 [61]. Low spatial resolution is a natural consequence of scalp EEG

measurements due to the conductive nature of the head. Nonetheless, EEG has previously been used to identify neural activation in response to stimuli and during movement tasks. Seminal works in EEG monitoring during dynamic movements have emphasized the portability and real-time measurements provided by this measurement technique and it has been employed in running and walking paradigms [62,63].

2.3 fNIRS measurements during movement tasks

Previous fNIRS studies have investigated neural activation during both stationary and movement tasks. The portable nature of this functional neuroimaging technique allows its use during walking studies. fNIRS and walking tasks are well represented in the literature and have involved a wide range of ages as well as various physical and cognitive abilities. Cortical activity has been measured during normal, forward walking [15,16,64,65] as well as specific tasks such as precision stepping [65], backwards walking [64], and under dual task conditions [15,16]. In these previous investigations, gait variables such as stride time and variability have been compared to neural activation. Neural activation has been measured through fNIRS during resistance training exercises such as squatting and has found an increase in motor cortex recruitment as barbell load increased [66]. The use of fNIRS during movement tasks is well documented. As research questions expand, becoming more dynamic, functional neuroimaging is expected to become more prevalent in study designs.

2.4 fNIRS measurement of neural activation through the hemodynamic response

fNIRS measures neural activation in the cerebral cortex using infrared light, leveraging the optical properties of blood in local cortical tissue [67]. Neurovascular coupling allows fNIRS

to measure neural activation through its temporal relationship with hemodynamic changes. Hyperemia (increased cerebral blood flow) is a direct result of increased metabolic demand in areas of high neuronal activity [68]. Generally, an increased hemodynamic response, increased oxygenated hemoglobin and decreased deoxygenated hemoglobin, is associated with increased neural activation [69].

For multichannel fNIRS measurements, source (light emitting) and detector (light detecting) optodes are placed around the head forming source-detector pairs [50]. Infrared light (photons) emitted from sources is scattered and absorbed as it penetrates through the scalp, skull, and cerebral tissue [67]. Photons that reach detectors are measured and reported. The depth of measurement of the specific source-detector pair is proportional to the distance between each source and detector [50,70]. For instance, a source and detector that are farther apart will measure deeper than a source and detector that are closer together. This principle holds if the detector can detect photons from the source, but measurement depth in a human adult head is generally limited to 3-4 centimeters, reaching cortical tissue but limiting measurement in deeper brain regions [71]. At greater distances, the signal-to-noise ratio (SNR) increases as less photons reach the detector [72]. Through signal processing, detector measurements are converted to optical density (Equation 1) [73]. Equation 1 defines optical density as a function of the ratio of light emitted by the source optode (I_o) and the light detected by the detector optode (I).

$$OD_\lambda = -\log\left(\frac{I}{I_o}\right) \quad (1)$$

The concentration of oxygenated (HBO) and deoxygenated (HBR) hemoglobin are then calculated through the modified Beer-Lambert Law (Equation 2) [73]. Equation 2 describes the changes in oxygenated and deoxygenated hemoglobin (Δc) from previously calculated changes

in optical density (ΔOD_λ). In this equation ε_λ represents the molar coefficient of extinction (specific to human brain tissue) at each measured wavelength, L is the pathlength that light travels through the tissue, and DFP is the differential pathlength factor, a parameter used to estimate the actual path length of a photon.

$$\Delta c = \frac{\Delta OD_\lambda}{\varepsilon_\lambda \cdot L \cdot DFP} \quad (2)$$

Concentrations of HBO and HBR are used to infer neural activation from the hemodynamic response following a stimulus or task onset. fNIRS results are either reported as changes in these chromophores (oxygenated and deoxygenated hemoglobin) or fitted to an expected hemodynamic response function (e.g. canonical or delta functions) [74]. If fitted to a hemodynamic response function, the strength of activation is typically described as a coefficient value. Oftentimes, neural activation is reported as β (Equation 3), a multiplier of the hemodynamic response function, or a t-statistic value which compares activation during task and baseline periods [75].

2.5 Physiological and motion artifacts in fNIRS signals

During fNIRS measurements, visually evident spikes in fNIRS measurements are apparent. Because fNIRS measures the hemodynamic response in cortical tissues, undesired measurements can arise from both physiological (i.e. blood pressure, respiration, heart rate changes, etc.) and non-physiological (wire movement, head movement, intracranial fluid movement, etc.) sources [76]. In tasks with large head movements, these artifacts become even more pronounced (Figure 2). Decoupling artifacts from the hemodynamic response has proven to be challenging. Previous works have relied on algorithms such as principal component analysis

(identifying signal component with greatest contribution to the signal variance [77]) or wavelet filtering (time-frequency localization of changes in signal amplitude [78]) to reduce the influence of artifacts on fNIRS neural activation measurements. High- and low-pass filters have also been used to mitigate the effects of heartbeat (0.8-1.4Hz [79]), Mayer waves (0.1Hz [80]), and signal drift (0.04-0.1Hz [47]). Oftentimes, these physiological frequencies overlap with the hemodynamic response, making their removal by filtering more difficult. Algorithmic techniques are generally effective at eliminating entire frequencies associated with noise but often do not have the capabilities to isolate the actual signal from the noise. The challenge of isolating the hemodynamic signal from motion artifact or other physiological noise arises due to their similar signal characteristics due to overlapping frequencies. Several studies have shown evidence for removal of motion artifact. However, filtering and algorithmic methods of motion artifact correction have largely not been tested in highly dynamic settings where large motion artifacts occur, limiting generalizability to larger movement paradigms.

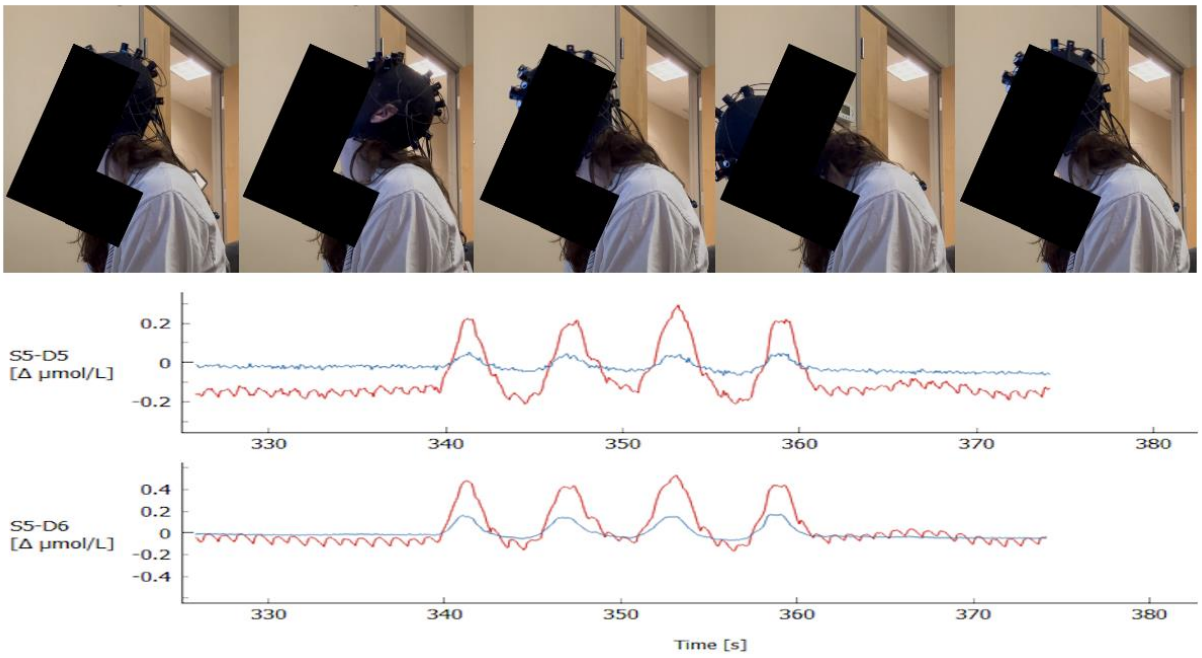

Figure 2: Motion artifacts in fNIRS signals during measurement with large head movements.

2.6 Short-separation channels remove physiological noise

Traditionally used to reduce the impact of physiological artifacts, fNIRS short-separation channels employ the source-detector proportionality principle to measure extracerebral artifacts [72]. The goal of these close distance (8.4 mm, NIRSport 2) source-detector pairs is not to measure into the cerebral cortex and instead measure non-neural artifacts in the scalp, skull, and cerebrospinal fluid (Figure 3) [72]. These physiological artifacts are assumed to be homogenous in the cerebral and extracerebral spaces [81]. In practice, their close distance substantially limits the amount of sensitivity to the brain but does not entirely remove neural measurements. Due to the highly vascularized nature of the scalp and skull, normally spaced source-detector pairs measure the hemodynamic response within cortical tissues and thus oxygenated and deoxygenated hemoglobin concentration differences in these areas as well [72]. Short separation channels have traditionally been used as a regressor for these artifacts and their efficacy has been

explored in stationary environments. They prove to be excellent regressors of subcortical physiological noise in stationary paradigms and their use is encouraged during fNIRS measurement [82–85]. The underlying principle motivates that short-separation channels may be useful as regressors of not only physiologically driven but also motion governed fluid movement. Characterizing their ability to account for the inertial effects of subcortical fluid during movement tasks has not been explored but exploration is warranted due to their value in stationary settings.

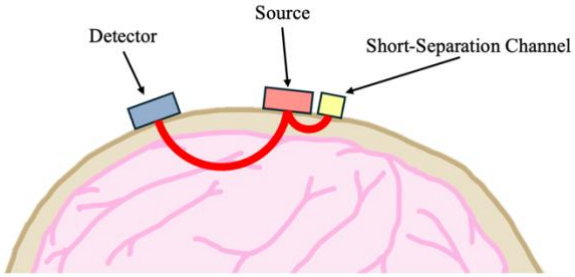

Figure 3: Illustration of source-detector proportionality principle. Light is emitted from sources and detected by detectors. Source-detector pairs further apart (3-4cm) are able to measure deeper into cortical tissue. Closer distance source-detector pairs (0.8cm) measure in the scalp, skull, and cerebrospinal fluid. (Figure adapted from image of human brain [86].)

2.7 Regression of physiological noise with short-separation channels

Statistical analysis of fNIRS data is performed with a general linear regression model (GLM) that describes neural activity, similar to fMRI (Equation 3). In Equation 3, Y represents the measurement (column) vector and contains a one measurement per time point. The design matrix, X, contains the timing of stimulus events, regressors of unwanted model data trends (e.g. motion artifacts, drifts), and a column modeling the mean of the signal. This matrix is designed

by the convolution of the boxcar function (identifies constant amplitude time periods of event blocks [73]) and a chosen hemodynamic response function (generally canonical response [73]) [87]. The β variable describes the weighted unknowns of the regression model and is estimated through linear regression. ε describes the measurement error. The linear regression model is solved for the β vector using autoregressive iterative least squares (AR-IRLS) and its statistically significant values are interpreted as an indication of neural activity [75]. AR-IRLS uses bisquare weighting to down weight outliers. This method accounts for the serial correlation of fNIRS timeseries data by applying pre-whitening filters. AR-IRLS reduces the risk of false positives due to the natural serial correlation of fNIRS data.

$$Y = X \cdot \beta + \varepsilon \tag{3}$$

On the subject level, one β value within the β vector is typically associated with a measurement channel (source-detector pair). As regions of interest (ROI) within the brain are identified, weighted averages of channels crossing the ROI are used to estimate the hemodynamic response [75]. Short-separation channels are essential components of the design matrix, X, where they are used as nuisance regressors when solving for β values.

2.8 Consequences of motion artifact on fNIRS neural activation measurements

Although studies that employ fNIRS as a neural measurement technique during movement paradigms have been published, without investigation into motion artifacts, spurious findings could mislead the field [88]. Concerning still is the difficulty discerning between motion artifact and neural activation when using human fNIRS recordings. Previous studies have superimposed simulated neural signals atop human measurements taking during resting or finger

tapping states [89,90]. Although the neural activation during these tasks is likely minimal, the confounding effects of any activation may influence the results of studies aimed at removing motion artifacts. Therefore, a knowledge gap exists in determining the efficacy of motion artifact reduction without the unintended impact of genuine neural activation, particularly during movement tasks. Accelerometers have been proposed as a method for quantifying head movement which could be used to remove motion artifacts in post processing. Although this method improved motion artifacts, it was limited to small movements [91]. Techniques for removal of artifacts in fNIRS signals have been established. However, best practices for motion artifact correction during fNIRS recordings in movement tasks remains varied across the literature.

2.9 Optical phantoms to assess neural activation measurement in fNIRS

Optical phantoms are traditionally used for calibration and sensitivity testing in fNIRS devices (Figure 4) [92,93]. Calibration phantoms allow for measurements on an environment where neural activation is undoubtedly absent, providing perspectives on maximal transmission of emitted light. Bridging from a stationary environment, dynamic phantoms (i.e. moving optical phantoms) allow fNIRS measurements in motion rich environments. fNIRS testing on optical phantoms removes the confounding effects of normal neural activation when using human data. A study investigating the effects of intracranial fluid dynamics on fNIRS signals created a phantom brain mimicking the optical properties of a piglet brain [94]. The approach allowed reliability testing of an fNIRS system compared to a standardized model. Other fluid flow models have aimed to imitate and measure fluid pulsation present in the forehead [95]. Other phantoms were designed for the purpose of processing method comparisons, specifically delving

into the accuracy of oxygen saturation measurements by a continuous wave fNIRS system [96]. To date, fluid motion artifact detection and correction has been understudied in fNIRS phantom research.

Figure 4: A) Example of an optical phantom designed to mimic the light absorption and scattering properties of the human brain. B) Optical phantom with fNIRS optodes attached.

2.9.1 Optical phantoms for motion correction in EEG

Phantoms have previously been employed in EEG study paradigms to quantify motion artifacts. Motion induced noise is present in EEG signals, similar to fNIRS recordings; however, EEG and fNIRS movement artifacts emerge from fundamentally different sources (i.e. cable

movement or movement of recording electrodes rather than physiological or inertial sources). The development of EEG phantoms to simulate human electrocortical activity under dynamic conditions has emerged as a technique for isolating neural activity from motion artifacts. Motion artifacts have been found in EEG recordings at vertical displacements over 4 cm and frequencies greater than 1.5Hz [88]. With the use of independent component analysis (ICA), these motion artifacts were able to be separated from the ground truth neural signals, indicating the utility of this dynamic phantom for EEG motion artifact reduction. Another study utilizing a dynamic phantom with electrical signal generation found that electrodes were less affected by motion artifact when they had a larger surface area and placed on top over the back of the head-shaped phantom. In this study, cable motion was deemed to be a large contributor to motion artifact while electrode mass had no effect [97]. Dynamic phantoms for motion artifact identification and reduction in EEG systems have provided insights into the sources and removal techniques of motion artifact. Their use for this portable neuroimaging system provides a promising foundation for use with fNIRS.

2.10 Motion artifact removal model comparison

Using a dynamic phantom provides ground-truth measurements where the detected signal in both long and short separation channels can be solely attributed to motion artifacts. Overlaying a simulated neural signal with a known amplitude on some (long) channels and incorporating short-separation channels as regressors in the GLM when solving for the β vector enables error calculation (i.e., difference between calculated signal and known signal) and provides an estimate of the analysis accuracy. In previous work, receiver operating characteristics (ROC) analysis has been used to compare algorithms and models [89]. This

technique plots the true positive rate (signal detected when signal was present) against the true negative rate (no signal detected when no signal was present) and calculates the area under the curve (AUC), indicating the probability of detecting a signal when it exists [98]. Analysis of β error and AUC in fNIRS analyses with and without short separation channels provides complementary insights into the performance and reliability of this motion artifact reduction technique. Information from both analyses could help to inform scenarios where short separation channels are useful in removing motion artifact and isolating true neural signals amidst noise.

