Dry EEG Measurement of P3 to Evaluate Cognitive Load During Sitting, Standing, and Walking

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Abstract

The impact of cognitive load on individuals with motor impairments is poorly understood. Cognitive load has been studied using subjective assessments, dual-task studies, physiological measures, and clinical metrics, which are specific to the motor task being performed and do not measure brain signals directly. Combining brain imaging with dual-task paradigms provides a quantitative, direct metric of cognitive load that is agnostic to the motor task. To better understand the impact of cognitive load during activities of daily living, we measured brain activity from a dry EEG headset as participants attended to an auditory stimulus paradigm during sitting, standing, and walking. The stimulus paradigm consisted of an auditory oddball task in which they had to report the number of oddball tones that were heard during each task. The P3 event-related potential, which is sensitive to cognitive load, was extracted from EEG signals in each condition. Results showed that P3 was significantly lower during walking compared to sitting (p = .039), indicating that cognitive load was higher during walking compared to the other activities. No significant differences in P3 were found between sitting and standing. Head motion did not have a significant impact on the measurement of cognitive load. These results encourage the use of a dry EEG system to further investigate cognitive load during dynamic activities in individuals with and without motor impairments.

Introduction

The cognitive requirements of motor tasks are important to understand in the evaluation of clinical interventions for populations with motor impairments. High cognitive load is a hindrance that prevents the full exploitation of assistive devices, such as upper limb and lower limb prostheses[1,2], exoskeletons[3], and powered wheelchairs[4]. Although the phenomenon of high cognitive load is well studied in the field of neuropsychology[5,6], measuring cognitive load while performing tasks in other contexts has been challenging. In the realm of wearable assistive devices for individuals with motor impairments, cognitive load has been defined as the mental demand of the device placed on the user[7]. While there are many clinical and non-clinical tools for the evaluation of a user's movement, such as postural stability[8], speed of walking[9], and symmetry of gait[10], traditional metrics in rehabilitation science do not directly measure the cognitive demand of using an assistive device. There is no single tool that can provide all measurement requirements, as there are many potential confounding factors such as type of physical activity, subject expertise, and ecological validity[7].

Performance-based clinical measures of individuals with motor impairments are often designed to identify the ability to complete a walking task rather than the cognitive difficulty of the task itself, as in the case of the Activities Balance Confidence scale (ABC)[11] and the Timed Up and Go test (TUG)[12]. Physiological indicators controlled by the autonomic nervous system, such as heart rate and metabolic oxygen consumption, are correlated with an individual's conscious effort on a cognitive task[13]. However, these indicators are also closely linked to physical exertion, thus tasks of varying cardiovascular engagement, such as sitting compared to walking, are not directly comparable using these methods. A

metric of cognitive load that is robust to cardiovascular engagement should be used to evaluate the impact of cognitive load across tasks.

Dual-task methods (e.g., a cognitive-based primary task paired with a motor-based secondary task) may reveal the influence of attentional demands on motor behavior. Compensatory patterns during walking have been shown to occur due to the addition of a cognitive task. For example, Pruziner et al. found lower-limb amputees exhibited a wider base of support and more stable gait patterns when tasked with a cognitive task compared to walking without any additional task[14]. While dual-task methods are suitable for various types of cognitive tasks, measuring the impact of the cognitive task on the motor task is dependent on the nature of the motor task. For example, for a cognitive task that is applied during standing and walking, the measurable impact on the motor task would depend on the biomechanical attributes of the motion occurring during that task, making the impact of the cognitive task on those motor activities not directly comparable. Different evaluative measures would be required according to the task, e.g., increased sway for a balance task[2] and wider step width for a walking task[14]. A task-agnostic measure of cognitive load would provide a method for measuring cognitive load across a range of different tasks.

