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***Abstract—Objective*. Human-computer interfaces (HCI) are potential tools for assisting (movement replacement) and rehabilitating (movement restoration) individuals with spinal cord injury (SCI). HCIs based on electroencephalography (EEG) have limited accuracy and hence control options; this could be improved by exploiting potential residual muscle activity (electromyography, EMG). The study objectives were to determine if combined EEG and EMG improves offline single-trial movement classification. Furthermore, the effect of number of classes and detection latency on the accuracies was investigated. *Methods*. Ten able-bodied and eight SCI subjects performed elbow flexion/extension at three force levels while EEG and EMG were recorded. Temporal and spectral features were extracted from the EEG and Hudgins time domain features were extracted from the EMG in 1-second time windows. The time window was shifted (200-ms shift) over 5-second epochs around the movement onset. Each segment was classified in three scenarios (2, 3 or 7 classes) using linear discriminant analysis. *Results*. The accuracies obtained with EEG (51.2%) was outperformed by EMG (95.5%) and combined EMG and EEG (96.2%). Immediately after the EMG onset, the accuracies increased and rapidly reached a plateau. High accuracies were obtained for the different number of classes. *Conclusion and Significance*. EMG was crucial for obtaining high accuracies, and potential residual EMG should be exploited in HCIs to improve the performance. Force proved to be a viable option for SCI subjects with residual EMG to increase the number of classes for HCI control. These findings could assist design considerations of HCIs for SCI individuals.**

Keywords— Hybrid HCI, spinal cord injury, EEG, EMG

I. INTRODUCTION

It has been estimated that up to 755 per million individuals are suffering from spinal cord injury (SCI) worldwide [1] and, with more than 43% suffering the injury before 30 years of age [2], a high percentage of people with SCI can expect a long life with disability. Additionally, 59% of people with SCI are living with complete or incomplete tetraplegia [3] making these individuals particularly dependent on assistance in various everyday tasks such as eating, bathing and toileting [4]. To enable these patients to become more self-reliant and enhance their interaction with the surrounding world, they may utilize a Brain-Computer Interface (BCI) [4], [5]. Traditionally BCIs have been used as a means for communication, controlling external devices and neurorehabilitation [6], [7]. The control of external devices with a BCI such as a robotic arm or a wheelchair [8], [9] can potentially provide a means to regain mobility and perform some activities of daily living for SCI individuals. A BCI works by using sensors to record the brain activity of the user, and using signal processing techniques to convert it into a meaningful command to some external device [10]. Even though SCI individuals have altered function of the brain regions associated with sensory-motor control of their impaired limbs [11], [12], it is possible to discern signal patterns usable in BCI applications, e.g. during attempted or imagined movement, with the latter even to an extent comparable to able-bodied subjects [8], [13]. Huggins et al. [14] found that 96% of a group of SCI individuals with low independency showed interest in using a BCI, but even at 80% classification accuracy only three out of four would accept its performance [14]. Thus, the potential users of BCI systems demand a quite high performance of the BCI to accept it. Higher BCI performance could be obtained by selecting a synchronous BCI paradigm where the user relies on different visual cues to elicit e.g. a steady-state visual evoked potential or P300, which have been associated with high information transfer rates (ITRs) [15] i.e. a measure of how fast and accurate external devices can be controlled using the brain [16]. If synchronous control is not feasible, a BCI can be controlled asynchronously as well where the BCI is always active and waiting for the user input. Such BCIs often rely on movement-related brain patterns which are evoked from imagined, executed or attempted movements [17], [18], and they are not dependent on external cues. Two distinct movement-related patterns are observed in association with a movement (executed, imagined, or attempted): 1) Movement-related cortical potentials (MRCPs), and 2) event-related desynchronization/synchronization (ERD/ERS). The MRCP is observed in the EEG as an increase in negativity (amplitude) up to two seconds prior the movement onset [19]. The ERD is a decrease in spectral power prior the movement onset with a similar time course as the MRCP while the ERS is an increase in spectral power, it is postulated that the MRCP and ERD/ERS are generated through different neuronal mechanisms [19]. The ERD and ERS are primarily extracted from the mu and beta rhythms in the EEG [20].