Statement of Purpose

The relevance of attention control in cognitive processes such as working memory, processing speed, and multitasking abilities warrant investigation into its use as a predictor of dual task performance. Beyond performance scores, neural activation during tests of attention control could give insight into allocation of neural resources during attentionally demanding tasks, such as dual tasks. Although measurement methods of neural activation using fNIRS during a stationary task, such as a computerized attention control test are well developed, reduction of fNIRS motion artifacts in a movement setting remains a knowledge gap. Identification of error magnitudes during fNIRS measurements in motion rich environments is crucial to accurately quantifying neural activation during movement tasks.

Therefore, the purposes of this body of work were to 1) clarify the role of attention control as a correlate of dual task performance, specifically in physically challenging dual-task scenarios and 2) investigate the sensitivity and specificity of short-separation channels regression for fNIRS measurements in motion rich environments.

CHAPTER TWO

COGNITIVE, MOTOR, AND NEURAL PREDICTORS OF PERFORMANCE IN COGNITIVE-MOTOR DUAL TASKS

Contribution of Authors and Co-Authors

Manuscript in Chapter 2

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Contributions: Conceptualization, Testing, Data collection, Formal analysis, Investigation, Visualization, Methodology, Writing – original draft, Writing – review and editing.

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Manuscript Information

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Abstract

Dual-task scenarios, where a cognitive and motor task must be performed simultaneously occur often in real-world tasks and sport scenarios. These situations involve dividing attention towards each task component which has performance implications. Attention control defines the ability to maintain overarching goals and selectively focus attention on relevant stimuli while ignoring distractions. This general ability to control focus is connected to other cognitive processes such as working memory and fluid intelligence and is typically associated with neural activation in the dorsolateral prefrontal cortex (DLPFC). The connection between attention control performance and DLPFC activation and dual-task deficits are unknown. The purpose of this study was to determine the extent that an attention control battery test, DLPFC activation during this test, as well as cognitive and motor single tasks could predict dual-task deficits. Participants completed an attention control test battery while DLPFC activation was measured. Cognitive and motor single-task performance was measured through repeated single-leg squats and the Antisaccade test of attention control and the dual-task condition combined these two single tasks. Correlations between attention control score, DLPFC activation, single task performance, and dual-task deficits were performed. The findings indicate that attention control and DLPFC may be independent predictors of dual-task deficits with increased performance in the attention control test and increased neural activation associated with less dual-task deficits. Further investigation is needed to clarify the relationship between attention control, DLPFC activation, and dual-task performance in varied dual-task scenarios.

Introduction

Multitasking exists broadly in most real-world tasks. From walking and talking on the phone to driving a car in busy traffic, attention is required to be split between two or more tasks. In sport, these so-called dual tasks are commonplace and often require elements of cognitive and motor demands. As attention is directed toward each component of the overall task, deficits in both cognitive and motor functions generally occur [1,2]. Performance implications are inherent in dual tasks due to competition for sensory processing resources from each subtask especially when the tasks use the same perceptual system [3]. To explain these deficiencies, the central capacity sharing model theorizes that individuals have a finite amount of cognitive resources available for a given task and these resources vary by individual [4,5]. It appears that individuals have control over the focus of attention to specific tasks and generally tend to devote more attention towards the portion of a dual task that is perceived as more difficult [5]. Despite this element of decision making related to task perception, resource allocation remains insufficient to allow the chosen subtask to be performed as effectively as it would be in isolation [5]. Due to the widespread nature of multitasking, understanding the mechanisms behind dual-task performance and cognitive resource allocation is critical not only for everyday life but also for enhancing athletic performance and reducing injury risk, particularly in sports like basketball or soccer, where attention is divided between both cognitive and motor demands.

Attention control refers to the ability of an individual to selectively focus attention on relevant stimuli and discriminate against unwanted distractions [6]. Switching between subtasks, maintaining overarching goals, and disengaging from no longer relevant information are facets of general attention control in the real-world [6,7]. It is paramount to our general ability to

perform everyday tasks and therefore, may play a pivotal role in dual task scenarios [8]. Attention control has been directly linked to military career aptitude evaluation [9] and police decision-making [6] as well as sports performance [6]. The pronounced role of attention control in daily tasks emphasizes its importance in sport-scenarios where athletes are constantly changing focus between multiple stimuli. Previous work has connected attention control to performance in sports settings (as reviewed by [10]). The general ability to avoid distractions has been tested in fast-paced sport scenarios including basketball and hockey [11]. In these studies, players who performed best on cognitive tasks were best able to determine best next courses of action in their respective sports (shoot, dribble/stick handle, or pass) amidst distractors (i.e. auditory messages or coach given (mis)information). These experiments provide evidence towards a connection between increased ability to resist distractions and performance in complex sport scenarios. However, cognitive tests in these studies were more related to working memory and storage rather than attention control. As multitasking scenarios exist in many facets of sport, the connection between attention control and dual tasks warrants further exploration to better understand how cognitive resources are allocated and managed, especially in sport scenarios.

Developing robust and time-efficient methods of assessing attention control has been challenging. Traditional measures of evaluation for dysfunctional attention control exist and are widely used, typically in preschool-aged children and adolescents [12]. For adults, dysfunctional attention control is assessed symptomatically and, similarly to pediatrics, focuses on diagnosing specific disorders rather than assessing where an individual falls on a continuum of attentional ability [13]. While these DSM-5-TR scales provide effective diagnosis and treatment pathways for their intended demographics, detection of deficits on a spectrum of attention control abilities

rather than dysfunctions is not defined. Tests for robust assessment of attention control abilities has been investigated in previous work [14,15]. These works have focused on the development and validation of an attention control measure and explored how a combination of three short tests could be used to assess attention control abilities. This short combination of three tests as a preventative screening measure has potential clinical value in providing reliable and timely assessments of individual attention control capabilities and predicting the likelihood of injury. The brevity and robustness of the test provide unique value when assessing attention control in relation to other cognitive processes, such as multitasking [9]. Although these attention control tests are reliable and robust and related to non-laboratory settings (i.e. military career aptitude tests [9]), their functionality in non-stationary settings (e.g. dual tasks) is unclear. Relationships between attention control and movement paradigms could be important in sport settings for predicting performance and potential injury risk.

In addition to cognitive assessments, neural activation plays a central role in the understanding of mechanisms that differentiate high versus lower attention control and its impact on real-world activities [9]. The dorsolateral prefrontal cortex (DLPFC) has been identified as a contributor to executive functions such as response inhibition, reasoning, problem-solving, and working memory among others. These cognitive abilities are all closely related to multitasking in both dual tasks and task-switching [3]. While direct links between attention control and specific neural activation patterns are limited, its close relationship with other cognitive abilities (i.e. processing speed, multitasking abilities, working memory [7,16]), suggests a connection to the DLPFC. Although neural efficiency is typically associated with lower brain activation with maintained performance, increased neural activation is seen in difficult tasks, including those

requiring abstract reasoning, working memory, and attention control [17,18]. Previous work has identified task difficulty and intelligence as modulators of cortical activation [19–21]. As the difficulty of the task increases, heightened activation is observed in response to increased cognitive demand. When considering the DLPFC, heightened task demand has been consistently associated with increased activation in retention and retrieval periods of cognitive tasks, underscoring its role in maintenance of working memory, regardless of high- or low-performance on a task [19]. These findings highlight the role of the DLPFC in complex tasks, such as those involving attention control, and emphasize its central function in supporting task performance.

Due to the shared cognitive processes of dual tasks and attention control, as well as their relevance in to both athletic performance and injury risk, a knowledge gap exists relating attention control to dual-task performance. The purpose of this study was to elucidate the extent that cognitive, motor, and neural activation correlates of attention control can predict performance in physically challenging, dual-task scenarios. We hypothesized: 1) Increased performance on attention control test battery would result in less dual-task deficits due to the increased demand of dual tasks compared to single tasks and the correlations between attention control and working memory, processing speed, and multitasking abilities. 2) Increased performance on cognitive and motor single tasks would result in less dual-task deficits because high performers may have more cognitive resources available to allocate to a second task. 3) Increased neural activation in the DLPFC during tasks of attention control would result in less dual-task deficits due to a strategic engagement framework.

Methods

Participants

Eighteen physically active, college-aged, healthy controls participated in this study. They were required to participate in activities involving running and cutting at least 2-3 times per week and to have a Tegner Activity Scale > 5, indicating at least recreational sports participation [22,23]. All participants were right leg dominant, as determined by the leg they would use to kick a ball as far as possible. Exclusion criteria included a history of concussion in the 6 months prior to their study visit, a history of any attention deficit disorders, or any lower limb injuries requiring surgery. All participants provided informed consent per Montana State University's Institutional Review Board before their participation in the study.

Protocol

Participants completed an attention control test battery followed by a cognitive task, motor task, and a cognitive-motor dual task. The order of the cognitive-motor tasks was randomized for each participant. Neural activation was measured using fNIRS during the attention control test.

Attention Control Test Battery

Attention control ability was assessed through the Stroop Squared, Flanker Squared, and Simon Squared tasks performed seated at a computer to assess baseline attention control [14]. In the Stroop Squared task, participants indicate the color of a printed word without interpreting its meaning. The Flanker Squared task asks participants to match the direction of a center arrow of 5 while disregarding the surrounding arrows. In the Simon Squared task, participants indicate the

direction of an arrow while disregarding the side of the screen it appears on. For each test, participants were given 90 seconds to respond with as many correct responses as possible. Neural activation was monitored using functional near-infrared spectroscopy (fNIRS). All participants completed a practice round and an fNIRS baseline (30 seconds still sitting with eyes open) prior to each test start.

The Attention Control test battery, including Stroop Squared, Flanker Squared, and Simon Squared tests, was scored by subtracting the number of incorrect responses from the number of correct responses for each test. Each individual test score was multiplied by a weight representing the relative contribution of that latent attention control factor to the participant's overall attention control (Stroop Sq. – 0.58, Flanker Sq. – 0.64, Simon Sq. – 0.82). These weights were selected from Burgoyne et al. due to their strong association with multitasking performance [14]. The weighted test scores were summed to capture the participant's attention control abilities as a composite variable. Higher scores indicated increased performance.

Neural activation was measured using fNIRS during all conditions but was analyzed only during the attention control task due to large movement artefacts during other tasks. After measuring participant nasion-inion distance, right-left preauricular point distance, and head circumference, to determine cap size, the fNIRS cap was placed on the head. Hair was moved, as needed, allowing sources and detectors to contact the scalp. Proper cap alignment was verified using the international 10-20 location of Cz, centralized using the distances between right and left preauricular points and nasion-inion distance. The fNIRS system (NIRSport 2) used 8 sources and 8 detectors with one detector used in a breakout cable for 8 short separation channels. Sources emitted near-infrared light at 690 nm and 830 nm and data were collected at a

sampling rate of 10.17 Hz. A montage consisting of 15 source-detector channels provided measurements over the left hemisphere of the brain as the motor tasks were performed only on the right leg (Figure 5). All source-detector combinations on the forehead were calibrated and verified for successful measurement. A black over cap was used to mitigate ambient light contamination.

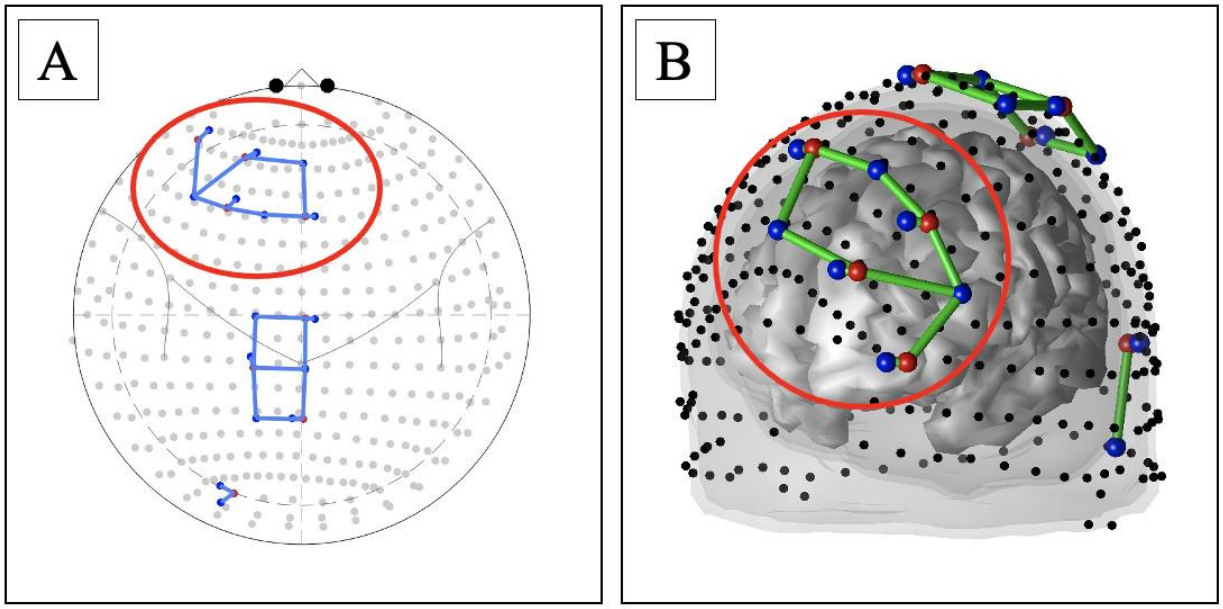

Figure 5: fNIRS measurement source (red) and detector (blue) locations on the 10-20 system (A) and mapped to a human head (B). This data was collected as part of a larger exploratory study involving source-detector pairs placed on various head regions. Only those located on the DLPFC (circled in red) were used for analysis.

fNIRS data were analyzed in a custom MATLAB (The Mathworks Inc.; Natick, MA; version R2022b) script using the NIRS Brain AnalyzIR Toolbox [24]. Raw signals were first visualized to ensure quality (i.e. no large spikes or shifts in data). Ultimately, no participants or channels were removed from the dataset due to fNIRS quality issues. The raw data were resampled to 4Hz to retain signal hemodynamic responses while reducing computational

demands. Optical density was calculated and temporal derivative distribution repair (TDDR) was applied to correct for motion artifacts [25]. Optical density values were filtered using a fourth-order Butterworth filter (0.5 Hz) to reduce the impact of physiological artefacts (i.e. heartbeat, respiration rate) and signal drift. Concentrations of oxygenated (HBO) and deoxygenated (HBR) hemoglobin were calculated using the modified Beer-Lambert law and a partial pathlength factor (PPF) of 0.1 [26]. An autoregressive iterative least-squares (AR-IRLS) general linear model using short-separation channels as regressors was performed on the data to determine channel β values [27]. The AR-IRLS model allows for robust down weighting of outliers (motion artifacts) through a bisquare weighting and corrects for the serial correlation of fNIRS timeseries data. The model assumes a canonical hemodynamic response function and controls for type I error and false positives that are linked to the serially correlated nature of fNIRS data. This GLM method (AR-IRLS with short separation channel regression) has demonstrated increased ability compared to other methods of physiological artefact correction [28]. Specific regions of interest (BA46 and BA9, DLPFC) were identified and computed based on the Talairach Daemon atlas [29]. Channels crossing and surrounding the region of interest (ROI) were assigned tapered weights based on their proximity to the desired region. As the ROI is unlikely to be covered equally and sensitivity to the specific ROI is maximal in the closest channel, tapered weights allow for more contribution to the expected region and decrease noise from unrelated channels [30]. Sources and detectors on locations unrelated to the DLPFC were not used in this analysis. The ROI analysis calculated β values as indicators of neural activation where a higher β is associated with more activation. The β values for BA46 and BA9 were used in subsequent analyses.