Brain imaging techniques such as electroencephalography (EEG) provide a task-agnostic modality for directly assessing cognitive load. One method for obtaining cognitive load from brain signals involves the application of stimuli that elicit event-related potentials (ERP). Stimulus paradigms used to elicit ERP commonly include the oddball paradigm, in which a participant attends to a train of target and non-target stimuli. The participant is asked to ignore the frequently-occurring non-target stimuli and keep a mental count of the target (oddball) stimuli[15]. The amplitude of the brain response, or the EEG signal at the time of stimulus onset, reflects the amount of cognitive processing that takes place when the stimulus is perceived. Due to the limited processing resources of the brain, the cognitive response to external stimuli is reduced during dual-task scenarios when more cognitive resources are required[5]. The P3 potential is the third positively going peak in the ERP, found at approximately 300 ms after stimulus presentation. The P3 potential is thought to represent context-dependent processing of external stimuli[5], and its amplitude has an inverse relationship to the cognitive difficulty of the task that is performed[15].

Evaluating the ability of populations with motor impairments to safely navigate outside the home includes the assessment of tasks associated with many activities. Three important tasks that are critical include sitting, standing, and walking[16]. To our knowledge, there was one other study to compare sitting, standing, and walking[17]. Protzak et al. used a visual cognitive task to induce P3 in both young and older populations[17]. In contrast, the present work uses an auditory oddball task to examine P3, since auditory stimuli are easier to administer in unconstrained activities compared to visual stimuli. This study also seeks to identify the impact of head movement artifact on the P3 amplitude.

Until recently, most studies have used EEG only during seated tasks due to the inability to identify and remove motion-related artifacts from the EEG signal, but mobile activities are now possible[18]. Advances

in wireless electrode technology now allow EEG measurement during movement in unconstrained environments, such as playing table tennis[19], jogging[20], and cycling[21]. Wireless dry EEG provides additional benefits of fast setup time (approximately 5-10 minutes, as in the current and previous study[22]), use in environments where gels are not allowed[23], and avoids the need for re-application of gel in prolonged experiments[24]. With the advent of dry, mobile EEG systems also comes the need to determine the effect of motion on EEG signal[25,26]. Some studies have shown walking-related motion artifacts are negligible in continuous and spectral gel-based EEG[27]. Other studies claim that motion artifact does impact signal from gel-based EEG during walking, and that motion related artifacts are not removable using traditional signal processing methods[28]. Missing from these studies is the impact of possible walking-related motion artifacts on ERP from gel-based EEG or dry EEG. Zink et al. examined the impact of motion on ERP recorded during biking in seated (non-moving), stationary (pedaling on a stationary bike), and moving (biking through a college campus) conditions, and no effect of movement artifacts was found on P3 amplitude[21]. The present study uses a dry (i.e., gel-free) electrode EEG headset, namely the DSI-7 from Wearable Sensing. Although not all dry electrode headsets provide the same level quality of signal[29], studies have found similar signal quality with dry electrodes compared to wet for some systems[29,30], including the DSI-7 during seated[31] and dynamic testing environments[32].

To our knowledge, this study is the first to compare P3 across the tasks of sitting, standing, and walking using dry EEG and an auditory oddball paradigm. Here we show that cognitive load can be measured from the P3 event-related potential during these three tasks. This work also examines the possible impact of motion on the P3 ERP component measured during walking, the most motion-inducing condition. We hypothesized that the cognitive requirements of walking will result in a reduction of the P3 amplitude compared to sitting and standing. We also hypothesized that standing will be more cognitively demanding than sitting, as suggested by prior studies using dual-tasks[33] and P3 amplitude[17].

Methods

All experiments were approved by the ethics committee of the Institutional Review Board of Northwestern University. Experiments were carried out in accordance with the Institutional Review Board guidelines and regulations. All subjects provided informed consent before participating in the study. Ten participants (5 female, 5 male, age mean 22 ± 3 years, age range 20-29 years) were recruited for this study. Results from one subject were excluded from the analysis due to artifacts in the EEG signal, thereby leaving data from nine participants in the final analysis.

Participants completed three sessions of three conditions: sitting, standing, and walking. The conditions were completed in a randomized counter-balanced order so that each session contained of one of each condition. As our pilot studies indicated participants were too fatigued with long sessions of 15 minutes each, the current study separated each condition into three separate 5-minute task, and each session was followed by a 5-minute break. Auditory stimuli were applied at random intervals between 675 and 1365 ms. Oddball stimuli (.i.e., Target stimuli) were infrequently-occurring high-pitched tones at 1200 Hz, and

standard stimuli (i.e., Non-target stimuli) were frequently-occurring low-pitched tones at 900 Hz. Stimuli were delivered in a random order including 90% standard tones and 10% oddball tones. Stimuli were played by a microcontroller (Arduino) with an audio wave shield to wired earbuds. Before beginning each experiment, participants were allowed to adjust the volume on the stimulus delivery and verified that they could clearly distinguish the two types of tones.

