Estimating the cognitive load in physical spatial navigation

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***Abstract*—Navigation is an essential skill that helps one to be aware of where they are in space and ambulate from a location to others. Many cognitive processes are involved in navigation tasks, even in the simplest scenario, such as landmarks encoding, cognitive map anchoring, goal-oriented planning, and motor executing. Engaging multiple tasks simultaneously could lead to higher cognitive load and attenuated navigation performance. In this study, we investigate the cognitive load of participants while they perform a navigation task.**

We demonstrated the ability to extract neural features from complex physical movement tasks, such as navigation. We found that retrosplenial complex (RSC) shows a distinct features for mental workload related task. We further evaluated participant's cognitive load with different machine learning algorithm and found that CNN is able to classify with 93% accuracy. The results provided a potential approach to study cognitive load in a more naturalistic scenario.

***Index Terms*—Spatial navigation, EEG, deep-learning, MoBI, brain-computer interfaces, CNN.**

I. Introduction

Ongoing research continues to look for new ways to get a better workload assessment that improves training methodologies and accelerates individual performance. Successful workload assessments can robustly identify predictive features and reduce the task workload. However, evaluating mental workload can be a difficult task. The main approaches use subjective feedback from domain experts and quantitative user studies.

Previous research works on mental workload has focused on individual neurophysiological measurements such as heart rate (HR) and heart rate variability (HRV), eye-blink frequency, pupil size, respiration, galvanic skin response, or electroencephalography (EEG) [1]–[3]. While these studies proposed mental workload assessment alternatives, there is still a limited number of works that proposed a reliable mental workload bio-marker that can be used in realistic environments and closer to real-life tasks. Unlike others, EEG could provide high temporal resolution, which can quickly reflect cognitive dynamics change. Using an EEG device involves a process of passively recording brain activity. EEG has shown to be the best indicator for mental workload in the N-back task when used alone or in combination with other measures [3]. However, most of the studies have investigated the cognitive load in static conditions with constrained physical movement. The simplicity of these experiment designs fails to reflect real-life cognitive load [3], [4]. Therefore, the underlying cognitive load mechanism is still poorly understood in more complex tasks that resemble our daily life activities, such as spatial navigation.

Along this line of work, we investigated if the cognitive workload can be detected in a more real-world settings such as active movement. To do so, we conducted a physical navigation experiment in which participants can freely ambulate from a location to several others. We recorded behavior and EEG simultaneously when participants performed different task load conditions. We hypothesize that despite the significant physical movement that generates noise in EEG signals, we will be able to detect cognitive load during a navigation experiment. The findings of this work has implication on the development of a model that can accurately estimate the individual's cognitive load, thus mitigation strategy can be taken such as adapting user interfaces.

II. Related Works

A. Spatial Navigation

Spatial navigation is an essential human skill that helps people orient themselves and keeps track of their locations in known and unknown environments. Navigation involves several cognitive tasks that need to be processed concurrently. An increase in task complexity leads to a higher cognitive load. It is well known how the complexity of the load affects

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participant performance. Participants can perform simple tasks with relative ease, but their performance can considerably decrease as soon as cognitive load increases. However, studies that focus on cognitive load in physical navigation is minimal.

Numerous efforts have investigated differences in navigation performances and strategies involved in navigation. These strategies include egocentric and allocentric reference frames and a mixture of both [5], [6]. Egocentric navigation utilizes spatial knowledge embedded in coordinate systems based on the navigator's body and conditioned upon the person's orientation in space. In contrast, the anchor of an allocentric coordinate system is the environment, objects, or relationship between them. Thus, being represented as an object among others, the navigators' orientation is not contained in an allocentric representation. The egocentric strategy mainly depends on the local landmark from the environment or the navigator's self-motion cues to anchor the orientations.

In contrast, the allocentric strategies rely upon global landmarks. Researchers often employ some simple tests to classify different spatial reference frames to check their reference preferences, such as the Reference Frame Proclivity Test [5], [6]. In short, there are mainly three types of navigators (a) tuners who use egocentric strategy, (b) non-tuners who use allocentric strategy, and (c) mixed users who change their navigation strategy in some cases. The underlying mechanisms that delineate a specific navigation strategy's proclivity include gender, age, and cultural background [6].