Cognitive and Motor Tasks

Participants performed a motor task of repeated single leg squats, a common movement to assess lower limb neuromuscular control, for 5 blocks of 54.4 seconds at 0.5 Hz with 2 minutes of rest between blocks [31]. Squats were performed from full extension to 45 degrees knee flexion. All participants performed the single leg squats on their right leg. The movement frequency was regulated through an auditory metronome that signaled the 'up' and 'down' positions of each squat to the participant. The participants performed a practice round of right single-leg squats for 15 seconds at the prescribed timing, with feedback regarding the squat depth and frequency. The Antisaccade test of attention control was performed for 5 blocks of 54.4 seconds with 1 minute of rest between blocks [15]. Briefly, the Antisaccade test requires participants to accurately identify a briefly presented stimuli ('O' or 'Q') on the opposite side of a screen from a distractor cue (flashing '*'). Participants indicated their response through handheld triggers and performed the task standing on two feet. A practice round of 15 seconds was completed prior to the first block of testing. The dual-task condition consisted of the repeated single-leg squatting and Antisaccade tests performed concurrently. Each condition was repeated for 5 blocks of 54.4 seconds with 2 minutes of rest between blocks (Figure 6). Participants were familiarized with the task during a 15 second practice round. The order of the motor-task, cognitive-task, and dual task were randomized for each participant.

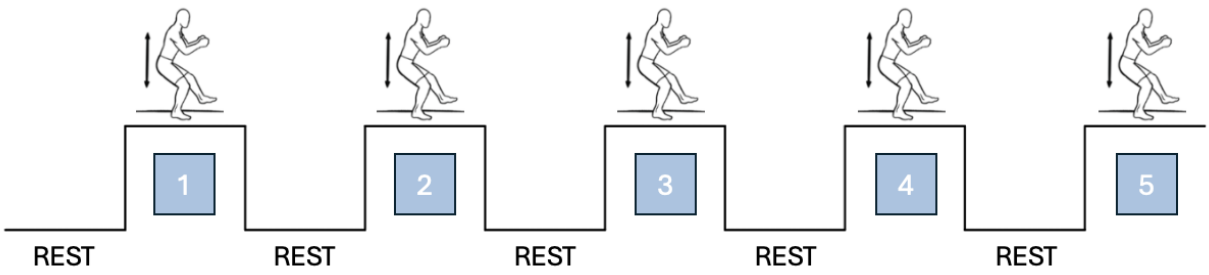

Figure 6: Block design of single cognitive (Antisaccade test). single motor (repeated single leg squats), and dual tasks (combined Antisaccade test and repeated single leg squats performed for 5 blocks.

During the repeated squatting task, ground reaction force data were sampled at 400Hz from 4 force platforms (AMTI, Watertown, MA, USA). Visual3D (C-Motion, Inc., Germantown, MD, USA) was used to calculate center of pressure (CoP) measures. A custom MATLAB (R2022b; The Mathworks, Inc., Natick, MA, USA) script first applied a fourth-order Butterworth filter (10Hz) and then calculated CoP ellipse areas from center of pressure values for each condition [32]. CoP ellipse area was calculated to measure postural control in the motor single-task with smaller ellipse areas indicating increased performance. CoP values were first trimmed from stimuli indicating the beginning and end of each trial. A buffer of 5 seconds was removed from the beginning and end of each trial to account for any initial or final fluctuations in the CoP data. CoP ellipse area (mm) was calculated for each block and then averaged over the number of blocks, providing one value for each participant [32]. Antisaccade (cognitive task) performance was measured by the number of correctly identified letters divided by the total number of stimuli presented (16 per block, balanced right and left side presentation of letters, 1 or 2 second randomized delay before letter presentation).

Dual-task performance was measured as the CoP ellipse area and Antisaccade performance, separately, during the dual task. In addition to overall dual-task performance scores, dual-task change scores [(*single task – dual task*) / *single task*] from both cognitive (DTC-COG) and motor (DTC-MOT) perspectives were calculated as dependent variables. For the DTC-MOT the single task and dual task scores were reversed to [(*dual task – single task*) / *single task*] to account for the reverse directionality of performance on CoP (smaller CoP, better performance). Lower DTC scores are indicative of better performance (i.e., less performance deficit during dual-task relative to single-task condition).

Power Analysis

Power analysis was performed in R (version 4.4.1) via R studio (version 2024.09.0, Posit Software, PBC) [33]. The smallest detectable correlation given the number of participants, significance level of $\alpha = 0.05$ and an 80% power is rho = 0.640. Due to the exploratory nature of this study, no corrections for multiple comparisons were performed.

Statistical Analysis

Statistical analysis was performed using R (version 4.4.1) via RStudio (version 2024.09.0, Posit Software, PBC) [33]. Dependent variables included attention control test scores as a composite outcome (AC), CoP Ellipse Area for single and dual tasks (ST-MOT, DT-MOT), Antisaccade test performance for single-and dual tasks (ST-COG, DT-COG), dual-task change – cognitive and motor (DTC-COG, DTC-MOT), and fNIRS β values ($\beta - BA46$, $\beta - BA9$).

Normality of all variables was assessed using the Shapiro-Wilk test. Pearson correlation coefficients were calculated to assess the linear relationship between variables AC, ST-MOT, DT-MOT, DT-COG, DTC-MOT and DTC-COG. All variables were normally distributed.

Results

Three participants were excluded entirely from the dataset as outliers due to ST-COG and DT-MOT variables (Grubb's Test), this left 15 participants as the total sample size for analysis (Table 1). At least four of the five blocks for each participant were available for both the motor task and the dual task. Five blocks out of the total of 144 blocks were excluded due to data collection issues.

Table 1: Descriptive Statistics (Mean ± SD) for Sample Population.

Measure	Mean ± SD
Age (years)	20.6 ± 1.7
Sex (n)	Male: 8, Female: 7
BMI (kg/m^2)	24.9 ± 3.5
Tegner	7.9 ± 1.5
Marx	13.4 ± 1.9

Attention Control and Dual-Task Performance

The attention control battery test scores (AC) were significantly associated with the cognitive dual-task cost (DTC-COG) scores (rho = -0.514*, p =0.05, Figure 7) and trended toward a significant association for motor dual-task cost (DTC-MOT) scores (rho = -0.485, p = 0.067, Figure 7). Attention control battery scores were positively associated with single-task cognitive (ST-COG) test score (rho = 0.584*, p = 0.022, Figure 8) and cognitive dual-task (DT-COG) test score (rho = 0.658*, p = 0.008, Figure 8).

Single- and Dual-Task Relationships

Neither single-task cognitive (rho = -0.109, p = 0.699) nor motor (rho = -0.425, p = 0.116) score was significantly associated with its respective dual-task cost score, however, a moderate effect size was seen for the motor single task to dual-task cost relationship (Figure 9A and Figure 9B).

Neural Activation and Dual-Task Cost

$\beta - BA46$ was associated with motor dual-task cost (DTC-MOT) scores (rho = -0.594*, p = 0.02, Figure 10) however, less so with cognitive dual-task cost (DTC-COG) scores (rho = -0.377, p = 0.166, Figure 10).

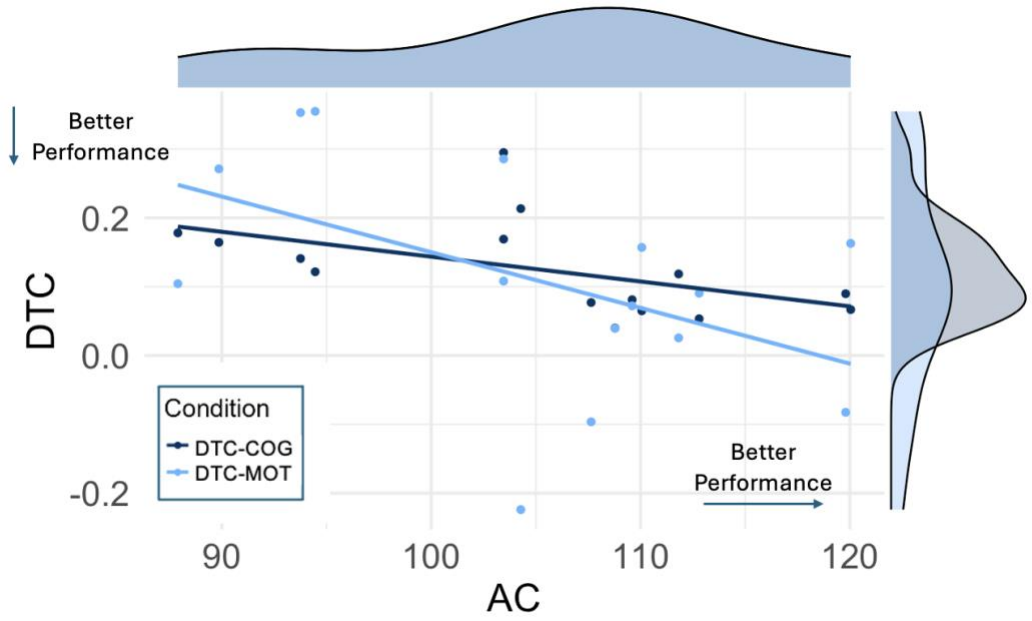

Figure 7: A) Correlations between attention control score and cognitive and motor dual-task costs (DTC-COG [rho = -0.559*] and DTC-MOT [rho = -0.304]) Significance indicated by *.

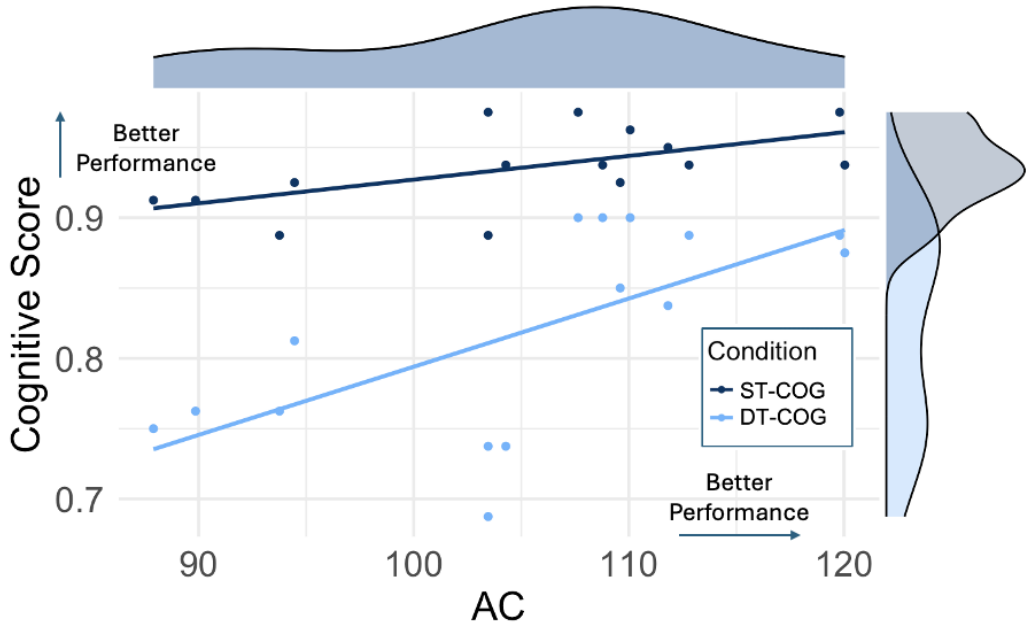

Figure 8: Correlations between attention control test battery and cognitive (Antisaccade) test scores in single- [rho = 0.584*] and dual- [rho = 0.658*] task conditions. Significance indicated by *.

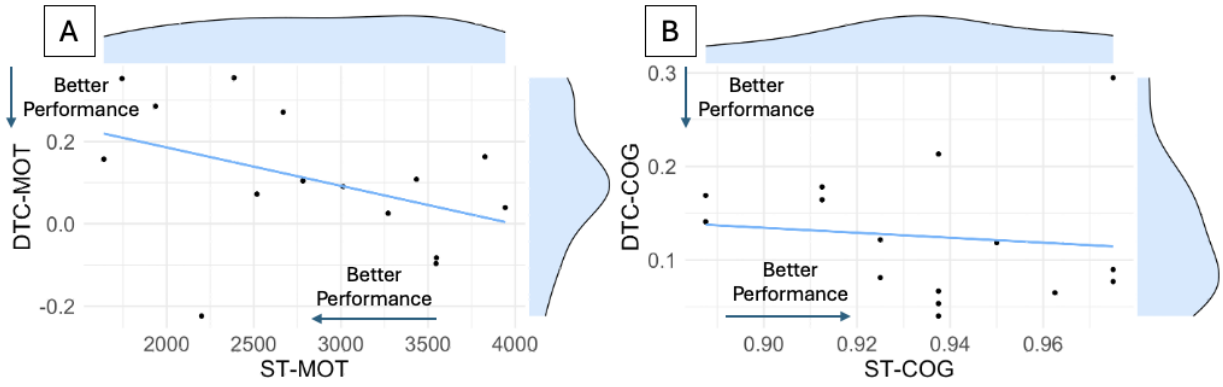

Figure 9: Non-significant relationships were seen between both motor (A) and cognitive (B) single tasks and their respective dual task. A moderate to strong effect size was seen for the relationship between motor single task and dual-task cost [rho = -0.424, p = 0.116].

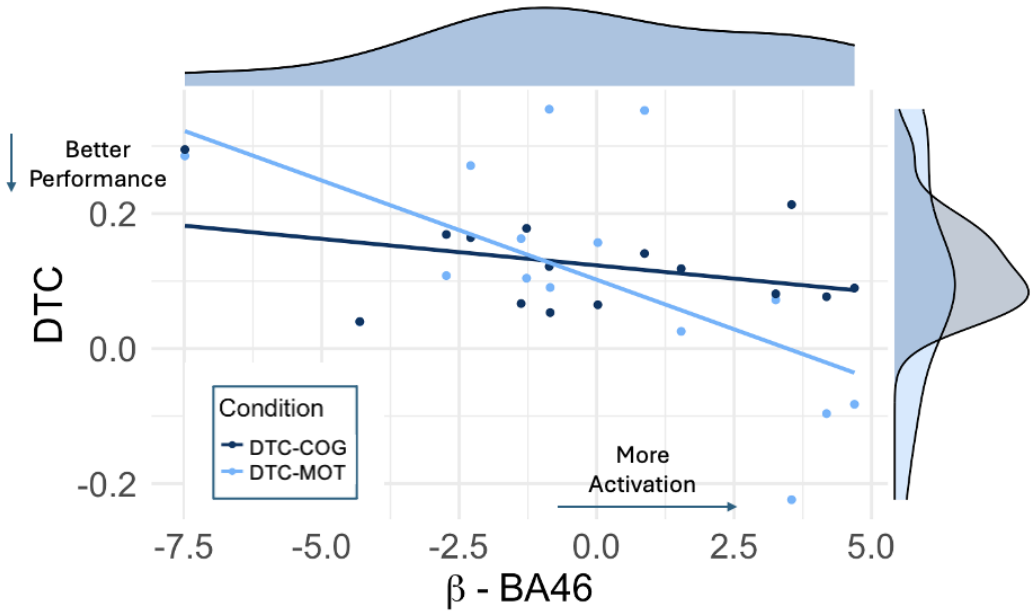

Figure 10: A) BA46 activation significantly predicted DTC-MOT scores [rho = -0.594*, p = 0.02]. Although non-significant, BA46 activation and DTC-COG showed a moderate effect size [rho = -0.377, p = 0.166].

Discussion

This study aimed to define the relationship between attention control scores, cognitive and motor single-task performance, dual-task deficits during a physically challenging dual-task scenario, and neural activation during a test of attention control. The findings of this study provide evidence for less change in dual-task performance for individuals who scored higher on a test of attention control, evidenced by a negative relationship between AC score and DTC-COG and DTC-MOT, supporting our first hypothesis. No relationship was found between cognitive or motor single-task performance and dual-task score from either perspective. This evidence does not support our second hypothesis. A negative relationship was found between BA-46 activation and DTC-MOT. A similar, although non-significant, relationship was found between activation in this region and DTC-COG, partially supporting hypothesis 3 that

individuals with greater neural activation on attention control tests would show less dual-task deficits. These results highlight the complex role of attention control and dorsolateral prefrontal cortex activation in supporting task performance during a physically challenging cognitive-motor dual-task scenario.