The audio signal was simultaneously delivered to the stimulus Trigger Hub (Wearable Sensing) which identified the timing onset for each stimuli so that it could be synchronized to the EEG signal. EEG signal was recorded using a DSI-7 (Wearable Sensing), a wireless headset with 7 dry electrodes located on the scalp at F3, Fz, F4, C3, C4, P3, Pz, and P4. Linked ears (LE) reference electrodes were placed on both earlobes. Signals were recorded at 300 Hz through an ultra-high impedance amplifier. The impedance at each electrode was monitored to ensure it was below 1 MΩ before starting the experiment. Participants wore a stabilization strap with velcro straps to secure the EEG cap.

Continuous EEG data were band-pass filtered between 0.5 Hz to 30 Hz through a zero-phase 4th order Butterworth filter. Infomax Independent Component Analysis (ICA) was applied to the filtered data to separate neural from non-neural components using EEGLAB[45] with built-in functions from ERPLAB[46]. EEG data was sectioned and aligned to the start of the stimuli to produce epochs surrounding the onset of each stimuli, from -200 ms prior to stimulus onset to 800 ms post stimulus onset. Epochs contaminated by artifacts were identified from the ICA components according to standard and previously-used parameters[22]: rejection criteria included abnormal values (i.e., those outside the range of -25 to 25 μV in the pre-stimulus period, and -75 to 75 μV post stimulus period), strong linear trends (maximum slope of 50 and r-squared up to 0.3), abnormal joint probabilities (single-component and all component probabilities of up to 5), strong kurtosis (distributions with kurtosis up to 5), and abnormal spectral properties (i.e., those outside the range of -50 to 50 dB between 0 to 2 Hz and from -100 to 25 dB between 20 to 40 Hz). After artifact trials were removed, each subject's data contained at least 37 oddball stimulus responses from each condition across all sessions. Excess trials were excluded from further analysis.

Grand average ERP were generated by aligning the onset of the stimuli and averaging across trials. The P3 timeframe was chosen to be 250-350 ms, since P3 is known to occur at approximately 300 ms. Similarly to EEG data, accelerometer signals were segmented and aligned to stimuli onset. The magnitude of the accelerometer RMS was taken to represent the head motion for each trial.

A linear mixed effects model was used to determine the effect of task (i.e., sitting, standing, and walking) on the average P3 voltage. This was done using the built-in Matlab function fitlme. Inter-subject differences were accounted for by treating subjects as a random factor. Sitting was used as the reference.

Results

Oddball auditory task applied during sitting, standing, and walking

Ten subjects performed a series of three activities: sitting, standing still, and walking on a treadmill, while wearing a dry EEG headset and associated stimulus synchronization equipment contained within a lightweight backpack (Figure 1a). EEG signals were analyzed and artifact trials were removed according to standard procedures, described in Methods. EEG sensor locations are shown in Figure 1b. Baseline RMS levels are shown in Figure 1c. One subject was excluded due to the presence of cardioballistic artifacts in the EEG signal. In each condition, participants listened to a series of high-pitch and low-pitch tones following an auditory oddball paradigm[22]. At the end of each activity, participants were asked to report the number of oddball tones they heard in that activity, as shown in Figure 1d for all conditions. Participants were able to complete the auditory oddball counting task with less than 8% task error. A two-way ANOVA was calculated for task error across all sessions and conditions. No significant differences in task error were found across conditions or sessions (p = .86).

ERP differentiates walking from that of sitting and standing

Figure 2 shows the grand average ERP taken from the central parietal (Pz) electrode across all three conditions for both target and non-target stimuli. Non-target ERP does not show any deflections, suggesting that motor-related cognitive activity did not impact cognitive responses to stimuli. In contrast to non-target ERP, the ERP for target stimuli showed a positive deflection at around 300 ms (P3) and a negative deflection at around 100 ms (N1) in all conditions. Average brain activity is also shown for electrodes across the scalp at the P3 timeframe (250 to 350 ms) and N1 timeframe (60 to 110 ms) for target stimuli in each condition (Figure 2, insets).