B. Brain Imaging in Spatial Navigation

Usually, the human brain's motor activities reflect the changes in the dynamic environment. Human cognitive function and brain dynamics are both coupled to both physical actions and the structure of the environment. If we are to understand the deeper neurocognitive processes in everyday life, experiment designs require participants to act as naturally as possible. This requirement has lead to the use of three-dimensional virtual environments, similar to different studies implementing virtual environments to simulate and test real-life scenarios [7]–[9]. However, the limitations of current brain imaging methods do not support brain imaging paradigms that investigate active movement.

While functional magnetic resonance imaging (fMRI) experiments provide a high spatial resolution of brain localization activation, participants' head needs to remain static during the measurement [10]. It is similar to the case of magnetoencephalography (MEG) or conventional EEG study, where the participant is immobile most of the time and can only move the body in a tiny scale-space due to the limitation of the movement-related artifacts removal methods.

Invasive methods can solve those limitations by using implanted electrodes [11]. Even though invasive methods provide high-quality signals from the brain, the number of participants willing to undergo this experiment is limited [11] due to the adverse health issues these setups might introduce.

Recently, another relevant approach surfaced: The Mobile Brain/Body Imaging (MoBI) method. This method investigates the human brain dynamics that accompany active human cognition in its most natural forms [12], [13]. Many studies have demonstrated that they could study brain activities at various levels, such as channel level [14], [15], cortical, and subcortical level [16]–[20].

C. Retrosplenial Complex

Previous works [21], [22] show how retrosplenial complex (RSC) plays a vital role in navigation. Modulation of RSC activity usually happens when a participant interacts with a navigation related-task [21], [23], [24]. Due to its conjunction with other brain regions in the anatomical level, RSC is an essential part of the brain network [24]. RSC directly connects V4 (occipital), parietal, hippocampus, and indirect to middle prefrontal [24].

The RSC and hippocampal are crucial in spatial navigation on rodent studies [25], [26] and human studies [24], [27]. An injury in the hippocampal or the RSC leads to substantial impairment in navigating environments [28]. However, unlike hippocampal injury, which still allows navigation of familiar environments, a patient with an RSC injury does not allow this [29], [30]. Hence, the RSC is considered the primary orientation processing unit in spatial navigation, which derives the environment's direction.

D. Previous Machine Learning Techniques in Cognitive Load Classification

The linear and non-neural network methods are very popular as the first choice of classification problem among research [31]. The linear discriminant analysis (LDA) method has been used in various cognitive classification problem [1] due to fast computation and straightforward interpretation. The cleaned EEG channel data was often used as the classifier's input or combining both EEG channels data and frequency data [2]. Recently, deep learning attracted lots of attention among cognitive neuroscience researchers in general [32]. Notably, among other models in deep learning, a convolutional neural network (CNN) showed significant mental workload classification [33], [34]. CNN alone can give good accuracy for cognitive load classification. Moreover, the final output of the classification can be improved in combination with temporal and spatial information in EEG [33] (91.9% accuracy in 3 classes), or temporal, spatial and spectral [34] (88.9% accuracy in 2 classes). Although the classifier in those studies gave the high accuracy (around 90% for two classes), the experiment design in those studies was limited to a stationary condition such that mostly lab environment, hence no real-world settings. Thus, those findings still need to be evaluated in a more complex experiment.

III. Methods

A. Participants

There were eighteen participants (age 27.8±4.2, 2 females) who completed this experiment. All participants reported normal or corrected-to-normal vision. Each participant received $60 for their compensation. The local university ethics committee approved the protocol.