Another way to improve the classification accuracy of BCIs is by developing hybrid BCIs that exploit two different control signals [21], [22]. Since two control signals are used, it may be necessary to use two different control strategies such as motor imagination and steady-state visual evoked potentials [23]. However, if a person with SCI has residual movement, it is possible to record the movement activity in two different ways using EEG and EMG, which potentially holds supplementary discriminative information [5]. Since EEG holds the potential to predict movements before they occur, through e.g. MRCP or ERD detection [24], and EMG is more reliably detected compared to EEG [25], it could be possible that by combining the two, the classification accuracy of the resulting Human-Computer Interface (HCI) will increase. The combination of EEG and EMG in hybrid HCIs is not novel, as it has been tested in able-bodied subjects and stroke patients; however, it needs to be tested in SCI individuals. Various ways of combining the two have been suggested, such as using the modalities as different "modes" or conditions [26], fusing the probabilities from two modality exclusive classifiers [27], making joint EEG-EMG features [28] or combining the feature vectors of the two modalities [29].

An important aspect of HCI for control of external devices is the number of available commands that are implemented in the HCI, as more commands will make the HCI more versatile. Previous studies have shown the possibility of classifying force based on both EEG [30] and EMG [31] suggesting that force may be a viable parameter to include for constructing separate commands. Additionally, when using an HCI for control of an external device for either control or rehabilitation purposes, the delay between the intention to send a command and the relay of the command to the external device matters. For control, a larger delay may be acceptable although it should be as low as possible without affecting the classification accuracy [14], while for rehabilitation the intention to move probably should be detected within 200-300 ms after the movement onset to allow time to trigger an external device that can provide relevant somatosensory feedback to induce Hebbian-associated plasticity [7].

Thus, the aim of this study was to investigate if classification of movements from EEG benefits from adding information from EMG in an offline HCI in subjects with SCI and in able-bodied subjects. Additionally, the association between classification accuracy based on EEG, EMG and the combination of EEG and EMG is investigated with respect to the detection latency and the classification task difficulty (number of available commands).

II. METHODS

This study used a dataset collected as part of previous studies that aimed at evaluating the alteration of spectral cortical activity and corticomuscular coherence after cervical SCI [32]–[34].

A. *Subjects*

Ten able-bodied subjects (mean age: 27 ± 4 years) and eight tetraplegic SCI subjects (mean age: 32 ± 6 years) were recruited. SCI subjects' level of injury ranged from C5-T1, seven had a complete injury and one had an incomplete injury. Full details on SCI subjects can be found in [32]. The study protocol followed the local ethic guidelines from the Faculty of Sport Sciences and Human Movement, Paul Sabatier University (Toulouse 3) in Toulouse, France.

B. *Recordings*

EEG signals were acquired using an active 64-channel system (Active II, Biosemi Inc., Amsterdam, The Netherlands) with a sampling frequency of 1024 Hz. Electrodes were positioned based on the International 10–20 System. Impedances were kept below 30 kΩ, and a common average reference was used. [32]

EMG signals were acquired from the Biceps Brachii, Brachioradialis and the long head and lateral head of the Triceps Brachii of the right arm with a sampling frequency of 1 kHz using a MP 150 amplifier (Biopac Systems Inc., Goleta, USA). The reference was placed on the left ulna styloid process. The skin was prepared following the SENIAM recommendation [35]. The reference electrode was placed on the left ulna styloid process. [32]

The synchrony across the two recordings systems was ensured using TTL pulses and was assessed pre-experiment. An adaptation of Dal Maso's protocol [36] was used in this experiment (see Fig. 1).

C. *Experimental Protocol*

After careful preparation, participants sat on a chair with a dynamometer (System 4 Pro, Biodex Medical Systems, Shirley, NY, USA). The right arm was fixed to the armrest with the elbow joint 90° flexed and the forearm supinated, which is a favorable position for maximal force production in flexion and in extension [37], [38]. Participants then performed 3 relative Maximum Voluntary Contractions (rMVC), i.e., the highest net moment around the right elbow joint in flexion and in extension while keeping all the muscles not involved in the task at rest [32]-[34]. rMVC were considered adequate when no artifacts were visually detected on the EEG recordings. This procedure was implemented to reduce neck and shoulder movements as much as possible during the submaximal contractions since these may contaminate the EEG recordings.

