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SSVEP based Wheelchair Navigation in Outdoor Environments*

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Abstract—**A promising application of Brain Computer Interfaces (BCIs), and in particular of Steady-State Visually Evoked Potentials (SSVEP) is wheelchair navigation which can facilitate the daily life of patients suffering from severe paralysis. However, the outdoor performance of such a system is highly affected by uncontrolled environmental factors. In this paper, we present an SSVEP-based wheelchair navigation system and propose incremental learning as a method of adapting the system to changing environmental conditions.**

I. Introduction

Brain Computer Interfaces (BCI) provide communication workarounds for in an attempt to foster social inclusion and interaction for people suffering from the locked-in syndrome (LIS), being unable to speak and perform limb or facial movements but having intact cognitive function. LIS is caused most often by bilateral ventral pontine lesions as a result of ischemic stroke or hemorrhage, traumatic brain injury, brain stem tumor or neuronal damage (i.e., end-stage amyotrophic lateral sclerosis) [1]. Electroencephalography (EEG) provides the means to noninvasively decode the subject's intentions by associating a control signal with distinct commands. Steady-State Visually Evoked Potentials (SSVEP) have been widely used as a control signal mainly due to its high success and information transfer rate (ITR) achieved with minimal training [2]. BCI controlled wheelchairs enable tetraplegic patients to operate an electric wheelchair with no help of a second person, granting autonomy and freedom. The most recent extensive review on BCI enabled wheelchairs may be found in [3]. Analysis of SSVEP signals include feature extraction methods such as FFT [4], PSD [2][5], and CCA [4][6] among others, whereas classification schemes most often include SVM followed by LDA [7]. Performance evaluation even not actually comparable due to heterogeneous experimental conditions reach 83±15% (success rate) and 70.3±28.8 bits/min (ITR) in controlled laboratory environments, highly affecting a system's feasibility and robustness [2]. Realistic conditions greatly influence the outcome of such applications mainly due to altered brain waves reflecting altered heart rate and cortisol levels affected from external stimulations including sounds, movements and smells [7]. Our work studies the applicability of SSVEP-based BCI in realistic indoor and outdoor wheelchair driving conditions and proposes adaptive classification schemes in an attempt to compensate for alternating environmental conditions.

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II. Methods

A. System Description

In our attempt to navigate a wheelchair in real world conditions using an online SSVEP-based BCI system and evaluate how the environmental conditions affect the performance of the system, we used an iChair MC Basic wheelchair from MEYRA GmbH that can be navigated both indoors and outdoors. The communication between the BCI system and the wheelchair is achieved by a custom made Electric Wheelchair Controller (EWC) (Fig. 1), which replaces the joystick module and provides a wired USB communication to the BCI. Particularly, the BCI system could directly send the detected user's commands to the EWC, thus controlling the wheelchair's direction.

The SSVEP-based BCI system utilized four flickering targets to perform four navigation options, FORWARD, TURN LEFT, TURN RIGHT and BACKWARD. The targets consisted of black-and-red checkerboards over a black background and they were arranged in a square layout at each corner (Fig. 1). The visual stimuli were displayed on a 15.6" Full HD monitor with 60Hz refresh rate and 1920x1080 px resolution. The checkerboards were flickering (i.e. reversing their pattern) at different frequencies (up: 3Hz, right: 4.28Hz, back: 3.33Hz and left: 3.75Hz). The SSVEP components elicited by the checkerboard stimuli are modulated at the second harmonic, i.e. at the pattern reversal rate of the target (6Hz, 8.56Hz, 6.66Hz and 7.5Hz, respectively) [8]. The STOP command is acquired by gazing the non-flickering center of the screen. The SSVEP stimulator was implemented using the Unity Real-Time Development Platform.

The EEG recording was performed using the wireless amplifier g.MOBIlab+ (Guger Technologies, Graz, Austria) at a sampling rate of 256 Hz using four wet cup electrodes (10 mm diameter, gold plated) located over the visual cortex, at positions O1, Oz, O2 and POz (international 10-20 system). The ground and the reference electrodes were positioned at FPz and behind the ear, correspondingly.

B. Experimental Procedure and Participants

Six healthy participants (5 males and 1 female) volunteered for this study, aged between 27 and 44. All participants were informed about the nature and the purpose of the experiment and they gave their informed consent to participate in the study. Both experiments and experimental procedures were in compliance with the EU General Data Protection Regulation (GDPR), in accordance to the Helsinki Declaration of 1975, as revised in 2000 and was approved by the FORTH Ethics Committee (95/22-9-2020). None of the participants had any history of epileptic seizures or other neurological disorders and did not use any drug or psychotropic medication, while they all had normal or corrected-to-normal vision.

