Distraction Classification During Target Tracking Tasks Involving Target and Cursor Flickering Using EEGNet

Hyunmi Lim, Sungmin Kim, and Jeonghun Ku

***Abstract*— Keeping patients from being distracted while performing motor rehabilitation is important. An EEG-based biofeedback strategy has been introduced to help encourage participants to focus their attention on rehabilitation tasks. Here, we suggest a BCI-based monitoring method using a flickering cursor and target that can evoke a steady-state visually evoked potential (SSVEP) using the fact that the SSVEP is modulated by a patient's attention. Fifteen healthy individuals performed a tracking task where the target and cursor flickered. There were two tracking sessions, one with and one without flickering stimuli, and each session had four conditions in which each had no distractor (non-D), a visual (vis-D) or cognitive distractor (cog-D), and both distractors (both-D). An EEGNet was trained as a classifier using only non-D and both-D conditions to classify whether it was distracted and validated with a leave-one-subject-out scheme. The results reveal that the proposed classifier demonstrates superior performance when using data from the task with the flickering stimuli compared to the case without the flickering stimuli. Furthermore, the observed classification likelihood was between those corresponding to the non-D and both-D when using the trained EEGNet. This suggests that the classifier trained for the two conditions could also be used to measure the level of distraction by windowing and averaging the outcomes. Therefore, the proposed method is advantageous because it can reveal a robust and continuous level of patient distraction. This facilitates its successful application to the rehabilitation systems that use computerized technology, such as virtual reality to encourage patient engagement.**

***Index Terms*— Attention, neurofeedback, brain–computer interface, flickering cursor and target, deep learning, steady-state visually evoked potential.**

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I. Introduction

PATIENTS with impaired motor function resulting from neuronal injuries require proper rehabilitation. Successful rehabilitation is mostly accompanied by neuronal reorganization, called brain plasticity, which is defined as the intrinsic ability of the brain to reorganize its function and structure in response to stimuli and injuries. Effective brain plasticity can be accomplished by a proper rehabilitation paradigm [1], including training environments and contents that can provide enriched stimuli [2]. In addition, the importance of patients' attentive participation in rehabilitation programs has been emphasized [3].

Several neuroscientific studies have suggested that attention is a critical modulator of plasticity [4], [5] and insisted that maintaining attention while performing motor exercises promotes neuronal plasticity and motor learning, which directly influences the outcome of patient rehabilitation [6].

However, during rehabilitation, patients are frequently distracted by distractors in their surroundings. These reduce attention on rehabilitation, which may reduce the effectiveness of brain plasticity [7]. In addition, the patient and their clinicians do not notice the loss of attention in the middle of training, which hinders intervention and mediation that return the patient's attention to the rehabilitation task.

Currently, the development of a method for monitoring a patient's level of being distracted is considered critical. To measure the level of attention of a patient to a task, brain signals, such as those of electroencephalography (EEG) signals, which respond to the activation of different brain areas, could be the first choice because they can trace variations in a patient's cognitive states. Attentional variation could cause changes in brain signal patterns in both the time and frequency domains.

The power of each EEG frequency band, such as alpha, beta, theta, and gamma, represents different cognitive states [8]. Therefore, there are several indices extracted for measuring attentional levels by deriving a formula using the spectrum pattern [9]. This method is very simple to implement and can calculate the engagement related indices continuously, but it is not relatively robust across individuals.

The EEG pattern regarding attention in the time domain can be represented as components of the event-related potential (ERP), such as P300, which is usually evoked by the oddball paradigm [10]. In the oddball paradigm, where standard and target (deviant) stimuli are represented by different frequencies and patients are asked to respond or attend to target stimuli exclusively, distinct EEG components (e.g., P300) that respond to the target stimuli can be observed in a specific time window (approximately 300 ms after stimuli onset) and compared to those corresponding to the standard stimuli. These components are more prominent when the patient pays more attention to the task than when they do not.