The experimental protocol included seven tasks: 25%, 50% and 75% rMVC in flexion, 25%, 50% and 75% rMVC in extension and a rest task (i.e., 0% rMVC). Participants performed 147 repetitions of these tasks distributed into seven sets. Each set consisted of three repetitions of each condition (21 repetitions per task in total) presented in a randomized order. Each active task consisted of a 6-seconds contraction followed by 6-seconds rest. Each set of tasks was followed by at least a 3-minutes rest period. The required force level was presented to the participant with visual feedback (Presentation program, NeuroBehavioral Systems Inc. Albany, USA). The Presentation software also generated the TTL pulses sent to the data acquisition computers to allow offline synchronization of all the data collected. Fig. 1 depicts the visual feedback used during the experiment. A full description of the experimental protocol is given in [34].

D. *Data Analysis*

1) *Pre-processing*

Following the experiment, the data were filtered using a Chebyshev type 2 IIR filter with a passband of 1-45 Hz and 20-500 Hz for EEG and EMG, respectively, both attenuating 40 dB. EMG was additionally filtered to remove 50 Hz powerline noise (notch filter: 49-51 Hz; 40dB attenuation).

At the beginning of each contraction or rest, a trigger was generated to be used for offline analysis of the data. This trigger was adjusted to correspond to the onset of EMG, using

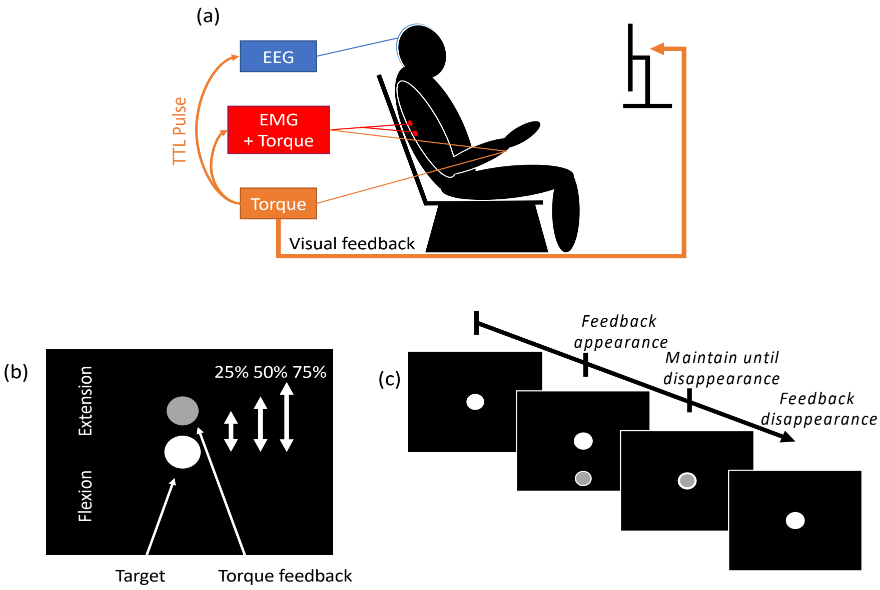

Fig. 1. Schematic representation of the experimentation and visual feedback. (a) EEG was recorded and stored on a separate computer using ActivView acquisition software. EMG and net elbow joint torque were recorded and stored on a computer using AcqKnowledge acquisition software. A third computer was used to display in real-time the net elbow joint torque and send TTL pulses to the two other computers. (b) Example of the visual feedback displayed to the participant. A fixed target (white point) was located at the center of the screen. The torque feedback (grey point) appeared at various distance from the target, according to the force level to be completed. It appeared above the target for elbow extension and below the target for elbow flexion. (c) Time course of the visual feedback. The target was always displayed on the screen. When the torque feedback appeared, participants were asked to move it over the target as quickly and accurately as possible, and to maintain it for six seconds. Once the six seconds were achieved, the feedback disappeared, and the participant could stop the contraction. Each contraction was separated by a 6-seconds rest period.

the toolbox for detecting EMG onsets introduced in [39]. The toolbox utilizes an extended double threshold algorithm and generates an initial guess on the onset of EMG based only on the expected number of EMG bursts in the data [39]. Following the initial guess of EMG onsets produced by the toolbox, the onsets were visually inspected and manually adjusted by a trained individual to ensure precision of onset detection. This was only done for the extension and flexion samples; triggers for the rest condition were not adjusted.

All data analysis was done in MATLAB 2019a.