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Figure 1. System Description

The experiment consisted of three different sessions: (i) an offline training session, (ii) an online indoor session, and (iii) an online outdoor session. During the training session participants were comfortably seated in a normal office environment with both natural and artificial light, at a distance of 60 cm from the monitor.

The *training session* consisted of 4 trials, with 1-2 min breaks in between. In each trial the participants had to fixate continuously for 5s at each one of the targets, randomly indicated by an arrow shaped visual cue. Each trial lasted 75s. We used 65% of the collected EEG data to train our system, whereas 35% of data were used to calculate the accuracy of the system.

In the *online indoor session*, the stimuli presentation was projected on a laptop monitor placed in front of the user. The participants had to navigate the wheelchair in a typical indoor area. The participants did not have to follow a predefined route and could navigate freely for about 7 min. They were instructed to equally use all four movement commands – including the STOP command. During the online session, both the EEG data and the desired command (ground truth) were recorded. For the latter, we instructed the participants to press the respective arrow keys of the laptop's keyboard when they wanted to change their direction (gaze on a target).

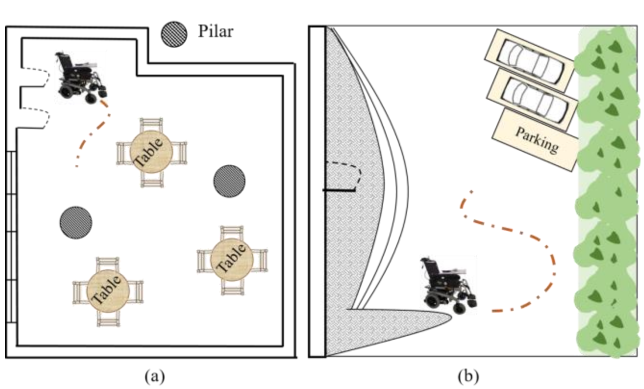

Figure 2. Online session's location (a) indoor, and (b) outdoor area

The space key was used for the STOP command (gaze at the center).

The experimental procedure of the *online outdoor session* was similar to the online indoor one, except that it took place in an outer courtyard. The weather conditions on the days of online outdoor sessions were mostly sunny with light winds. Fig. 2 depicts the top view of the places where the online sessions were held.

C. Data Processing

The EEG data were segmented into epochs of 3s, overlapping by 0.5s. They were filtered using a 5th order Butterworth bandpass filter with cut-off frequencies of 4-40Hz. Epochs at which the participants changed their gaze from one target to the other, were removed.

We performed feature extraction on filtered epochs using Canonical Correlation Analysis (CCA). CCA is a multivariate statistical technique that has been widely used in SSVEP-based BCI systems due to the amplification of signal-to-noise-ratio of the SSVEP signals [9][10][11]. The calculated CCA correlations were the input of three simple and fast classification algorithms: Stochastic Gradient Descent (SGD), Naïve Bayes (NB) and Random Forest (RF). The above classifiers have also been applied in incremental online learning [12], a method that we will employ later in our analysis. For the algorithms' implementations, we used the scikit-learn [13] and scikit-multiflow [14] packages.

As mentioned before, the data from the training session were used to train all three classifiers to detect five classes (corresponding to four movement options and STOP command) and to calculate the offline accuracy of the system. Using one of the three trained classifiers, in this case the SGD, we performed the two online navigation sessions. We selected SGD for online navigation because its default parameters fit a linear SVM model, that is widely used on SSVEPs. The recorded online indoor data were utilized for the evaluation of system's performance in an indoor environment, whereas the online outdoor data were used for the offline incremental learning of the aforesaid classifiers.

We performed incremental learning only on outdoor data because the environmental conditions change immensely from indoors to outdoors. Our goal was to assess how severely real-life outdoor conditions (i.e., bright natural light, noise and vibrations caused by wheelchair movement) affect classifiers' performance and study how the classifiers could improve their performance using incremental learning in such an exemplar online outdoor session.