The ERP responses during the P3 timeframe were compared across all trials and conditions. A linear mixed effects model accounting for individual subject differences indicated that the average voltage during the P3 timeframe was significantly lower for walking compared to sitting (p = .039). This result indicates that cognitive load is greater during walking than during sitting and standing.

Head motion does not impact ERP during walking

Baseline EEG across 7 scalp locations (F3, Fz, F4, C3, C4, P3, Pz, and P4) during times prior to stimuli presentation indicated there was more variation in EEG signal across scalp positions during walking as compared to sitting and standing (Figure 1c). As such, the impact of motion on the EEG signal during walking was also analyzed. A 3-axis accelerometer located inside the EEG cap measured the head movement in each condition. Figure 3a shows the distribution of motion across all trials in the sit, stand, and walk conditions. The mean and standard deviation of the RMS magnitude of the acceleration vector tended to be greater during the walking condition as compared to that of the sitting and standing

conditions, as expected due to increased motion of the head during walking. Figure 3b shows the average voltage during the P3 timeframe at the Pz electrode as a function of the motion during the corresponding P3 timeframe for each condition. The variation in motion (Figure 3b) was not correlated to voltage during the P3 timeframe for any condition ($r < .5$). Gaussian probability distributions (Figure 3 and Table 1) show that while the means in P3 for sitting and standing were similar ($m = 6.651$ and $m = 6.733$ mV, respectively), the mean P3 for walking was less ($m = 2.809$ mV) and the variability in the walk condition ($s = 8.39$ mV) was greater than for sit ($s = 4.58$ mV) and stand ($s = 5.54$ mV). To account for individual differences, the correlation was calculated for individual subjects, but no trends were found ($r < .5$) suggesting that head motion did not impact the P3 responses.

To further investigate the impact of motion on the P3, all walking trials were sorted according to their corresponding RMS magnitude from the accelerometer and binned according to eight motion levels. Average ERP for each motion level is shown in Figure 3c. The average voltage in the P3 timeframe was plotted against the motion level during walking, as shown in Figure 3d. The average P3 voltage as a function of motion level during walking did not yield a significant trend ($r = .24$, $p = .125$).

Discussion

Cognitive requirements known to impact activities of daily living in both healthy individuals and those with motor impairments have been difficult to measure due to methodological limitations. Currently, subjective assessments and EEG are the closest tools available for direct or indirect measurement of the internal feeling of naturalness and ease of using an assistive device such as a prosthesis. EEG provides a possible method to directly measure the ease of completing a task with high temporal resolution. This study uses EEG to measure the cognitive load of three tasks: sitting, standing, and walking. The P3 response found in this study was lowest during walking, indicating that walking was the most cognitively burdensome task. These results support those of prior studies including those that have compared the P3 responses during walking and sitting[2,14,17,34,35].

Dual task methods have shown that balance control is affected by divided attention in sitting, standing, and walking in individuals with motor impairments[14,36] and without motor impairments[37,38]. EEG studies have also shown decreases in cognitive load as task complexity increases during sitting[39], across tasks of standing and walking[18,40,41], and across tasks of sitting, standing and walking[17]. In EEG during walking, cortical fluctuations have been shown to be coupled with phases of the gait cycle[42], but understanding the cognitive requirements of various motor tasks remains elusive. One study that measured the impact of supraspinal input on walking found that obstacle avoidance could be seen from spectral fluctuations in EEG signal[43].

In agreement with the results of Protzak et al.[17], our results indicate that walking had the lowest P3 amplitude (Figure 2); however, we showed similar P3 amplitude for both the sitting and standing tasks. This finding was in contrast to at least one other study which compared the cognitive load of sitting and standing: a dual-task study that found slower reaction times during standing compared to sitting[38]. While

not significantly different, Protzak et al. also showed higher cognitive load for standing compared to sitting[17]. Furthermore, the visual task used by Protzak et al.[17] was different from that of the current study, in which we used an auditory oddball task since it is easier to administer auditory stimuli compared to visual stimuli in unconstrained environments.