2) Feature Extraction

Every contraction or rest was divided into multiple 1-second epochs lasting from two seconds before the trigger to three seconds after the trigger. In these epochs, features were extracted in 1-second windows, in shifts of 0.2 seconds, resulting in 21 windows (see Fig. 2). However, features for the resting epochs were only derived in a single window (the first of each epoch, time: -2 to -1 second with respect to the trigger), as the resting condition was expected to be similar in any 1-second window within the same epoch.

Features were derived from four EEG channels (FCz, C3, Cz and C4) and the four EMG channels. The EEG channels were chosen to increase the early accuracy gain in classifying EEG, as the early components of the MRCP is of highest amplitude at Cz, and symmetrically distributed in the hemispheres for hand movements [19]. Only a few electrodes were used to improve the feasibility of the investigated system for out-of-lab applications [40]. As it was expected that both MRCPs (negative amplitude [19]) and ERD/ERS (changes in spectral power [20]) would be present during the active tasks in the study, the EEG features included a simple mean feature (mean amplitude for the epoch), and power within the mu (8-13 Hz), low beta (13-21 Hz) and high beta (21-30 Hz) bands [20]. The mean feature was calculated as the average amplitude of the window; the power of the three frequency windows were calculated using the 'bandpower' function in MATLAB (based on a periodogram estimated using a Hamming window). These features were chosen as they are commonly used for classification of movement intentions in BCI studies [24], [29]. The EMG features used in this study were four of Hudgins' time domain features: mean absolute value, waveform length, zero crossings and slope sign changes [41]. The mean absolute value is a simple mean of a rectified data segment. The waveform length is the cumulative length of the waveform in the analysis window. The zero crossings feature is the number of times within a segment that the EMG signal crosses zero. The slope sign changes feature is the number of times the slope of the EMG signal within a data segment changes. [41] These features were chosen as they are have been commonly used in classification of EMG [31], and has shown to be different between various active upper-extremity tasks and rest [42]. It was expected to see an increase in the features during the movement compared to the rest condition.

Following the extraction of EEG and EMG features, the two feature vectors were concatenated, resulting in three vectors, containing 16 (EEG), 16 (EMG) and 32 features (COMB) per window, respectively.

3) Classification

The primary aim of this study was to investigate if classification accuracies could benefit from using COMB compared to EEG and EMG exclusively. Additionally, it was of interest whether any such benefit was dependent on the difficulty of the classification task, i.e. the number of classes. Therefore, three classification difficulties were considered. The first case combined all the movement tasks into one class (different force levels and movement types were pooled),