Attention control scores proved to have a negative relationship with both cognitive and motor dual-task cost scores. Although the relationship between AC and DTC-MOT was non-significant relative to the standard alpha level of 0.05, its large effect size (rho = -0.485) suggests a relationship between the two variables. The ability to selectively focus attention on task components and maintain overarching goals are key pillars of attention control and its role in multitasking [7]. Together, these results show that those who are better able to maintain their focus on a task of attention control transferred that ability to a physically challenging cognitive-motor dual task. The relationships between attention control and other cognitive processes such as working memory, processing speed, and multitasking, among others, have been well established in the literature [7,14]. Those with higher attention control ability are better able to leverage these cognitive processes to overcome distractions from the addition of a cognitive or motor task in a dual task scenario and perform better in this setting than their lower scoring counterparts. These findings were supported by positive relationships found between attention control and cognitive single-task (ST-COG) and overall dual-task (DT-COG) scores (Figure 4). These positive relationships suggest that attention control is a consistent cognitive ability across testing settings [14]. Although cognitive performance was higher during the cognitive single-task, attention control scores show a stronger correlation with dual-task performance. These results suggest that these high performing individuals were able to resist the motor distraction

during this dual-task scenario and continue to be high performers on the cognitive portion of the dual-task, consistent with an increased ability to maintain overarching goals in the face of distractions. Conversely, low AC scores were less able to maintain focus between the two tasks and showed greater decreases in cognitive performance during the dual-task scenario. These relationships between attention control test battery scores, dual-task cost, and cognitive single- and motor-task performance show that increased attention control capabilities could reduce the impact of dual-task interference in physically challenging dual-task scenarios where attention is directed toward both cognitive and motor tasks.

No significant relationships were found between baseline (single-task) performance and dual-task cost; however, motor single-task (ST-MOT) performance was negatively associated with motor dual-task cost (DTC-MOT). The moderate to strong effect size of rho = -0.424 suggests that higher performers in the motor single task were associated with worse motor dual-task performance. These high performers were more likely to experience cognitive interference when faced with a dual-task situation. As the cognitive task was added to the dual task, their focus split between tasks which negatively affected their motor performance. For these individuals, the cognitive task may have been prioritized during the dual-task scenario leading to greater dual-task costs. One explanation for these findings is low performers struggled with the motor single task alone, so adding a cognitive task had less of an impact on their performance. This is corroborated by the positive correlation between ST-MOT and DT-MOT scores (Figure 11). Individuals who showed worse performance in the single task condition continued to perform poorly in the dual task, they just did not exhibit as much of a change in performance between single and dual tasks. It is possible that these poor performers focused their attention on

the subtask that they perceived as more difficult (motor) during the dual-task condition. This finding is similar to the concept of dynamic prioritization that has previously been demonstrated in healthy young adults [34]. As the difficulty of the motor task increases in a cognitive-motor dual task, prioritization shifts to focus on the motor demands. This effect was shown in dual-task walking conditions but could be applied to the single-leg squatting task in this study. Individuals who perceived the motor single task as more difficult tended to prioritize it in the dual-task scenario.

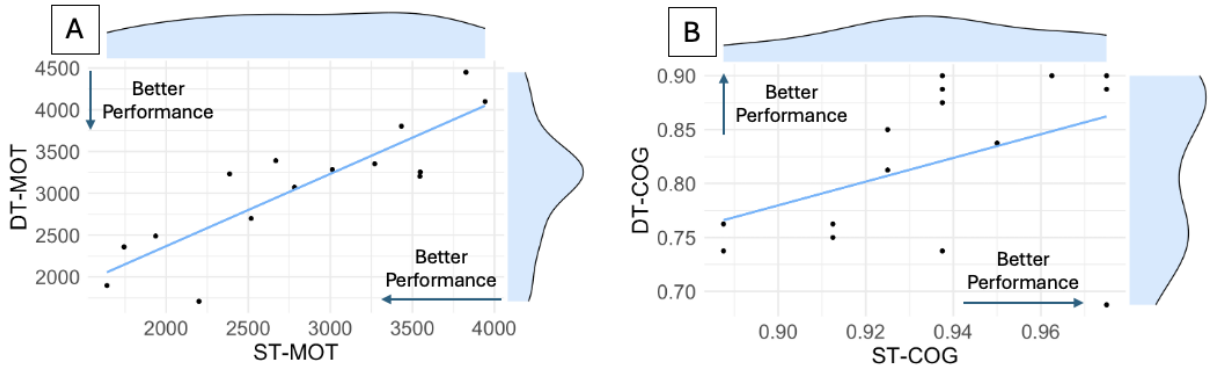

Figure 11: A) Correlation between motor single- and dual-task performance [rho = 0.863*, p < 0.0001]. B) A moderate to high effect size was found between cognitive single- and motor-task performance [rho = 0.430, p = 0.110]. Significance indicated by *.

Negative correlations were found between DLPFC activation dual-task cost performance in β-BA46, but no relationship was found for β-BA9 and these variables. Specifically, a strong negative correlation (rho = -0.594*) defined the relationship between β-BA46 and motor dual-task cost (DTC-MOT). A moderate effect size (rho = -0.377) was found between β-BA46 and cognitive dual-task cost (DTC-COG), suggesting an appreciable relationship although significance was not found. This implies that individuals with greater DLPFC activation during

the attention control battery were better able to maintain focus in the dual task amid cognitive and motor distractions. In some instances, increased activation during task performance is associated with a neural inefficiency framework where individuals must activate more to achieve the same goal [18]. Under other conditions, increased activation may be associated with a strategic engagement framework, where more neural resources are recruited to meet task demands [35]. The positive (albeit weak and non-significant) effect size (rho = 0.283) indicates that better performers in the attention control test battery were associated with increased neural activation. Interestingly, the correlation between BA46 activation and cognitive dual-task (DT-COG) performance showed a moderate effect size (rho = 0.470). Although weaker, a negative relationship (rho = -0.276) was seen between BA46 activation and motor dual-task (DT-MOT) performance, associating BA46 activation with increased DT-MOT scores. Although the correlations between increased activation and cognitive-motor dual-task (DT-COG and DT-MOT) performance were non-significant they may have practical relevance. Notably, no relationship was found between BA46 activation and either single task. This indicates that BA46 activation plays a key role in high-demand requiring navigation of multiple interference sources, as seen in the attention control test battery or a dual-task scenario. Although both $\beta - BA46$ and $\beta - BA9$ are responsible for adaptation to tasks within the brain [36], $\beta - BA46$ is more closely associated with higher order cognitive functions, flexibility, and decision-making while $\beta - BA9$ is involved in sustained attention, which may explain these results [37]. As neural activation was measured during the short attention control task battery, the participants may have had less reliance on $\beta - BA9$ as sustained attention was not required for the task. Neural activation patterns during the daul task may have yielded different relationships; however, accounting for

the substantial motion artifact in this setting would have introduced obstacles for robustly evaluating neural activation.

Together, the attention control battery test scores and DLPFC activation help to account for some of the variance seen in dual-task cost scores. There is some overlap in the variance that these predictor variables individually explain due to their moderate correlation (rho = 0.283). However, they each contribute unique information to predictions of cognitive and motor dual-task performance. Although attention control scores and BA46 activation are predictors of dual-task performance separately, considering both variables as indicators of cognitive-motor dual-task abilities may provide a more comprehensive understanding of their connectedness in the underlying mechanisms of cognitive control.

In sport, the ability to activate neural regions appropriately to support behavior is crucial for performance and injury risk mitigation. In these scenarios, athletes are faced with tasks of attention control as they regulate specific goal-directed behavior and direct focus toward subtasks. Connections between suboptimal neural activation and injured populations have been identified in the literature. Previous research has emphasized the importance of attention control in sport, linking individual abilities to performance and suggesting that training enhances outcomes [38]. Beyond sports performance, attention control's relationship with other cognitive processes and dual task performance suggests that it may be an underlying factor in injury mechanisms [14]. In injured populations (anterior cruciate ligament reconstruction [39–42], chronic ankle instability [43–45], concussion [46], among others), the effects of dual tasks on cognitive and motor performance may be exacerbated, potentially leading to future injuries. Previous research has urged the inclusion of dual-task measures in return-to-sport protocols as it

continues to be proven as a predictor of secondary injury risk [47]. Given to the link between baseline neurocognitive function and injury risk and attention control's relevance in other cognitive processes, attention control may be a worthwhile candidate as a measure for assessing return-to-sport readiness in injured populations. However, the current findings are based on a relatively small sample size, which limits the broad application of these results.

The results of this study show novel and complementary connections between attention control, BA46 activation, and dual-task performance, however, there are some limitations that should be considered when interpreting the findings. First, relatively high scores in the Antisaccade test of attention control in both single- ($\mu = 0.93 \pm 0.03$) and dual-task ($\mu = 0.82 \pm 0.07$) scenarios may have influenced dual-task costs. If one subtask of a dual task is less challenging, participants may prioritize the other. Conversely, this imbalance in task difficulty could have led some individuals to focus on the task they perceived to be more difficult (motor), leading to less dual-task costs for low motor performers. Cognitive task score inflation was further evidenced through a ceiling effect in the ST-COG variable, a key component of dual-task cost calculation. The Antisaccade test was adapted from its original format to match the block design of this study, and it is plausible that this task performed in the original design would have yielded more dispersed outcomes, an increased spread of scores, and less grouping at higher scores. Furthermore, it appears that the participants in this study represent a high performing population evidenced by the clustering of high cognitive scores [15], high Tegner scale scores (approximately 8 out of a maximum score of 10), and an overall larger mean in attention control scores than found in previous literature [14]. As a result, these findings may not generalize to populations with lower cognitive or physical function. Notably, the relatively small sample size

(n = 15) could have also contributed to non-significant correlations. This limits generalizability and could have affected the spread of results.

Given the high cognitive performance of these participants, the chosen tasks my not have been challenging enough to reveal true individual differences in dual-task performance. Choosing two tasks with more balanced difficulty, or different cognitive and motor tasks entirely, may have led to different results. Moreover, the chosen cognitive-motor dual task was designed as a sport-like test, but it was performed in a lab setting. More research is necessary to explore these findings in true sport environments. Additionally, a generalized source-detector montage was used for fNIRS analysis rather than individualized optode location consequently leading to potential inaccuracies in measurement of regions of interest. Although the investigated regions ($\beta - BA46$ and $\beta - BA9$) are distinctly different, we cannot be sure that these regions were measured for each participant without specific anatomic registration. To decrease some error in calculating these regions of interest, the head circumference of each participant was used to scale the source-detector montage. Lastly, the extent that these results transfer to other cognitive-motor tasks is unknown. Further research is needed to determine whether these findings apply to other cognitive-motor tasks or outside of the lab in sport-like scenarios. Despite these limitations, this study connects attention control, BA46 neural activation as independent predictors of dual-task performance during a physically challenging dual-task scenario.

Conclusion

Attention control's connection to cognitive deficits in this specific cognitive-motor dual task points to its potential value as an indicator of dual-task performance in other settings. Leveraging a time-efficient attention control test could provide utility in sports performance and

rehabilitation settings where dual task performance is measured. However, future work is necessary to confirm relationships between this attention control test battery and sports performance or injury risk. These findings support independent contributions from attention control test scores and BA46 activation to dual-task performance.

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CHAPTER THREE

APPLICATION OF SHORT-SEPARATION CHANNELS FOR FLUID-INDUCED MOTION ARTIFACT CORRECTION IN FUNCTIONAL NEAR-INFRARED SPECTROSCOPY

Contribution of Authors and Co-Authors

Manuscript in Chapter 3

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Contributions: Conceptualization, Testing, Data collection, Formal analysis, Investigation, Visualization, Methodology, Writing – original draft, Writing – review and editing.

Co-Author: Ka'Jean Tallette

Contributions: Conceptualization, Phantom creation, Testing

Co-Author: Corey A. Pew

Contributions: Conceptualization, moving platform creation

Co-Author: Keith A. Hutchison

Contributions: Conceptualization

Co-Author: Scott M. Monfort

Contributions: Conceptualization, Testing, Data collection, Formal analysis, Investigation, Visualization, Methodology, Writing – review and editing

Manuscript Information

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☐ Accepted by a peer-reviewed journal
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Abstract

Functional near-infrared spectroscopy (fNIRS) is a portable method for measuring cerebral neural activation using near-infrared light. This technique relies on the hemodynamic response following neural activation to quantify relative changes in oxygenated and deoxygenated hemoglobin. During movement tasks, such as walking or squatting, fNIRS signals are contaminated with artifact from physiological sources (e.g. heartbeat and respiration rate) as well as those attributed to fluid (e.g. blood or cerebrospinal fluid) motion within the head. Short-separation channels have previously been employed as a method to correct for physiological artifact but have not been validated in dynamic settings to correct for artifact due to fluid movement. In this study, a dynamic optical phantom with biological fluid and tissue contents was developed and actuated during fNIRS measurements to produce motion artifacts. Following the collection of this motion artifact data, a simulated hemodynamic response of known magnitude (true signal) was superimposed on the fNIRS signal and short-separation channel regression was performed. Area under the curve (AUC) in receiver operating characteristics (ROC) analysis was used to test the specificity (true positive rate) and sensitivity (true negative rate) of analyses with and without short-separation channel regression. Additionally, measurement error (calculated signal – true signal) was compared in regressions with and without short-separation channels. Short-separation channels were shown to have improved AUC and decreased error, indicating improved performance, at low contrast-to-noise ratios (CNR) where neural signal may be masked by motion artifact. These findings expand on previous uses of short-separation channels to remove physiological noise and highlight their benefit in human movement paradigms.

Introduction

Functional near-infrared spectroscopy (fNIRS) is a portable and noninvasive neuroimaging technique that measures neural activation in the cerebral cortex using near-infrared light, leveraging the optical properties of blood [1]. Although fNIRS measurements lack the spatial resolution of functional magnetic resonance imaging, its lightweight, compact, and low-cost design make it suitable for many study designs. Specifically, in studies that require participants to move freely or to interact with stimuli, functional neuroimaging with fNIRS is a viable solution for measuring neural activation [2,3]. Numerous studies have employed fNIRS to measure neural activation during movement paradigms. Walking tasks including forward walking [4–7], backward walking [4], precision stepping [5], and walking under dual-task conditions [6,7] are well represented in the literature. These studies have established neurobehavioral connections between activation in brain regions, such as the supplementary motor area and pre-central gyrus, and spatiotemporal gait variables [4]. In addition to walking, fNIRS has been used in other movement paradigms such as barbell squatting [8]. Measurement with fNIRS does not come without its challenges. Previous works have noted limitations such as limited depth of measurement, susceptibility to motion artifact [9], and difficulty with probe placement standardization across subjects [10]. Despite these challenges, fNIRS enables neural activation to be measured across various research and clinical settings including psychology studies and physical therapy clinics and provides valuable insights into region-specific patterns.

fNIRS allows indirect measurement of neural activation through changes in relative concentrations of oxygenated (HBO) and deoxygenated (HBR) blood. To support neural activation, the hemodynamic response increases HBO and decreases HBR in involved brain

areas [11,12]. The accuracy of fNIRS measurements of HBO and HBR has been validated through numerous fMRI studies [13,14]. Due to the highly vascularized scalp and the nature of this measurement technique, fNIRS signals are susceptible to extracerebral signal contamination from physiological sources such as heart rate (~1Hz), blood pressure, Mayer waves (~0.1Hz), respiration rate (0.2-0.4Hz) as well as physical sources (wire and head movement) [15]. Systemic physiological noise may mask neural activity, leading to false positives or negatives, and its removal can be challenging due to overlapping neural activation frequencies [16,17]. Although some frequencies of these systemic artifacts can be removed with filtering (i.e. lowpass filter for heart rate and respiration rate), Mayer waves, in particular, prove difficult to account for because of their similar frequency to neural activation [16]. As Mayer waves are produced by arterial changes in response to blood pressure, movement is likely to cause increases in their spectral power [18]. During movement tasks, physiological noise often increases due to autonomic responses such as increased heart rate, blood pressure, and respiration rate [17]. In addition to physiological contamination, artifacts are present in fNIRS measurements involving whole body movements [9]. These artifacts may be attributed to fluid within the scalp, skull, and cerebrospinal fluid during tasks that involve head movement.