A limitation of this study is that the auditory task did not distinguish between the cognitive load between sitting and standing. Tasks that are nearly equally easy, as in the case of sitting and standing in able-bodied individuals, are not expected to yield differences in P3 unless the cognitive task is difficult enough. In contrast to the auditory task used in the current study, the visual task used by Protzak et al.[17]was able to distinguish the cognitive load for standing compared to sitting in younger participants. This may have been due to the fact that visual tasks are more difficult to complete during activities that require trunk support, as the balance required to maintain posture relies heavily on the visual system. Thus the auditory oddball task used here may have been too easy to distinguish between cognitive load of sitting and standing **Figure 3.** (a) Histogram of accelerometer RMS magnitude for each condition (sit, stand, and walk). (b) Mean P3 voltage at Pz plotted against the associated motion RMS vector for each subject in each session and condition. Axes show the Gaussian probability distributions for each condition. (c) Averaged ERP for 8 levels of head motion during walking. (d) Mean P3 voltage at Pz from ERP data presented in (c), plotted against motion level, with each head motion level represented by a different color.

Table 1
Estimated gaussian parameters for RMS head motion and average P3 for each condition, computed from averaged subject data shown in Figure 3b.

Condition	RMS Head Motion	Average P3 (μV)
	mean (st. dev.)	mean (st. dev.)
Sit	.0085 (.002)	6.651 (4.58)
Stand	.0111 (.004)	6.733 (5.54)
Walk	.1209 (.022)	2.809 (8.39)

for the able-bodied individuals who participated in this study. The advantage of using auditory tasks is that they only require headphones, as compared to visual tasks which require an environment outfitted with LEDs such as those used in the aforementioned study[17]. Future work may consider the use of a more difficult auditory task, or a visual task in augmented reality to maintain the possibility of administering them in unconstrained, outdoor environments.

While the auditory oddball task used in this study is appropriate for distinguishing cognitive requirements of sitting compared to walking, it might be too simple to cause a change in the cognitive response shown in the ERP in populations without motor impairments when comparing sitting to standing. However, the lack of a difference in P3 between sitting and standing is an interesting finding that could inform future work with different tasks and populations with motor impairments. We expect, for example, that

individuals with poorer trunk support and balance would not find sitting and standing to be equally easy and thus would have lower P3 amplitude for standing compared to sitting. Another area of interest is for lower-limb prosthesis users. It is possible to use this paradigm to evaluate changes in cognitive load for users of different devices. For example, a microprocessor knee that provides stance support may be easier for a person to use while standing compared to a purely mechanical device that does not provide stance control.

We also investigated the possible impact of motion artifacts on the walking trials, which has the most head movement of all the tasks. We did not find any significant results indicating that motion artifacts affected the interpretation of the results. A significant trend in Figure 3c would indicate there is an increase in voltage as a function of motion, which would mask a possible decrease in P3 potential during a more difficult dual-task condition. This could lead to the erroneous result that cognitive load is not as high for activities that increase head motion, such as walking and jogging compared to sitting and standing.

This study utilized artifact removal processes including independent components analysis (ICA) to separate out the

contribution of motion (among others, such as eye-blink, muscular, and cardiovascular artifacts). Trials with artifacts were discarded, resulting in a sufficient number of trials (37 per subject in each condition). Despite the availability and usage of ICA methods, dry EEG headsets have not been widely used in dynamic environments due to poor signal quality, which may vary greatly across dry EEG systems[29,30]. Oliveira et al.[44] reported that no data was usable (i.e., 100% of epochs were discarded) using their dry EEG system after excluding epochs that exceeded a threshold difference of 75 μV from baseline. In contrast, our results yielded a suitable amount of clean epochs from EEG recorded during walking using the same standard threshold as in Oliveira et al.[44] While there is proprietary information that may help explain the differences in dry EEG technology, the system used in the current study may provide superior signal quality in part due to a stabilization strap, spring-loaded electrodes, and a common mode follower. The common mode follower measures the external electrical activity from the environment so that it can be removed from the EEG signal.