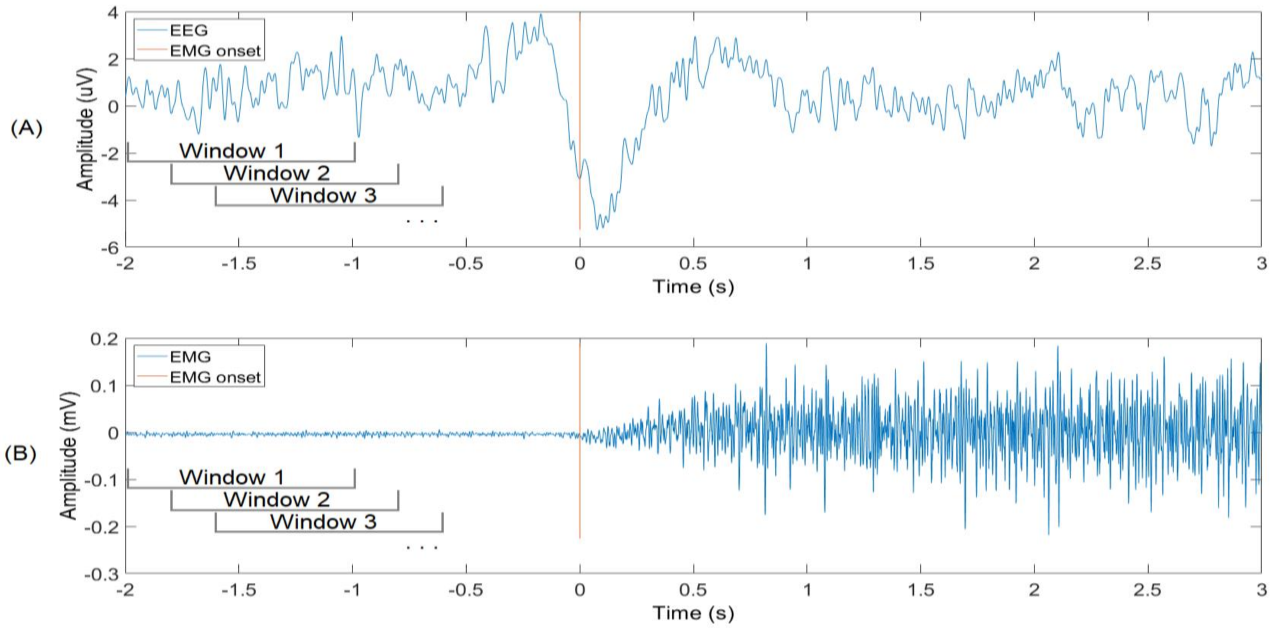

Fig. 2. The figure depicts (A) the average EEG (from Cz) and (B) EMG (from Biceps Brachii) response during the extension tasks for a single SCI subject, and the time-denotation for windows used for calculating features, relative to the cue for action onset.

effectively making a 2-class problem: move or rest. The second case combined all extension and flexion tasks respectively, making a 3-class problem: extension, flexion or rest. The final case considered all original conditions, making a 7-class problem.

Since the 2-class and 3-class problem included more samples per class compared to what was available for the rest class, additional rest class samples were extrapolated to match the number of epochs per active class. This was done by extracting features of the same rest epoch multiple times, using only 0.2-second overlaps of data. The number of extrapolated samples were three per original in the 3-class problem, and seven per original in the 2-class problem.

The abovementioned classification scheme was performed using a linear discriminant analysis (LDA). The LDA was chosen as it is one of the most popular classification algorithms and feasible for online application [43]. The LDA was implemented with the assumption that all classes had the same diagonal linear covariance matrix. This was done since some of the included features, in rare cases had close to zero variance, where the wider assumption of equal covariance matrix was violated. All classification accuracies reported are an average of a 10-fold cross-validation.

4) *Information Transfor Rate*

Calculation of Information Transfer Rate (ITR, bits/min) in this study was based on the highest achieved accuracy per subject and calculated using the formulas in [16]:

$$B = log_2 N + P\, log_2 P + (1 - P)\, log_2 \left[\frac{(1 - P)}{(N - 1)}\right] \quad (1)$$

$$ITR = B * (\frac{60}{T}) \quad (2)$$

where B is the bit rate (bits/symbol), N is the number of classes available, P is the probability of correct classification (accuracy of the classifier), and T is the time needed to convey each symbol. Note that in this study, this calculation is based on offline analysis and thus the time T will not correspond to any real-life scenario or application. Here it will be based on the duration needed to sample the data necessary to make a prediction (one second). Therefore, the ITR calculated in this study will be dubbed “theoretical ITR” (tITR) to signify its difference from ‘real’ ITR

5) *Statistics*

For the statistical analysis, only the highest classification accuracies per subject were used. A general linear model (GLM) was calculated with three factors: Signal modality (three levels: EEG, EMG, and COMB), number of classes (three levels: 2, 3, and 7 classes) and subject type (two levels: able-bodied, and SCI). The model additionally included all two-way interactions. This was done in order to investigate the effects of the various factors and possible interactions on the achieved accuracies. The GLM was corrected for effects of individual subject performance. Post hoc investigations were made with a Bonferroni corrected paired t-test. Levene’s test of equal variance of error was violated in this study. Therefore, the p-value for a significant result was set to 0.01.

III. RESULTS

A. *Accuracy Over Time*

In Fig. 3 and 4, the LDA classification accuracies are shown over time for the three different signal modalities and the three levels of classification difficulty for able-bodied and SCI subjects, respectively.

The classification accuracies at times -1 s to 0 s are generally around chance level, as defined by [44]. At these times, the classification accuracy most notably improved by using COMB rather than EEG or EMG when using the LDA classifier in the 2- and 3-class problem. In all other cases the COMB modality performed roughly the same as either EEG or EMG or slightly worse than the best of the two.