Consensus in the field has not been reached on the management and correction of motion artifact noise in fNIRS data; however, a number of mitigation techniques have been explored. Methods such as Principal Component Analysis (PCA) and Temporal Derivative Distribution Repair (TDDR) have been explored in depth as computational noise reduction methods. PCA identifies the components in the data that contribute to the largest amount of variance [19] and TDDR removes temporally correlated data (e.g. drift) by computing the temporal derivative,

identifying and applying observation weight, and integrating the weighted derivative to produce a corrected signal [20]. Another method of data correction, short-separation channels, targets data contaminants superficial to the brain. To combat these physiological interferences, short-separation channels rely on the source-detector distance proportionality principle [21]. This states that fNIRS channel measurement depth is proportional to the distance between the source and detector. The depth of measurement of short-separation channels does not penetrate the cerebral cortex and instead only measures superficial signals in the scalp, skull, and cerebral spinal fluid [22]. Any signal in these short-separation channels is deemed extracerebral as they do not arise from cortical tissue. In post-processing, short-separation channels are used as regressors, effectively removing the non-cortical signal measured in these channels [23]. Short-separation channels provide robust regression of physiologically driven fNIRS data contaminants and are essential for improving the interpretability and accuracy of fNIRS signals [24].

Prior validation efforts of short-separation channels as regressors to reduce extracerebral artifact have used benign movements [24,25], physiological sources for artifacts, and in vivo data [25–29], preventing systematic control over movement-induced artifacts. Although these studies provide strong evidence for the use of short-separation channels as regressors of physiological motion artifact (e.g. heartbeat, Mayer waves, respiration rate, etc.), their efficacy in accounting for inertial fluid artifact, expected during large head movements, has not been investigated. As research questions expand in biomechanics and other real-world scenarios with considerable movement, validating short-separation channels for inertial fluid movement artifacts is essential for accurately reporting neural activation. Without addressing the validity of noise regression techniques, spurious findings may mislead the field regarding neural activation during movement

paradigms [16,28]. Therefore, leveraging previously published techniques and principles enables new opportunities for research in noise regression during isolated movement and allows us to fully understand our ability to use fNIRS in biomechanics settings.

Validation of other neuroimaging modalities (e.g. EEG) has relied on phantoms to simulate human head characteristics. These works have mainly relied on simulated neuroelectric activity, unrelated to fNIRS measurements. Investigation into motion artifact in these modalities has been impactful, showing that moving phantoms can be used to assess motion artifact removal techniques that would have continued to limit the field [30]. The translation of phantom-based validation for fNIRS short-separation channels requires a different approach. fNIRS capitalizes on the optical properties of brain tissue, HBO, and HBR. Prior optical phantoms have been designed to mimic these characteristics [31–34]; however, these phantoms have either represented the stationary brain to validate fNIRS measurements [32,33], a dynamic brain to investigate the impact of lateral movement on scalp hemodynamics [34] or involved a fluid dynamics-based approach [31] to uncover the effects of superficial artifacts on fNIRS data collection. These investigations into fNIRS data quality and noise regression have shown promising results. However, none have investigated the use of short-separation channels on motion-induced artifact in fNIRS data.

Therefore, the purpose of this study is to validate the use of short-separation channels as regressors in isolated movement paradigms using a dynamic optical phantom alongside computer simulated hemodynamics. We hypothesize that short-separation channels will exhibit an increased area under the curve (AUC) in receiver operating characteristics (ROC) analyses, indicating improved sensitivity and specificity. Additionally, short-separation channels will

reduce error in detecting simulated neural signals amidst simulated motion artifacts compared to analyses without short-separation channel correction.

Methods

Phantom Development

An *in vitro* optical phantom was constructed to mimic the optical properties of the human brain and allow for conditional testing of short-separation channels in functional near-infrared spectroscopy (Figure 12) [35]. Using this approach, brain-like inclusions can be tested to determine their effects on short-separation channel measurement abilities, and ultimately the effect of short-separation channel regression on the credibility of measured neural activation. The phantom was created using a clear epoxy resin and hardener in a 1:1 volumetric ratio. The density of epoxy resin and hardener were calculated as 1.16 g/mL and 1.02 g/mL, respectively. Titanium dioxide (TiO) powder was added to the unpolymerized epoxy resin in an amount that equaled 1.2 mg TiO/1 g epoxy resin and hardener, combined, to mimic the light scattering that occurs inside the brain and stirred well [35–37]. Black ink was mixed into the hardener in an amount that equaled 13.8 mg black ink/1 g epoxy resin and hardener, combined [36]. The unpolymerized epoxy resin and TiO were combined with the mixture of hardener and black ink and cured in a custom, rectangular mold [36]. Minimal settling of TiO was observed during the curing process. Both TiO and ink were measured to mg accuracy. The dimensions of the phantom measured 140mm by 240mm by 40mm with a fluid reservoir measuring 111mm by 220mm by 4.5mm. A thin, translucent Mylar sheet was used to seal the contents of the fluid reservoir.

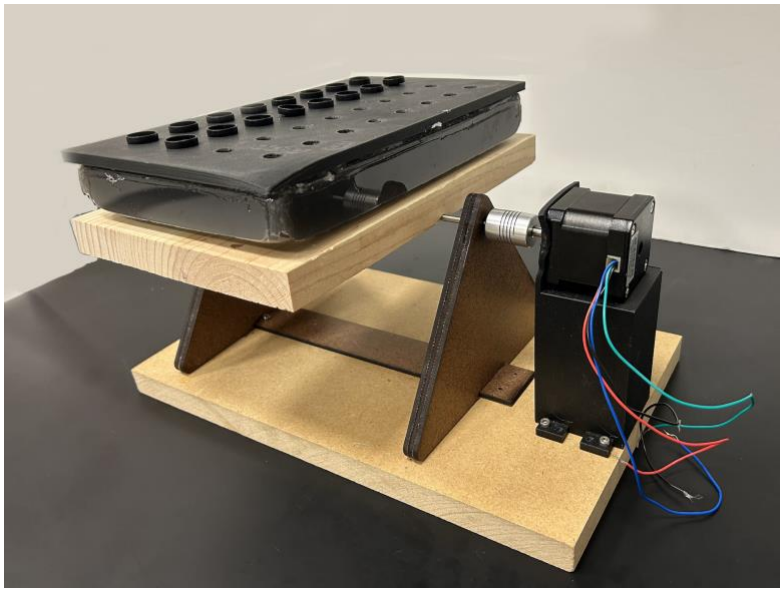

Figure 12: Image of dynamic phantom on rotating platform with stepper motor.

A dynamic platform (Figure 12) was constructed to rotate the optical phantom uniaxially at specific amplitudes and frequencies mimicking human head movements observed in a biomechanics laboratory (i.e. during a squat). A stepper motor (KOCO MOTION, 17H2041-REV 03) and Arduino UNO (R3) were used to rotate the dynamic platform and were programmed to perform series of amplitudes and frequencies of movement. The Arduino UNO sent digital trigger signals, which were aligned with the movement of the motor, to fNIRS data collection software (Aurora, Version 2021.9). This setup allowed precise control over the movement of the platform enabling fNIRS recordings over several conditions.

fNIRS Set-Up

An fNIRS device with 8 sources and 8 detectors was used (NIRSport 2, NIRx, Orlando, FL). One detector, connected to a breakout cable, served as a detector for 8 short-separation channels. The fNIRS device was secured to the dynamic optical phantom through the grommets

and spring caps used for human subjects on a custom holding device (Figure 12). This device fixed the distances between sources and detectors (standard length channels) for all tested source-detector configurations. Distances between sources and short-separation channels were fixed at 8.26 mm, the default configuration for the NIRx system. Source wavelengths emitted by the fNIRS LED sources were equivalent to those used on human subjects (760nm and 850nm) and the data were sampled at 10.17 Hz. Before recording, signal and channel quality were checked through the NIRX Aurora software. All channels achieved good signal quality, designated by the Aurora software calibration.

Motion Artifact Testing

The phantom was tested over 12 dynamic conditions and one stationary condition (0Hz, 0.119 Hz, 0.147 Hz, 0.151 Hz, 0.156 Hz, 0.208 Hz, 0.217 Hz, 0.227 Hz, 0.357 Hz, 0.385 Hz, 0.417 Hz, 1.250 Hz, and 1.667 Hz). Each condition was tested three times. Frequencies ranging from 0.119 to 1.667 Hz were chosen to align with head movements during repeated movement tasks and available control settings of the motor. The frequency of 0.417 Hz aligns with head movements observed during a repeated single leg squatting task. The lowest bound of the frequency range was selected to reflect head motions typically seen when looking down, while the upper bound corresponds to head scanning movements seen when visually scanning a court or field in a sports setting. The vertical amplitude of movement was 0.63 cm. The fluid reservoir was filled with ground bovine muscle tissue (89g) with bovine blood (72 g), to add biological relevance and provided resistance against fluid movement in the phantom [38]. fNIRS data were collected for 5 blocks of 30 seconds of movement preceded by 30 seconds of stillness (baseline).

Data Processing

The fNIRS intensity signals were processed using a custom MATLAB script pipeline and the Brain AnalyzIR toolbox (The MathWorks Inc.; Natick, MA; version R2022b; Toolbox Commit: v.2022.4.26) [23]. Raw intensity data were visualized to ensure quality (no spikes or unexpected shifts). No trials were excluded in this step. The stimulus duration was fixed to 30 seconds to align with the platform movement timing. Baseline periods, time before the stimulus onset for each movement period were trimmed to include only the 10 seconds prior to the onset of movement.

As the dynamic phantom did not produce a neural signal, any detected responses were attributed to motion artifact. Simulated hemodynamic responses with known and physiologically relevant β-values (1, 3, 5, 7, 9) [39] were added to raw signals using the SimData function in the Brain AnalyzIR toolbox [23]. Neural signal was superimposed on half of the (non-short separation) channels generating simulated and null channels for subsequent sensitivity and specificity analyses [38]. This created 5 true (known) β levels for each recorded trial in the collected fNIRS data. Simulated signals were limited to movement periods only to align with increased neural activation in humans during movement tasks [27,39].

Using the 5 true β levels for each condition, optical density was calculated from the raw hemoglobin values. The data were resampled (4Hz) to ensure consistency across conditions. The modified Beer-Lambert law with a partial pathlength factor of 0.1 calculated oxygenated (HBO) and deoxygenated (HBR) hemoglobin concentrations from the resampled optical density values [40]. Autoregressive iterative least squares (AR-IRLS) general linear model analyses were run for each condition, one with SS channels as regressors and one without on each trial [39]. This

robust statistical method where outliers are iteratively down weighted is used for human data with substantial motion artifact. The AR-IRLS GLM assumed a canonical hemodynamic response and calculated β values, representing the strength of neural activation, for each channel (source-detector pair) for both HBO and HBR that best align the model with the observed data. In this algorithm, false positives and type I error are controlled by correcting the serial correlation of noise due to physiological oscillations through an autoregressive model. To reduce the impact of statistical outliers, bisquare weighting was applied to enhance the robustness of the regression analysis.

Because HBO generally has a higher/better response, these values were used for analysis [27]. β values are used to infer neural activity with a higher value corresponding to an increased hemodynamic response and thus more activation for that channel. If the short-separation channels were a perfect regressor of motion artifact, the β value from the GLM would be equal to the true β value (1, 3, 5, 7, 9), aligning with the programmed β value in the simulated hemodynamic response (Figure 13).

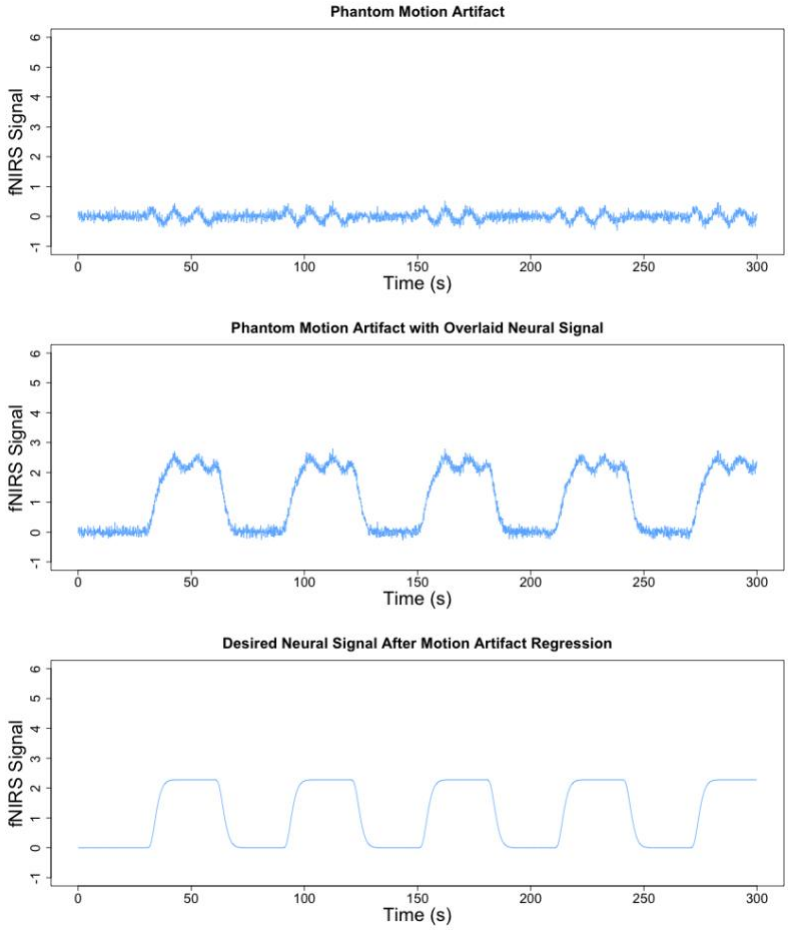

Figure 13: Ideal short-separation regression of motion artifact. fNIRS motion artifact collected with dynamic phantom (top). Simulated neural signal (true β) superimposed on motion artifact (middle). Desired neural signal after short-separation channel regression removes motion artifact (bottom).

Statistical Analysis

Receiver Operating Characteristics Analysis

The β values calculated for each condition were compared quantitatively against the simulated (known) neural signal using receiver operating characteristics (ROC) using the Brain AnalyzIR toolbox Toolbox in MATLAB (version R2022b) [23]. ROC analysis allows the performance of the model using short-separation channels as regressors to be assessed and compared over all testing conditions, evaluating its ability to discriminate between neural signal

and signal noise effectively [41]. The analysis compares theoretical and observed data, resulting in sensitivity values plotted against corresponding false positive rate values (1-specificity). A model that can perfectly discriminate between true and true negative rates (true signal and noise) would pass through the point (0, 1) on the ROC grid, yielding an area under the curve (AUC) of one. Conversely, a test that is no better than random chance at discriminating between true and false positives would give an AUC of 0.5. Therefore, an AUC greater than 0.5 would show an ability to discriminate greater than random chance in correctly identifying neural signal amidst motion artifacts. Each ROC analysis was performed for 1000 iterations, selecting a random channel (with replacement) from the dataset that combined simulated motion artifact and hemodynamic response for each iteration, and testing the true positive versus true negative rate. An AUC was calculated for every trial at each condition and true β value.

General Linear Model and Mixed-Effects Models

β-error (calculated β value – true β value) for each condition was analyzed across channels. A general linear model (with interaction terms) was used to describe the effects of method (short-separation channel or no short-separation channel), true β value (1, 3, 5, 7, 9), and movement frequency on the AUC value for each condition. A log link function in the inverse gaussian family was chosen to account for the non-normal, negative skewedness of the AUC data. Additionally, two linear mixed effects models, with interaction terms, were performed to describe the effects of method (short-separation channel or no short-separation channel), true β value (1, 3, 5, 7, 9), and movement frequency across simulated and null channels. Method, true β value, and frequency were treated as fixed effects while source-detector pair was included as a random effect to account for variability between channels. All analyses were performed in R

Statistical Software via R Studio using the lme4 and base R packages (v4.4.1; R Core Team 2021) [42,43].

Results

AUC Analysis

The general linear model predicting AUC values from true β, frequency, and short-separation channels revealed a three-way interaction term between the three terms (estimate = 0.0308, p = 0.0058) (Figure 14, Figure 15, Figure 16). Two-way interactions between frequency and short-separation channels (estimate = -0.235 p = <0.0001) and true β and short-separation channels (estimate = -0.0553, p = <0.0001) exist. Main effects of true β and short-separation channel use (estimate = 0.0583, p = <0.0001; estimate = 0.2784, p = <0.0001, respectively) were also present. Two-way interaction terms and main effects must be interpreted in the context of the three-way interaction term.

