

EEG-Based Identification of Individuals With Spinal Cord Injury Using Motor-Related and Visual Evoked Potentials

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ABSTRACT: A growing area of brain computer interface (BCI) research focuses on user identification, where individual neural signatures support secure authentication and personalization. Visual evoked potentials (VEPs) are widely used for their reliability, yet the integration of multiple neural modalities for identification remains underexplored. This study investigated, for the first time, the combined use of movement-related cortical potentials (MRCPs) and VEP features for electroencephalography (EEG)-based identification of individuals with spinal cord injury (SCI). We analyzed a publicly available EEG dataset from ten participants with cervical SCI who attempted five hand movements: pronation, supination, palmar grasp, lateral grasp, and hand open. VEPs were elicited by visual cues instructing the movement attempts, while MRCPs reflected the motor preparation and execution processes. Classification results showed that the “hand open” movement achieved the highest identification accuracy (40.28%, $4.03 \times$ above the 10% chance level). These findings demonstrate that combining MRCP and cue-evoked VEP features offers a promising multimodal biometric approach for identifying individuals with SCI.

INTRODUCTION

A brain-computer interface (BCI) is a technology that facilitates direct communication between the brain and external devices by capturing, interpreting, and converting brain signals into commands for controlling prosthetics, computers, or other assistive technologies [1,2]. Among the brain signals commonly employed in BCIs, event-related potentials (ERPs) are voltage changes generated in brain structures in response to specific sensory, cognitive, or motor events [3]. They are typically measured with electroencephalography (EEG) and time-locked to discrete events to isolate event-related neural activity from background brain signals [4]. Visual evoked potentials (VEPs) are a specific subtype of ERPs that represent the electrical activity generated in the

visual cortex in response to visual stimulation, providing a non-invasive method to assess the functional integrity of the visual pathway from the retina to the occipital cortex [5]. Beyond clinical and neurophysiological applications, VEPs have been explored as biometric signatures for user identification and authentication. Unlike traditional biometrics based on iris patterns, facial features, or fingerprints [6], VEPs offer neural-level distinctiveness, high reliability, and robustness to spoofing due to their stimulus-locked nature. Identification accuracies exceeding 99% have been reported under controlled visual stimulation [7], and recent code-modulated VEP paradigms have achieved authentication accuracies of 92% with F1 scores of 0.89 [8–11].

While VEPs capture individual differences in visual processing, other EEG components can similarly reflect user-specific brain dynamics in non-visual domains. Movement-related cortical potentials (MRCPs) have been extensively used in BCIs to detect and classify movement intentions. MRCPs are slow negative EEG shifts that begin 1-2 seconds before voluntary movement, reflecting sequential activation of motor-preparation regions (Supplementary Motor Area) and execution areas (Primary Motor Cortex) [12]. Crucially, MRCPs are generated not only during actual motor execution but also during movement attempts in paralyzed individuals and during motor imagery, where no overt movement occurs [13–15]. The amplitude and temporal characteristics of MRCPs systematically change based on different movement types, varying with movement complexity, force, and effector involved, making them sensitive and adaptable markers of motor intention and planning [13,15,16]. This makes MRCPs particularly valuable for BCIs aimed at detecting different movement intentions, enabling intuitive control of prosthetics, computers, and rehabilitation devices [17,18]. Moreover, their sensitivity to individual motor control patterns makes MRCPs a promising complementary feature for user characterization beyond visual responses, extending their

potential use from motor decoding to user identification and authentication.

The goal of this study is to explore, for the first time, the combined use of VEPs and MRCPs for user identification, with a particular focus on individuals with spinal cord injury (SCI). Specifically, we aim to determine whether integrating visually evoked and motor-induced neural responses enhances discriminative power and to identify which movement type contributes most effectively to user differentiation.

Unlike most previous EEG-based biometric studies conducted exclusively on healthy participants, this work targets a neurologically distinct population. SCI individuals often exhibit altered sensorimotor cortical activity patterns due to reorganization following injury, offering a unique opportunity to evaluate whether neuro-based authentication methods remain robust across different neural profiles. Investigating such a population not only broadens the potential applicability of EEG-based identification systems but also aligns with the broader goal of developing neurotechnologies that are inclusive and clinically relevant.

