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A Review of Error-Related Potential-Based Brain–Computer Interfaces for Motor Impaired People

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ABSTRACT Regaining the lost functionality of limbs is the top priority for people with motor skills impairment as it directly affects their ability to execute activities of daily living and hence, worsens their quality of life. In the last two decades, a great deal of research has focused on error-related potential (ErrP) based brain-computer interfaces (BCIs). Many applications have been developed to assist motor-impaired people in their rehabilitation and among these are robots, spellers, gesture recognition systems, and brain-controlled wheelchairs. In this paper, we present a review of various ErrP based BCI that can potentially aid motor-disabled people in their rehabilitation and execution of their daily activities. First, we describe the ErrP phenomenon and its characteristics followed by a comprehensive application-driven discussion on ErrP based rehabilitation and assistive strategies for motor-impaired people, including studies conducted since the inception of ErrP to the current state-of-the-art applications. Lastly, we discuss the potential issues and challenges being faced by current state-of-the-art applications as well as important future pathways and research directions that might be adopted for advanced ErrP-BCIs used in clinical settings.

INDEX TERMS Assistive devices, brain-computer interface, electroencephalography, error-related potential, rehabilitation devices, stroke rehabilitation.

I. INTRODUCTION

Stroke is the second leading cause of death and the third leading cause of disability in the world [1]. Stroke survivors suffer from various types of body functional disability, such as motor impairment, cognitive impairment, speech, and language impairment [2]. Motor impairment results in a limited ability to perform physical activities known as activities of daily living (ADLs) [3].

Brain-computer interface (BCI) has gained recent attention as a tool for rehabilitation and assistance to enable stroke survivors to recover from motor disability. Several studies have reported BCI-based exoskeletons [4], [5], prosthetics [6], spellers [7], [8], robotic systems [9], [10] and functional electrical stimulation (FES) devices [11], [12] for post-stroke rehabilitation and assistive technology. For the implementation of these approaches, electroencephalography (EEG) signals are utilized to translate human brain-activities into actions that the user can control. EEG is currently the most popular technique to analyze the human brain due to its temporal resolution, low-cost, ease of use, and non-invasive procedure [13]. However, non-stationary, non-linear, and noisy characteristics of EEG signals along with small datasets, especially in the case motor-impaired subjects, decrease the performance of EEG-based BCIs [14]–[16].

A typical BCI provides an alternative path of communication to a disabled person with the aim of decoding their intention through their neurophysiological signals recorded using EEG [13], [17]. Misclassification of the user's intent results in an erroneous condition which elicits an error-related potential (ErrP) signal in the human brain following the perception of the error [18], [19]. The ErrP signal can be integrated with conventional BCIs to form a hybrid-BCI system that can take corrective action on the detection of ErrP to prevent the erroneous action from being executed and ultimately improving the efficacy of the BCI [20]–[22]. ErrP can also be used as a feedback mechanism to an adaptive BCI system that learns from its mistakes, thus, reducing the probability of misclassification of a user's intentions [23]–[26]. ErrP signals have proven to be inherent intrinsic

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human feedback mechanism, which means that ErrP signals can be implicitly generated in the human-brain following an erroneous condition without any training [27]. The passive conduct of the ErrP makes it easier to combine with other active-BCIs in which users consciously modulate their brain activity in order to control an application or in response to a cue/event [28]. Extensive research has shown that an ErrP signal can be reliably detected in a single-trial and can form part of a real-time BCI system [21], [29]–[31].

Motor-impaired people face difficulty in executing ADLs and communicating with the external world. In the last two decades, a great deal of research has focused on ErrP-BCI based robots, P300 spellers, gesture recognition systems, brain-controlled wheelchairs for assisting motor-impaired people and aiding their rehabilitation. This article aims to provide an application-driven review of existing error-related potential based brain-computer interfaces that can potentially aid motor-disabled people in their rehabilitation and execution of daily activities. This paper has been divided into four sections. The second section provides a general view of ErrP signals. Then the third section sums up ErrP driven rehabilitation and assistive techniques for motor-disabled people since the inception of ErrP to the current state-of-the-art approaches. Lastly, in section four, the current challenges in this field and possible future directions are discussed.

II. ERROR-RELATED POTENTIALS

Error-related potential (ErrP) signal was first reported in the early 1990s in an experiment in which participants committed errors in the speeded choice reaction task [32], [33]. The ErrP has been reported to be a difference waveform (*error* minus *correct*) of an error-related negativity (ERN) signal and a correct-related negativity (CRN) signal [34]. The error-related negativity (ERN) is an event-related potential (ERP) signal which is measured as an electrical activity in the brain using EEG. It occurs when an individual makes or perceives an error while performing or observing experimental tasks, including, choice reaction task, Go/Nogo reaction task and Eriksen task [34]. The ERN signal is characterized by a negative deflection (Ne, see Fig. 1) over the frontocentral scalp areas of the brain at approximately 50-200 ms following the error and, subsequently, a centroparietal positive deflection (Pe, see Fig. 1) at approximately 200-500 ms [34]–[37]. On the other hand, the correct-related negativity (CRN) has been observed in the brain following the correct responses with a morphology similar to the ERN; however, with a smaller amplitude [35], [37].

The existing body of research on the ErrP suggests that ErrP signal is elicited under certain task situations. Response ErrP occurs when the subject is asked to respond as quickly as possible (e.g., choice reaction task) [36]–[38]. Feedback ErrP occurs when the subject realizes an error upon given feedback on a task [39, 40]. Interaction ErrP occurs when the subject is interacting with a machine, and the machine misinterprets an instruction given [41], [42]. Observation ErrP occurs when

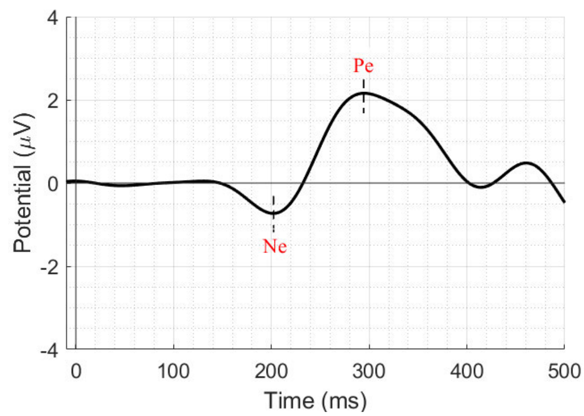


FIGURE 1. Typical characteristics of error-related negativity (ERN) signal: a first negative deflection (Ne) followed by a positive activity (Pe). The 0 ms time represents the event of perception of an error.

the subject recognizes an error made by a machine or external system [11], [43]. Recently, three new types of errors: target, outcome, and execution ErrPs have been reported [44], [45]. The vast majority of studies, with a focus on ErrP-BCI for rehabilitation and assistance to motor-impaired people in ADL, have utilized interaction and observation ErrP in their BCIs [6], [27], [30], [31], [46]–[49].

It is worth noting that, although an ErrP signal has an initial negative deflection followed by a positive deflection, many variations have been observed in this regard. In an experiment of observation of robot operation, Iturrate *et al.* [50] reported the opposite polarity of an ErrP signal, i.e., positive deflection followed by a negative deflection. Consistently, Zhang *et al.* [4] and Zhang *et al.* [51] found a similar pattern in the left and right-hand motor imagery task. Interestingly, many studies have reported more than two peaks in the ErrP with dissimilar latencies as well [39], [41], [43], [52]–[55], and this pattern continues even in studies with similar tasks [43], [52], [53]. Irrespective of the peaks' polarities and latencies, ErrPs have exhibited similar frontocentral and centroparietal scalp signal distributions (see Fig. 2(c, f)) [18], [41], [56]–[58]. Many sLORETA based source localization studies [59] have estimated the anterior cingulate cortex (ACC) as the primary neural source of the ErrP signal [30], [40], [50], [55], [60], the phenomenon which also has been supported by many functional magnetic resonance imaging (fMRI) based studies [61]–[63]. On the other hand, despite incoherence of temporal features of the ErrP signal, spectral-domain features have shown consistency across tasks [64]. Specifically, activity in θ-frequency band (4-7 Hz) increases post-erroneous response [65]–[67]; α-band activity (10-14 Hz) increases and then decreases post-correct response in a quadratic manner, a trend which has been absent following error response [68]; stronger β-modulations post-erroneous trial in comparison to the correct trials [69]. Nevertheless, the combination of temporal and spectral domain features has shown the best overall performances in terms of classifying error-potentials [45].

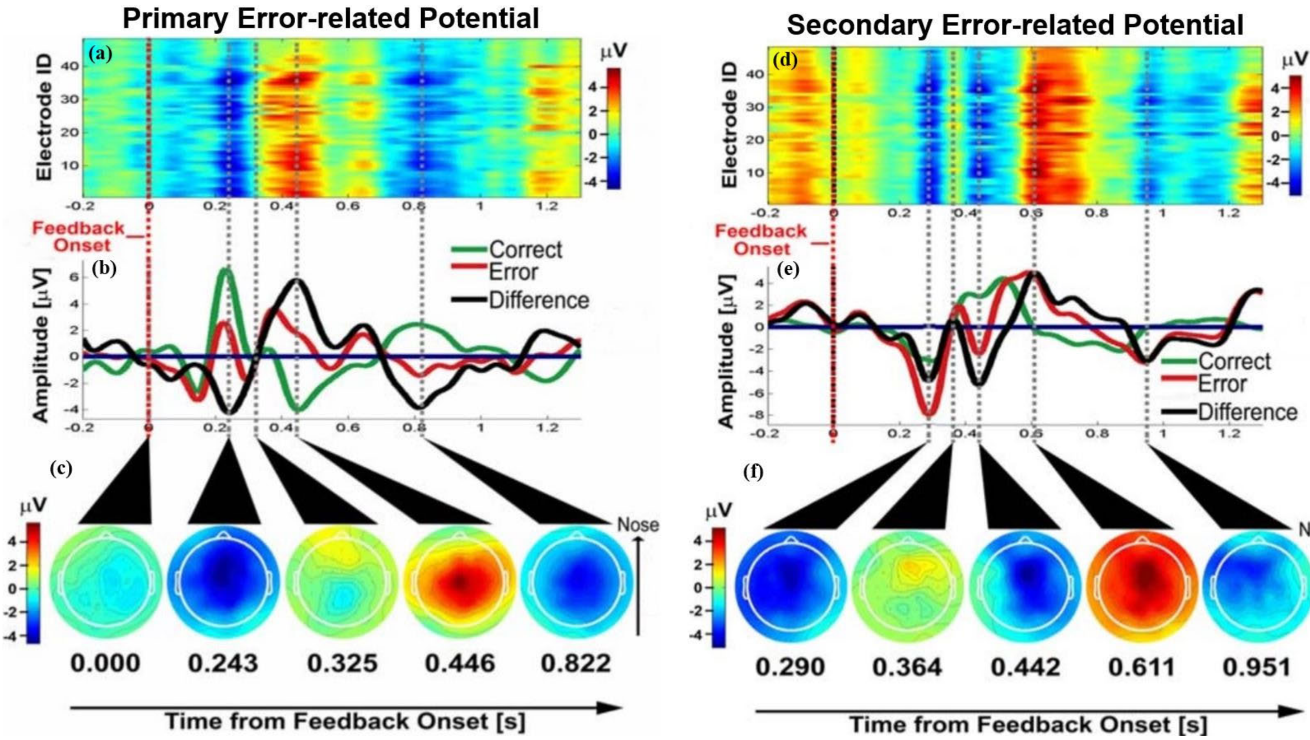


FIGURE 2. Primary and secondary ErrP signals evoked when a human observes a robot performing a binary object selection task. Primary ErrP elicits when the robot selects a wrong target between the two choices and secondary ErrP elicits when the robot misinterprets human feedback, i.e., failed to recognize the primary erroneous signal or misclassify the primary correct signal as an erroneous signal. The left & right column of figures show the characteristics of primary & secondary ErrP signals, respectively. Feedback onset in the picture shows the reference point for ErrP detection. (a & d) depict the electrode activity of 48 electrodes. (b & e) depict the average EEG activity at FCz electrode location (as per extended 10-20 international system). (c & f) depict the interpolated EEG activity across the scalp. Republished with permission from Salazar-Gomez *et al.* [43], ©2017 IEEE.