Many methods have been proposed using this paradigm for detecting a patient's distraction from rehabilitation tasks, such as motor tasks, where the patient should be engaged [11], [12]. In these studies, subjects were asked to perform a motor task and an oddball task simultaneously. Then, the EEG responses to the oddball paradigm would be weak when they pay attention to the motor task, while the responses would be strong when they get distracted and sidetracked to the oddball task. This can be interpreted as a classification problem, a robust and accurate solution to which can be obtained using machine learning and deep learning classifiers that comprise fewer individual differences in the detection state.

However, this ERP-based paradigm has some shortcomings. First, the task should be completed within a specific time-locked window for ERP components to be observed (e.g. approximately 1.5 s period from 1 s before stimulus onset to 0.5 s after onset). Second, the classification should wait for more time after this window for the target stimuli to appear, which makes the classification process trial-wise and the classification interval longer because target stimuli in the oddball task are seldom observed. In addition, the oddball paradigm requires the user to count the number of target stimuli or respond to the target; thus, it would necessarily become a type of distraction by taking the patient's attention from the task that should be performed.

The steady-state visual evoked potential (SSVEP) paradigm can be expected to ensure robust classifier performance and a seamless classification process [13]. The SSVEP is an EEG oscillation pattern with a frequency of the flickering visual stimuli (e.g., a light source) that a patient is looking at. This is mostly observed in electrodes over the occipital and parietal lobes of the human brain. Therefore, whether a patient is looking at the stimuli or not can be detectable by observing the frequency spectrum of EEG because SSVEP appears as an oscillation pattern with the same frequency as the flickering visual stimuli when the patient is looking at the stimulus. Several brain–computer interface (BCI) studies have used the SSVEP paradigm to select one command from several flickering visual stimuli, each representing different operations under different situations, such as spelling [14], virtual telephony [15], and robot control [16]. This is because the SSVEP response to the target stimulus is enhanced when the subject attentively stares at the target stimulus among several stimuli. This shows that the SSVEP response is perturbed by whether an individual is looking at a stimulus attentively or is distracted [17]–[19]. Therefore, we hypothesized that the EEG responses would be modulated by one's attention while performing motor tasks if the SSVEP paradigm is adopted, and it could help classify one's state of being distracted while ensuring robust and seamless monitoring of the patient's state of being distracted from the task; this can be accomplished by adopting the SSVEP paradigm into the motor exercise system. Here, we introduce a simple motor task that can detect whether a user is distracted using an SSVEP-based classification system. This was accomplished using a flickering target and cursor in the motor task, which evokes SSVEP. The motor task introduced here can be potentially used for computerized motor rehabilitation for ensuring that patients are paying attention.

II. Methods

A. Subjects

We recruited 15 healthy right-handed adults (8 men and 7 women) in this study. This study was approved by the Institutional Review Board (IRB) of Keimyung University, Daegu, South Korea (IRB number: 40525-202106-HR-024-03), and informed consent was obtained from all the participants. The mean age of the participants was 25.67 years ($\pm$ 3.48 years).

B. Task Description

The subjects were asked to perform a motor task in which they were asked to track a semicircular target and make a circle with another semicircular cursor using a mouse. The target was moving around on an arc of a virtual circle generated randomly on the screen to prevent rapid changes in the target's direction, ensuring that the subjects' movements were smooth. Because the direction of the target was always toward the cursor, the subject had to move the cursor toward the target and did not need much effort to make the circle.

To evoke the SSVEP pattern in the brain signal, the target and cursor were flickering at 15 Hz and 12 Hz, respectively.

There were two types of distractors: visual and cognitive. With visual distractors, the target comprised 20 half circles of the same radius, and their color was set as close as possible to that of the flickering target; hence, they were gray because the target flickered between black and white. The distractors were moved on the screen in the same manner as the target but with different trajectories.