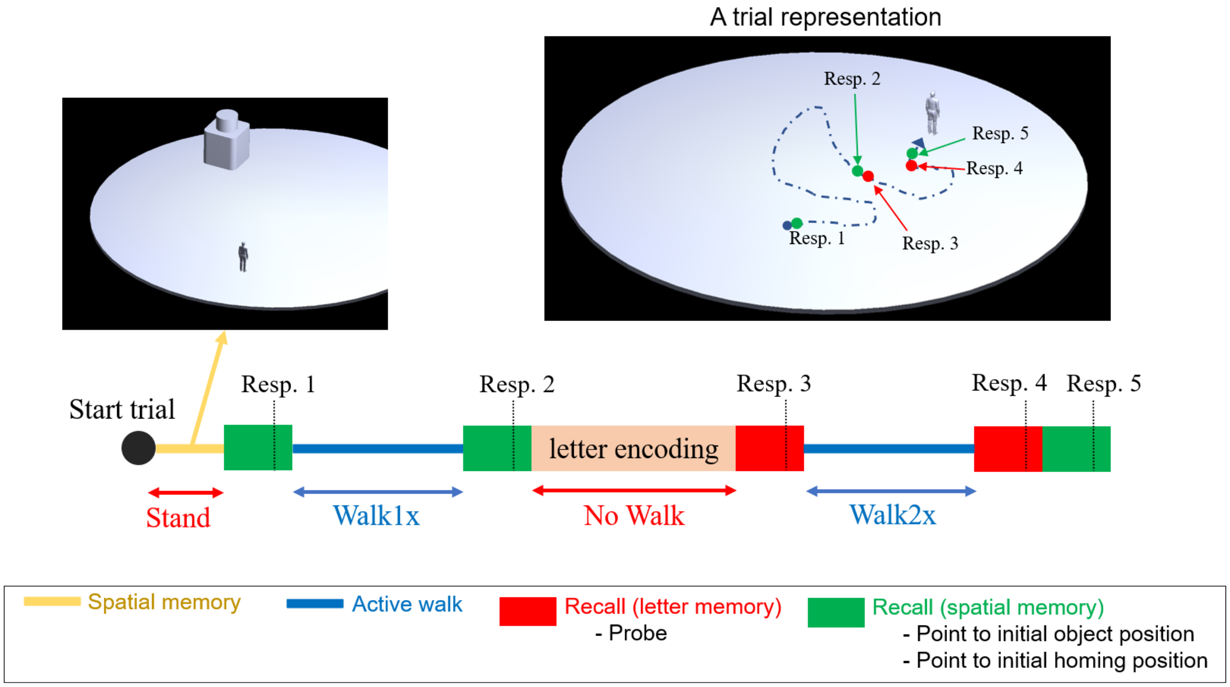

Fig. 1. The experiment design of the scenario.

B. Experiment Protocol

The experiment covered a set of simple physical navigation exercises interspersed with spatial encoding/retrieval tasks. It was complicated by letter encoding/retrieval tasks to impose an additional cognitive workload on the participants. Each participant first performed four learning trials to familiarize themselves with the tasks and instructions. Subsequently, they completed three sessions, each consisting of 30 trials, throughout the full experiment. Each trial proceeded as follows:

1) Landmark Encoding: At the beginning of the trial, participants have 4 seconds to encode the landmark location, shown in front of them approximately 10 meters away. Next, the landmark disappeared, and participants then answered to the instruction: ”Point to the landmark location.” They responded by pointing their Vive controller at their recalled location and clicking the controller’s trigger button (R1, figure 1).

2) First Navigation Segment: Once their response was registered, the neutral beep sound indicated that they need to start the first navigation walking segment. Participants walked toward a red sphere that appeared at the participant’s eye height. The red sphere disappeared once participants walked inside an area of 0.2 meters around each sphere. Next, the next sphere appeared, and participants had to walk towards it. Only one sphere appeared at a time. Each trial had either two or three spheres, and the number of spheres was random order in the first walking condition (walk 1x, figure 1). Our researchers regularly walked with our participants to track their orientation and location in the virtual environment during the navigation task and avoid any potential collisions or accidents they might have.

3) Spatial Retrieval: Once participants reached the last red sphere, a text saying ”Attention” appeared in front of them for 3 seconds. This event signaled that the first spatial retrieval task was about to begin. First, a virtual sign instructed participants to ”Point to the landmark location” by pointing their controller to the landmark location as they remembered it and clicking the Vive controller’s trigger (R2, figure 1). Next, two arrows appeared in front of the user: one pointing left, the other pointing right. These arrows came with a sign that asked: ”Where is the starting location?”. Responses were given by pointing their controller at one of the arrows and clicking the trigger (R2, figure 1).

4) Letter Encoding: The letter encoding task followed; this task intended to impose an additional cognitive burden on the user. The participants were shown a series of 3, 5, or 7 letters of the English alphabet at one-second intervals between letters, and asked to remember them. The number of letters chosen and the order in which the letters appeared was both random. The task included three levels of difficulty to avoid familiarity with the task to ensure the cognitive load remained high. Three seconds after the last letter appeared, participants were shown a random letter and asked whether that letter belonged to the letter list previously shown. Clicking the trigger indicated yes; pressing the touchpad indicated no (R3, figure 1). Participants then had 2 seconds of rest before starting the second walk session.