Due to non-stationary and non-linear characteristics of EEG signals along with the external artifacts and the limitations of data recording techniques, the signal to noise ratio of EEG signals is often very low [14]. Nevertheless, the ErrP signal has been demonstrated to be a robust signal. Firstly, the ErrP waveform has been shown to be steady over a significantly long period (>600 days), and the ErrP classifier recognition rates have been shown to be stable even when tested on data recorded several months after training data without recalibration [41], [54], [70].

Furthermore, there is a large number of published studies that manifest the detection of ErrP in a single trial in a variety of tasks [30], [50], [71]–[73]. Also, ErrP signals are shown to be time-locked to the event of perception of error which makes it easier to interpret and visualize even with methods as simple as averaging multiple trials [20], [43], [74], [75]. Moreover, ErrP signals have been shown to be highly correlated ($r \approx 0.70$) and consistent when recorded using different EEG hardware [76]. Together these features play a key role in developing a reliable ErrP-BCI for rehabilitation and ADL assisted functions. Besides, ErrP has been observed in children as young as five years old [77], young and older adults [78], [79].

It is interesting to note that the ErrP has been shown to be affected by fatigue [80], [81], motivation [82], [83], anxiety [84], [85], personality traits [86], [87], age [78], [79], [88], ethnicity [89] and even gender [89] that increases the inter-trial and inter-subject variability. Remarkably, the variability of the ErrP signals due to the traits mentioned above has led to the use of ErrP signals in a variety of fields. Firstly, ErrP signals are being increasingly used in clinical psychology and psychiatry for analysis of various mental disorders, including attention-deficit/hyperactivity disorder (ADHD), depression and other anxiety disorders [76], [90], [91]. In particular, larger ERN signals have been observed in people with obsessive-compulsive disorder (OCD) and other anxiety disorders [90], [92], [93]; whereas, ADHD and substance use disorders (SUDs) have been linked to reduced ERN [94]–[96]. Secondly, the ErrP signal has also found its way in performance monitoring due to its relationship with motivation levels, stress regulation, and cognitive-control processes [35], [97]–[99]. Accordingly, Hirsh and Inzlicht [100] linked larger ERN amplitudes with better grades in undergraduate students. Furthermore, due to the association of ErrP with mental states, it can be utilized in neuromarketing and consumer behavior research as well. A full discussion of the effects of personality and biological traits on ErrP lies beyond the scope of this study. We refer the interested reader to [76], [89], [101], [102], among others.

The studies presented thus far suggest that the ErrP signal has robust features that enable its faithful detection in a single trial in a variety of tasks. The next section describes various rehabilitation and assistive approaches that utilize error-potentials.

III. ERROR-RELATED POTENTIALS BASED BCI FOR MOTOR IMPAIRED POPULATION

Table 1 presents a summarized overview of ErrP based BCIs for the motor impaired people, grouped by targeted application. Detailed discussion is as follows.

A. ROBOT CONTROL

Robots have considerable potential for rehabilitation and in improving the quality of life for motor-disabled people. A great deal of previous research has focused on the integration of the ErrP-based correction mechanisms in robot control. Iturrate *et al.* [50] showed that the error detection mechanism of the brain is active when a group of four healthy participants observed the operation of a real robot. The experiment employed observing the operation of a five degrees-of-freedom (DOF) robotic arm, while the robotic arm performed erroneous or correct reaching tasks to five predefined positions. The authors reported an average sensitivity and specificity of 78.97% and 82.58% respectively in classification of the ErrP signal, which suggest the possibility of detection of error and correct robotic behaviors in a single trial.

Another interesting study utilized a shared-control strategy and used an ErrP signal as feedback for controlling a robot in a real 2D-movement task [52]. Without prior training, the robot reached the participant chosen goal in less than 120 seconds by utilizing the ERN and CRN signals. Penaloza *et al.* [104] used a similar strategy in a navigation task and utilized the ERN signal as an emergency signal to stop the robot's navigation due to any perceived threat. In another study, Penaloza *et al.* [46] used human error perception to evaluate a robot's learning performance in an object manipulation task. In their framework, the authors teleoperated the robot and utilized a probability-based object selection task which selects the second-best action if the first action causes an ERN signal to be elicited. Notably, Penaloza *et al.* [104] used a low-cost commercially available EEG headset, Emotiv EPOC in their study [46], [104] and reported an ERN classification rate as high as 82%. A step further, Salazar-Gomez *et al.* [43] reported how a secondary ErrP signal can be elicited when the system wrongly classifies the ERN signal as the CRN and *vice versa* and can improve the performance of a robot performing a binary choice task. Using an offline analysis, they further reported that integrating the secondary ErrP mechanism can boost the classification performance of the system by over 20%. Interestingly, the reported secondary ErrP signal (see Fig. 2(d, e, f)) possesses more robust characteristics and has been shown to be easier to classify than the primary ErrP signal (see Fig. 2(a, b, c)) [43].

So far, we have focused on robotic control, in which the participant's task was to observe the robot's behavior passively, and the robot uses the ErrP signal as feedback to perform/reach the desired goal. Let us now consider the active control of robots. Bhattacharyya *et al.* [9] reported a positional control of a robotic arm to reach a target using three different EEG signals: sensorimotor rhythm (SMR), P300, and ErrP. ErrP was used to undo any misclassified motor imagery (MI) action and to align the arm with the target in case it misses the target. The authors reported a reaction time in the order of 1 sec. In [42], the authors implemented a fixed-order continuous control mechanism for a three-link robotic arm using SMR and ErrP signals. After the selection of a robotic link using MI, the link moves at a constant speed in the selected direction until ERN is elicited. As the links follow a predefined sequence of activation, participants would have to wait for the required link to become active before trying to control them. As a result, a time taken to reach the intended "goal position" will increase, which makes the sequential control of the robotic links a limitation/drawback of these studies. More recently, Rakshit *et al.* [10] integrated MI, ErrP, and steady-state visually evoked potentials (SSVEP) for a three-link robot control. They utilized three different LEDs flickering at 8Hz, 10Hz, and 13Hz for random order control of the three robotic links instead of the sequential control that would considerably improve the usability of the robotic arm control. Again, ErrP was used to align the robotic arm with the target position in case of misalignment.

Other studies have provided further support to the feasibility of using ErrP for robotic control. For instance, Ehrlich and Cheng [24] employed an ErrP signal for the co-adaptation of a robot's gaze behavior pattern in the object selection task, in which a user tried to estimate the object that the robot would select from its gazing patterns. Unlike previous studies [43], [46], [50], [52], [104], in which the participant is the master and the robot must adapt according to the user perspectives, in this study, the optimal behavior of the robot was negotiated between the user and the robot in a co-adaptive fashion. With this approach, the efficacy of correct estimation of the robot's behavior increased from the initial chance-level (~33%) to 70–90% within 10–40 trials. Surprisingly, none of the reported studies tested their approach on the motor impaired population.

B. BCI SPELLERS

P300 is an event-related potential signal that is elicited in response to a relevant stimulus in an oddball paradigm. The ErrP signal has been widely used as a correction mechanism in P300 based BCI-spellers. In these spellers (see Fig. 3(a)), on the detection of the ErrP, the system can cancel the currently selected character and select the character with the second-highest probability instead. Dal Seno *et al.* [105] demonstrated the use of the ErrP signal in P300 spellers with two participants. However, in this study, the use of the ErrP in a speller showed little to no improvement. A major problem in their experiment was the low ErrP classification accuracy that may have led to the poor performance of the speller. Combaz *et al.* [106] tested the performance of the Mind Speller with nine participants to figure out the effects of

TABLE 1. Overview of error-related potential based brain-computer interfaces for motor impaired population.

Application	Ref.	Year	# subjects	User task	Signals	Description
Robot control	[50]*	2010	4 healthy	Observe robotic arm movement	ErrP	Observe 5 DOF robotic arm performing correct/incorrect reaching tasks at five predefined positions
	[52]*	2013	1 healthy	Observe the movement of real mobile robot	ErrP	Using ErrPs for controlling the continuous movement of a robot in a 2D navigation task
	[46]*	2014	5 healthy	Observe robot actions through a camera	ErrP	Modifying the object-manipulation skills of a robot using ErrPs and low-cost EEG headset and showed the applicability of a probability-based second-best action selection if the first action elicits ERN signal
	[9]*	2014	5 healthy	Controlling a robotic arm	ErrP, SMR, P300	Positional control of a robotic arm to reach a target
	[104]*	2015	5 healthy	Observe movement of a robot	ErrP	Using ErrP to send an emergency stop command to a robot performing a navigation task with a low-cost EEG headset
	[53]*	2016	13 healthy	Pressing a button to turn humanoid robot head	ErrP	Evaluating robot behavior using ErrPs in a human-robot interaction
	[10]*	2016	5 healthy	Controlling a robotic arm	ErrP, SMR, SSVEP	Random order positional control of a robotic arm to reach a target
	[43]*	2017	12 healthy	Observe the actions of a robot	ErrP	Using ErrP to correct erroneous actions of a robot in an object-selection task and showed the use of secondary ErrP signal
	[42]*	2017	12 healthy	Controlling a robotic arm	ErrP, SMR	Continuous control of a robotic arm to reach a target
	[24]*	2018	16 healthy	Observe and predict robot behavior	ErrP	Using ErrPs for the co-adaptation of the robot's gaze behavior policy in an object selection task
BCI spellers	[105]*	2010	3 healthy	Focus on intended character	ErrP, P300	Integrated the use of ErrP in P300 based BCI-spellers
	[103]*	2010	6 healthy	Focus on intended character	ErrP, P300	Integrated the use of ErrP in P300 based BCI-spellers and presented the use of iterative ErrP mechanism
	[110]*	2010	5 healthy	Focus on intended character	ErrP, P300	Combined the RB-ARQ algorithm in an ErrP-P300 BCI to maximize the speller's performance
	[7]*	2012	3 healthy	Focus on intended character	ErrP, P300	Employed one-class classification algorithm and improved the overall classification rate of the speller
	[31]*	2012	12 healthy	Focus on intended character	ErrP, P300	Online detection of ErrP in a gaze-independent P300-speller
	[107]*+	2012	6 ALS and 17 healthy	Focus on intended character	ErrP, P300	Implemented automatic error detection mechanism and tested on motor-impaired as well as healthy participants and showed improvement in bitrate of the speller
	[8]*	2012	16 healthy	Focus on intended character	ErrP, P300	Implemented automatic error-correction mechanism based on the second-best guess of a probabilistic classifier
	[111]*	2014	6 healthy	Focus on intended character	ErrP, P300	Combined RB-ARQ algorithm and ErrP based error-correction mechanism for performance improvement
	[19]*	2016	11 healthy	Focus on intended character	ErrP, P300	Suggested a hybrid error detection and correction strategy with a dynamic stopping criterion for improved performance
	[112]*	2016	11 healthy	Focus on intended character	ErrP, P300	Proposed the adaptation of inter-stimulus interval and stimulus duration to account for changes in the participant's concentration level
	[20]*	2018	1 tetraplegic, 9 healthy	Focus on intended character	ErrP, P300	Implementation of iterative ErrP based error-correction mechanism for improved performance