In the cognitive distractor case, the participants were given a subtraction problem every second. The problems were generated and provided through a PC speaker using a text-to-speech module. These problems required participants to subtract one-digit numbers from two-digit numbers and carrying was required in each problem. Then, the participants were asked to call the solution to the math problem aloud while performing the tracking task.

The subjects performed the tasks with all combinations of distractors: 1) no distractor (non-D), in which they performed only the tracking task, 2) visual distractor (vis-D), or 3) cognitive distractor (cog-D), in which they performed the tracking task with visual distractors or subtraction calculation, respectively, and 4) both distractors (both-D), in which they performed the tracking task with both distractors.

Each session was composed of two trials, and one trial had all four conditions given in random order, and each condition was 60 seconds long. In addition, identical sessions were performed without SSVEP stimuli, the so-called non-flickering paradigm, wherein the target and cursor did not flicker. Therefore, a total time of 32 min was required to complete all tasks.

C. EEG Data Acquisition and Analysis

EEG data were collected from 19 dry electrodes at a sampling rate of 300 Hz using a DSI-24 (wearable sensing, San Diego, USA). The electrodes were placed with a standard 10-20 scheme over Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2. Fpz was used as the ground channel, and the average of A1 and A2 was used as the reference. A signal-quality check was performed before conducting the experiment to ensure that the impedance values of all the channels were below 1 MΩ, which meets the manufacturer's recommendation, and that the stability of the EEG signal was under 70 μV amplitude.

The collected EEG was band-pass filtered to extract a spectrum component in the 4–30 Hz frequency range. Furthermore, the artifact subspace reconstruction (ASR) [20] and independent component analysis methods [21] were applied to the signal to eliminate unwanted noise signals, such as the physiological noise components.

Given the preprocessed EEG signal, only the EEG data of the most distracted condition, which has both visual and cognitive distractor types (both-D), and the non-distracted condition (non-D) that comprised no distractors were used for training a deep learning model. The model training was on non-D and both-D only because the generality of the model was going to be tested. After training the model, the EEG data of the condition with one distractor was also going to be used to show whether the level of distraction could be estimated.

D. EEGNet Training and Validation

For training, the signals were segmented every 1 s, and they went through the training process. An EEGNet model [22] was used to classify whether a signal epoch would be distracted or not. The model was fitted using the Adam optimizer to minimize the categorical cross-entropy loss function. Two hundred training iterations (epochs) were performed, and validation was stopped, and the model weights were saved when the lowest validation-set loss (patience = 50) was produced. The batch size and learning rate for this model were 16 and 0.01, respectively. The validation was conducted using the leave-one-subject-out cross-validation method to test the possibility of the general use of the model. The following is a detailed description of the EEGNet model architecture used in this study:

In block 1, there were Conv2D and DepthwiseConv2D steps in sequence. The block begins with an input layer in which there are two convolution steps. The first step is composed of a two-dimensional convolution filter, followed by a second filter with a depth-wise convolution. Both steps had batch normalization at the end. Depth-wise convolution reduces the number of trainable parameters to fit a deep predictive model. Notably, depth-wise convolution is not fully connected to all previous feature maps, which fit fewer parameters.

Block 2 includes separable convolution, which performs depth-wise convolution, followed by point-wise convolution after receiving inputs from block 1. The separable convolution has two main advantages: giving the number of parameters to be fitted and principally separating the relationship with and across the feature map by learning a kernel and summarizing each feature map individually through optimally merging the output. In other words, this method separates learning how to summarize individual feature maps in time using depth-wise convolution and learns how to optimally combine feature maps using point-wise convolution. This method represents different feature maps at different timescales and then combines the outputs.

Block 3 represents a classification step where the retrieved features make one decision and then pass it to the cross-entropy loss function for error calculation.

E. Classification Result Analysis

Several steps were used to examine the efficacy and usability of the proposed model.