5) Second Navigation Segment: Another neutral beep sound signaled the beginning of the second navigation task (walk 2x, figure 1), which followed the same simple walk to the red sphere format as before. However, this time, the participants had to remember the letter list and track their orientation toward the landmark location and starting position. When the second walk finished, we instructed the participants to do three things: first, to confirm whether or not a random letter belonged to their letter list (R4, figure 1); second, to point to the landmark location; and, third, to point to the starting location (R5, figure 1). The next trial started when the participant indicated their readiness by clicking both grips on a controller.

C. Experiment Setup

1) VR Scenario: We developed the VR scenario using the Unity3D (version 2017.3) engine with the help of the VRTK[1] plug-in for VR development. The scenario consisted of a default empty Unity scene with a gray quad used as a floor. The quad was 1000 by 1000 to give the illusion that it was infinite space.

The experiment used an HTC Vive Pro head-mounted display (HMD) (2x 1440 x 1600 resolution, 90 Hz refresh rate, 110° field of view) and one controller. The second controller was held by our researcher, in case that the scenario needed any adjustment. The experiment space consisted of 5 by 7 meters, where the user was allowed to walk freely.

2) Data Recording: All data streams from the EEG cap and head-mounted display were synchronized using the Lab Streaming Layer protocol [35]. The EEG data came from 64 active electrodes placed equidistantly on an elastic cap (EASYCAP, Herrsching, Germany) with a sampling rate of 500 Hz (LiveAmps System, Brain Products, Gilching, Germany). The data was referenced to the electrode located closest to the standard position, FCz. The impedance of all sensors was kept below 5 kΩ.

D. EEG analysis

1) Pre-processing: All the pre-processing steps were performed in MATLAB 2018a (Mathworks Inc., Natick, Massachusetts, USA), and custom scripts based on the EEGLAB (version 14.2.0) [36]. The EEG data were first downsampled from 500 Hz to 250 Hz to reduce the computation. Next, we applied the band-pass filter (1-100 Hz). Then line noise (f = 50 Hz) and its harmonic frequencies were removed. Subsequently, the bad channels and bad segments (flatline, high power) were rejected before interpolating the missing channels by using the sphere method. Next, we run AMICA [37], [38] to decomposite data into the independent components (ICs) data. Furthermore, finally, the dipole fitting routine was used to estimate the location of ICs [39].

2) Clustering: The epoched data was extracted from the cleaned data at the walking event's onset with a length of 14.5 seconds, including 2.5 seconds baseline. The bad epoch was automatically removed based on its raw value. Then, all the ICs with residual variance less than 30% were imported to EEG STUDY. We then clustered all ICs based on the power spectrum (weight = 1), ERSP (weight = 3), and IC location (weight = 6). The predefined number of clusters was n = 25. We then analyzed the power of frontal and RSC from the output of the cluster solution.

[1]https://vrtoolkit.readme.io/

E. Classification

1) Classifiers and parameters: We have selected six classifiers considering the computational complexity and popularity of classifying biomedical signals [31] to evaluate the efficacy of detecting cognitive load. We have chosen these classifiers with increasing level of space and computational complexity in order from LDA, Logistic Regression (LR), Support Vector Machine with a linear kernel (L-SVM), Support Vector Machine with a Radial Basis Function kernel (RBF-SVM), Multi-Layer Perceptron (MLP), and CNN.

For the RBF-SVM algorithm, we set γ = scale, with γ defining the influence of a single training trial. In case of MLP, we have used 100 hidden layers with learning rate α = 1, maximum iterations = 1000 with Adam optimizer [40] and auto batch size selection. The other parameters were set as default following SciKit[2]. For CNN, we have used Deep Convolution Network (DeepConvNet) [32]. This CNN model consists of four convolutional blocks and a classification block. The first convolutional block is to handle EEG inputs, followed by three standard convolution layer. The classification is performed using a softmax [41] with Adam optimizer. We have used batch size = 16, dropout rate = 0.50 with 300 epochs. The number of filters used in four CNN layers was 25, 50, 100, and 200, respectively, with each layer consist of five kernels.

All models were trained on a machine powered by NVIDIA Quadro P5000 GPU, with CUDA 9 and cuDNN v7, developed using Keras[3].

2) Evaluation metrics: The parameters for all the classifiers compared in this paper have been set up before training and testing for all participants. In this work, the classes are imbalanced, therefore stratified random sampling [42] has been used on the data with the machine learning algorithms described above.