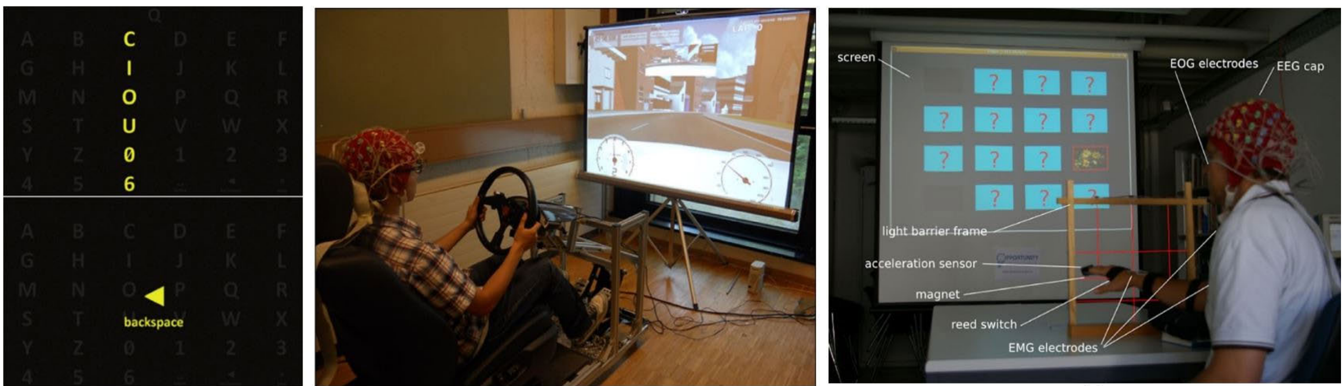
TABLE 1. ***(Continued.)*** **Overview of error-related potential based brain-computer interfaces for motor impaired population.**

Prosthetics and exoskeletons	[6]#	2006	Simulation	Intend and observe the robotic arm movement	N/A	Proposed an online adaption scheme for the control of a prosthetic arm
	[47]*	2012	10 healthy	Controlling the artificial arm	ErrP, SMR	Implemented the use of MI and ErrP for the control of an artificial arm
	[4]*	2018	8 healthy	Controlling the lower-limb exoskeleton	ErrP, SMR	Proposed the conceptual idea of MI-based lower limb exoskeleton
Gesture-enabled BCI	[23]*	2010	7 healthy	Making gestures and observing computer response	ErrP	Using human gestures to send commands to a computer to play an image-pair game. The computer re-calibrate itself on detection of ERN
	[113]*+	2015	20 healthy	Making gestures and observing computer response	ErrP	Using human gestures to send commands to a computer in a pointing gesture-task. Compared various post-ERN detection correction strategies
	[27]*	2017	7 healthy	Making gestures and observing robot response	ErrP	Gesture-based human-robot interaction employing reinforcement learning for enabling the robot to learn the optimal behavioral strategy
Cursor control	[114]*	2000	3 healthy, 1 with abnormal gait	Cursor control using motor imagery	ErrP, SMR	During a task of controlling the vertical movement of a 1-D cursor, ErrP signal elicits following erroneous cursor movement
	[30]*	2009	6 healthy	Cursor control using motor imagery	ErrP, SMR	Controlling cursor movement on a screen using motor imagery elicits ERN when the system misclassifies the intended movement
	[51]*	2018	5 healthy	Cursor control using motor imagery	ErrP, SMR	Left- and right-hand motor imagery for cursor control
	[115]*	2018	10 healthy	Cursor control using motor imagery	ErrP, SMR	Controlling horizontal cursor movement to hit a target on a screen using left- and right-hand motor imagery
	[54]*	2010	6 healthy	Observe cursor	ErrP	Erroneous movement of the cursor in 1-D elicited an error-potentials which was used to tailor the agent behavior to the participant's necessity and preferences
	[116]*	2013	4 healthy	Observe cursor	ErrP	Autonomous agent-based cursor control using ErrP signals to reach a target chosen by the user on a 5×5 grid
	[25]*	2015	8 healthy	Observe cursor	ErrP	Solely self-calibrated autonomous agent-based cursor control using ErrP signals to reach a target chosen by the user on a 5×5 grid
	[117]*	2016	3 healthy	Observe cursor	ErrP	Asynchronous detection of ErrP signal evoked during cursor monitoring
	[48]*	2005	3 healthy	Progress bar control using joystick	ErrP	Error-potential elicited when an external system failed to recognize participants' intent
	[118]*	2007	15 healthy	Cursor control using joystick	ErrP	Uncorrectable errors during cursor control evoked error-potentials in a computer aiming task
	[119]*	2008	15 healthy	Cursor control using stylus	ErrP	ErrP elicited during an aiming movement using a stylus
	[41]*	2008	5 healthy	Cursor control using keypress	ErrP	ERN elicited following the errors made by the interface even when the response of the user was correct
	[120]*	2018	15 healthy	Cursor control using joystick	ErrP	ERN signal evoked following incorrect execution of a continuous cursor control task
Wheelchair control	[49]*#	2010	N/A	Monitoring wheelchair propositions	ErrP	Proposed a semi-autonomous navigation strategy using a wheelchair with minimal user involvement
	[121]*	2014	10 healthy	Control the simulated wheelchair	ErrP	ErrP signal elicited following incorrect response of the simulated brain-actuated wheelchair
Vehicle Driving assistance	[58]*	2013	7 healthy	Controlling the car in simulated environment	ErrP	Using ErrP signals to determine the user's intended direction in a realistic car simulator
	[122]*	2015	22 healthy in simulator, 8 healthy in real driving task	Controlling the car in simulated & real environment	ErrP	Using ErrP signals to determine the user's intended direction in a car simulator as well as in a real driving task
SSVEP	[123]*	2017	5 healthy	Focusing on a screen	ErrP,	Used error-potentials to improve the SSVEP based BCI

TABLE 1. ***(Continued.)*** **Overview of error-related potential based brain-computer interfaces for motor impaired population.**

based BCI					SSVEP	
	[124]*	2018	10 healthy	Focusing on a screen	ErrP, SSVEP	Used error-potentials to improve the SSVEP based BCI & proposed a new performance measure for ErrP-based BCI
Miscellaneous	[125]*	2003	18 healthy	Isometric-force production with left or right index finger	ErrP	ERN evoked following erroneous response in the force production task
	[26]*	2011	6 healthy	Motor imagery of right arm flexion	ErrP, MRCP	An adaptive strategy using error-potentials to improve the performance of MRCP based multiclass-BCI
	[11]*	2014	1 healthy, 1 with SCI	Hand open and close motor imagery	ErrP, MI	An adaptive BCI using error-potentials to control the functional electrical stimulation device
	[126]*	2019	12 healthy	Perform non-MI cognitive tasks such as mental arithmetic, counting	ErrP,	ErrP signal elicited following incorrect feedback in cognitive tasks based BCI

* denotes studies in which data were experimentally recorded and utilized, + denotes studies in which previously recorded dataset was utilized, # denotes studies based on simulations. Abbreviations: ErrP = Error-related potential, DOF = Degree of Freedom, ERN = Error-related negativity, SMR = Sensorimotor rhythm, SSVEP = Steady-state visual evoked potential, RB-ARQ = Reliability-based automatic repeat request, BCI = Brain-computer interface, MI = Motor imagery, MRCP = Movement-related cortical potential.



(a) (b) (c)

FIGURE 3. Error-related potentials based BCI. (a) User display for P300 based BCI speller. Upper: Rows and columns of the matrix display are randomly intensified. Participant's task is to focus on the character of interest. Below: The identified character is displayed on the screen as feedback. Republished with permission from [103], ©2010 IEEE. (b) Participant sitting in a car simulator and driving in a virtual reality environment while simultaneously EEG data are being recorded. Republished with permission from [58], ©2013 IEEE. (c) Gesture recognition system setup using magnets, reed switches, accelerometers, and light barrier frame, while simultaneously EEG, EOG, and EMG signals are being recorded for offline analysis. Republished with permission from [23], ©2010 IEEE.

the ErrP integration. With the assumption of the perfect ErrP classification, they concluded that up to 15% improvement in typing performance can be achieved. Combaz *et al.* [103] also proposed the selection of the second-best character based on the classifier's ranking along with an iterative ErrP mechanism to detect the second ErrP if the second-best character is also wrong.

Finally, Schmidt *et al.* [31] assessed the improvement of the speller performance with the incorporation of ErrP. With twelve participants, they reported an increase of 49% in the spelling speed compared to the case without the ErrP. Interestingly, this study observed a negative correlation between the accuracy of a P300 decoder and the performance improvement due to the ErrP detection on which Margaux *et al.* [8] showed a disagreement. It is worth noting that the studies undertaken so far were focused on and included healthy participants only.

In 2012, Spuler *et al.* [107] conducted experiments with six severely motor-impaired subjects along with eight age-matched healthy participants. A performance improvement of 0.37 bits/trial in the motor-impaired subjects and 0.73 bits/trial in the age-matched healthy participants was observed. It is worth mentioning here that Spuler *et al.* [107] reported similar ErrP patterns in the motor-impaired participants and healthy counterparts, which supports the use of the error correction mechanism in BCI spellers for disabled people as well.

Whereas the approaches so far employed the ErrP signal for deletion of the wrong character, a natural progression would be to implement the automatic error correction.

Margaux *et al.* [8] and Spuler *et al.* [107] led the work and employed the automatic error correction system (ECS) in their BCI speller. More recently, Zeyl *et al.* [19] employed a two-step row-column speller and reported a 13.67% improvement in selection accuracy for 2.54 symbols/minute with the ECS.

A potential hurdle in improving the BCI speller performance is the false positives in ErrP detection. Higher P300 decoder accuracies leave a narrower room for improvement through the ErrP correction mechanism. In such cases, ErrP false positives deteriorate the speller performance instead of improving it and establishes a state of equilibrium. Recently, Cruz *et al.* [20] implemented the iterative ErrP detection idea, which was proposed by Combaz *et al.* [103] to counter the ErrP false positives. On the detection of ErrP, the authors' system selected the character with the second-highest probability and presented it to the user, if the second character again elicits an ErrP, the authors treated the first ErrP as false positive and thus, re-selected the first selected character. The authors reported a performance of 2.92 effective-symbol/minute which was the highest among reported studies and an information transfer rate of 14.19 bits per minute, which was again the highest reported.

C. PROSTHETICS AND EXOSKELETONS

Prosthetic devices add value to the lives of the population that have missing body parts. These devices utilize the neural activity of the motor cortex area of the brain to determine the intended movement of the user [108], [109]. However, due to the non-stationary properties of these signals, re-learning procedures are required to keep-up the efficacy of such devices. Rotermund *et al.* [6] presented a model that makes use of a hypothetical neural error signal to automatically adapt prosthetic devices to the non-stationary EEG signal and eliminate the requirement for tedious supervised re-learning. In their simulation study, the participant task was only to intend for an action to occur and observe the movement of the prosthetic arm. The model characteristics were adapted based on the hypothetical error signal which is assumed to be correlated with the mismatch in the perceived and the intended movement of the prosthetic arm. Kreilinger *et al.* [47] employed a combination of occasional discrete and continuous feedbacks for the movement of an artificial arm using the upper-limb MI. The main limitation of the experimental method is that the ERN elicited due to a series of discrete feedbacks using LEDs needed to be correctly classified especially for more prolonged arm movements, otherwise, the performance of the approach suffers considerably.

Zhang *et al.* [4] proposed the MI-based lower limb exoskeleton. They made use of the upper-limb MI for the left and right lower limb movements. Similar to the study of Rotermund *et al.* [6], Zhang *et al.* [4] also gave only a conceptual idea and did not implement it on the real exoskeleton. Previous studies have pointed out the difficulty of manipulating MI signals as well as its slower reaction time, which can be a potential issue in the application of MI-based exoskeletons.

D. GESTURE-ENABLED BCI

In a typical BCI system, participants are asked to limit their physical movements in order to avoid artifacts. However, in partially motor-disabled stroke patients, a residual limb movement can be utilized for sending a command to the system. Gestures of such patients are often misclassified due to weak muscle control; nevertheless, the ErrP signal can assist in these gesture-based human-computer interactions (HCI). Recently reported studies have suggested applications of the hybrid-BCI systems that combine the use of muscle activities for sending commands and ErrP signals as a feedback for interpretation of such commands [23], [113].