First, the amplitude of the SSVEP response was analyzed to determine if the SSVEP responses are affected by the conditions, and the response amplitudes were compared using Analysis of variance (ANOVA). Second, the classification accuracy of the two-class classifiers from each paradigm with and without flickering stimuli was compared using a t-test to determine whether the flickering paradigm is beneficial. Third, the classification patterns were examined when the two-class classifier was applied to the trials with only one distractor, which could show us how the two-class classifier classified the trails placed between not distracted and extremely distracted. Finally, the windowing and averaging methods were applied to the time-point classification results, which revealed several levels of classification results for each window. The levels could represent the level of distraction. A value close to 0 would represent not distracted, and those close to 1 would be fully distracted. In this study, the window size, which refers to the number of points required for averaging, was set to 5; hence, the averaged value could be 0, 0.2, 0.4, 0.6, 0.8, or 1. With the windowing and averaging method, the classification result for the three-class case, when two successive values were assigned for non-distracted, moderately, and extremely distracted, respectively, could be obtained, and compared between the paradigm with and without flickering stimuli. The windowing method also showed a change in the level of distraction over time. The significance level of the statistical analysis was set to $p < 0.05$.

F. Performance Analysis

The error distances between the cursor and target while tracking the target using the cursor were averaged across a single session and were compared for various conditions using ANOVA.

III. Results

SSVEP responses were observed in the paradigm with the flickering target and cursor. The amplitude of the responses tended to show systematic variation according to the number of distractors. The ANOVA test revealed a significant main effect ($p = 0.013$), and post-hoc analysis showed a strong tendency for a higher SSVEP response in the non-D condition than in the both-D condition ($p = 0.050$).

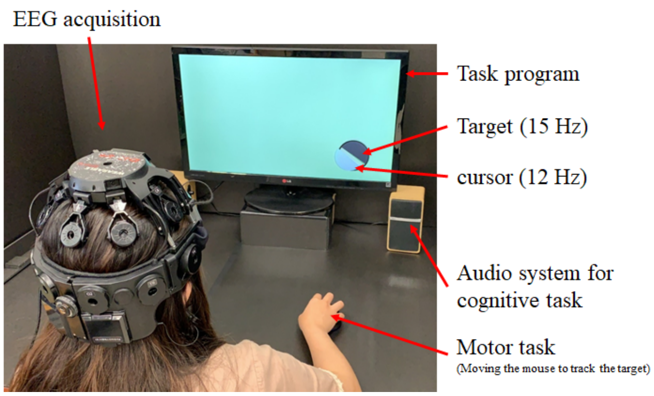

Fig. 1. Experimental configuration. A participant sits in front of a screen that shows the moving flickering target (15 Hz) and uses a mouse to make a circle by placing the flickering cursor (12 Hz) on the target, while EEG is recorded. A speaker that is giving the mental subtraction tasks is placed in front of the participant.

Block	Layer	Filters	Size	Output	Params	Activation	Option
1	Input			(-1,19,300)	0		
	Conv2D	8	(1,32)	(-1,8,19,300)	256		
	BatchNorm			(-1,8,19,300)	16		
	DepthwiseConv2D	16	(19,3)	(-1,16,1,300)	304		
	BatchNorm			(-1,16,1,300)	32		
	Activation			(-1,16,1,300)	0	ReLU	
	AveragePool2D		(1,16)	(-1,16,1,18)	0		p=0.5
	Dropout			(-1,16,1,18)	0		
2	SeparableConv2D		(1,16)	(-1,16,1,18)	256		
	BatchNorm			(-1,16,1,18)	32		
	Activation			(-1,16,1,18)	0	ReLU	
	AveragePool2D		(1,18)	(-1,16,1,1)	0		
	Dropout			(-1,16,1,1)	0		p=0.5
Classifier	Flatten			(-1,16)			
	Linear			(-1,2)		CrossEntropyLoss	

Fig. 3. EEGNet architecture used in this study.