Classification accuracies generally increase, leading up to and following the EMG onset (time 0 s), reaching a plateau roughly at time 0.4-0.6 s at close to 100% classification accuracy for the three different numbers of classes, in able-bodied subjects (see Fig. 3). This level of classification

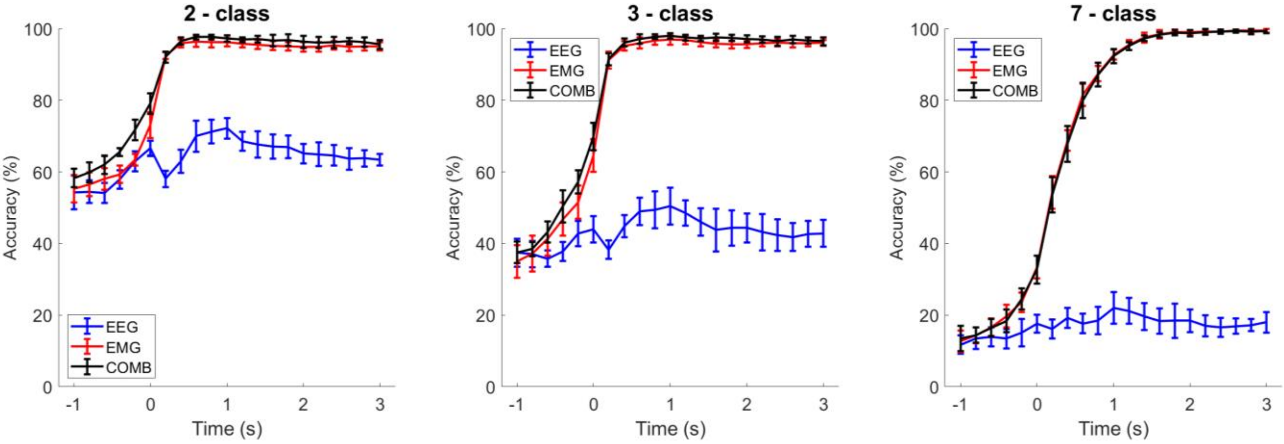

Fig. 3. LDA classification accuracy (%) with standard deviations for able-bodied subjects, relative to EMG onset. "Time" denotes the last segment of data included in the window used for feature calculation (see figure 2), with time "0" denoting the onset of EMG.

accuracy, however, is only true for the EMG and COMB signal, whereas the EEG signal has a less pronounced increase in classification accuracy, which peaks around time 1 s and then diminishes. The same tendency was present for SCI subjects except for the 7-class problem where COMB and EMG reached a plateau at ~80% (see Fig. 4).

B. *Maximal Accuracy*

The maximal accuracies achieved for the LDA classifier are presented in table 1. The classification accuracies approached a plateau at 100% for the EMG and COMB modalities except the 7-class problem for SCI subjects that reached 85-86%. The maximal classification accuracies of the EEG were higher than chance level as defined by [58]; they decreased when the number of classes increased.

The statistical analysis showed that there was a significant effect of signal modality ($F(2,142) = 247.0$, $p \leqslant 0.001$). Post hoc tests revealed that the accuracies obtained for EEG were significantly lower compared to both EMG and COMB ($p \leqslant 0.001$). No difference was found between accuracies obtained using EMG compared to COMB ($p = 1.000$). The maximal classification accuracies of COMB, EMG and EEG, when adjusted for the effect of number of classes and subject type, were 96.2%, 95.5% and 51.2% respectively.

As seen in table 2, differences exist in classification accuracies dependent on the classification difficulty, confirmed with statistics ($F(2,142) = 32.4$, $p \leqslant 0.001$). Post hoc tests showed that a significant difference existed between all classification difficulties ($p \leqslant 0.001$). The maximal classification accuracy of the 2-class, 3-class and 7-class scenarios adjusted for the effect of control signal and subject type problem, was 89.9%, 82.8%, and 70.2%, respectively.

There was a no significant effect of subject type ($F(1,142) = 0.202$, $p = 0.654$).