Chavarriaga *et al.* [23] presented a sophisticated gesture recognition system that uses magnets and reed switches to recognize the gestures of seven healthy participants while they were playing a memory game (see Fig. 3(c)). ErrP signals were used to recognize any errors in command interpretation. Participants gesture movements were combined with the ErrP feedback to accomplish a user-specific recalibration that improved the gesture recognition rates by 6.4%. Putze *et al.* [113] extended the work further and developed an inertial-measurement unit (IMU) based gesture recognition interface that can recognize six different classes. They mainly compared the performance of three ErrP-based correction strategies: *Manual, Reprompt,* and *2nd-best*, and showed that self-correction-based strategies improve the efficacy of the gesture recognition system and have greater acceptance among participants compared to the manual correction. A significant problem with these experimental methods is that as the number of actions/gestures increases, the system complexity increases significantly and consequently, the system performance will suffer. Recently, Kim *et al.* [27] demonstrated the reinforcement learning based human-robot interaction system in which the robot repeats gestures made by the user. Due to the inherent property of the reinforcement learning, the number of gestures is not limited in this approach. Moreover, the authors achieved 90% accuracy in the ErrP detection in an asynchronous manner.

E. CURSOR CONTROL

BCI systems can decode user intent using his/her neural signals of the brain to control the screen cursors, which can assist disabled people in communication. The literature identifies three key strategies to accomplish this task: 1) using μ and β-rhythms, 2) combination of monitoring the cursor and ErrP signals, and 3) using joysticks or stylus. The physically impaired population's flimsy movements are error prone in joystick control; similarly, manipulating μ and β-rhythms is also prone to error. ErrP signals are utilized to work out misclassifications and false responses. Let us now discuss the three strategies:

1) MOTOR IMAGERY

MI-based cursor controls ask participants to modulate their sensorimotor rhythm (SMR) brain waves that comprise μ and β-rhythms. Schalk *et al.* [114] indicated the presence of the ErrP signal in an experiment in which four healthy participants were controlling the vertical movement of a 1-D cursor using their μ and β-rhythms. The ErrP was elicited following erroneous cursor movement. Ferrez *et al.* [30] carried out a similar experiment with six healthy participants, in which participants were controlling the horizontal movement of a cursor using two-class motor imagery - the cursor moved in discrete steps. The authors showed that the ERN elicited whenever the cursor moved opposite to the targeted direction and achieved an average classification rate for the ERN and CRN signals of 76.2% and 81.8% respectively and a recognition rate of 73.1% for the participant's intended cursor direction. Interestingly, this finding implies that it is possible to extract neural information of motor imagery and ErrP signal at the same time in a single trial. Zhang *et al.* [51] and Mousavi *et al.* [115] also studied the ErrP elicited in a cursor controlling task using left and right-hand motor imagery.

2) MONITORING CURSORS

To learn how to modulate the SMR requires weeks of training and SMR are often misclassified, which makes the cursor control difficult. Chavarriaga and Millán [54] presented a different approach, in which, instead of continuously engaging in generating control commands through MI, the participants were asked only to monitor the movement of the cursor which was supposed to follow a target on a screen. Any incorrect movement of the cursor which was controlled by an external autonomous agent elicited an ErrP which was ultimately utilized to tailor the agent behavior to the participant's necessity and preferences. In this six-subjects' experiment, the agent learned the optimum behavior of the cursor control from the participant perspective in less than 50 trials for almost all participants. One limitation of this approach is that the target location is selected by the system itself, which may reduce its usability. More recently, Iturrate *et al.* [116] presented an autonomous-agent based 2-D cursor control. Notably, in this study, the participant can select the target location for the cursor to reach. The experimental results showed that the cursor could reach any location on the 5×5 grid in only 23 movements based on the ERN and CRN signals. A significant advantage of this approach is that the system does not require any calibration procedure and can be purely self-calibrated [25], however, it does affect the efficacy of the system in the initial warm-up period.

3) JOYSTICK CONTROLLED

In many reported studies, the ErrP was elicited by joystick-controlled cursors [118]–[120]. This strategy of cursor control can be used with the motor-impaired population that has residual muscle activity. Krigolson and Holroyd [118] showed that controlling a cursor using a joystick elicits ERN signal when the execution is erroneous. An idea which was supported by Krigolson *et al.* [119], Demchenko*et al.* [127] and Lopes Dias *et al.* [120] as well. Lopes Dias *et al.* [120] reported the occurrence of an ERN signal in the incorrect execution of a continuous cursor control task. The task was to hit the target using joystick control. Surprisingly, unlike other cursor control studies, when the cursor did hit the target, i.e., a correct execution, no event-related potential was elicited.

F. WHEELCHAIR CONTROL

Wheelchairs have been proven to be a mobility-aid for the physically disabled population. Various types of brain signals, specifically, P300, SSVEP, SMR, muscle potentials have been used to control the brain-controlled wheelchairs (BCW) [128]. Similar to other BCI applications, BCW are prone to errors in identifying human intent; therefore, the ErrP signal can be used to improve its efficacy. Perrin *et al.* [49] proposed the use of error-potentials in brain-controlled semi-automatic wheelchair system. To assess the viability of the ErrP usage in this application, they performed an experiment in which the participants monitored navigation of a robotic wheelchair in realistic simulation as well as a real environment. Reportedly, the ErrP was elicited when the semi-automatic wheelchair made a wrong move that restrained it from reaching a predefined target. Taeb *et al.* [121] also confirmed the existence of the ErrP signal in a simulated brain-actuated wheelchair experiment which involved ten healthy participants. The ErrP signal was elicited following feedback that indicated erroneous response from the BCI system.

G. MISCELLANEOUS

Several studies have highlighted many other ErrP-based rehabilitation and ADL assistance techniques. Roset *et al.* [11] demonstrated an MI driven functional electrical stimulation (FES) devices for post-stroke rehabilitation. They employed the ErrP signals as passive feedback in a reinforcement learning loop to continuously adapt the FES device in response to a participant's brain's MI activity. Reportedly, one healthy and one spinal-cord injury (SPI) patients participated in the study; however, the authors did not assess their rehabilitation over a time period.

Zhang*et al.* [58] presented the feasibility of using ErrP signals to predict a participant's intended turning direction in a realistic car simulator that consisted of the accelerating pedal, braking pedal and steering (see Fig. 3(b)). Zhang *et al.* [122] further tested this approach in a real car environment with eight participants. In their experiment, before the car reached an intersection, a directional cue was shown on a screen and following the cue, an ErrP signal was elicited when the directional cue did not match with the participant's intended direction at the intersection. They reported 0.733 ± 0.150 maximum online classification accuracy in the real car experiment.

Movement-related cortical potential (MRCP) signals have capability for use in detecting motor movement using neural signals before the start of actual motor movement. Several studies have shown its applications in stroke rehabilitation programs. Similar to other EEG signals, MRCP signals suffer performance degradation due to non-stationary properties of EEG as well. Artusi *et al.* [26] utilized ErrP signals to address this problem in the MRCP multiclass classification problem. In the experiment, six healthy subjects were asked to perform motor imagination of the right arm flexion at a slow or fast pace with a similar frequency. With the use of ErrP, the initial average bit transfer rate improved by 76% and the global error rate reduced to 14% compared to 26% without ErrP. However, MRCP is often used to detect motor movement before the actual movement starts and the ErrP signal elicits after the actual movement has been performed, therefore, the integration of the ErrP and MRCP poses a fundamental problem which must be considered.

Gaze-based-keyboards are used for typing using eye-gaze data; specifically, in this approach, users have to focus their eyes on a character (on a digital keyboard) they want to type. Commonly, eye-trackers are used to register the eye-gaze data. Kalaganis *et al.* [18] proposed a hybrid BCI system integrating a gaze-based-keyboard with ErrP signals and showed how a regular gaze-based-keyboard can be improved in terms of typing speed with incorporation of ErrP. In an online experiment with ten healthy subjects, authors implemented an error detection system and showed that with the error-aware typesetting, typing speed improved by 9.3% and participants required 2.7sec less to write a sentence compared to a regular gaze-based-keyboard. Notably, it can be a good alternative to P300 spellers for the disabled population.

IV. POTENTIAL ISSUES AND CHALLENGES

The published studies reviewed in this article support the idea that the ErrP signals have the potential to improve the current state-of-the-art BCI rehabilitation and assistive approaches. Nevertheless, several challenges need to be overcome before the motor-disabled population can use such applications in real life.

A. INCLUSION OF MOTOR-DISABLED POPULATION

Rehabilitating and assisting disabled population form the central focus of BCI applications. However, only a few research studies have included disabled people in their experiments. Surprisingly, none of the studies that were targeting robot control, motor imagery, prosthetics, and exoskeletons included disabled participants. Nevertheless, Spuler *et al.* [107] have shown that ErrP patterns in healthy subjects are similar to those observed among the disabled population, and the experiments performed on healthy people can be directly applicable and translated to disabled people. However, in the case of rehabilitation, it is the other way around; the effectiveness of a rehabilitation technique cannot be assessed on healthy people and instead requires a longitudinal study on the motor-disabled population. Moreover, the inclusion of the motor-disabled population in the studies will allow us to identify problems and requirements in BCIs, which may not be easily identifiable with healthy participants.

B. HIGHER ERRP CLASSIFICATION RATES

With the advent of machine learning techniques and powerful computational resources, classification rates of neural signals have improved substantially [129]. With the integration of the ErrP automatic error correction mechanism in BCIs, it is expected to advance further. However, the low ErrP classification rates, especially the false positives (misclassifying correct events as errors events) in ErrP classification, have posed a major challenge. As an example, Dal Seno *et al.* [105] reported little to no improvement in their P300 speller with the ErrP integration due to the low ErrP classification rate. Also, Putze *et al.* [113] reported that participants found the automatic correction strategy more confusing and unpredictable in comparison to the *Reprompt* strategy. Furthermore, Margaux *et al.* [8] reported that a majority of users that were even having reasonable ErrP detection rates preferred the use of P300 speller without corrections because they perceived no benefit from it. Clearly, it is vital to develop confidence among users for the use of ErrP-BCIs, which highly depends on the detection rates.

A good rule of thumb is that the classification rate of error events must be higher than the accompanying BCI signal (e.g., P300, SSVEP, MI); otherwise, the overall performance will degrade [20]. One of the reasons for the low performances of ErrP detectors is the small dataset. Unlike other BCI interventions, BCIs for rehabilitation and assistive devices require the user to perform a physical activity repetitively. Over such a period, development of muscle fatigue limits the experiment length and with it, the size of the data as well. Moreover, higher BCI classification rates introduce a class-imbalance problem in error and correct trials, which further reduces the erroneous events classification rates. A number of studies have been using the false-feedback technique in which they deliberately label the correct event as an error event to collect more error trials [24], [48]. However, the false feedback technique can be counter-productive if the error-rates are chosen to be high as the patients can lose confidence in using the BCI. In another approach, Combaz *et al.* [103] reduced the number of repetitions in P300 BCI speller to increase the error rates in spelling a character to achieve more error trials. Indeed, reducing the number of repetitions will help in collecting more error trials and can also reduce the time required to spell a character; however, with the reduced repetitions, the accuracy of P300-BCI speller itself will reduce which can in turn impact the overall accuracy of the system.

The problem even worsens with the motor-disabled population, as weak muscle control results in fewer trials that further decrease the size of the data. Kim *et al.* [130] demonstrated a classifier transfer approach in which the feasibility of classifying interaction ErrPs is tested on a classifier trained on the observation ErrPs data. This approach can decrease the calibration time; however, the overall accuracy of the detector is being affected and was shown to be decreased [130]. Notably, in observation ErrPs experiments that employ flanker task [36] and cursor monitoring [54], it is easier to record large datasets with minimal physical efforts. Iturrate *et al.* [131] also presented a delay-correction algorithm for classifier-transferring across different observation tasks to reduce calibration time. Nevertheless, the performance of this technique will be decreased as the morphology of the test signal changes in comparison to the base signal.