The integration of motor-induced and visually evoked neural responses may therefore represent a promising step toward next-generation neuro-based biometric systems, bridging clinical and security-oriented applications.

MATERIALS AND METHODS

Dataset description: In this work, we analyzed the publicly available dataset by Ofner et al. [19]. The study investigated whether attempted arm and hand movements by individuals with cervical SCI could be decoded from low-frequency, time-domain EEG signals, specifically focusing on MRCPs, with the aim to advance BCIs that can control neuroprosthetic devices. Ten individuals with cervical SCI participated in the study, with neurological injury levels ranging from C1 to C7 and American Spinal Injury Association Impairment Scale (AIS) scores from A to D. The participants had an average 49.22 ± 18.44 years and they were right-handed. All participants had restricted hand function, with some retaining minimal movement capability while others had no active hand movement. During the experiments, participants sat in front of a computer screen with their arm resting on a pillow or table to ensure comfort and stability throughout the recording sessions. The experiment employed a paradigm where each trial began with a fixation cross and an audible beep (Fig. 1a). Participants were instructed to focus their gaze on the cross, which was displayed for 5 seconds throughout the trial, to minimize eye movements and were asked to avoid swallowing or blinking during this period. At 2 seconds into each trial, a class cue appeared and remained for 3 seconds, representing one of five movement classes: pronation, supination, palmar grasp, lateral grasp, or hand open, as shown on Fig. 1b.

Depending on their motor ability, participants either attempted or executed the cued movement immediately

upon cue presentation. After each trial, participants were requested to return to the original resting position, followed by a random break lasting 1-3 seconds before the next trial commenced. EEG data was sampled at 256 Hz using 61 electrodes positioned according to the 10-5 system, with four additional electrodes for electrooculogram (EOG) monitoring.

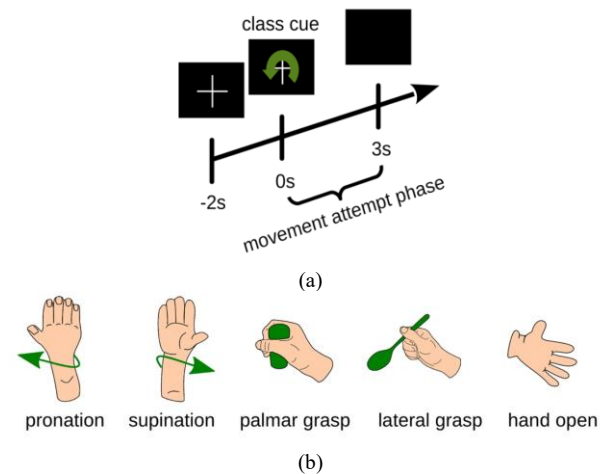


Figure 1: The experimental procedure described in [19]. (a) A fixation cross was presented, and after 2 seconds, a cue appeared and remained on the screen for 3 seconds, during which the participant attempted the corresponding movement. (b) The different attempted movements. Modified with permission from Ofner et al. [19] under the Creative Commons CC-BY license.

Preprocessing of the data: The EEG preprocessing pipeline comprised two sequential stages to optimize signal quality for offline analyses. First, raw data were imported at 256 Hz, filtered with a fourth-order Butterworth bandpass (0.5 – 40 Hz), and zero-phase filtered to avoid phase distortion. In the second stage, the data were loaded into EEGLAB [20]. We applied Independent Component Analysis (ICA), leveraging the assumption of non-Gaussian source distributions, to decompose the signals. We also used ICLabel [21] to automatically classify and remove artifactual components (e.g., eye blinks, muscle activity, etc.). As MRCPs are predominantly contained within the low-frequency range of 0.5–3.5 Hz, the EEG signals were resampled to 16 Hz (applying a low-pass antialiasing filter). Movement-related events were then identified and epochs extracted from -2 to +3 seconds around each cue onset.