To compare the results of different classifiers, we have evaluated overall accuracy and mean-squared error (MSE) over five-fold cross validation (CV). To better understand the performance of classification algorithms, we have also assessed the precision (Pre), recall (Rec), and F1-score (F_1) for a targeted level of mental-workload.

3) Data description: There were a total of 2167 trials from 18 participants with 940 for low cognitive workload and 1227 for the high cognitive workload. Each trial consists of dimension 64×1525, where 64 is the number of EEG channels, and 1525 is the number of sample points in each channel. We have used 64×1525 as input data without feature extraction and has been divided by 60% 20% 20% for training, validation, and testing using stratified sampling [42].

[2]https://scikit-learn.org

[3]https://keras.io

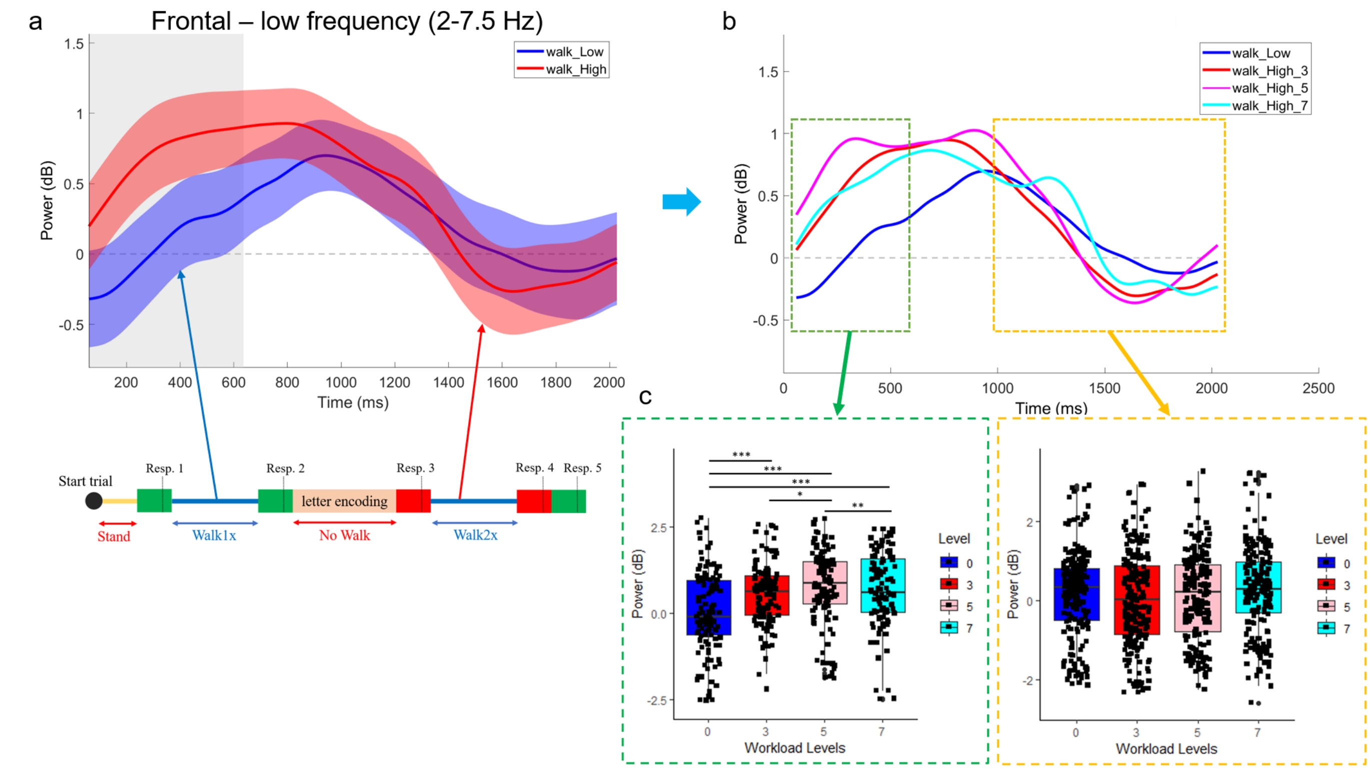

Fig. 2. Frontal power (dB) in low frequency (2-7.5 Hz). (a) The frontal power in low (blue) and high (red) workload conditions. (b) The frontal power in the four distinct walk conditions. The green dashed box indicates an early walking period, while the orange dashed box indicates the late walking period. (c) The corresponding power with respected walking conditions. The *, **, *** indicates for p<.05, 0.01, and .001, respectively.