Each of the techniques discussed above has pros and cons associated with them. Further studies with more focus on higher ErrP classification rates are therefore suggested.

C. ASYNCHRONOUS AND CONTINUOUS BCIS

Event-related potentials are time-locked events - after a certain period following the event, the participant's brain responds in a specific manner depending on the event/stimulus. In stimulus-locked synchronous BCIs, due to the use of cues, the time-locked event is easily known. However, a large number of rehabilitation and assistive BCIs are continuous in their operation; consequently, detection of the ErrP becomes difficult due to the absence of otherwise evident time-locking events. Moreover, with the possibility of the untimely realization of error in asynchronous approaches as in [27], [120], a brain's error-response mechanism may trigger prematurely. As a result, a variation in latencies of ERPs will occur in subsequent trials, which will reduce the signal-to-noise ratio of evoked event-related potential resulting in ineffective temporal features and lower ErrP decoding performance [45]. A potential method to investigate is utilization of spectral features instead of time-domain features. Notably, there is evidence that shows that θ-band power increases post-erroneous response [65]–[67]. Furthermore, a greater extent of non-phase locked θ-activity was observed post-error-event in comparison to phase-locked activity [67], which reportedly remains stable across tasks as well [64]. As an example, Spüler *et al.* [45] reported considerably higher performance with spectral features in the asynchronous ErrP BCI. The use of spectral features can be promising in rehabilitation and assistive BCIs, which identifies this as an area for further research.

D. PERFORMANCE EVALUATION METRICS

Another potential issue of concern is the lack of standard evaluation metrics in assessing the performance of ErrP-BCIs. Many different metrics such as information transfer rate (ITR) [20], classification accuracy [8], utility metric [132], effective-symbol per minute (ESPM) [20] have been reported in the literature for the evaluation of ErrP-BCI. Each of these evaluation metrics explain different aspects of the performance of a BCI, e.g., ITR defines the maximum information-carrying capacity of a BCI communication channel in bits/minute, classification accuracy defines the number of correct predictions made by a classification model over the total number of predictions, utility metric can be defined as the average benefit a user gets by using a BCI divided by the average time required to get it [132] and ESPM defines the number of symbols communicated in a minute without errors in a BCI [20]. Clearly, due to the usage of different evaluation metrics and consequently lack of a standard framework, a comprehensive objective comparison among the studies is difficult to make. More recently, Kalaganis *et al.* [124] have reported a new evaluation method, the so-called Inverse Correct Response Time (ICRT), to quantify the performance of BCIs that employ ErrPs. ICRT combines the performance gain in BCI due to the integration of the ErrP as well as the cost introduced due to it and provides a single reliable metric for the evaluation of the ErrP-BCI. In future investigations, it will be beneficial to provide a comprehensive assessment of ErrP-BCIs using various metrics to facilitate comparison among different studies.

V. FUTURE DIRECTIONS

In terms of directions for future research, a number of possible pathways have been identified that can be adopted in order to design more reliable and usable ErrP based BCIs for motor impaired people.

A. CONSIDERATION OF PSYCHOLOGICAL AND COGNITIVE STATES

Participants' mental fatigue, attention level and other psychological traits affect their EEG responses, which increases the inter-subject variability that deteriorates classification rates. Only a few studies have investigated the relationship of the above with the ErrP signal [81], [82], [84], [100]. The participant's engagement level in the task can be calculated in real-time [133], [134], however, assessing other traits such as mental workload, motivation level, awareness of error is difficult and requires challenging approaches. Therefore, further research is required to establish methods for determining the participant's psychological traits in real-time. With the advent of new methods, a genuinely versatile interface can be developed that can alter its characteristics dynamically in response to changes in a participant's psychological and cognitive states.

B. ITERATIVE ERRPS

In detecting the ErrP signal, various strategies are employed to handle the erroneous condition, such as *Reprompt, Selective Reprompt* and *2nd-best* [113]; however, all of these strategies suffer from troublesome false positives. Utilization of the iterative ErrP can be a potential approach in reducing false positives [103]. The idea behind an iterative ErrP is to search for the secondary/second ErrP signal that can potentially be evoked if the participant realizes that the detection of primary/first ErrP signal is a false positive and then take the corrective actions. As an example, Salazar-Gomez *et al.* [43] and Cruz *et al.* [20] showed how the implementation of the iterative ErrP can reduce the false positives and increase the overall performance in robotic control and BCI-speller, respectively. However, the applicability of such techniques is yet to be tested on the disabled population. Therefore, future studies with more focus on iterative ErrPs are recommended.

C. MULTIMODAL BCI

Besides EEG, error-related potential signals have also been observed in Magnetoencephalography (MEG) [135] and Electrocorticography (ECoG) [44], [136]. fMRI based studies have also shown discriminable patterns for differentiating the error from the correct response [63]. However, each of these techniques has its own set of disadvantages when it comes to BCIs. Several studies have highlighted the use of multimodal brain-computer interfaces, which combines multiple single-mode BCIs to achieve higher performance [137]–[139]. Moreover, ECoG, MEG, and surface-Electromyography (sEMG) signals have also shown promising results when it comes to decoding real-time complex limb-movements from physiological signals [140]–[144]. Summarizing, a multi-model ErrP based BCI can form an effective strategy for assistance as well as rehabilitation applications. Nevertheless, future studies are suggested to establish the viability of such approaches.

D. ASSIST-AS-NEEDED APPROACH

Regaining the upper-limb movement is the top-priority of people with quadriplegia as it directly affects their ability to execute ADLs [3], [145]. Post-stroke, stroke patients undergo a rehabilitation procedure in which they perform physical exercises using their affected limb that accelerates the brain's natural process of recovery from the aftermaths of stroke [5]. Several studies have highlighted the significance of the intensive, repetitive and active participation of the patients in performing the rehabilitation exercises to promote motor recovery [5], [146], [147]. However, due to their motor impairment, stroke patients cannot perform the rehabilitation exercises repetitively and actively [3, 148]. Robotic devices and exoskeletons can assist them in performing the rehabilitation exercises; however, to date, there has been no reliable evidence for any such ErrP-based approach for rehabilitation in motor-disabled people.

Recently, assist-as-needed (AAN) robot therapy-based rehabilitation programs have gain popularity [3], [146]. In AAN based robot therapies, assistance is provided to the patient in performing the rehabilitation exercise when a participant is unable to perform it on his/her own and *vice versa*. Several strategies have been used to implement the AAN approach [3], [148]. ErrP can serve as a useful measure for the modulation of assistance level in the AAN methods. However, the existence of the ErrP has not been confirmed in methods that employ stroke patients performing rehabilitation exercises. This is an important issue to be addressed in future research.

Recently, the study led by Rodgers *et al.* [149] compared robot-assisted training using MIT-Manus robotic gym with enhanced upper limb therapy (EULT) and with usual care for stroke patient upper-limb rehabilitation. Interestingly, the assist-as-needed robot-therapy (RT) did not show any significant gain of upper-limb function defined using Action Research Arm Test (ARAT) scores in comparison to EULT and usual care when delivered at the same frequency and duration. We propose and believe that by including the ErrP signal as a feedback loop in AAN RT designs, RT based training programs can be made more engaging and minimal assistive and thereby improving state-of-the-art rehabilitation methods.

VI. SUMMARY

ErrP signal has emerged as a reliable event-related potential signal that intrinsically serves as a brain-feedback loop and describes the perception of an error. ErrPs can be measured using a variety of brain-imaging techniques in a single-trial and be integrated with conventional BCIs to form hybrid-BCIs for performance improvement. Psychological, physical, and other cognitive aspects in affected individuals have introduced variability in the ErrP that has given it a broader meaning in the field of clinical psychology and performance monitoring, amongst others. ErrPs have been increasingly utilized in the development of rehabilitation applications for motor-disabled people which is evident from the reasonably large number of studies that have been reviewed in this article which describes a diverse range of rehabilitation and assistive applications including robotic devices, BCI spellers and motor-imagery BCIs. Nevertheless, several aspects remain to be further investigated, including improvement in the classification of ErrPs in hybrid BCIs, legitimately handling erroneous events, iterative ErrPs, multimodal BCIs and managing asynchronous ErrP approaches. More importantly, longitudinal studies, including motor-disabled people, must be undertaken for the identification of optimal parameters for rehabilitation and assistive techniques from the end-user perspective. Lastly, we believe that collaborations across disciplines will provide new insights in the utility of ErrPs and lead to the development of integrated ErrP-BCIs that can be used in clinical settings.

REFERENCES

[1] W. Johnson, O. Onuma, M. Owolabi, and S. Sachdev, "Stroke: A global response is needed," *Bull. World Health Org.*, vol. 94, no. 9, pp. 634A–635A, 2016.
[2] R. N. Kalaria, R. Akinyemi, and M. Ihara, "Stroke injury, cognitive impairment and vascular dementia," *Biochimica Et Biophysica Acta (BBA)-Mol. Basis Disease*, vol. 1862, no. 5, pp. 915–925, May 2016.
[3] A. Basteris, S. M. Nijenhuis, A. H. A. Stienen, J. H. Buurke, G. B. Prange, and F. Amirabdollahian, "Training modalities in robot-mediated upper limb rehabilitation in stroke: A framework for classification based on a systematic review," *J. Neuroeng. Rehabil.*, vol. 11, no. 1, 2014, Art. no. 111.
[4] Y. Zhang, W. Chen, C.-L. Lin, J. Chu, and F. Meng, "Research on command confirmation unit based on motor imagery EEG signal decoding feedback in brain-computer interface," in *Proc. 15th Int. Conf. Control, Automat., Robot. Vis. (ICARCV)*, Nov. 2018, pp. 1923–1928.
[5] D. Liu, W. Chen, Z. Pei, and J. Wang, "A brain-controlled lower-limb exoskeleton for human gait training," *Rev. Sci. Instrum.*, vol. 88, no. 10, 2017, Art. no. 104302.
[6] D. Rotermund, U. A. Ernst, and K. R. Pawelzik, "Towards on-line adaptation of neuro-prostheses with neuronal evaluation signals," *Biol. Cybern.*, vol. 95, no. 3, pp. 243–257, Sep. 2006.

[7] N. V. Manyakov, A. Combaz, N. Chumerin, A. Robben, M. van Vliet, and M. M. Van Hulle, "Feasibility of error-related potential detection as novelty detection problem in P300 mind spelling," in *Proc. 11th Int. Conf. Artif. Intell. Soft Comput. (ICAISC)*, 2012, pp. 293–301.

[8] P. Margaux, M. Emmanuel, D. Sébastien, B. Olivier, and M. Jérémie, "Objective and subjective evaluation of online error correction during P300-based spelling," *Adv. Hum.-Comput. Interact.*, vol. 2012, Jan. 2012, Art. no. 4.

[9] S. Bhattacharyya, A. Konar, and D. N. Tibarewala, "Motor imagery, P300 and error-related EEG-based robot arm movement control for rehabilitation purpose," *Med. Biol. Eng. Comput.*, vol. 52, no. 12, pp. 1007–1017, 2014.

[10] A. Rakshit, R. Lahiri, S. Ghosal, A. Sarkar, S. Ghosh, and A. Konar, "Robotic link position control using brain computer interface," in *Proc. Int. Conf. Microelectron., Comput. Commun. (MicroCom)*, Jan. 2016, pp. 1–6.

[11] S. A. Roset, K. Gant, A. Prasad, and J. C. Sanchez, "An adaptive brain actuated system for augmenting rehabilitation," *Frontiers Neurosci.*, vol. 8, p. 415, Dec. 2014.