The incremental online learning of the classifiers involved their continuous adaptation to new (outdoor) data in order to extend their previously acquired knowledge [15]. To this scope, we divided the outdoor data into four batches. Each batch consisted of about 200 epochs that had relatively similar class distributions. Epochs of shift gazing where removed. For each batch we repeated the following steps: (i) we evaluated the classifiers' performance based on their prior knowledge, and (ii) we partially trained them to update their knowledge using the calculated CCA correlations in each new batch. The analysis started using the "vanilla" classifiers, the ones that have been trained on the training

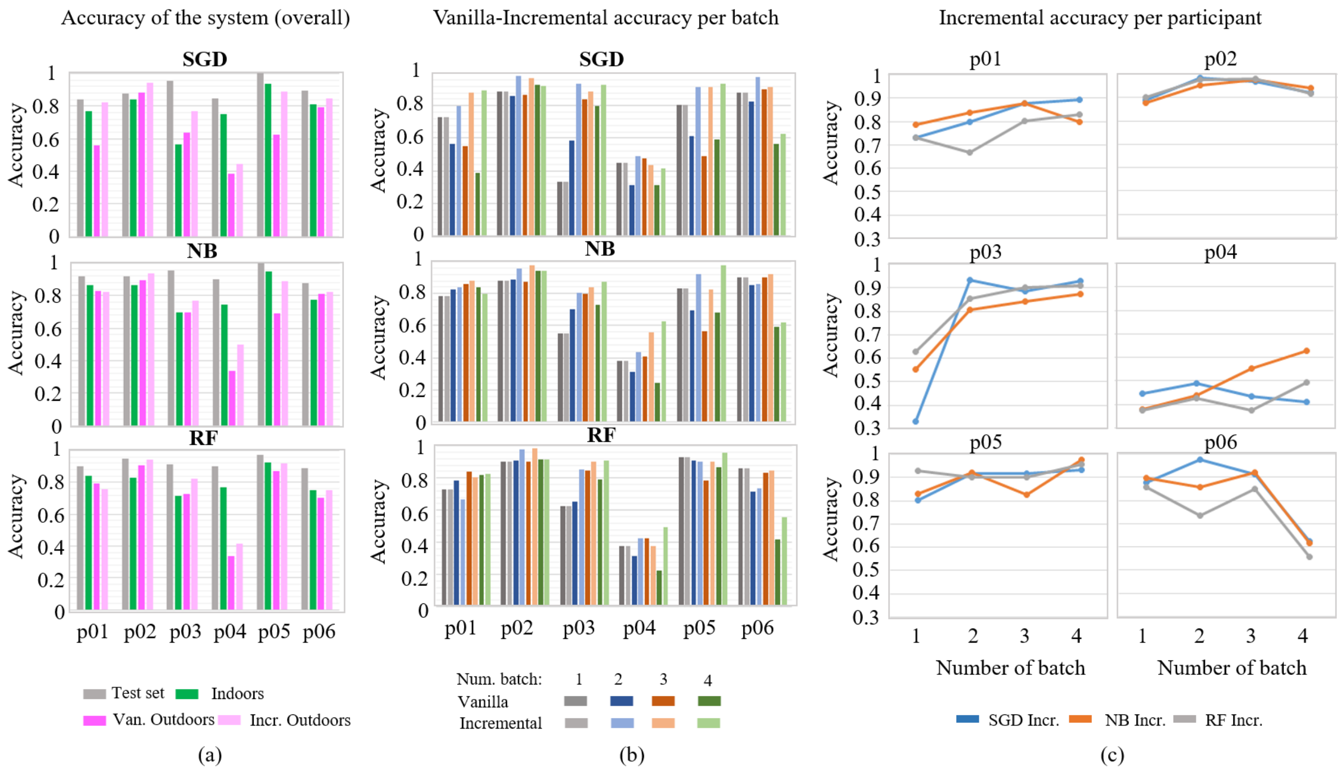

Figure 3(a) Evaluation of the SSVEP-based navigation system on test set (offline test data of training session), on online indoors data and on online outdoors data per algorithm per participant. Evaluation on test and indoors set were performed with vanilla classifiers. (b) Vanilla and incremental system's accuracy on online outdoors data per algorithm per participant per batch. (c) Accuracy of incremental classifiers per participant.

session's data only. Subsequently we evaluated the "incremental" ones, being trained continuously.

III. Results

To evaluate our system, we calculated the respective accuracies, for each classification algorithm and for each participant, in both offline and online data and examined the use of incremental learning as a method to adapt to changes in real world conditions. Figure 3(a) presents the overall accuracy of the system in various environments: (i) the ideal environment of the training session, (ii) the environment of an indoor common area, and (iii) an outer courtyard. In Figure 3(b) we compare the performance between the vanilla and incremental classifiers in each batch of online data in order to assess the ability of incremental classifiers to learn and adapt in an outdoor environment. Furthermore, for each participant, we provide the incremental algorithms' evaluation in Figure 3(c). In TABLE I we list the mean recorded time of incremental learning for each classifier, as well as the time needed in order to infer a prediction on an Intel Hades Canyon 8i7HVK (Intel Corei7-8809G 8, 8GB RAM, AMD Radeon RX Vega M).