The results of the GLM revealed that there was a significant interaction between classification difficulty and subject type, and classification difficulty and signal modality. The interaction between classification difficulty and subject type revealed that able-bodied subjects performed better in the 2-class (90.2% vs. 89.6%, adjusted for control signal) and 7-class problem (74.7% vs. 65.7%, adjusted for control signal). In the 3-class problem, both able-bodied and SCI subjects achieved an accuracy of 82.8%, adjusted for control signal). The interaction between classification difficulty and signal modality only strengthened the existing tendencies: COMB > EMG > EEG, and 2-class > 3-class > 7-class, except that the EMG outperformed the COMB in the 7-class problem (92.9% vs. 92.8%, adjusted for subject type). The average classification accuracy for the 2-class, 3-class and 7-class problem respectively, was for the COMB: 98.0%, 97.8% and 92.8%, EMG: 97.0%, 96.7% and 92.9% and for EEG: 74.8%, 54.0% and 24.9%, adjusted for subject type.

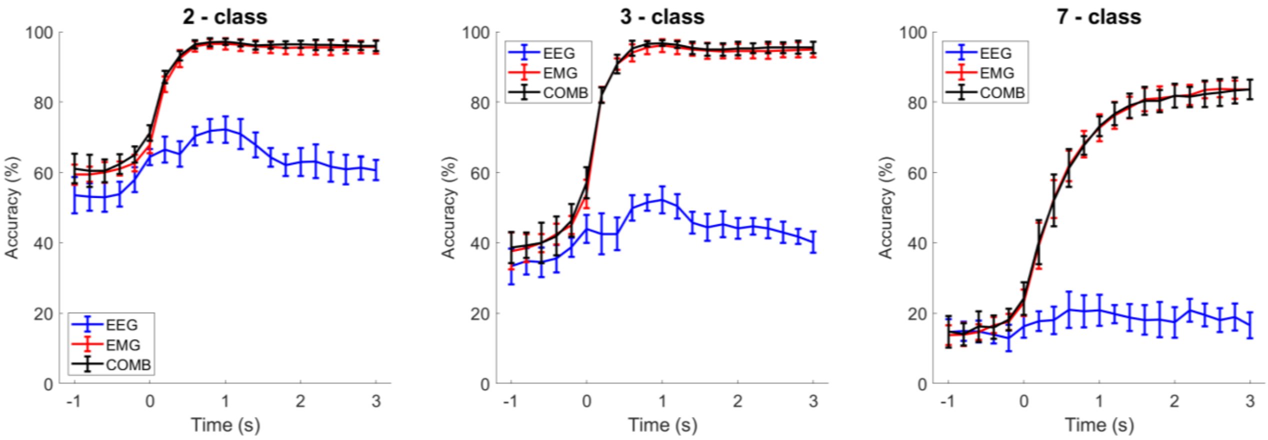

Fig. 4. LDA classification accuracy (%) with standard deviations for SCI subjects, relative to EMG onset. "Time" denotes the last segment of data included in the window used for feature calculation (see figure 2), with time "0" denoting the onset of EMG.

TABLE I. MAXIMAL CLASSIFICATION ACCURACY (%) OBTAINED WITH THE LDA CLASSIFIER. VALUES ARE MEANS ACROSS SUBJECTS ± STANDARD DEVIATION. ALL ACCURACIES ARE GREATER THAN CHANCE LEVEL [58].

Group	EEG			EMG			COMB		
	2-Class	*3-Class*	*7-Class*	*2-Class*	*3-Class*	*7-Class*	*2-Class*	*3-Class*	*7-Class*
Able-bodied	11 ± 7	7 ± 3	3 ± 1	52 ± 12	85 ± 16	166 ± 4	54 ± 9	88 ± 10	167 ± 4
SCI	10 ± 6	9 ± 5	5 ± 2	42 ± 18	82 ± 17	116 ± 49	44 ± 16	84 ± 16	118 ± 45

C. Latency

The latency denotes the time of the last data segment with respect to EMG onset (see Fig. 3 and 4) used to achieve the highest classification accuracy. The latencies of the maximal accuracies achieved by the LDA are seen in table 2. It is observed that the maximal accuracies on average are achieved at time 0.7 s with respect to the movement onset, or later. Generally, the latencies of the maximal achieved accuracies also tend to be later for SCI subjects. However, despite the maximal accuracies being achieved relatively late with respect to the movement onset the difference between the maximal accuracies and those at time 0.4-0.6 s are minimal (see Fig. 3 and 4).