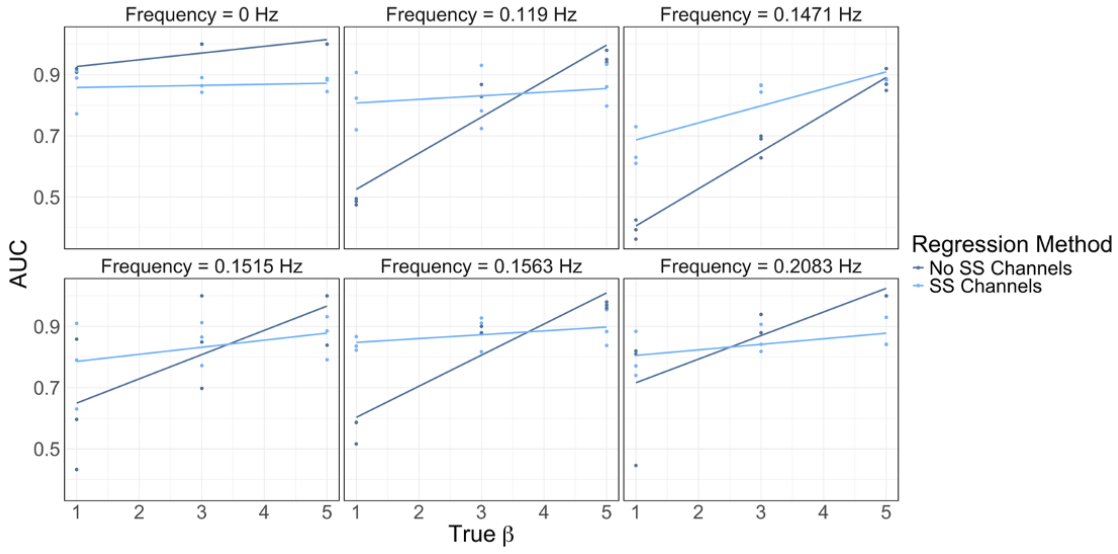

Figure 14: The changing effects of true β (β values 1,3 and 5 pictured) versus method (short-separation (SS) channel or no short-separation channel) on AUC over the truncated frequency range from 0 to 0.2083 Hz.

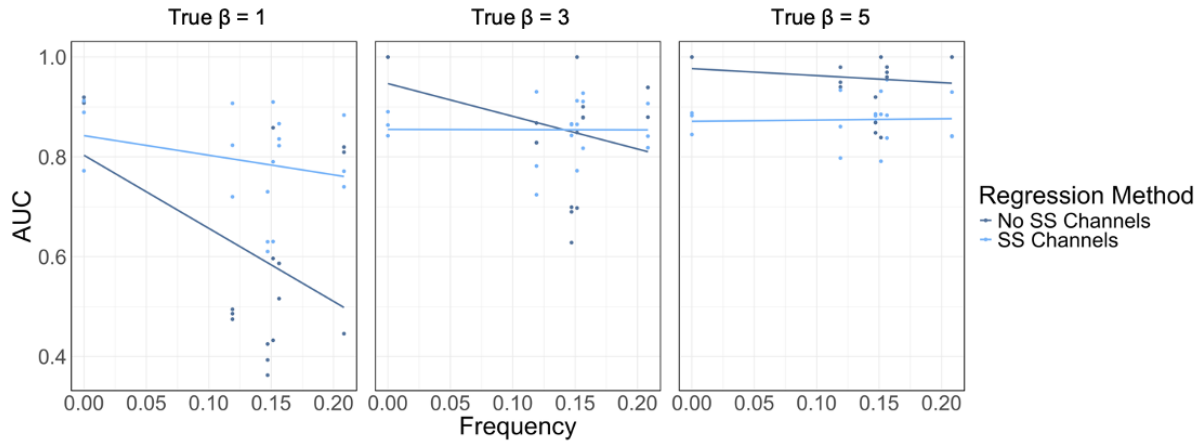

Figure 15: Second visualization of three-way interaction term, the effects of frequency (truncated) and short-separation (SS) channel use on AUC changes over true β values 1, 3, and 5.

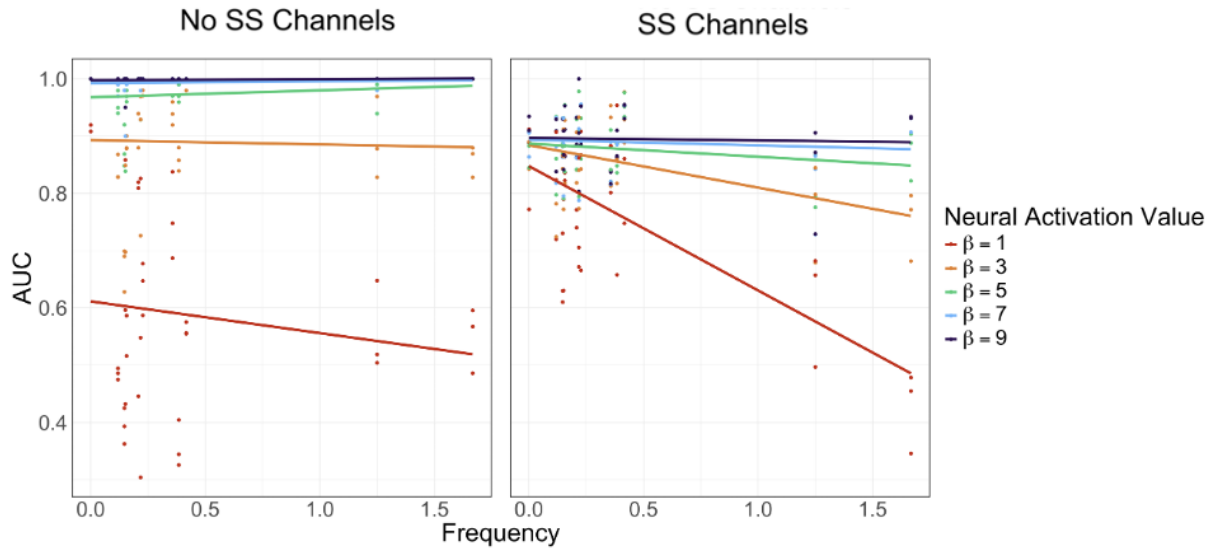

Figure 16: Third visualization of three-way interaction term, the effects of all frequencies and true β values on AUC for analysis with and without short-separation (SS) channels.

Simulated Channels Analysis

For the simulated channels mixed effects model, the intercept term of 0.266 indicates the β-error present when all other variables are set to zero (i.e. frequency = 0, true β = 0, and no short-separation channel use). Significant interaction effects were present between short-separation channels and frequency (estimate = -0.418, $p < 0.0001$, Figure 17A). The interaction between short-separation channels and true β was also significant (estimate = 0.476, $p < 0.0001$, Figure 17B). Main effects of frequency (estimate = 0.476, p = <0.0001) and short-separation channel use (estimate = -0.285, p = <0.0001) were significant but must be interpreted in the context of the interaction terms.

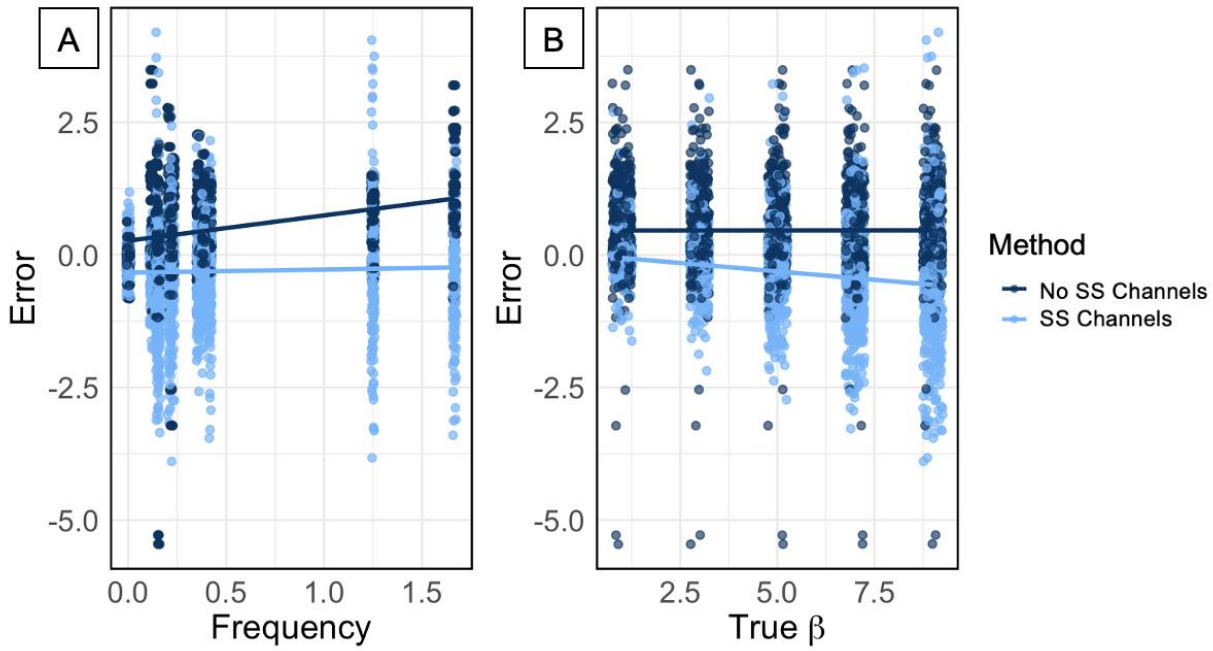

Figure 17: Visualization of significant Interaction terms between A) frequency and method (short-separation (SS) channels versus no short-separation channels) averaged across true β values, and B) true β and method (short-separation channels versus no short-separation channels) in channels with a simulated hemodynamic response averaged across frequencies.

Null Channels Analysis

The mixed effects model of null channel β-error produced an intercept of -0.626 indicating negative β-error when all other variables in the model are set to zero (i.e. frequency = 0, true β = 0, and no short-separation channel use) (Figure 18). Null channel effects were seen in the interaction between short-separation channels and true β (estimate = -0.278, p = <0.0001). A main effect of true β was observed (estimate = 0.333, p = <0.0001) but must be interpreted in the context of the interaction term.

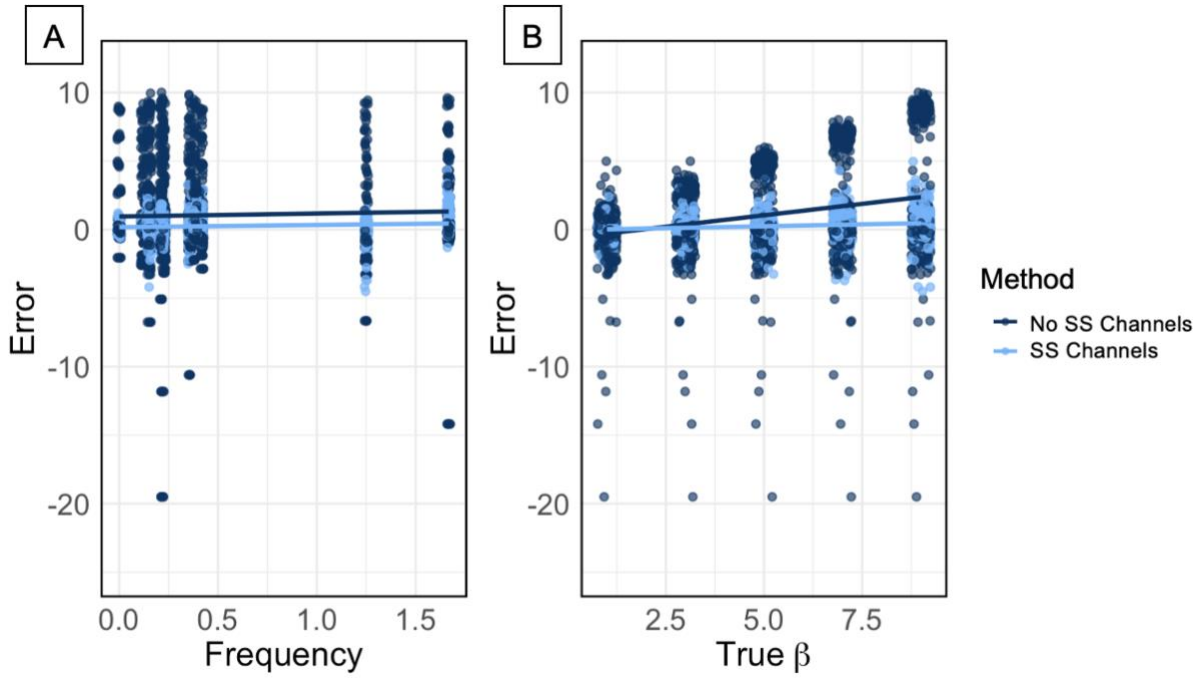

Figure 18: Interaction between A) frequency and method (short-separation channels versus no short-separation channels) and B) true β and method (short-separation channels versus no short-separation channels) in null channels. An error outlier at -40 across all true β values was removed for visualization purposes.

Discussion

The purpose of this study was to validate the use of short-separation channels in movement paradigms and across neural activation strengths. Our hypothesis was partially supported. ROC analyses revealed increased AUC, greater probability of detecting a signal when present, with short-separation channels at lower neural activation and lower frequencies. As simulated neural activation (true β) and frequency increased, AUC values remained high but were eventually outperformed by analyses without short-separation channels. In channels with a simulated neural signal added, the results show consistent, but negative, β-error with short-separation channel use in channels with increasing movement frequency when compared to analyses without short separation channels. Conversely, as the magnitude of true neural signal (true β) increased, short-separation channels drove β-error further negative (i.e., underestimating neural activation). The analyses without short-separation channels remained positive but consistent in channels with an added simulated signal. In null channels (no simulated signal), short-separation channels held β-error constant around zero. β-error increased with increased neural signal (higher true β) for analyses without short-separation channels. These findings demonstrate the value of short-separation channels for regression of motion artifact, especially at low neural activation strengths (small true β) and lower frequencies. The application of short-separation channels as regressors has the potential to improve human functional neuroimaging data quality with fNIRS by reducing fluid-induced motion artifacts in dynamic environments.

At high movement frequency, but lower neural activation (low true β), short-separation channels appear to have the greatest protective effect against rising β-error or false positive neural activation. This is evidenced by higher AUC values for analyses with short-separation

channels at low neural activations and the large majority of tested frequencies (with the exception of the highest frequency). Additionally, in channels with an added simulated signal, short-separation channels decreased β-error at higher frequencies and maintained an β-error value close to zero at lower beta values, consistent with the pattern observed through ROC analysis. In null channels, β-error did not change across frequencies. However, short-separation channels protected against false positive results as neural activation increased.

Previous fNIRS studies during seated tasks (i.e., limited motion artifact) reported an AUC of 0.68 using AR-IRLS at a contrast-to-noise ratio (CNR) of 2.0 [27]. Another study observed an AUC of 0.645 and 0.653 when comparing two autoregressive prewhitening models used on human fNIRS data [44]. These reported values are lower than the AUC values found in this study at neural signal values greater than 1 (Figure 19). The difference between these reported AUC values could be due to an increased CNR at higher true β values, across frequencies. CNR is calculated as the magnitude of hemodynamic response divided by the standard deviation of the oxygenated hemoglobin data [27]. To protect against the influence of outliers, the standard deviation is calculated as 1.4826 multiplied by the median absolute deviation. A greater CNR value indicates less noise and a cleaner signal. Previous work has noted that ROC analyses may provide trivial results with saturation near one (Figure 19) at large CNR values, as seen in this analysis (Table 2).