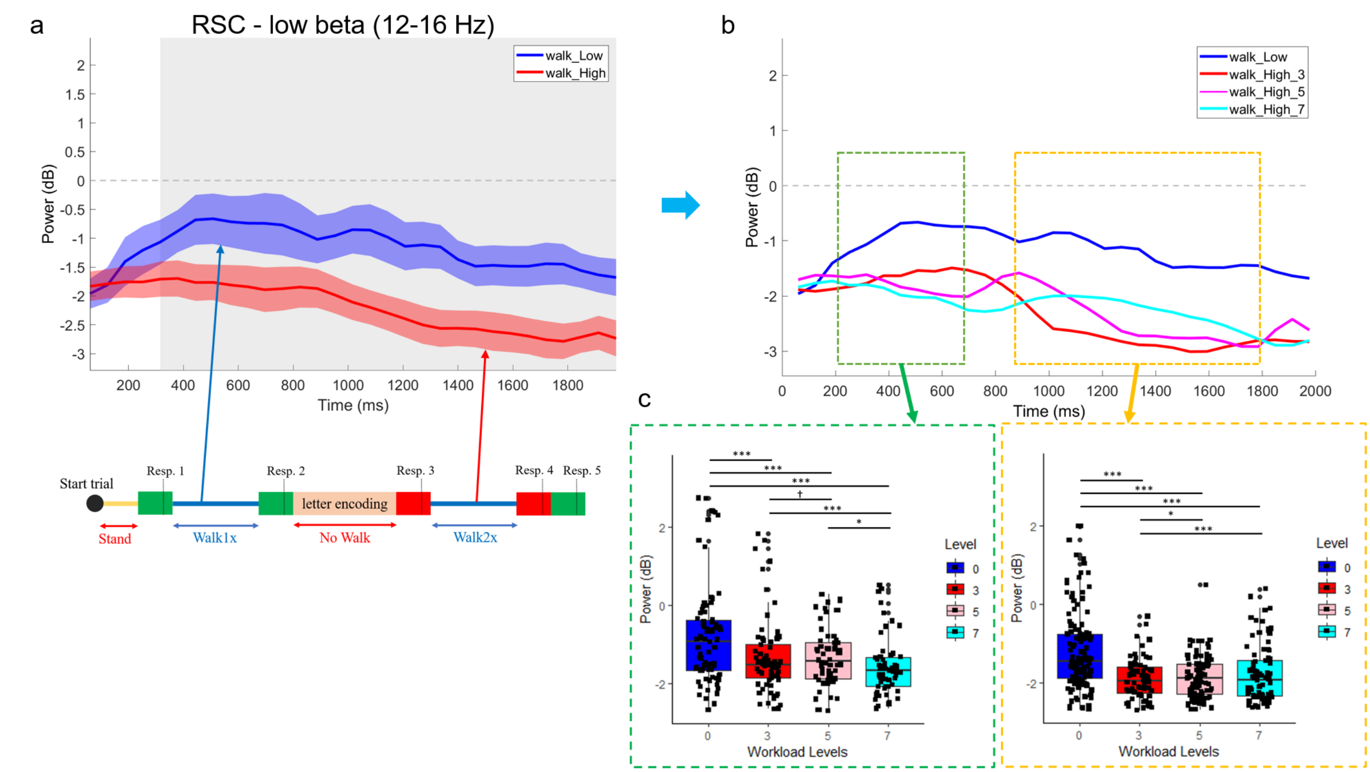

Fig. 3. RSC power (dB) in low beta band (12-16 Hz). (a) The RSC power in low (blue) and high (red) workload conditions. (b) The RSC power in the four distinct walk conditions. The green dashed box indicates an early walking period, while the orange dashed box indicates the late walking period. (c) The corresponding power with respected walking conditions. The *, **, *** indicates for p<.05, 0.01, and .001, respectively.