This study provides a method for measuring cognitive load using a dry EEG interface that is robust to tasks of various dynamic movement artifact. Current methods in EEG allowed the measurement of EEG during mobile activities in ecologically relevant settings. Future work could use this methodology to understand the impact of cognitive load during dynamic activities. Variation in P3 across days, stress level, cognitive function, and levels of motor impairment for a range of dynamic tasks is important to identify in order to understand factors that influence cognitive load.

Declarations

Author contributions statement

M.S. and L.H. conceived the experiment, M.S. conducted the experiment and prepared the figures, M.S. and L.H. analyzed the results. All authors reviewed the manuscript.

Additional information

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Competing interests

The authors declare no competing interests.

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Figures

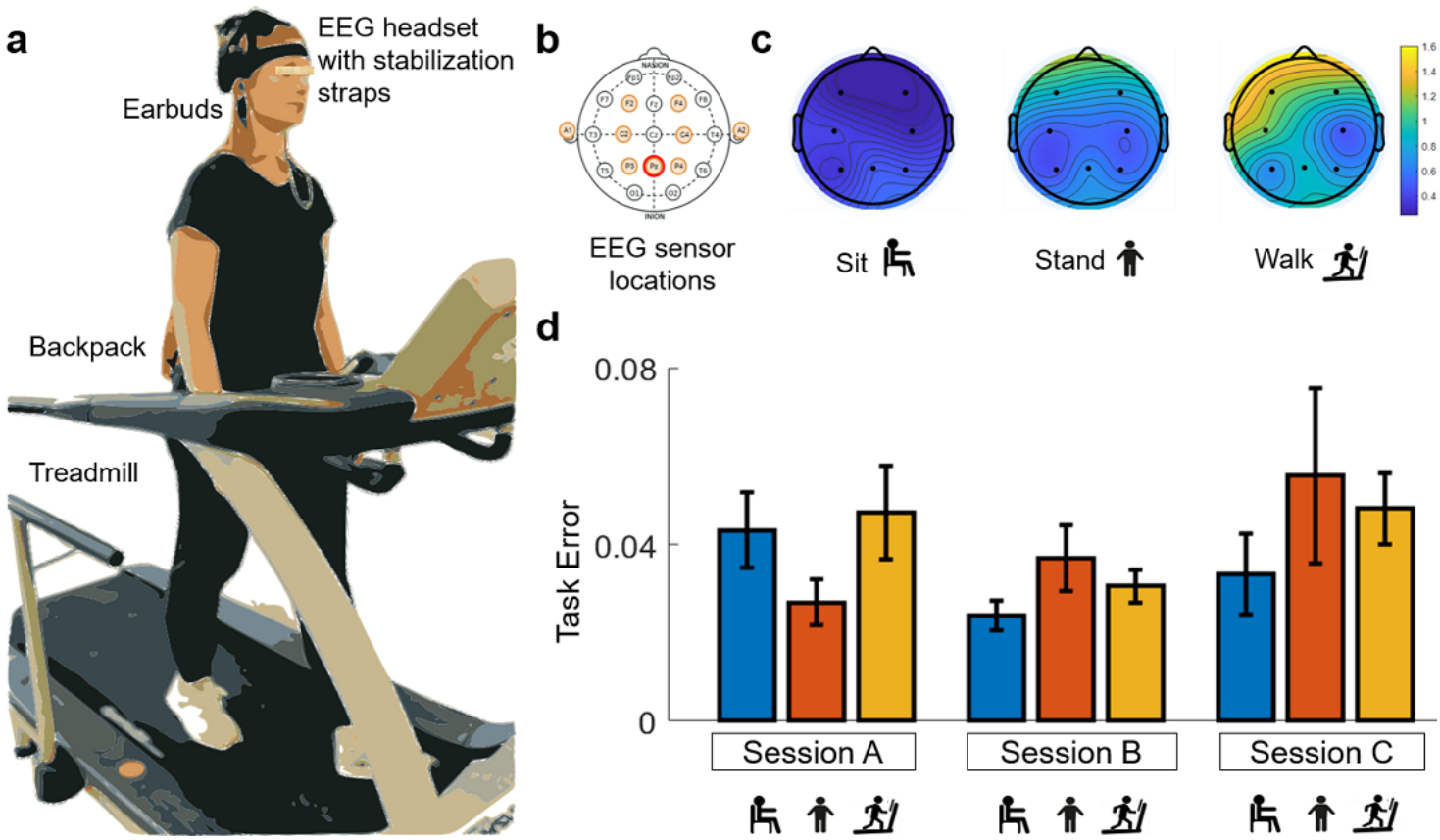

Figure 1