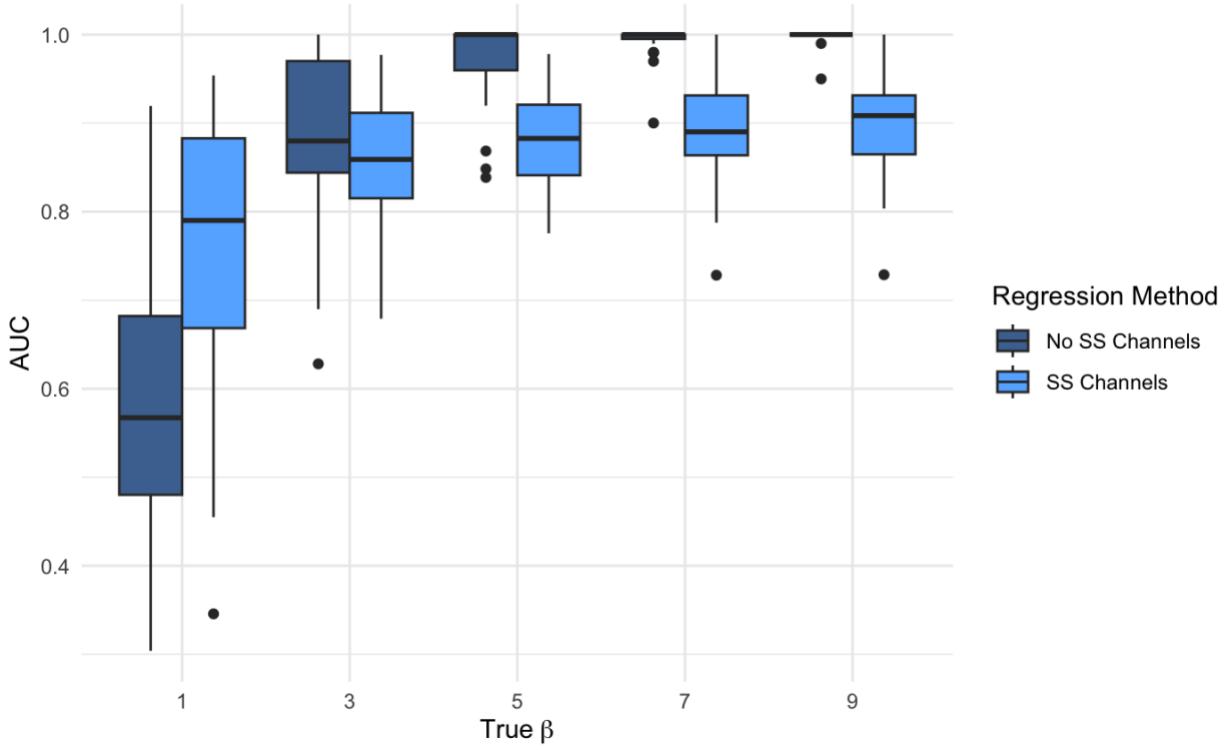

Figure 19: Range of AUC values over all frequencies for each neural activation level (true β).

Table 2: Contrast-to-noise ratios (CNR) of fNIRS recordings across frequencies and simulated neural activation levels. * Indicates CNR within biologically relevant range of 0.5-2.0 seen in human fNIRS data.

Frequency (Hz)	β = 1	β = 3	β = 5	β = 7	β = 9
0	0.2*	0.5*	0.9*	1.2*	1.6*
0.119	0.9*	2.7	4.5	6.3	8.0
0.147	1.2*	3.7	6.1	8.6	11.0
0.152	0.7*	2.1	3.5	4.9	6.3
0.156	1.3*	4.0	6.6	9.2	11.8
0.208	0.8*	2.3	3.8	5.2	6.7
0.217	0.8*	2.5	4.2	5.8	7.5
0.227	1.4*	4.3	7.2	10.1	13.0
0.357	0.7*	2.1	3.4	4.8	6.2
0.384	2.0*	6.1	10.1	14.1	18.2
0.417	2.6	7.9	13.1	18.4	23.7
1.250	0.6*	1.9*	3.2	4.5	5.8
1.667	1.1*	3.2	5.3	7.5	9.6

Although a relevant true β neural activation signal was added to the phantom created motion artifact, this study lacks the physiological noise that would be introduced by heart rate, Mayer waves, respiration rate, etc. This could explain the large CNRs seen as true β and frequencies increase in this study. The addition of these physiological noise sources in human data could potentially provide more relevance to the ROC analysis at higher simulated neural activation values. Nonetheless, at biologically relevant (0.5 - 2.0) CNR values [27], our analyses with short-separation channels outperform those without short-separation channels, as evidenced by increased AUC values. We expect short-separation channels to continue to excel at similar (low) CNR values, especially when neural activation and deviations in motion artifact increase proportionally. In these scenarios, large neural signals may be obscured by increased motion artifacts, resulting in a low CNR. At low these low CNR values, short-separation channel use may show the same benefits as were seen at low neural activation and low frequency measurements in this study.

This work demonstrated the value of short-separation channels to reduce the effects of fluid-induced motion artifact at low frequency and lower neural activations, indicating its use in low CNR scenarios. These may arise in human movement studies when neural activation is measured under conditions with high movement. Existing literature leverages fNIRS as a neural activation measurement tool in stationary and motion paradigms [4–8] and has identified short-separation channels as a valid tool to decrease the influence of physiological artifacts [24–28]. These studies include investigation into neural activation during seated tasks [27], walking paradigms [4–7], as well as other movements such as squatting [8]. The present work aims to broaden our understanding of short-separation channels and add to the previously established

value of this motion artifact regression technique. Understanding the impact of short-separation channels on β-error across a physiologically relevant range of neural activation and frequencies during fNIRS data collection is essential for accurately interpreting neural activation measurements in movement paradigms. This study highlights the use of short-separation channels in low CNR movement paradigms and adds to the breadth of knowledge surrounding short-separation channel utility.

The ability of these results to extend to neural activation monitoring on human subjects has limitations. On human subjects, short-separation channels are used to regress out physiologically driven motion artifact. This study aimed to isolate movement without the influence of a human brain and expand our understanding of short separation channel use while only investigating inertially driven fluid movement. Although this provided insights into their use in movement settings, the absence of physiological artifacts limits the generalizability of these results to real, human subjects. Additionally, bovine blood and tissue were used inside the dynamic phantom. While these are biologically relevant and were likely similar to the tissues and fluid moving inside the head, they are not human blood, neural tissue, or interstitial fluid. Their movement inside the fluid reservoir of the phantom did not account for the complex microfluidic structure of intracranial vessels. The environment inside the human head would likely influence fluid movement, which was not captured in this study. Furthermore, neural signal was overlaid on the fNIRS signal during movement blocks only. While human neural activation likely increases during a task, it is unrealistic to assume that no activation occurs during rest periods. Finally, the geometry of the phantom (rectangular prism) and location of the rotation axis is markedly different than the human head. As a result, sources and detectors closer to the motor

shaft were impacted differently by movement than those on the ends of the phantom. Despite these limitations, this study provides important insights into short-separation channel use in dynamic settings with fluid-induced motion artifacts.

Future studies should consider the impact of physiological movement and signals as well as cranial anatomy on the inertial effects of intracranial fluids. Accounting for the intricacies of intracranial vessels and their impact on fluid movement would improve the relevance of these results in human fNIRS measurements. As previously noted, short-separation channel use could be especially beneficial in situations with low CNR, such as those where high neural activation is obscured by high frequency movement. Studies investigating the use of short-separation channels in these scenarios with increased motion artifact (higher frequencies and higher amplitudes of movement) relative to neural signal could clarify the extent of their added value. Presently, it is unknown if experimental adaptations such as more or longer blocks of measurement are needed to improve signal quality and remove motion artifacts with short-separation channels. Further investigation into measurement length and number of blocks could provide perspectives on methodological adjustments for improved signal quality in dynamic settings and optimizing sensitivity. Additionally, future variations could include neural activation added over rest and movement periods to increase relevance and mimic more natural activation patterns in human subjects.

Conclusion

This study analyzed AUC from ROC analysis and individual channel β calculations to identify simulated neural signals amid motion artifacts across 13 frequency conditions and 5 neural activation levels. Short-separation channels protected against false positives at low

frequencies and neural activations, highlighting their value at low contrast-to-noise ratio (CNR) conditions. These findings support short-separation channel use in movement paradigms characterized by low CNR. Incorporating short-separation channels helps mitigate motion artifact when neural activation is obscured by the inertial effects of subcortical fluid. At low CNR, short-separation channels help to improve neural signal isolation and therefore improve measurement reliability by reducing the impact of motion induced artifact.

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CHAPTER FOUR

GENERAL DISCUSSION

The purposes of this body of work were to 1) fill knowledge gaps relating attention control and dorsolateral prefrontal cortex (DLPFC) activation to performance in a physically challenging cognitive-motor dual task and 2) characterize the efficacy of short-separation channels to address motion artifacts due to fluid movement in fNIRS recordings during high movement tasks using short-separation channels. These purposes were fulfilled with two studies. The first, "Cognitive, Motor, and Neural Predictors of Dual-Task Performance", examined how attention control test scores and DLPFC activation relate to performance on a physically challenging dual task. The second, "Application of Short-Separation Channels for Fluid-Induced Motion Artifact Correction in Functional Near-Infrared Spectroscopy", evaluated short-separation channels as regressors to reduce fluid induced motion artifact in fNIRS recordings using a dynamic phantom.

Study 1: Results and Conclusions – Attention control, dorsolateral prefrontal cortex activation, and dual-task performance

To address the first purpose, we tested the relationships between attention control scores, dorsolateral prefrontal cortex (BA46 and BA9) activation during tests of attention control, and performance during a physically challenging dual task. The attention control test battery was performed in a seated position while neural activation was recorded. Cognitive and motor baseline performance was measured through the Antisaccade test and repeated single-leg squats, respectively. The dual-task condition consisted of the combined cognitive and motor single tasks.

Our findings from the investigation into connections between attention control, DLPFC activation, and physically challenging dual-task performance show attention control and neural activation as predictors of dual-task performance. These relationships highlight the potential utility of a short attention control test battery in sports performance or clinical rehabilitation settings. The low correlation between attention control test scores and DLPFC (BA46) activation during tests of attention control, yet both predicting dual-task decrements, shows that they independently account for some of the variability in the dual-task scores. Specifically, individuals with higher attention control scores and DLPFC activation were more likely to mitigate dual-task deficits during a cognitive-motor dual-task scenario.

Study 2: Results and Conclusions – Motion artifact correction in functional near infrared spectroscopy

To address the second purpose, we developed a dynamic phantom with a fluid reservoir to mimic the light scattering and absorption properties of the human brain and to test the ability of fNIRS short separation channels to remove artifact caused by fluid movement. The phantom was filled with bovine muscle tissue and blood for biological relevance and uniaxially actuated at a range of frequencies commonly seen in human movement studies, while fNIRS recorded optical signal changes. A range of physiologically relevant neural signals were added to the collected fNIRS data and short-separation channels were used as regressors to remove motion artifacts.

The results of the second study highlight the benefits of short-separation channel use in paradigms involving large head movements. Analyses with short-separation channels showed increased specificity and sensitivity compared at low contrast-to-noise ratios (CNR). At low

CNR, the simulated neural signal was masked by fluid-induced motion artifact and short-separation channels were able to provide the greatest value. These results are impactful for future human studies that rely on fNIRS as a measure of neural activation during movement tasks. The ability of short-separation channels to reduce false positive and false negative signals under conditions where movement artifact obscures neural signals highlights benefits beyond their traditional removal of physiological noise such as heartbeat, Mayer waves, respiration rate, etc. Therefore, the results of this study provide first steps towards future investigations into short-separation channel use in more complex dynamic study designs. This work adds to previous recommendations of short-separation channels regression during fNIRS measurements and extends their application to regressors of fluid-induced motion artifact in human studies.

Are all cognitive-motor tasks equal? Further investigation into a task-switching task

A separate investigation into the relationship between attention control, DLPFC activation, and task-switching performance was completed. These findings were submitted to present at the 2025 annual meeting of the American Society of Biomechanics.

Introduction

Although Study One's findings are promising, they also highlight the need for further exploration into attention control's connection to other cognitive-motor scenarios such as task-switching tasks. Like dual-tasks, the ability to adaptively switch between tasks underpins decision making and goal-directed behavior [25]. In sport scenarios, athletes continuously direct attention toward multiple stimuli. These rapid shifts in focus generally lead to performance decrements in executive control and switch costs, due to reconfiguration

of task sets and inhibitions of previous tasks. Consequently, slower reaction times and increased errors are seen during task-switching events when compared to non-task-switching conditions [99]. Executive dys(function) during task-switching can be quantified and monitored through functional neuroimaging, and activation is expected in the dorsolateral prefrontal cortex (DLPFC) [100,101]. Strengthening our understanding of cognitive and neural correlates of sport-relevant task-switching could provide deeper insight into individual factors that differentiate high and low performers. Understanding these factors may help develop injury risk screening and/or intervention tools to improve performance. The specific purpose of this additional investigation was to assess performance in task-switching involving whole body movement through attention control scores and neural activation. We hypothesized higher attention control scores would be associated with decreased reaction time and decreased neural activation in the DLPFC, and decreased reaction time would be associated with decreased neural activation during a novel, sport-like, task-switching paradigm, following a neural efficiency framework.

Methods

Eighteen healthy controls participated in this study (20.5±1.6 years, 9 females, 1.75±0.08 m, 77.2±12.8 kg, 7.9±0.5 Tegner, 13.3±1.9 Marx). Attention control was assessed through the Stroop Squared, Flanker Squared, and Simon Squared tests with weighted scores loaded onto a latent variable, as described in Study One [17]. Task-switching performance was measured through a novel, sport-like paradigm where both reaction time and accuracy were emphasized. Participants were asked to shift their weight to either foot in response to a visual stimulus shown on either side of a screen (away from a defender or towards a ball). This

paradigm was repeated for 5 blocks of 16 randomized pictures with a randomized 1 or 2 second delay. Performance was assessed by average reaction time (RT) to a correct decision (away from the defender, towards the ball), across all trials. DLPFC activation (BA46 and BA9) was monitored during the task-switching paradigm using functional near infrared spectroscopy (fNIRS; 8-source, 7-detector, 8-short separation channels, NIRSport2). A 30 second baseline period was collected prior to each block of pictures. fNIRS data analysis followed methods identical to those presented in Chapter Two. T-statistic values characterized subject-specific neural activation. Pearson correlations (Spearman if not normally distributed) were used to assess correlations between neural activation (i.e. T-values), RTs, and AC scores.

Results and Discussion

A negative, albeit non-significant, relationship was found between RT and DLPFC activation (BA46 rho = -0.33, p = 0.187; BA9 rho = -0.30, p = 0.221; Figure 20A, Figure 21A, Figure 21B). No other correlations were found between dependent variables (Figure 20A). Post-hoc bootstrap analysis (1000 resamples with replacement) for RT correlations (BA46 [-0.681, 0.093] and BA9 [-0.653, 0.1] indicated a clustering of moderate-strength correlation coefficients (Figure 20B), albeit with large variance for the current small sample size. Although not reaching statistical significance and needing additional data to verify, the data are more aligned with increased DLPFC activation associating with improved performance (i.e. faster reaction times) indicating strategic engagement over a neural efficiency framework (i.e. less activation to perform the same task) for this challenging task.

These results are likely due to individual differences in strategy in the task-switching task and have been previously noted in dual-task walking studies [13].

Although individuals were instructed to equally focus on reaction time and correct decisions, differences in interpretation of the task goals could influence neural activation patterns and ultimately dissociate AC scores from task performance. AC performance appears to be a strong predictor of various cognitive processes and cognitive multitasking; however, its ability to serve as a correlate for cognitive-motor function appears limited in this task-switching paradigm.