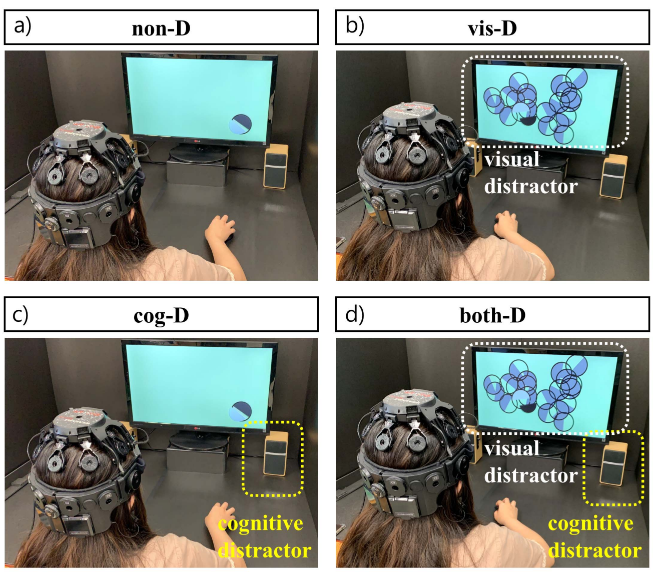

Fig. 2. Experimental conditions. There were four conditions: a) non-D, b) vis-D, c) cog-D, d) both-D.

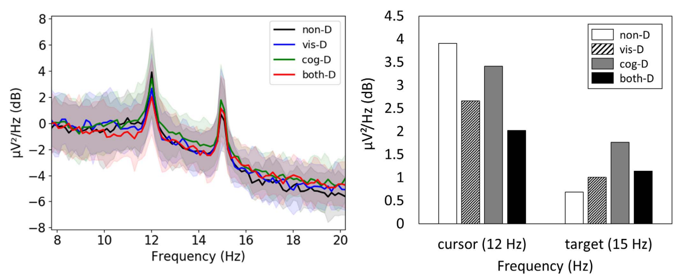

Fig. 4. Spectrum of average of all SSVEP responses of participants under each condition. The bar graph shows SSVEP amplitudes of cursor and target, respectively.

		w/ Flickering Stimuli		w/o Flickering Stimuli	
		Predicted Class		Predicted Class	
		Not Distracted	Distracted	Not Distracted	Distracted
Actual Class	Not Distracted	0.82	0.18	0.64	0.36
	Distracted	0.26	0.74	0.41	0.59

Fig. 5. Confusion matrix of a two-class classifier between non-D and both-D for paradigms with and without flickering stimuli, respectively. The flickering condition had superior classification results.

The model trained with the data obtained from the condition including the flickering cursor and target had an average accuracy of 78%, while the non-flickering paradigm showed a lower accuracy of 61.5%. The accuracy varies significantly between the paradigm with and without flickering ($p = 0.005$) (please refer to Figure 5 for a detailed confusion matrix).

The model trained with both the no- and two-distractors conditions was applied to the condition with only one type of distractor (visual or subtraction); for the visual and cognitive distractor data, 58.5% and 49.8% of the data, respectively, were classified as distracted in the paradigm with flickering stimuli, while these were 65.2% and 58.7%, respectively, for the paradigm without flickering stimuli. Hence, there was a gradual change in the classification as the number of distractors was changed in the paradigm with flickering stimuli, while for the paradigm without the flickering stimuli the change was not observed (see Figure 6 for details).

In detail, the graph of the classified results for all four conditions showed that non-D was mostly classified as "non-distracted," while the classifier classified both-D as "fully distracted." In addition, the condition with one distractor (e.g., vis-D and cog-D) was evenly categorized as either non-D or both-D. This tendency was prominent in the flickering paradigm but not in the non-flickering paradigm.