(a) A participant during treadmill walking, wearing an EEG headset with stabilization straps, headphones for listening to auditory oddball stimuli, and backpack containing stimulus-synchronization equipment. (b) EEG electrode placement used in the DSI-7. The Pz electrode, located on the posterior parietal midline,

is circled in red. (c) Scalp plots showing median RMS EEG signal during baseline periods of no stimulus presentation (i.e., from -200 to 0 ms). (d) Counting task error during oddball stimulus task. Sit, stand, and walk icons (also shown in (c) above) on the horizontal axis indicate the condition represented by each bar. Error bars represent standard error. No significance differences were found for task error across conditions or sessions (*p* = .86).

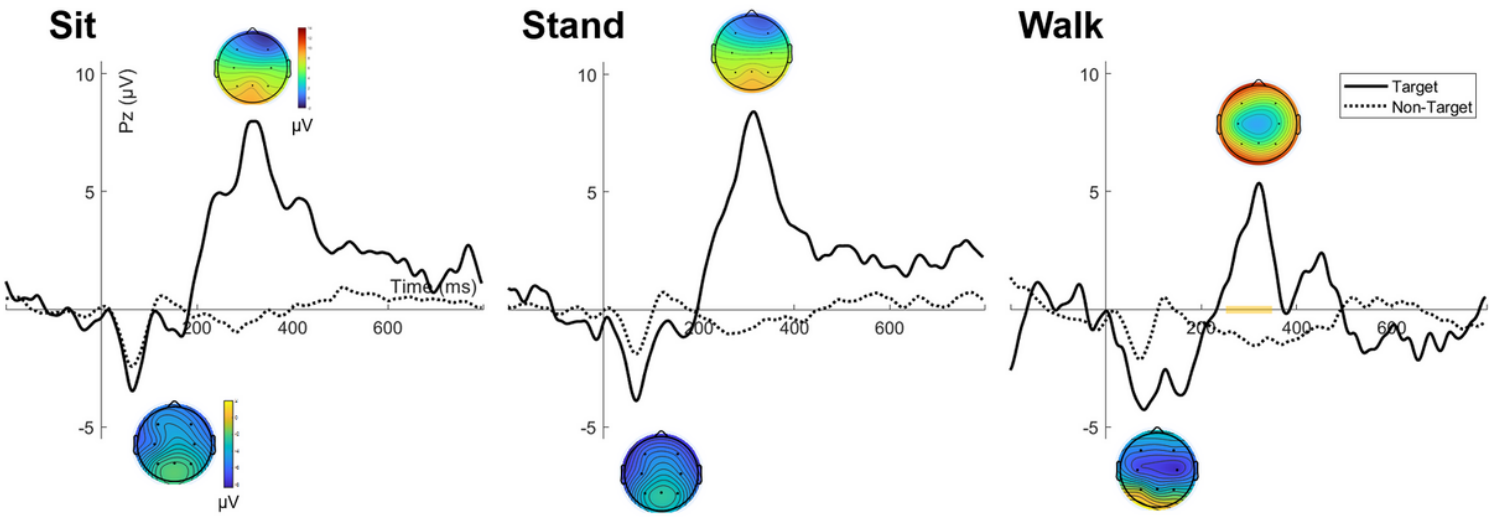

Figure 2

Grand average ERP from all conditions (sit, stand, and walk) for oddball (Target) and frequently-occurring (Non-Target) tones, combined for all sessions. Yellow shading indicates significant difference in average voltage during the P3 interval (250 ms to 350 ms) during the walk condition compared to the sitting condition (*p* = .039).