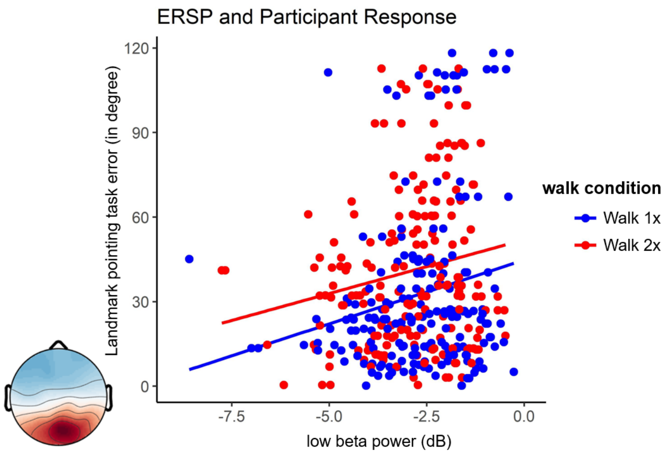

Fig. 4. Linear regression between landmark pointing task behavior and RSC low beta power (dB) in two walking conditions: low (walk 1x - blue) and high (walk 2x - red).

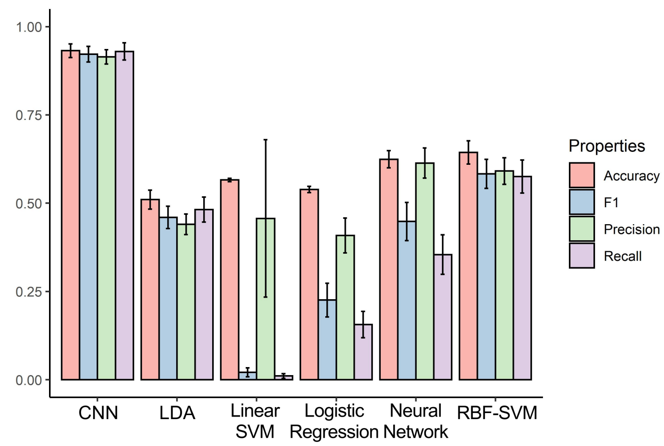

Fig. 5. Accuracy, F1-score, precision, and recall from CNN, LDA, Linear SVM, Logistic Regression, Neural Network, and RBF-SVM classifier.

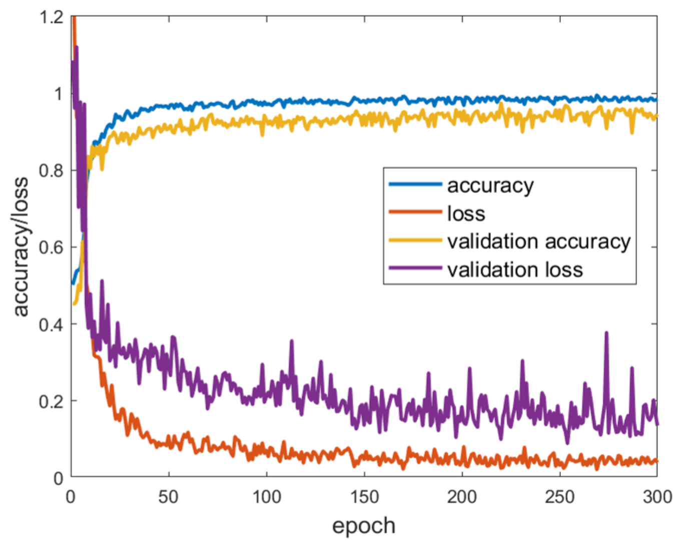

Fig. 6. Accuracy and loss from each epoch during training and validation from CNN.

IV. Results

Because this experiment involves physical movement, we expected noise-contaminated EEG data. For that reason, we first evaluated the EEG data quality by examining the neural features. Afterward, we explored several machine learning techniques on classification.

A. Evaluation of Brain Features

This task aims to confirm that the EEG data from the physical navigation task can be useful for the machine learning algorithm in the next step. We demonstrated that cognitive load (reflected by low-frequency power in frontal) in walking conditions increased at the beginning of the walking segments, where participants estimated their head direction, planned toward the next destination (figure 2). The low-frequency power results in frontal also showed a significant difference between walk 1x and walk 2x.

Then, we further evaluated the power of RSC, which is an essential region in the navigation task. We found that there was a decrease in low beta power across the navigation segment. Also, there was a significant difference between walking conditions in low beta power in RSC (figure 3).

Finally, we checked the relationship between RSC low beta power and participant's pointing task performance using linear regression. The results showed that there was a significant correlation between participant performance and low beta power. The results further showed that the participant landmark pointing task made higher error than walk 1x (figure 4). Based on the results above, we believe that the processed EEG data could provide good quality for machine learning later on. We, therefore, moved to the testing of machine learning techniques on a classification problem.