Furthermore, when the window-averaging scheme was applied, the level of distraction could be assigned to one of three levels for all the conditions, non-D, vis-D, cog-D, and both-D, even though vis-D and cog-D were not used for the training. This windowing method with 5 points demonstrated an accuracy of 63.3% for the paradigm with flickering stim-

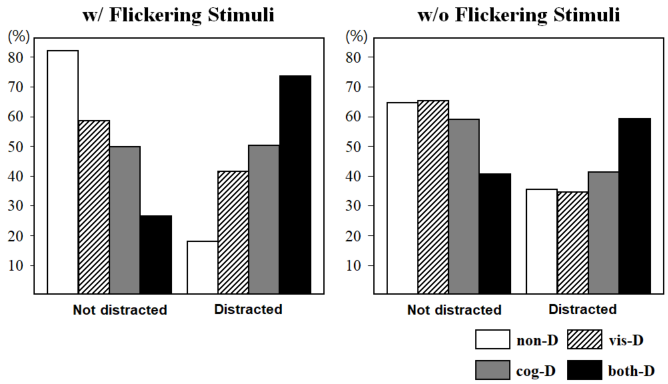

Fig. 6. Percentage of the classified results. The classification percentage showed a gradual change as the number of distractors changed in the 5 paradigm with the flickering cursor and target, but that in the paradigm without flickering stimuli did not.

		Flickering condition			Non Flickering condition		
		Predicted Class			Predicted Class		
		Not Distracted	Moderately Distracted	Extremely Distracted	Not Distracted	Moderately Distracted	Extremely Distracted
Actual Class	No Distractor	0.765	0.192	0.043	0.539	0.248	0.213
	Single Distractor	0.309	0.493	0.199	0.443	0.402	0.155
	Both Distractor	0.1	0.259	0.641	0.210	0.353	0.436

Fig. 7. Confusion matrix for three-class classification. The results were obtained using a two-class model for a window size of 5; therefore, values of 0 and 0.2 represent non-distraction, 0.4 and 0.6 represent moderate distraction, and 0.8 and 1 represent extreme distraction.

uli and 45.9% for the paradigm without flickering stimuli ($p = 0.002$) (Figure 7 depicts the confusion matrix).

In addition, the windowing method can also show the variation in the level of distraction with time. Figure 8 shows a representation of the level of distraction according to the elapsed time for a representative individual for each condition. The levels of distraction in the paradigm with flickering remained lower in the non-D condition than that in vis-D and cog-D. The latter two conditions have the same type of distraction, and their results were consistently between non-distracted and extremely distracted, and those of the both-D condition, which represents an extreme distraction, remained high. However, the trend of the paradigm without flickering stimuli was not as prominent as that of the flickering paradigm, although it also showed a slight tendency of increasing with the increase in the number of distractors.

The windowing scheme reflects the level of distraction with respect to the number of distractors, and a smoother graph for the level of distraction can be obtained by increasing the window size. The comparison between flickering and non-flickering paradigms demonstrated that the values of the level of distraction in the flickering paradigm were mostly fitted between the thresholds of each class, while the non-flickering paradigm could not accurately classify the levels for different conditions because the prediction value for the both-D class mostly overlaps with prediction values for vis-D and cog-D. Lastly, there was no significant difference observed in the error

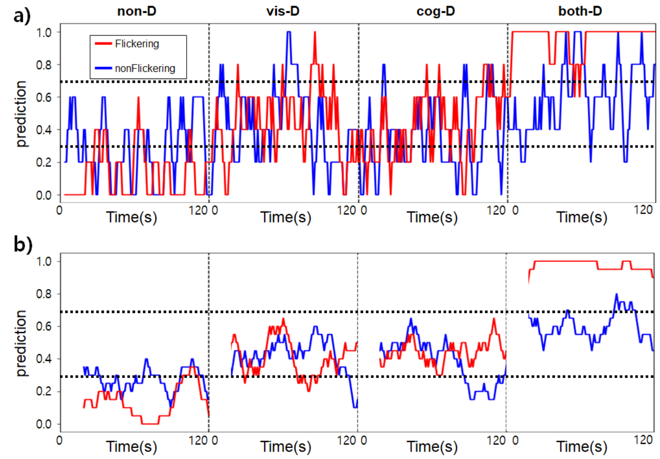

Fig. 8. Representative individual graph of continuous change in distraction level under each condition when window size equals (a) 5 and (b) 10. The dotted horizontal lines indicate thresholds for three classes (0–1/3: non-distraction, 1/3–2/3: moderate distraction, and 2/3–1: severe distraction).