User Identification: The classification task was formulated as a multi-class identification problem, performed separately for each movement condition (Fig. 1b). Its objective was to identify individual participants based on their neural signatures during specific motor tasks. In other words, the model aimed to discriminate among subjects using their EEG data, simulating a user identification scenario in which an unknown EEG pattern is matched to a corresponding individual within a predefined database. To achieve this, we employed shrinkage linear discriminant analysis (sLDA), which is

an extension of classical linear discriminant analysis. This sLDA stabilizes covariance matrix estimation by shrinking the sample covariance matrix toward a scaled identity matrix using a data-driven shrinkage coefficient λ . To perform covariance shrinkage within the LDA framework, we utilized the covShrinkage toolbox [22,23], which applies the Ledoit-Wolf closed-form solution to compute the optimal shrinkage coefficient directly from the data. The method was specifically chosen for this identification study because it effectively handles the inherent challenges of EEG classification: the high dimensionality of multi-channel time-domain signals, the limited number of available training trials per participant, and the need for robust classification in noisy biological signals, while maintaining computational efficiency for BCI applications, by selecting automatically the EEG features that hold the most predictive power [24–26].

Classification was performed in a trial-wise manner using overlapping temporal windows centered around the cue onset. Five window lengths (0s, 0.0625s, 0.125s, 0.3125s and 0.625s) were evaluated to examine the influence of temporal integration on classification accuracy, as different window sizes capture distinct aspects of brain dynamics: shorter windows preserve fine temporal detail, while longer windows integrate information over broader time scales and may improve signal-to-noise characteristics [27]. Within each window, amplitude values from all EEG channels were concatenated into a single spatiotemporal feature vector, combining both spatial (multi-channel) and temporal (multi-sample) information. Separate sLDA classifiers were trained and cross-validated for every window size and at each temporal position along the trial, allowing identification of the time point yielding optimal class separation around the cue onset. Performance was quantified through a 10×1-fold cross-validation procedure applied independently within each temporal window, providing reliable estimates of time-resolved discriminative capacity for each participant while preventing overfitting.

RESULTS

The grand average low-frequency EEG time series around the cue onset (−2 to +3 s) is shown in Fig. 2. Following the cue onset ($t = 0$ s), a clear VEP can be observed (around 0.5 s), elicited by the visual cue and superimposed on the ongoing MRCP activity (i.e., negative deflection around 1.5s after cue onset) [19]. Additionally, a smaller positive deflection appears at approximately −1.5 s, corresponding to visual responses elicited by the presentation of the fixation cross at the beginning of each trial.

The time-resolved classification performance is illustrated in Fig. 3, which presents the cross-validated identification accuracy around the cue onset ($t = 0$ s). Five causal EEG window lengths were evaluated (0 s, 0.0625 s, 0.125 s, 0.3125 s, and 0.625 s), shown in distinct colors, while dotted lines indicate the

corresponding mean chance levels [28]. The results demonstrate that identification accuracy varies dynamically over time, increasing after cue presentation and reaching its peak shortly thereafter. The highest accuracy occurs in the early post-cue interval, where VEPs and MRCPs overlap, providing stronger discriminative features. A slight increase in accuracy is also observable at the beginning of the trial, likely due to the fixation cross presentation, which elicits an early VEP contributing additional subject-specific information.

The peak accuracy values for each movement condition are summarized in Tab. 1, which lists the corresponding window length and time point (after cue onset) at which maximum performance was achieved. Across all movements, the 0.3125-second window consistently yielded the best results. Among the five attempted movements, the “hand open” condition achieved the highest identification accuracy of 40.28%, corresponding to 4.03 times the 10% chance level for ten participants.

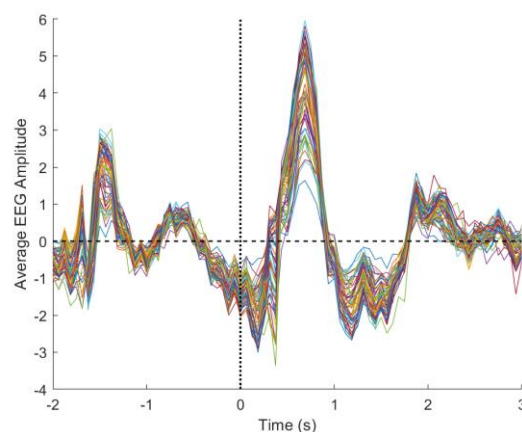


Figure 2: Grand average low-frequency EEG time series across all channels, aligned to the cue onset ($t = 0$ s) and displayed over the [−2, 3] s interval. The plot shows the mean EEG activity used to examine cue-related visual and motor responses across participants.

Table 1: Classification results for all five attempted movements, showing the highest identification accuracy along with the corresponding time point and window length.