[12] N. Mrachacz-Kersting, M. Voigt, A. J. T. Stevenson, S. Aliakbaryhosseinabadi, N. Jiang, K. Dremstrup, and D. Farina, "The effect of type of afferent feedback timed with motor imagery on the induction of cortical plasticity," *Brain Res.*, vol. 1674, pp. 91–100, Nov. 2017.

[13] E. López-Larraz, A. Sarasola-Sanz, N. Irastorza-Landa, N. Birbaumer, and A. Ramos-Murguialday, "Brain-machine interfaces for rehabilitation in stroke: A review," *NeuroRehabilitation*, vol. 43, no. 1, pp. 77–97, 2018.

[14] W. Klonowski, "Everything you wanted to ask about EEG but were afraid to get the right answer," *Nonlinear Biomed. Phys.*, vol. 3, May 2009, Art. no. 2.

[15] V. Lawhern, W. D. Hairston, K. McDowell, M. Westerfield, and K. Robbins, "Detection and classification of subject-generated artifacts in EEG signals using autoregressive models," *J. Neurosci. Methods*, vol. 208, no. 2, pp. 181–189, 2012.

[16] G. Johnson, N. Waytowich, and D. J. Krusienski, "The challenges of using scalp-EEG input signals for continuous device control," in *Proc. Int. Conf. Found. Augmented Cognition*, 2011, pp. 525–527.

[17] I. Lazarou, S. Nikolopoulos, P. C. Petrantonakis, I. Kompatsiaris, and M. Tsolaki, "EEG-based brain–computer interfaces for communication and rehabilitation of people with motor impairment: A novel approach of the 21st century," *Frontiers Hum. Neurosci.*, vol. 12, p. 14, Jan. 2018.

[18] F. P. Kalaganis, E. Chatzilari, S. Nikolopoulos, I. Kompatsiaris, and N. A. Laskaris, "An error-aware gaze-based keyboard by means of a hybrid BCI system," *Sci. Rep.*, vol. 8, no. 1, 2018, Art. no. 13176.

[19] T. Zeyl, E. Yin, M. Keightley, and T. Chau, "Adding real-time Bayesian ranks to error-related potential scores improves error detection and autocorrection in a P300 speller," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 1, pp. 46–56, Jan. 2016.

[20] A. Cruz, G. Pires, and U. J. Nunes, "Double ErrP detection for automatic error correction in an ERP-based BCI speller," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 1, pp. 26–36, Jan. 2018.

[21] R. Chavarriaga, A. Sobolewski, and J. D. R. Millán, "Errare machinale EST: The use of error-related potentials in brain-machine interfaces," *Frontiers Neurosci.*, no. 8, p. 208, Jul. 2014.

[22] G. Pfurtscheller, B. Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, T. O. Zander, G. Mueller-Putz, C. Neuper, and N. Birbaumer, "The hybrid BCI," *Frontiers Neurosci.*, vol. 4, Apr. 2010, Art. no. 3.

[23] R. Chavarriaga, A. Biasiucci, K. Förster, D. Roggen, G. Tröster, and J. D. R. Millán, "Adaptation of hybrid human-computer interaction systems using EEG error-related potentials," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol.*, Aug./Sep. 2010, pp. 4226–4229.

[24] S. K. Ehrlich and G. Cheng, "Human-agent co-adaptation using error-related potentials," *J. Neural Eng.*, vol. 15, no. 6, 2018, Art. no. 066014.

[25] I. Iturrate, J. Grizou, J. Omedes, P.-Y. Oudeyer, M. Lopes, and L. Montesano, "Exploiting task constraints for self-calibrated brain-machine interface control using error-related potentials," *PLoS ONE*, vol. 10, no. 7, 2015, Art. no. e0131491.

[26] X. Artusi, I. K. Niazi, M.-F. Lucas, and D. Farina, "Performance of a simulated adaptive BCI based on experimental classification of movement-related and error potentials," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 1, no. 4, pp. 480–488, Dec. 2011.

[27] S. K. Kim, E. A. Kirchner, A. Stefes, and F. Kirchner, "Intrinsic interactive reinforcement learning—Using error-related potentials for real world human-robot interaction," *Sci. Rep.*, vol. 7, no. 1, 2017, Art. no. 17562.

[28] T. O. Zander, C. Kothe, S. Jatzev, and M. Gaertner, "Enhancing human-computer interaction with input from active and passive brain-computer interfaces," in *Brain-Computer Interfaces: Applying our Minds to Human-Computer Interaction*, D. S. Tan and A. Nijholt, Eds. London, U.K.: Springer, 2010, pp. 181–199.

[29] L. C. Parra, C. D. Spence, A. D. Gerson, and P. Sajda, "Response error correction—A demonstration of improved human-machine performance using real-time EEG monitoring," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 173–177, Jun. 2003.

[30] P. W. Ferrez and J. D. R. Millán, "EEG-based brain-computer interaction: Improved accuracy by automatic single-trial error detection," in *Proc. Conf. Adv. Neural Inf. Process. Syst.*, Vancouver, BC, Canada, 2009, pp. 441–448.

[31] N. M. Schmidt, B. Blankertz, and M. S. Treder, "Online detection of error-related potentials boosts the performance of mental typewriters," *BMC Neurosci.*, vol. 13, no. 1, 2012, Art. no. 19.

[32] M. Falkenstein, J. Hohnsbein, J. Hoormann, and L. Blanke, "Effects of crossmodal divided attention on late ERP components. II. Error processing in choice reaction tasks," *Electroencephalogr. Clin. Neurophysiol.*, vol. 78, no. 6, pp. 447–455, 1991.

[33] W. J. Gehring, B. Goss, M. G. H. Coles, D. E. Meyer, and E. Donchin, "A neural system for error detection and compensation," *Psychol. Sci.*, vol. 4, no. 6, pp. 385–390, 1993.

[34] M. Falkenstein, J. Hoormann, S. Christ, and J. Hohnsbein, "ERP components on reaction errors and their functional significance: A tutorial," *Biol. Psychol.*, vol. 51, nos. 2–3, pp. 87–107, 2000.

[35] G. Hajcak, J. S. Moser, N. Yeung, and R. F. Simons, "On the ERN and the significance of errors," *Psychophysiology*, vol. 42, no. 2, pp. 151–160, 2005.

[36] H. T. van Schie, R. B. Mars, M. G. H. Coles, and H. Bekkering, "Modulation of activity in medial frontal and motor cortices during error observation," *Nature Neurosci.*, vol. 7, no. 5, pp. 549–554, 2004.

[37] R. Vocat, G. Pourtois, and P. Vuilleumier, "Unavoidable errors: A spatio-temporal analysis of time-course and neural sources of evoked potentials associated with error processing in a speeded task," *Neuropsychologia*, vol. 46, no. 10, pp. 2545–2555, 2008.

[38] D. M. Olvet and G. Hajcak, "The stability of error-related brain activity with increasing trials," *Psychophysiology*, vol. 46, no. 5, pp. 957–961, 2009.

[39] E. Lopez-Larraz, I. Iturrate, L. Montesano, and J. Minguez, "Real-time recognition of feedback error-related potentials during a time-estimation task," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. (EMBC)*, Buenos Aires, Argentina, Aug./Sep. 2010, pp. 2670–2673.

[40] B. Yazmir and M. Reiner, "Monitoring brain potentials to guide neurorehabilitation of tracking impairments," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, Jul. 2017, pp. 983–988.

[41] P. W. Ferrez and J. D. R. Millán, "Error-related EEG potentials generated during simulated brain–computer interaction," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 3, pp. 923–929, Mar. 2008.

[42] S. Bhattacharyya, A. Konar, and D. N. Tibarewala, "Motor imagery and error related potential induced position control of a robotic arm," *IEEE/CAA J. Automatica Sinica*, vol. 4, no. 4, pp. 639–650, Jun. 2017.

[43] A. F. Salazar-Gomez, J. Delpreto, S. Gil, F. H. Guenther, and D. Rus, "Correcting robot mistakes in real time using EEG signals," in *Proc. IEEE Int. Conf. Robot. Automat.*, May/Jun. 2017, pp. 6570–6577.

[44] T. Milekovic, T. Ball, A. Schulze-Bonhage, A. Aertsen, and C. Mehring, "Detection of error related neuronal responses recorded by electrocorticography in humans during continuous movements," *PLoS ONE*, vol. 8, no. 2, 2013, Art. no. e55235.

[45] M. Spüler and C. Niethammer, "Error-related potentials during continuous feedback: Using EEG to detect errors of different type and severity," *Frontiers Hum. Neurosci.*, vol. 9, p. 155, Mar. 2015.

[46] C. I. Penaloza, Y. Mae, M. Kojima, and T. Arai, "BMI-based framework for teaching and evaluating robot skills," in *Proc. IEEE Int. Conf. Robot. Automat. (ICRA)*, New York, NY, USA, May/Jun. 2014, pp. 6040–6046.

[47] A. Kreilinger, C. Neuper, and G. R. Müller-Putz, "Error potential detection during continuous movement of an artificial arm controlled by brain–computer interface," *Med. Biol. Eng. Comput.*, vol. 50, no. 3, pp. 223–230, 2012.

[48] P. W. Ferrez and J. D. R. Millán, "You are wrong!—Automatic detection of interaction errors from brain waves," in *Proc. Int. Joint Conf. Artif. Intell. (IJCAI)*, Edinburgh, U.K., 2005, pp. 1413–1418.

[49] X. Perrin, R. Chavarriaga, F. Colas, R. Siegwart, and J. D. R. Millán, "Brain-coupled interaction for semi-autonomous navigation of an assistive robot," *Robot. Auton. Syst.*, vol. 58, no. 12, pp. 1246–1255, 2010.

[50] I. Iturrate, L. Montesano, and J. Minguez, "Single trial recognition of error-related potentials during observation of robot operation," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. (EMBC)*, Buenos Aires, Argentina, Aug./Sep. 2010, pp. 4181–4184.

[51] Y. Zhang, W. Chen, J. Zhang, and J. Wang, "Extracting error-related potentials from motion imagination EEG in noninvasive brain-computer interface," in *Proc. 8th IEEE Int. Conf. Cybern. Intell. Syst. (CIS) IEEE Conf. Robot., Automat. Mechatronics (RAM)*, Nov. 2018, pp. 768–773.

[52] I. Iturrate, J. Omedes, and L. Montesano, "Shared control of a robot using EEG-based feedback signals," in *Proc. 2nd Workshop Mach. Learn. Interact. Syst.*, Beijing, China, 2013, pp. 45–50.

[53] S. Ehrlich and G. Cheng, "A neuro-based method for detecting context-dependent erroneous robot action," in *Proc. IEEE-RAS 16th Int. Conf. Hum. Robots*, Nov. 2016, pp. 477–482.

[54] R. Chavarriaga and J. D. R. Millán, "Learning from EEG error-related potentials in noninvasive brain-computer interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 4, pp. 381–388, Aug. 2010.

[55] J. Omedes, A. Schwarz, G. R. Müller-Putz, and L. Montesano, "Factors that affect error potentials during a grasping task: Toward a hybrid natural movement decoding BCI," *J. Neural Eng.*, vol. 15, no. 4, 2018, Art. no. 046023.

[56] G. Padrao, M. Gonzalez-Franco, M. V. Sanchez-Vives, M. Slater, and A. Rodriguez-Fornells, "Violating body movement semantics: Neural signatures of self-generated and external-generated errors," *NeuroImage*, vol. 124, pp. 147–156, Jan. 2016.

[57] B. Yazmir and M. Reiner, "I act, therefore I err: EEG correlates of success and failure in a virtual throwing game," *Int. J. Psychophysiol.*, vol. 122, pp. 32–41, Dec. 2017.

[58] H. Zhang, R. Chavarriaga, L. Gheorghe, and J. D. R. Millán, "Inferring driver's turning direction through detection of error related brain activity," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 2196–2199.