distance between the cursor and the target in all the conditions ($p = 0.971$; $0.72\ \text{cm} \pm 0.26$ for non-D, $0.702\ \text{cm} \pm 0.19$ for vis-D, 0.708 ± 0.22 for cog-D, and 0.70 ± 0.14 for both-D).

IV. Discussion

In this study, we proposed a classification paradigm for distraction during motor performance. For this, a tracking task was designed in which a target should be tracked using a mouse interface. In this task, the cursor and target were flickered at different frequencies on the screen while the motor task was performed.

The EEGNet training and validation were conducted using the leave-one-out cross-validation paradigm to classify one of two states (non-distracted and most distracted with two kinds of distractors). The EEGNet successfully classified the state of being distracted in cases that included flickering targets and cursors, while the task without the flickering did not produce an accurate classification. This indicates that our suggested method is more suitable for measuring a user's state of being distracted, which also suggests that the EEG signature evoked by flickering stimuli during motor execution played a more important role in the classification of the state than the EEG signature from the endogenous characteristics of an individual's brain; this may not be sufficient for detecting the attention level of a user, although the endogenous characteristics give some detectable changes such as changes in its spectrum.

As expected, there was a significant difference in the amplitude of the SSVEP response between the two extreme conditions, and the conditions with one distractor were positioned between the two. This shows that the SSVEP responses tended to be modulated according to the number of distractions. This agrees with the evidence that the SSVEP can be modulated by the presence of distractors [17], [23], [24]. Our results showed only the modulation effect in the cursor but not in the target. This could indicate that the subject mostly paid attention to the cursor rather than the target during their movements.

The proposed method for detecting a user's state of being distracted during a motor task using the SSVEP has the following advantages: First, the classification system proposed in this study can provide the state of being distracted seamlessly, while ERP-based BCI systems utilize a time-locked scheme; hence, they can only provide the state with some interval, such as every second. Although some EEG spectrum-based systems have been introduced that can provide continuous feedback, they usually require a pre-data acquisition session for calibration before main use because of individual variations. The second advantage of the proposed method is that the SSVEP is more robust across subjects; thus, many individuals consistently show similar patterns under this paradigm compared to other paradigms. Therefore, our system could be used more robustly across subjects without any pre-calibration sessions. The final advantage of our system is that it is less distracting than ERP paradigms. The ERP paradigm requires the user to count or attend to the target stimuli while ignoring the non-target stimuli, which might interfere with engaging in the main task. Conversely, the SSVEP paradigm has fewer disturbances during the motor task execution since it only requires the user to stare at the flickering stimuli. It would be the same as the natural motor exercise because looking at the flickering cursor or target is necessary for successful motor execution. Therefore, our method would make it possible to not give the user additional mental burden, reserving their attention for the motor exercise.

Particularly, the method proposed in this study can be effectively applied in motor rehabilitation. For effective motor learning, the user's attention is very important, and the external focus of attention is considered an important factor in motor learning [25], [26]. The external focus of attention refers to the attention directed toward the effects of movement in the environment or the end goal. Therefore, it is crucial for rehabilitation systems to provide users with the outcomes of movements and encourage users to pay attention to outcomes. The outcomes are mostly represented as positional changes of the target and cursor in a computerized rehabilitation system. Our method could provide a great synergy to augment the effectiveness of rehabilitation by encouraging users' attention to be directed to the flickering cursor and target, which reflect their movements when using game-based rehabilitation paradigms.