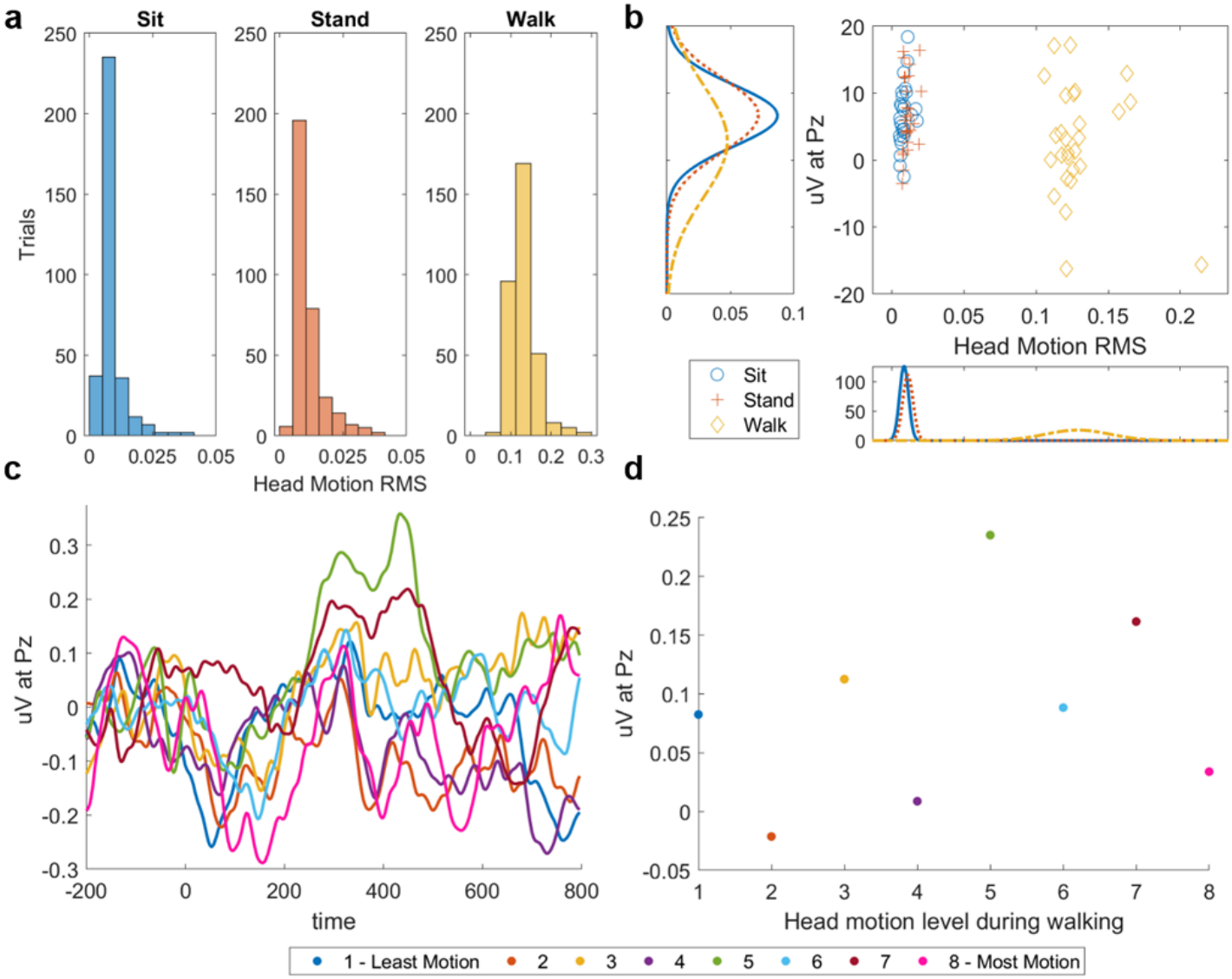

Figure 3

(a) Histogram of accelerometer RMS magnitude for each condition (sit, stand, and walk). (b) Mean P3 voltage at Pz plotted against the associated motion RMS vector for each subject in each session and condition. Axes show the Gaussian probability distributions for each condition. (c) Averaged ERP for 8 levels of head motion during walking. (d) Mean P3 voltage at Pz from ERP data presented in (c), plotted against motion level, with each head motion level represented by a different color.