Movement	Accuracy (%)	Window Length (s)	Timestamp (s)
Supination	34.02	0.3125	0.6875
Pronation	24.74	0.3125	0.6250
Hand open	40.28	0.3125	0.6875
Palmar grasp	27.07	0.3125	0.7500
Lateral grasp	29.44	0.3125	0.6875

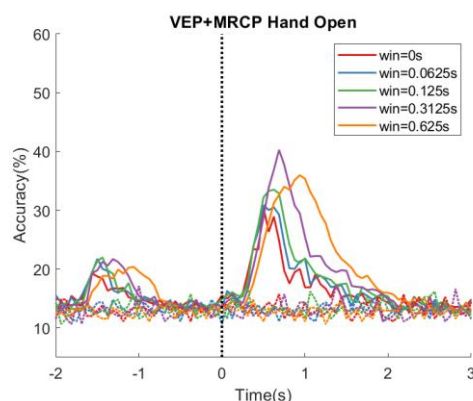


Figure 3: Time-resolved cross-validated classification accuracy for participant discrimination based on combined VEP+MRCP features around the cue onset ($t=0s$). Solid lines represent five causal window sizes: 0s, 0.0625s, 0.125s, 0.3125s and 0.625s. Dotted lines indicate the corresponding estimated mean chance levels for each window size [28]. The vertical dashed line marks the cue onset at $t=0s$. Peak accuracy ($\sim 40.3\%$) was achieved immediately after cue presentation using the 0.3125 s window. Time frame: -2 to 3 seconds relative to cue onset.

DISCUSSION

The results demonstrate that a combination of MRCPs and VEPs can effectively be used for the identification of individuals with SCI. An SCI cohort was specifically selected because their altered sensorimotor cortical activity, resulting from injury-induced neuroplasticity, provides a challenging and clinically relevant model to evaluate whether EEG-based biometric systems remain robust across neurologically distinct profiles. This finding is particularly significant, as it suggests that distinct gesture-related neural patterns, as also observed by Ofner et al [19], can serve as reliable user-specific features. Beyond its clinical relevance for improving the day-to-day life of SCI individuals, this approach also holds promise for enhancing the security and integrity of BCI systems by enabling robust, user-specific authentication and reducing potential misuse or unauthorized access. Also, the consistent superior performance of the 0.3125 window approach across all five movement types suggests that immediate neural responses following cue presentation contain the most discriminative information for user identification. Furthermore, the time-resolved performance, where identification accuracy drops to near chance levels outside the cue window, strongly indicates that the model is capturing true event-related neural dynamics rather than constant session-specific artifacts such as cap positioning.

While the present study demonstrates the feasibility of using combined MRCP and VEP features for user identification in individuals with SCI, several limitations should be acknowledged. First, the relatively small sample size (ten participants) constrains the generalizability of the findings and may limit the robustness of the classification results. As noted in [20], increasing the number of subjects typically enhances model performance in unbiased analyses, as larger datasets capture a broader range of interindividual

variability and reduce overfitting. Similarly, prior work has shown that classification accuracy tends to drop sharply when the number of samples per class falls below 15, emphasizing the need for larger and more diverse participant cohorts in future studies [29].

Another limitation concerns the use of a single classifier (sLDA). While sLDA provides computational efficiency and robustness for small-sample, high-dimensional EEG data, exploring alternative or complementary algorithms could further improve performance. Methods such as Support Vector Machines (SVMs), Common Spatial Pattern (CSP) analysis, or even deep learning approaches (e.g., convolutional neural networks (CNNs)) may more effectively capture nonlinear or spatiotemporal dependencies in EEG signals.

Future research should therefore focus on expanding the dataset, increasing participant diversity, and systematically comparing classification methods to identify the most effective strategies for EEG-based user identification. Additionally, incorporating multi-session recordings could help evaluate the stability and reproducibility of neural signatures over time, an essential step toward real-world deployment of secure and reliable BCI-based biometric systems.

CONCLUSION

This research successfully demonstrates the potential of combining MRCPs and VEPs as a novel biometric identification method for spinal cord injured individuals. This work establishes a promising foundation for developing practical BCI-based identification systems that could significantly impact assistive technology and security applications for individuals with spinal cord injuries.

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