The performance of the proposed method was lower than that of the methods that adopted the odd-ball paradigm for distraction detection [11], [12]. However, these methods used the within-subject approach for classifier validation. This implies that all the subjects' EEG data or an individual's EEG data were used for training and validating the classifier, which makes it necessary to perform separate training-data acquisition for new individuals before operating the BCI system; In our method, the classifier can be readily used for any independent subject without any pre-acquisition period.

However, it should be emphasized that our study was validated with a leave-one-subject-out cross-validation scheme, in which the model was trained with the data of all participants except for one subject, and the model was validated with the data of the omitted subject, suggesting that our training model could be more generalized to new participants who were not involved in model training. This also means that our proposed method can be used independently for new participants without any pre-model training session.

Furthermore, the results obtained using the model trained with non-D and both-D only, which represent the extremes of being distracted, that is, never distracted and fully distracted, respectively, under conditions that consider only a single distractor type were expected to be between the classification of the two extremes of being distracted; indeed, the results demonstrated that the likelihood of being classified as fully distracted or never distracted lies between the two extreme conditions. This may suggest that the model sometimes classifies the condition with one distractor as fully distracted or sometimes as never distracted.

This suggests that any amount of distraction in a certain period could be classifiable by applying a windowing scheme with the binary classification model and then counting the number of classifications of being distracted. The results of applying the windowing and averaging scheme show that our method can provide a continuous level of distraction according to the number of distractors. This type of strategy, in which a model is trained with data from the extreme ends and then applied to other conditions, has a great advantage in that the model could be used for any situation with various conditions instead of re-training every time as the level of distraction is changed.

The proposed paradigm, which uses the SSVEP response to measure the user's attention towards the task, requires the patients to keep staring at the cursor and target. This may interfere with their motor attention towards muscle movements, which is known as the internal focus of attention. However, the external focus of attention, which refers to focusing on the outcomes or effects of movements made during exercise is more beneficial for better motor learning than the internal focus of attention [3], [27]. The effect of the VR rehabilitation paradigm for motor learning demonstrates this concept [28]. In the VR environment, movements are prescribed to subjects in a natural manner, to achieve certain objectives while focusing on the effects based on their movements. Furthermore, in this study, the subjects were asked to simply track the target and there was no instruction to stare at the target and cursor. This suggests that the proposed paradigm did not require the subjects to make an additional effort to stare at the cursor and target while performing the motor task. Some patients may have issues too severe to allow for the use of the proposed paradigm, which requires external focus of attention; such patients would be needed to focus their attention on their muscle movements. In this case, other paradigms, such as mirror therapy and FES, can be used for interventions.

The individual's behavioral performance can be utilized to determine how the patients maintain their focus on the task. However, there was no significant difference observed among the various conditions. Furthermore, the classification performances were accomplished based on the SSVEP responses in the EEG, and not based on an individual's behavioral performance. This implies that the proposed paradigm can be applied even in the cases where there is no difference in the behavioral performance of an individual.

The SSVEP paradigm can cause mental fatigue despite its various advantages because the patients are required to keep staring at uncomfortable flickering stimuli, which may worsen the SSVEP signal quality and consequently, degrade the classifier's performance [29]. Therefore, the application of high-frequency flickering stimuli in our paradigm could be considered to reduce visual fatigue for convenience [30]. Furthermore, the frequency and time of use of flickering stimuli must be carefully selected in practice.

In conclusion, we proposed a method to detect the level of distraction while performing motor exercise. This method uses a flickering target and cursor in the motor exercise paradigm. This method could be used for monitoring a patient's engagement during rehabilitation. The proposed system provides real-time feedback, which assistants could use for real-time patient-state monitoring. Therefore, it could be applied in any computerized rehabilitation system, such as rehabilitation games and virtual reality systems, to encourage and maximize patient engagement during rehabilitation.

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