[59] R. D. Pascual-Marqui, "Standardized low-resolution brain electromagnetic tomography (sLORETA): Technical details," *Methods Find Exp. Clin. Pharmacol.*, vol. 24, pp. 5–12, Jan. 2002.

[60] M. J. Herrmann, J. Römmler, A.-C. Ehlis, A. Heidrich, and A. J. Fallgatter, "Source localization (LORETA) of the error-related-negativity (ERN/Ne) and positivity (Pe)," *Cogn. Brain Res.*, vol. 20, no. 2, pp. 294–299, 2004.

[61] C. B. Holroyd and M. G. H. Coles, "The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity," *Psychol. Rev.*, vol. 109, no. 4, pp. 679–709, 2002.

[62] M. Ullsperger and D. Y. von Cramon, "Subprocesses of performance monitoring: A dissociation of error processing and response competition revealed by event-related fMRI and ERPs," *NeuroImage*, vol. 14, no. 6, pp. 1387–1401, 2001.

[63] S. F. Taylor, E. R. Stern, and W. J. Gehring, "Neural systems for error monitoring: Recent findings and theoretical perspectives," *Neuroscientist*, vol. 13, no. 2, pp. 160–172, 2007.

[64] J. Omedes, I. Iturrate, L. Montesano, and J. Minguez, "Using frequency-domain features for the generalization of EEG error-related potentials among different tasks," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Osaka, Japan, Jul. 2013, pp. 5263–5266.

[65] J. Yordanova, M. Falkenstein, J. Hohnsbein, and V. Kolev, "Parallel systems of error processing in the brain," *NeuroImage*, vol. 22, no. 2, pp. 590–602, 2004.

[66] P. Luu, D. M. Tucker, and S. Makeig, "Frontal midline theta and the error-related negativity: Neurophysiological mechanisms of action regulation," *Clin. Neurophysiol.*, vol. 115, no. 8, pp. 1821–1835, 2004.

[67] L. T. Trujillo and J. J. B. Allen, "Theta EEG dynamics of the error-related negativity," *Clin. Neurophysiol.*, vol. 118, no. 3, pp. 645–668, 2007.

[68] J. Carp and R. J. Compton, "Alpha power is influenced by performance errors," *Psychophysiology*, vol. 46, no. 2, pp. 336–343, 2009.

[69] T. Koelewijn, H. T. van Schie, H. Bekkering, R. Oostenveld, and O. Jensen, "Motor-cortical beta oscillations are modulated by correctness of observed action," *NeuroImage*, vol. 40, no. 2, pp. 767–775, 2008.

[70] A. Kumar, E. Pirogova, and J. Q. Fang, "Classification of error-related potentials using linear discriminant analysis," in *Proc. IEEE-EMBS Conf. Biomed. Eng. Sci. (IECBES)*, Dec. 2018, pp. 18–21.

[71] L. Boubchir, Y. Touati, B. Daachi, and A. A. Chérif, "EEG error potentials detection and classification using time-frequency features for robot reinforcement learning," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 1761–1764.

[72] J. N. da Cruz, Z. Wang, C. M. Wong, and F. Wan, "Single-trial detection of error-related potential by one-unit SOBI-R in SSVEP-based BCI," in *Advances in Neural Networks—ISNN 2014* (Lecture Notes in Computer Science: Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). New York, NY, USA: Springer-Verlag, 2014, pp. 524–532.

[73] C. Wirth, E. Lacey, P. Dockree, and M. Arvaneh, "Single-trial EEG classification of similar errors," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 1919–1922.

[74] M. B. Pontifex, M. R. Scudder, M. L. Brown, K. C. O'Leary, C.-T. Wu, J. R. Themanson, and C. H. Hillman, "On the number of trials necessary for stabilization of error-related brain activity across the life span," *Psychophysiology*, vol. 47, no. 4, pp. 767–773, 2010.

[75] A. Meyer, A. Riesel, and G. H. Proudfit, "Reliability of the ERN across multiple tasks as a function of increasing errors," *Psychophysiology*, vol. 50, no. 12, pp. 1220–1225, 2013.

[76] G. Hajcak, J. Klawohn, and A. Meyer, "The utility of event-related potentials in clinical psychology," *Annu. Rev. Clin. Psychol.*, vol. 15, pp. 71–95, May 2019.

[77] D. C. Torpey, G. Hajcak, and D. N. Klein, "An examination of error-related brain activity and its modulation by error value in young children," *Dev. Neuropsychol.*, vol. 34, no. 6, pp. 749–761, 2009.

[78] F. L. Colino, F. L. Colino, H. Howse, A. Norton, R. Trska, A. Pluta, S. J. C. Luehr, T. C. Handy, and O. E. Krigolson, "Older adults display diminished error processing and response in a continuous tracking task," *Psychophysiology*, vol. 54, no. 11, pp. 1706–1713, 2017.

[79] E. M. Reuter, G. E. P. Pearcey, and T. J. Carroll, "Greater neural responses to trajectory errors are associated with superior force field adaptation in older adults," *Exp. Gerontol.*, vol. 110, pp. 105–117, Sep. 2018.

[80] M. A. S. Boksem, T. F. Meijman, and M. M. Lorist, "Mental fatigue, motivation and action monitoring," *Biol. Psychol.*, vol. 72, no. 2, pp. 123–132, 2006.

[81] M. M. Lorist, M. A. S. Boksem, and K. R. Ridderinkhof, "Impaired cognitive control and reduced cingulate activity during mental fatigue," *Cogn. Brain Res.*, vol. 24, no. 2, pp. 199–205, 2005.

[82] L. Y. Ganushchak and N. O. Schiller, "Motivation and semantic context affect brain error-monitoring activity: An event-related brain potentials study," *NeuroImage*, vol. 39, no. 1, pp. 395–405, 2008.

[83] P. E. Pailing and S. J. Segalowitz, "The error-related negativity as a state and trait measure: Motivation, personality, and ERPs in response to errors," *Psychophysiology*, vol. 41, no. 1, pp. 84–95, 2004.

[84] G. Hajcak, N. McDonald, and R. F. Simons, "Anxiety and error-related brain activity," *Biol. Psychol.*, vol. 64, nos. 1–2, pp. 77–90, 2003.

[85] A. Takács, A. Kóbor, K. Janacsek, F. Honbolygó, V. Csépe, and D. Németh, "High trait anxiety is associated with attenuated feedback-related negativity in risky decision making," *Neurosci. Lett.*, vol. 600, pp. 188–192, Jul. 2015.

[86] T. Rosburg, G. Deuring, C. Boillat, P. Lemoine, M. Falkenstein, M. Graf, and R. Mager, "Inhibition and attentional control in pedophilic child sexual offenders—An event-related potential study," *Clin. Neurophysiol.*, vol. 129, no. 9, pp. 1990–1998, 2018.

[87] N. I. Khan, K. L. Burkhouse, L. Lieberman, S. M. Gorka, J. A. DiGangi, C. Schroth, A. Frederick, A. E. Kennedy, D. M. Aase, J. E. Greenstein, E. Proescher, G. Hajcak, and K. L. Phan, "Individual differences in combat experiences and error-related brain activity in OEF/OIF/OND veterans," *Int. J. Psychophysiol.*, vol. 129, pp. 52–57, Jul. 2018.

[88] K. J. Mathewson, J. Dywan, and S. J. Segalowitz, "Brain bases of error-related ERPs as influenced by age and task," *Biol. Psychol.*, vol. 70, no. 2, pp. 88–104, 2005.

[89] K. E. Hill, B. A. Oumeziane, K. D. Novak, D. Rollock, and D. Foti, "Variation in reward- and error-related neural measures attributable to age, gender, race, and ethnicity," *Int. J. Psychophysiol.*, vol. 132, pp. 353–364, Oct. 2018.

[90] W. J. Gehring, J. Himle, and L. G. Nisenson, "Action-monitoring dysfunction in obsessive-compulsive disorder," *Psychol. Sci.*, vol. 11, no. 1, pp. 1–6, 2000.

[91] W.-P. Chang, P. L. Davies, and W. J. Gavin, "Error monitoring in college students with attention-deficit/hyperactivity disorder," *J. Psychophysiol.*, vol. 23, no. 3, pp. 113–125, 2009.

[92] M. Carrasco, C. Hong, J. K. Nienhuis, S. M. Harbin, K. D. Fitzgerald, W. J. Gehring, and G. L. Hanna, "Increased error-related brain activity in youth with obsessive-compulsive disorder and other anxiety disorders," *Neurosci. Lett.*, vol. 541, pp. 214–218, Apr. 2013.

[93] T. Endrass, A. Riesel, N. Kathmann, and U. Buhlmann, "Performance monitoring in obsessive–compulsive disorder and social anxiety disorder," *J. Abnormal Psychol.*, vol. 123, no. 4, pp. 705–714, 2014.

[94] A. S. Euser, B. E. Evans, K. Greaves-Lord, A. C. Huizink, and I. H. A. Franken, "Diminished error-related brain activity as a promising endophenotype for substance-use disorders: Evidence from high-risk offspring," *Addiction Biol.*, vol. 18, no. 6, pp. 970–984, 2013.

[95] A. Riesel, J. Klawohn, R. Grützmann, C. Kaufmann, S. Heinzel, K. Bey, L. Lennertz, M. Wagner, and N. Kathmann, "Error-related brain activity as a transdiagnostic endophenotype for obsessive-compulsive disorder, anxiety and substance use disorder," *Psychol. Med.*, vol. 49, no. 7, pp. 1207–1217, 2019.

[96] M. J. Herrmann, K. Mader, T. Schreppel, C. Jacob, M. Heine, A. Boreatti-Hümmer, A.-C. Ehlis, P. Scheuerpflug, P. Pauli, and A. J. Fallgatter, "Neural correlates of performance monitoring in adult patients with attention deficit hyperactivity disorder (ADHD)," *World J. Biol. Psychiatry*, vol. 11, no. 2, pp. 457–464, 2010.

[97] S. Hsieh, T. H. Li, and L. L. Tsai, "Impact of monetary incentives on cognitive performance and error monitoring following sleep deprivation," *Sleep*, vol. 33, no. 4, pp. 499–507, 2010.

[98] R. J. Compton, M. D. Robinson, S. Ode, L. C. Quandt, S. L. Fineman, and J. Carp, "Error-monitoring ability predicts daily stress regulation," *Psychol. Sci.*, vol. 19, no. 7, pp. 702–708, 2008.

[99] Y. Yokota, T. Soshi, and Y. Naruse, "Error-related negativity predicts failure in competitive dual-player video games," *PLoS ONE*, vol. 14, no. 2, 2019, Art. no. e0212483.

[100] J. B. Hirsh and M. Inzlicht, "Error-related negativity predicts academic performance," *Psychophysiology*, vol. 47, no. 1, pp. 192–196, 2010.

[101] D. M. Olvet and G. Hajcak, "The error-related negativity (ERN) and psychopathology: Toward an endophenotype," *Clin. Psychol. Rev.*, vol. 28, no. 8, pp. 1343–1354, 2008.

[102] U. Vaidyanathan, L. D. Nelson, and C. J. Patrick, "Clarifying domains of internalizing psychopathology using neurophysiology," *Psychol. Med.*, vol. 42, no. 3, pp. 447–459, 2012.

[103] A. Combaz, N. Chumerin, N. V. Manyakov, A. Robben, J. A. K. Suykens, and M. M. Van Hulle, "Error-related potential recorded by EEG in the context of a P300 mind speller brain-computer interface," in *Proc. IEEE Int. Workshop Mach. Learn. Signal Process. (MLSP)*, Kittila, Finland, Aug./Sep. 2010, pp. 65–70.

[104] C. I. Penaloza, Y. Mae, M. Kojima, and T. Arai, "Brain signal-based safety measure activation for robotic systems," *Adv. Robot.*, vol. 29, no. 19, pp. 1234–1242, 2015.