B. Cognitive Load Classification

We used the cleaned data from the experiment for classification. The objective was to find if low vs. high cognitive load can be detected using machine learning. To do so, we evaluated the classification performance of LDA, LR, L-SVM, RBF-SVM, MLP, and CNN to find the most promising classifier. As seen in figure 5, CNN has outperformed almost by double compare to other classifiers. CNN shows the accuracy of 93% with F1-score of 0.95 and high precision (0.94) and recall (0.97) followed by L-SVM with 56% and others below 55%.

As CNN performed exceptionally well to classify cognitive load, we evaluated the performance over each epoch iteration. As per figure 6, it can be seen that after about 100 epoch iteration, validation accuracy stays above 85%, which is a good sign that the CNN model is not over-fitting and perform robustly.

V. Discussion

Cognitive load is one of the main factors that affect human performance on different tasks. However, most of the studies investigate the human brain dynamics in simple experiments.

Thus, it is still unknown whether those findings apply to real-life applications. Understanding the cognitive brain function underlying more natural setup, such as physical navigation, could benefit not only cognitive neuroscience but also artificial intelligence [43]. Nevertheless, most studies have been relied on a stationary experiment to investigate cognitive function due to the limitation on brain imaging. This study used the MoBI approach to overcome those limitations to investigate human brain dynamics in a more natural setup.

We first evaluated the EEG data quality by checking the low-frequency power in the frontal region. The results showed that the frontal midline region exhibited higher power in the low-frequency band in the high workload condition (walk 2x) (figure 2), consistent with previous studies [4]. Unlike the walk 1x condition, participants needed to hold additional memory about the positive letter set in the walk 2x. When the brain holds additional memory, it could lead to a higher cognitive load in participants. The results further revealed that the significant difference in low-frequency power in the frontal region appeared at the beginning of the walking (figure 2), where the multiple processing happens, including heading computation. Hence, this study's frontal power could be a useful feature that reflected the participant's mental workload.

Furthermore, we examined the RSC power due to its role in the navigation task. In the previous studies, the RSC beta power showed a strong desynchronization, which indicates for translating between egocentric and allocentric information [21], [22]. This study found the same features: a low beta desynchronization happens in the navigation segment. Moreover, the low beta showed stronger desynchronization in the higher workload condition (figure 3). We further evaluate the relationship between the RSC low beta power and the participant's behavior (figure 4). There was a positive correlation between landmark pointing task error with the RSC low beta power, where the participant showed better performance in the strong desynchronization in low beta frequency. Thus, the data from the experiment could provide good quality for machine learning evaluation.

As can be seen from figure 5, CNN significantly outperform other classifiers, including neural network with 100 hidden layers. One reason behind this is the use of raw EEG signals (cleaned) used as input for classification. The raw EEG signals are non-stationary in nature [44], and it is challenging to classify them without extracting any specific features or properties generally known as bio-signature [45]. However, we found good bio-signature in RSC region of brain but in a real-world real-time scenario, need to rely on raw EEG signals. That could be one of the potential reasons behind the poor performance of other classifiers.

Another reason could be imbalance classes. The number of classes was in the 60-40 ratio. Therefore more number of classes for low workload compare to high-workload. In general, non-neural network-based classifier (LR, LDA, L-SVM, and RBF-SVM) performance affected significantly due to imbalance in classes and could be another reason behind the poor performance [46]. However, we have used stratified sampling while dividing data in training, validation, and testing but seems does not help for non-neural network-based classifiers. Besides for MLP, we have an additional strategy to use a specific batch size in a way that covers enough number of classes for generalization. However, results suggest that MLP is unable to generalize for two classes. Regardless, CNN performs very well due to the unique property of deep learning to adapt based on provided data for generalization over multiple iteration [47] as well method used to specifically developed for EEG signals [32].

VI. Conclusion

Altogether, this study provides an insight into the brain dynamics of active navigation. We can eliminate the noise and extract the meaningful features from EEG data in a complex experiment. Then the classification was performed in binary condition with two classes, the model provided a high accuracy of 93%. Therefore, we believe that this approach can bring more insightful results. For future works, we intend to develop the model in a higher number of classes, which can predict the mental workload in higher resolution.

Acknowledgments

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