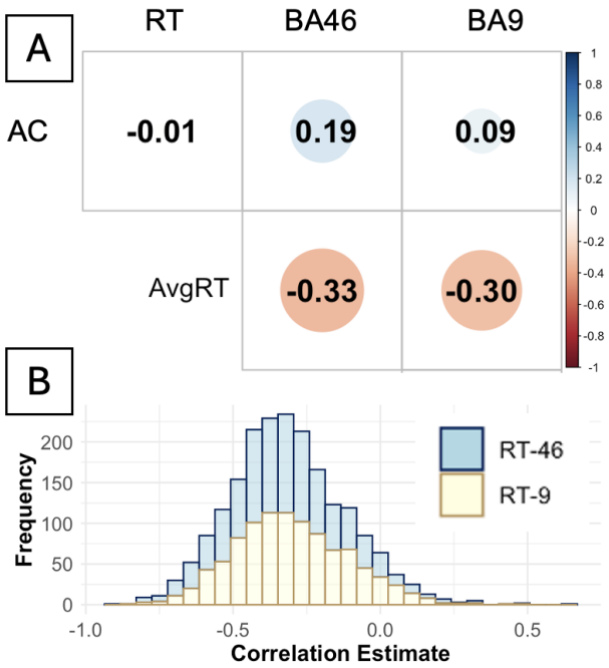

Figure 20: A) Correlations between neural activation (BA46/BA9), RT, and AC performance. B) Frequency of correlation estimates between RT-BA46 and RT-BA9 from bootstrap analysis.

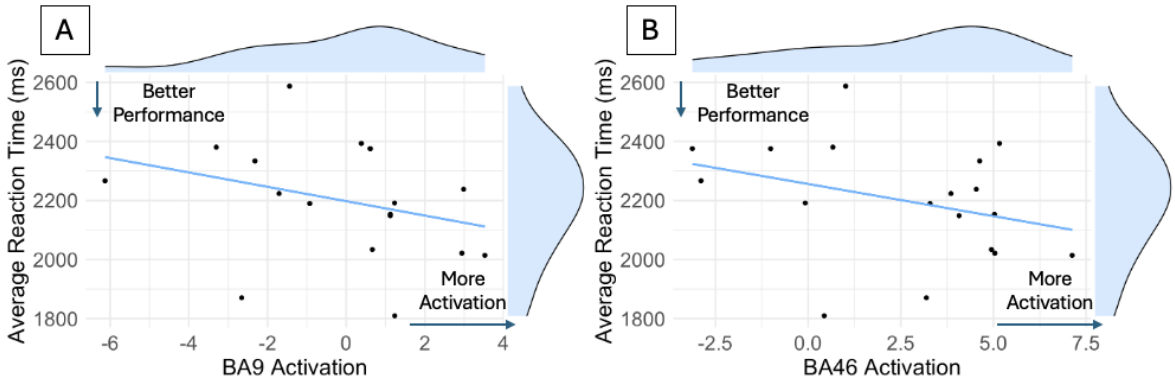

Figure 21: A) Correlations between BA9 activation and reaction time [rho = -0.30, p = 0.22]. B) Correlations between BA46 activation and reaction time [rho = -0.33, p = 0.18].

In both this task-switching study and Study One, better performance on the cognitive-motor task was associated with increased DLPFC activation. The alignment of neural activation patterns between these two tasks (dual task and task-switching task) provides context for increases in dorsolateral prefrontal cortex activation during cognitive-motor dual task scenarios. Activation of BA9 in the task-switching task could be an artifact of the task length (5 blocks of 54 seconds – task-switching; 3 blocks of 90 seconds – attention control battery) as BA9 is more related to maintenance of task goals rather than the higher order cognitive functions, flexibility, and decision-making activities of BA46 [96]. These findings provide further evidence for a strategic engagement framework where high performance is associated with increased neural activation.

However, mixed findings in attention control scores across studies (strong relationships with dual-tasking and little to no relationship in task-switching) highlight how task selection may influence the predictive ability of attention control scores. These preliminary findings may provide evidence for varied cognitive-motor tasks, such as dual-task and task-switching

tasks when evaluating neurocognitive function. Notedly, the neural activation pattern was similar between the two tasks, indicating similar neural recruitment is present in both tasks. Different correlation strengths are seen between BA46 although the two tasks share the same (positive) directionality. This suggests that BA46 explains less variance in the task-switching task than the dual task.

Conclusion and Future Work

In the task-switching study, weak-to-moderate strength correlations between DLPFC activation and task-switching performance may become clearer upon increasing statistical power with a larger sample size. In this study of n = 18, large variability was seen in the confidence interval of correlations between neural activation and reaction times. Thus, it remains uncertain if these results reflect the true relationships or noise. This effect could be seen in the attention control scores as well. A small sample size introduces uncertainty into measurements, especially when statistical significance is not reached. Further refining this relationship could provide a neural correlate of sport-relevant task that could augment screening and training efforts, injury prevention, and performance optimization in addition to dual-task performance. However, the lack of relationship between task-switching performance and attention control outcomes may indicate a variable strategy towards the novel, task-switching task. This finding contrasts with the results from Study One where a clear relationship was seen between attention control abilities and cognitive motor dual-task performance.

Future Directions

Future work is needed to clarify the role of attention control scores and DLPFC activation during more cognitively challenging dual-task scenarios and other applications of cognitive-motor control. In Study One, high performance on the cognitive portion of the dual task may have influenced the cognitive dual-task cost calculations. A cognitive task that is comparably challenging to the repeated single-leg squatting (motor) task could help to distinguish between individual performances without artificially inflating cognitive performance. This may help to distribute scores more evenly, reducing score clustering and increasing the sensitivity of the analysis by minimizing ceiling effects in the cognitive task.

Previous work has noted motor performance differences during a dual task under varied cognitive loads [102]. The literature shows evidence for prioritization of either the cognitive or postural task within a dual-task scenario. In some studies, individuals appear to develop a 'posture first' strategy when faced with a cognitively challenging dual task. This effect has been seen in healthy individuals [102,103], older adults [103], as well as injured populations [32]. It suggests that when faced with a dual-task scenario, many individuals will default to an automatic postural control state. Conversely, other studies show a decrease in postural control when faced with a cognitive challenge. In these studies, it is generally argued that competition for limited attentional resources affects postural control, resulting in decreased dual-task performance when compared to single tasks. Another, 'U-shaped', relationship between postural control under various levels of cognitive processing has been proposed (Figure 22) [104]. In this model, either high or low cognitive loads improve postural control while moderate loads disrupt motor function during a dual task. At low cognitive loads, more attentional resources are available to

direct towards the motor task and at high cognitive loads, postural control becomes more automatic, requiring less cognitive resources. At a moderate load, competition for attentional resources is high, but not enough for full postural control automaticity. It is noteworthy that previous works have used standing on two feet or walking as the postural control task which inherently require less motor control than our single leg squatting task. Increasing the cognitive loads during this physically challenging dual-task scenario could provide more insight into the allocation of attentional resources during demanding cognitive-motor tasks, such as those seen in sport scenarios.

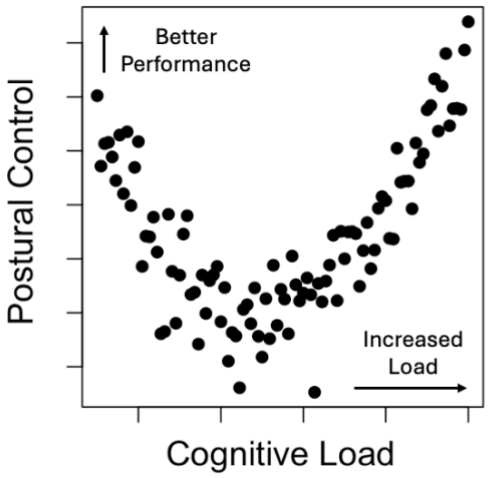

Figure 22: 'U-shaped' distribution of postural control as cognitive load increases. In this model, postural control abilities increase at low or high cognitive loads but decrease ad moderate loads.

Study One focused on healthy young adults, but its findings could be especially valuable for populations such as older adults or those recovering from injury, where attention control and neural resource allocations plays a crucial role in cognitive-motor dual-task performance. Older adults tend to adopt a 'posture first' strategy during a cognitive-motor dual task, where postural

control is prioritized over cognitive demands [105,106]. However, the extent that attention control and neural activation modulate dual-task performance is understudied in these populations. Untangling the relationship between attention control abilities as a modulator of performance in a challenging cognitive-motor dual task could provide insights into fall-prevention strategies in older adults. In previous work, increased activation in the prefrontal cortex has been associated with decreased dual-task performance on a dual-task combining a cognitive task with walking [107]. While a comparable increase in neural activation to the present study was seen under dual-task conditions, it was connected to decreased performance outcomes during the dual task. This maladaptive performance seems to be consistent with previous work noting neural inefficiencies in older adults during dual-task walking conditions [21]. Older adults appear to increase neural activation during a cognitive-motor dual-task compared to young adults indicating a decrease in neural activation that could be given to other tasks. Future studies have been suggested to investigate the causal influence of maladaptive neural activation on complex cognitive-motor behaviors, such as walking, and its relationship to falls in older adults [21].

The results Study One may also be beneficial for populations returning to sport from injury. Individuals post anterior cruciate ligament reconstruction (ACLR) are known to exhibit high dual-task interference. In balance control studies, this population tends to adopt a ‘posture first’ strategy when faced with a dual-task scenario [32]. This decrease in postural automaticity has been seen across double-limb stance tasks and more dynamic movements in this population. For example, individuals post ACLR have exhibited increased time to stability following a vertical jump [33]. It is theorized that loss of peripheral information from the injured ligament

could contribute to altered movement patterns as well as neural activation changes following reconstruction. For instance, neural activation increases in the motor cortex, lingual gyrus, secondary somatosensory area, precuneus, and posterior cingulate gyrus have been shown in this population compared to healthy controls during tests of knee motor control [33,108]. Similar to older adults, individuals post ACLR tend to adopt neural inefficiency frameworks where increased activation is seen for the same task when compared to healthy individuals. These changes are associated with an increased reliance on visual information processing systems [33] and decreases in visual memory scores [30,33], potentially due to the loss of sensory information from the injured joint. It is theorized that this reliance on visual information could be a way for the ACLR population to mediate deficiencies in knee joint proprioception but is also typically reinforced through movement strategies during the injury rehabilitation process. These cognitive decrements and neural inefficiencies noted in the ACLR population are seen in single-tasks but could be worsened in dual-task scenarios where neural resources must be split between multiple tasks. High activation, relative to healthy controls, during single tasks (such as cognitive tests) could limit neural engagement as task demands increase in a dual-task situation. Further investigation into the connection between neural activation and attention scores as predictors of performance in during demanding cognitive-motor dual-task scenarios may reveal inefficiencies that could contribute to primary or secondary ACL injuries.

Notably, attention control and dual-task performance appears to benefit from training although challenges with transfer beyond the trained task are debated. In older adult populations, there appears to be a substantial effect of training on the accuracy percentage and reaction time in a dual-task paradigm [109]. In both training tasks and transfer tasks, older adults were able to

mitigate the effect of age and perform comparably to younger adults after training. This study did not investigate longevity effects of the trained dual-task. Another study investigating the effect of working memory training showed benefits in tests of word recognition and repetition [110]. Moreover, in young athletic populations, inhibition control appears to be trainable. A sample of recreational tennis players showed improvements in attention control measured through the Antisaccade test when trained on a novel inhibition control task [111]. This study also found increased visual attention with training. After inhibition training, recreational tennis players improved their performance in a volleying task where they were required to place a ball inside a target area. Additionally, improvements in eye tracking were seen in this task. Post training, the tennis players decreased the time from when the ball hit their racket to visualizing the target area. Together, these findings tentatively suggest that attention control can be trained. The transferability of this skill across tasks remains inconclusive. It is possible that incorporating targeted attention control training efforts into rehabilitation strategies may have a positive impact on dual-task performance across populations.

From the functional neuroimaging perspective, future studies should establish optimal measurement durations for fNIRS data in environments with motion artifacts. Human fNIRS data is typically collected in a block format with baseline periods (or rest periods) preceding task periods (Figure 23). Blocks are repeated multiple times and activation is commonly averaged over the length of the total task, rather than considering each block individually. Considerations for future work in fNIRS data collection include optimization of task and baseline period lengths in dynamic settings with large amounts of motion artifact. As task length increases, habituation – either hemodynamically or neuronally in response to a stimulus – takes effect [112,113]. For

example, one block of 10 minutes is unlikely to elicit the same neural activation as 10 blocks of one minute, due to both the hemodynamic response and stimulus habituation. Previous work has demonstrated effective use of discreet event stimuli [46] and single trial designs [47]. These authors argue that without a block design and long data collection periods, and early increase in deoxygenated hemoglobin can be detected and isolated without artifacts. It is also noted that although fNIRS measurements in these collection paradigms correlate with fMRI data for some tasks, further research is needed. This type of task design is notedly less prevalent in the literature. Future work could further investigate this type of short task design along with longer data collections to clarify the effect of block length on neural activation measurement in dynamic environments with substantial motion artifacts.

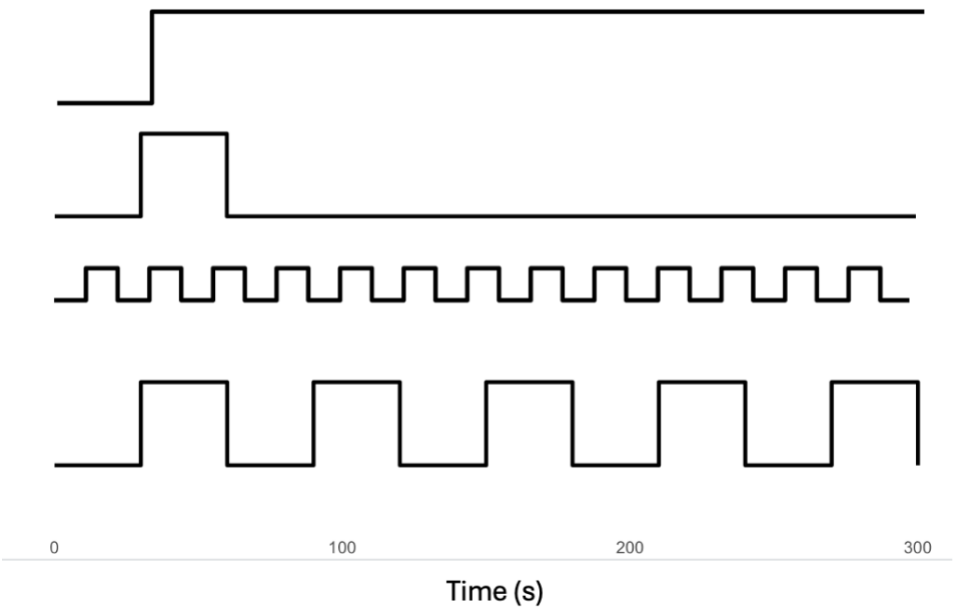

Figure 23: fNIRS block designs with alternating task and rest periods. Each step up indicates a task period while a step down denotes rest. These block designs can be varied in duration and repetitions to test the effects of block design on fNIRS signal accuracy in stationary and dynamic environments.

Overall Conclusions

The cumulative findings of this body of work show DLPFC activation and attention control as indicators of dual-task performance. By leveraging these findings, functional neuroimaging during dual-task conditions could provide novel perspective on individual strategies and altered activation in injured populations during movement tasks and has the potential to uncover new risk factors for future injury and improve rehabilitation efforts. In a dual-task scenario, the ability of an individual to direct focus towards multiple stimuli while maintaining overarching goals is paramount to successful performance. Considering the collective results of both studies, investigation into neural activation under movement tasks, such as those seen during a challenging cognitive-motor dual task, may provide critical insights into distinct neural strategies and resource allocation across populations. The results from Study Two further validate the benefit of short-separation channel use during fNIRS recordings in these dynamic environments to protect against fluid movement artifact. Although fNIRS has been employed previously in movement settings, including cognitive-motor dual tasks, these findings show the value of short-separation channels in mitigating false positive and false negative signals, ensuring more accurate interpretations of neural activity in these settings. Given the results from Study One, it is evident that single-task performance scores alone are insufficient for predicting dual-task performance, highlighting the relevance of these considerations for fNIRS in use in dynamic environments. Therefore, utilizing neural activation measurements in these complex tasks provides a pathway to uncover novel mechanisms underlying task performance. Advancing our knowledge of neural activation in dual-tasks and other movement paradigms is essential to the identification of novel injury risk factors and improving rehabilitation outcomes.

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