[105] B. Dal Seno, M. Matteucci, and L. Mainardi, "Online detection of P300 and error potentials in a BCI speller," *Comput. Intell. Neurosci.*, vol. 2010, Jan. 2010, Art. no. 307254.

[106] A. Combaz, N. Chumerin, N. V. Manyakov, A. Robben, J. A. K. Suykens, and M. M. Van Hulle, "Towards the detection of error-related potentials and its integration in the context of a P300 speller brain–computer interface," *Neurocomputing*, vol. 80, pp. 73–82, Mar. 2012.

[107] M. Spüler, M. Bensch, S. Kleih, W. Rosenstiel, M. Bogdan, and A. Kübler, "Online use of error-related potentials in healthy users and people with severe motor impairment increases performance of a P300-BCI," *Clin. Neurophysiol.*, vol. 123, no. 7, pp. 1328–1337, Jul. 2012.

[108] A. B. Schwartz, "Cortical neural prosthetics," *Annu. Rev. Neurosci.*, vol. 27, pp. 487–507, Jul. 2004.

[109] R. A. Andersen, J. W. Burdick, S. Musallam, B. Pesaran, and J. G. Cham, "Cognitive neural prosthetics," *Trends Cogn. Sci.*, vol. 8, no. 11, pp. 486–493, 2004.

[110] H. Takahashi, T. Yoshikawa, and T. Furuhashi, "Combination of reliability-based automatic repeat request with error potential-based error correction for improving P300 speller performance," in *Proc. Joint 5th Int. Conf. Soft Comput. Intell. Syst. 11th Int. Symp. Adv. Intell. Syst. (SCIS ISIS)*, Okayama, Japan, 2010, pp. 987–990.

[111] H. Takahashi, T. Yoshikawa, and T. Furuhashi, "A study on combination of reliability-based automatic repeat request with error potential-based error correction for improving P300 speller performance," *Electron. Commun. Jpn.*, vol. 97, no. 1, pp. 12–21, 2014.

[112] T. Zeyl, E. Yin, M. Keightley, and T. Chau, "Partially supervised P300 speller adaptation for eventual stimulus timing optimization: Target confidence is superior to error-related potential score as an uncertain label," *J. Neural Eng.*, vol. 13, no. 2, Apr. 2016, Art. no. 026008.

[113] F. Putze, C. Amma, and T. Schultz, "Design and evaluation of a self-correcting gesture interface based on error potentials from EEG," in *Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst.*, Seoul, South Korea, 2015, pp. 3375–3384.

[114] G. Schalk, J. R. Wolpaw, D. J. McFarland, and G. Pfurtscheller, "EEG-based communication: Presence of an error potential," *Clin. Neurophysiol.*, vol. 111, no. 12, pp. 2138–2144, 2000.

[115] M. Mousavi, A. S. Koerner, Q. Zhang, E. Noh, and V. R. de Sa, "Improving motor imagery BCI with user response to feedback," *Brain-Comput. Interfaces*, vol. 4, nos. 1–2, pp. 74–86, Apr. 2017.

[116] I. Iturrate, L. Montesano, and J. Minguez, "Shared-control brain-computer interface for a two dimensional reaching task using EEG error-related potentials," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 5258–5262.

[117] J. Omedes, I. Iturrate, R. Chavarriaga, and L. Montesano, "Asynchronous decoding of error potentials during the monitoring of a reaching task," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2015, pp. 3116–3121.

[118] O. E. Krigolson and C. B. Holroyd, "Hierarchical error processing: Different errors, different systems," *Brain Res.*, vol. 1155, no. 1, pp. 70–80, 2007.

[119] O. E. Krigolson, C. B. Holroyd, G. Van Gyn, and M. Heath, "Electroencephalographic correlates of target and outcome errors," *Exp. Brain Res.*, vol. 190, no. 4, pp. 401–411, 2008.

[120] C. L. Dias, A. I. Sburlea, and G. R. Müller-Putz, "Masked and unmasked error-related potentials during continuous control and feedback," *J. Neural Eng.*, vol. 15, no. 3, 2018, Art. no. 036031.

[121] M. Taeb, M. B. Shamsollahi, F. Ghassemi, and B. Asefisaray, "Error-related potential-in brain-actuated wheelchair," in *Proc. Int. Work-Conf. Bioinf. Biomed. Eng. (IWBBIO)*, Apr. 2014, p. 1685.

[122] H. Zhang, R. Chavarriaga, Z. Khaliliardali, L. Gheorghe, I. Iturrate, and J. D. R. Millán, "EEG-based decoding of error-related brain activity in a real-world driving task," *J. Neural Eng.*, vol. 12, no. 6, Dec. 2015, Art. no. 066028.

[123] F. Kalaganis, E. Chatzilari, K. Georgiadis, S. Nikolopoulos, N. Laskaris, and Y. Kompatsiaris, "An error aware SSVEP-based BCI," in *Proc. IEEE 30th Int. Symp. Comput.-Based Med. Syst.*, Jun. 2017, pp. 775–780.

[124] F. P. Kalaganis, E. Chatzilari, S. Nikolopoulos, N. A. Laskaris, and Y. Kompatsiaris, "A collaborative representation approach to detecting error-related potentials in SSVEP-BCIs," in *Proc. Thematic Workshops ACM Multimedia*, 2017, pp. 262–270.

[125] E. R. A. De Bruijn, W. Hulstijn, R. G. J. Meulenbroek, and G. P. Van Galen, "Action monitoring in motor control: ERPs following selection and execution errors in a force production task," *Psychophysiology*, vol. 40, no. 5, pp. 786–795, 2003.

[126] R. Yousefi, A. R. Sereshkeh, and T. Chau, "Exploiting error-related potentials in cognitive task based BCI," *Biomed. Phys. Eng. Express*, vol. 5, no. 1, Jan. 2019, Art. no. 015023.

[127] I. Demchenko, R. Katz, H. Pratt, and M. Zacksenhouse, "Distinct electroencephalographic responses to disturbances and distractors during continuous reaching movements," *Brain Res.*, vol. 1652, pp. 178–187, Dec. 2016.

[128] Á. Fernández-Rodríguez, F. Velasco-Álvarez, and R. Ron-Angevin, "Review of real brain-controlled wheelchairs," *J. Neural Eng.*, vol. 13, no. 6, 2016, Art. no. 061001.

[129] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, "A review of classification algorithms for EEG-based brain–computer interfaces: A 10 year update," *J. Neural Eng.*, vol. 15, no. 3, 2018, Art. no. 031005.

[130] S. K. Kim and E. A. Kirchner, "Handling few training data: Classifier transfer between different types of error-related potentials," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 3, pp. 320–332, Mar. 2016.

[131] I. Iturrate, R. Chavarriaga, L. Montesano, J. Minguez, and J. D. R. Millán, "Latency correction of error potentials between different experiments reduces calibration time for single-trial classification," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBS)*, Aug./Sep. 2012, pp. 3288–3291.

[132] B. D. Seno, M. Matteucci, and L. T. Mainardi, "The utility metric: A novel method to assess the overall performance of discrete brain–computer interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 1, pp. 20–28, Feb. 2010.
[133] A. T. Pope, E. H. Bogart, and D. S. Bartolome, "Biocybernetic system evaluates indices of operator engagement in automated task," *Biol. Psychol.*, vol. 40, nos. 1–2, pp. 187–195, 1995.
[134] S. Coelli, R. Barbieri, G. Reni, C. Zucca, and A. M. Bianchi, "EEG indices correlate with sustained attention performance in patients affected by diffuse axonal injury," *Med. Biol. Eng. Comput.*, vol. 56, no. 6, pp. 991–1001, 2018.
[135] A. Llera, M. A. J. van Gerven, V. Gómez, O. Jensen, and H. J. Kappen, "On the use of interaction error potentials for adaptive brain computer interfaces," *Neural Netw.*, vol. 24, no. 10, pp. 1120–1127, 2011.
[136] T. Milekovic, T. Ball, A. Schulze-Bonhage, A. Aertsen, and C. Mehring, "Error-related electrocorticographic activity in humans during continuous movements," *J. Neural Eng.*, vol. 9, no. 2, 2012, Art. no. 026007.
[137] S.-K. Yeom, S. Fazli, J. Mehnert, B. Blankcrtz, J. Steinbrink, K.-R. Müller, and S.-W. Lee, "Multimodal imaging technique for rapid response brain-computer interface feedback," in *Proc. Int. Winter Workshop Brain-Comput. Interface (BCI)*, Feb. 2013, pp. 92–94.
[138] M.-C. Corsi, M. Chavez, D. Schwartz, L. Hugueville, A. N. Khambhati, D. S. Bassett, and F. De Vico Fallani, "Integrating EEG and MEG signals to improve motor imagery classification in brain–computer interface," *Int. J. Neural Syst.*, vol. 29, no. 1, 2019, Art. no. 1850014.
[139] J. Zhang, B. Wang, C. Zhang, Y. Xiao, and M. Y. Wang, "An EEG/EMG/EOG-based multimodal human-machine interface to real-time control of a soft robot hand," *Front. Neurorobot.*, vol. 13, p. 7, Mar. 2019.
[140] R. Fukuma, T. Yanagisawa, Y. Saitoh, K. Hosomi, H. Kishima, T. Shimizu, H. Sugata, H. Yokoi, M. Hirata, Y. Kamitani, and T. Yoshimine, "Real-time control of a neuroprosthetic hand by magnetoencephalographic signals from paralysed patients," *Sci. Rep.*, vol. 6, Feb. 2016, Art. no. 21781.
[141] K. Hu, M. Jamali, Z. B. Moses, C. A. Ortega, G. N. Friedman, W. Xu, and Z. M. Williams, "Decoding unconstrained arm movements in primates using high-density electrocorticography signals for brain-machine interface use," *Sci. Rep.*, vol. 8, no. 1, 2018, Art. no. 10583.
[142] O. Talakoub, C. Marquez-Chin, M. R. Popovic, J. Navarro, E. T. Fonoff, C. Hamani, and W. Wong, "Reconstruction of reaching movement trajectories using electrocorticographic signals in humans," *PLoS ONE*, vol. 12, no. 9, 2017, Art. no. e0182542.
[143] C. Lambelet, M. Lyu, D. Woolley, R. Gassert, and N. Wenderoth, "The eWrist—A wearable wrist exoskeleton with sEMG-based force control for stroke rehabilitation," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, Jul. 2017, pp. 726–733.
[144] I. Batzianoulis, S. El-Khoury, E. Pirondini, M. Coscia, S. Micera, and A. Billard, "EMG-based decoding of grasp gestures in reaching-to-grasping motions," *Robot. Auton. Syst.*, vol. 91, pp. 59–70, May 2017.
[145] K. D. Anderson, "Targeting recovery: Priorities of the spinal cord-injured population," *J. Neurotrauma*, vol. 21, no. 10, pp. 1371–1383, Oct. 2004.
[146] A.-G. Grosmaire and C. Duret, "Does assist-as-needed upper limb robotic therapy promote participation in repetitive activity-based motor training in sub-acute stroke patients with severe paresis?" *NeuroRehabilitation*, vol. 41, no. 1, pp. 31–39, 2017.
[147] G. Tacchino, M. Gandolla, S. Coelli, R. Barbieri, A. Pedrocchi, and A. M. Bianchi, "EEG analysis during active and assisted repetitive movements: Evidence for differences in neural engagement," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 6, pp. 761–771, Jun. 2017.
[148] Z. Yue, X. Zhang, and J. Wang, "Hand rehabilitation robotics on poststroke motor recovery," *Behav. Neurol.*, vol. 2017, Nov. 2017, Art. no. 3908135.
[149] H. Rodgers *et al.*, "Robot assisted training for the upper limb after stroke (RATULS): A multicentre randomised controlled trial," *Lancet*, vol. 21, no. 10192, pp. 51–62, 2019.

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