TABLE I
MEAN TIME OF INCREMENTAL LEARNING IN A BATCH OF DATA AND MEAN TIME PREDICTION FOR A MOVEMENT COMMAND PER CLASSIFICATION ALGORITHM

	Incr. Learning Time (s)	**Prediction time (s)**
SGD	0.006767	**0.000103**
NB	**0.003202**	0.000175
RF	1.475511	0.001077

IV. Discussion

Wheelchair navigation is a very promising application of SSVEP-based BCIs because it offers the unique sense of autonomy and independence to patients with neuromuscular dysfunctions. Of crucial importance is its performance, which is significantly affected by the environment in which the user desires to navigate the wheelchair.

The results of this study indicate that all participants had high accuracy scores (above 84%) on the test data of the training session for all three classifiers (Fig. 3 (a)). The test data were recorded in the ideal environment of an office, where participants could sit comfortably and the lighting conditions were mild.

In the *online indoor session*, where the BCI was mainly affected by the wheelchair movement, the performance worsened slightly (SGD: +8%, NB: +9.2%, RF: +10.7%) for 5 out of 6 participants, compared to the corresponding test set (Figure 3(a)). Participant p03 had a high decrease in performance (SGD: -40.8%, NB: -16.9%, RF: -21.9%) even though we noticed a good system's response during the online session. However, the participant informed us about having difficulties in synchronizing the use of keyboard with the BCI layout.

The conditions of the *online outdoor session* included bright natural light and intense vibrations due to the wheelchair movement. The system performance for the majority of participants was highly reduced compared to both test set and online indoors (Fig. 3(a)). Participants p02 and p06 did not encounter any problems during the outdoor navigation. Although the EEG artifacts were similar during both online sessions, during the outdoor navigation they tended to be more intense (mostly motion related) due to the roughness of the ground.

The results in Fig. 3(a) show that the use of incremental learning as a method of system's adaptation to the outdoor environmental conditions can improve the performance of the system and therefore its reliability. Fig. 3(b) displays the incremental classifiers' accuracy per batch in comparison to the vanilla one.

We notice that the incremental SGD, NB and RF perform better than the respective vanilla classifiers in each batch of data. Nevertheless, incremental SGD has higher improvement scores than incremental NB and RF classifiers. That is, participants p01, p03, p04 and p05 using the incremental SGD classifier for the outdoor navigation could improve their navigation accuracy by 47.5%, 20.4%, 15.6% and 42.7%, correspondingly. The respective percentages for incremental NB are -0.3%, 10.6%, 48.9%, 28.3% and for incremental RF are -4.7%, 12.7%, 24.6%, 5.7%. We believe that p01's negative score for NB is insignificant due to the overall high score of the subject whereas for RF it is a result of classifier's inability to learn from the first batch of data.

Fig. 3(c) presents the performance of the incremental classifiers for each participant. Specifically, incremental SGD performs better for participants p01 and p06, incremental RF for participants p03 and p05 and incremental NB for p04, whereas for participant p02 incremental SGD and RF have similar performances. These results show a preference for SGD and RF. However, in an online application in which the time needed for learning and prediction is pivotal, incremental SGD outperforms incremental RF (Table I).

It should be noted though that the integration of incremental learning in a real-life wheelchair navigation system can be tricky. We suggest the following scenario: A user desires to navigate in an outdoor area, however, the system, due to bright lightning or intense movement vibrations, does not translate commands correctly. The system would recognize such a weakness by sensing an unusual sequence of predicted commands (e.g. repeatedly sequence "LEFT") or by inferring an unusual path using GPS and navigation maps. Then, it would automatically initiate an incremental learning session in which the system would instruct the user (e.g. via voice commands or arrows) to follow some predefined commands by gazing at the corresponding targets in order to adapt the system to the new conditions.

V. Conclusion

In this study, we present an SSVEP-based wheelchair navigation system. We evaluate its performance both offline and online, using SGD, NB, and RF classification algorithms, in heterogeneous environments including an indoor common area and an outer courtyard to see how the real-world conditions affects its accuracy. We propose, for the first time to our knowledge, incremental learning as the means to adapt the system to new environments. By comparing "incremental" performances with the respective "vanilla" ones, we show that incremental learning is a promising method achieving system's adaptation to environmental changing conditions. It works best in real time applications, as it is fast, memory efficient and can enhance the system's efficiency, safety and reliability.

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