D. Theoretical Information Trasnfer Rate (tITR)

The tITR based on maximal accuracies achieved by the LDA is seen in table 3. The tITR follows the same trend as the maximal accuracies reaching 166-167 bits/min in the 7-class problem using the EMG and COMB signal modalities

IV. DISCUSSION

In this study, it was shown that residual EMG in SCI patients could be successfully decoded and that EEG did not add much additional discriminative information to the EMG. The number of classes did not affect the performance of the EMG modality for able-bodied subject and only slightly for SCI subjects. The classification accuracy rapidly increased to a plateau of 80-100% after the onset of EMG activity

A. Results

This study investigated whether movement classification accuracies could be boosted by combining EMG and EEG (COMB) compared to the two signals separately. It was expected that the COMB modality would have higher accuracies as compared to EEG and EMG respectively, as these two modalities hold discriminative, yet different information. However, the classification accuracy using COMB did not perform significantly better than the classification accuracy using EMG signals alone; it only performed 0.7 % better (adjusted for other factors). These results agree with those of López-Larraz et al., who employed a paradigm comparable to the 2-class control paradigm in the present study [29]. In their study, López-Larraz et al. found that there was no significant difference between EMG and COMB [29], though the difference between the EMG and COMB were 3.7%, in favor of COMB. Despite López-Larraz et al. recruited stroke patients and generally had a lower classification accuracy, the results regarding the indifferent performance of COMB as compared to EMG agree. These results suggest that when using the framework employed in the present study there is no reason to utilize COMB as compared to EMG.

The decoding of movements based on EEG was close to chance level [44]; however, it was expected to see higher classification accuracies prior and around the movement onset for the EEG especially for the 2-class system (movement vs. no-movement). Accuracies have been reported to be in the range of 75-90% [17], [24], [30], the discrepancies between these accuracies and those obtained in the current study could be due to methodological differences in the decoding of movements. The accuracies could probably be improved by performing spatial filtering [45], and using subject-specific features from e.g. template matching or identifying subject specific spectral patterns (channels and frequencies) to be used for classification [24].

The high classification accuracies in this study when using EMG led to high tITR, which is important for the application of an HCI that can control external devices that support SCI users in their activities in their daily living. Additionally, the number of classes employed also affects the achievable tITR. In this study, force proved a viable parameter to include to boost the number of classes complete SCI subjects can use for controlling external devices. The tITR achieved in this study would be enough to control a robotic humanoid hand (maximum: 72 bits/min) and arm (maximum: 60 bits/min) and to provide decent control of a rehabilitation manipulator + hand (median: 90.80 bits/min) [46].

In terms of latency, the results show that the classification accuracy increases rapidly after the movement onset, which could be an important feature to use for neurorehabilitation. In neurorehabilitation, devices such as BCIs have been used to induce neuroplasticity, which is the underlying factor of motor learning [47], through Hebbian-associated mechanisms [7]. In a recent study it was, however, shown that a BCI may not be needed if a device (rehabilitation robot or functional electrical stimulation) that can deliver relevant somatosensory feedback is triggered using EMG [48]. It should, however, be noted that only the 2-class and 3-class problem, using either EMG or COMB, could be used for rehabilitation purposes, as the 7-class problem may not achieve a feasible accuracy within the necessary 200-300 ms after movement onset [7] for SCI individuals.

B. Limitations

One of the limitations in the current study is the limited sample size and the fact that only a small subsection of SCI

TABLE II. LATENCY (S) OF MAXIMAL CLASSIFICATION ACCURACY OBTAINED WITH LDA. VALUES ARE MEANS ACROSS SUBJECTS ± STANDARD DEVIATION AND ARE RELATIVE TO EMG ONSET (0 S).

Group	EEG			EMG			COMB		
	2-Class	*3-Class*	*7-Class*	*2-Class*	*3-Class*	*7-Class*	*2-Class*	*3-Class*	*7-Class*
Able-bodied	0.9 ± 0.6	1.1 ± 0.7	1.0 ± 0.4	0.9 ± 0.3	0.8 ± 0.2	2.0 ± 0.6	0.9 ± 0.3	0.8 ± 0.2	2.2 ± 0.6
SCI	1.1 ± 0.2	1.2 ± 0.8	1.4 ± 1.1	1.5 ± 0.9	1.2 ± 0.7	2.3 ± 0.6	1.2 ± 0.4	1.1 ± 0.6	2.4 ± 0.7

TABLE III. THEORETICAL INFORMATION TRANSFER RATE (BITS/S) OBTAINED WITH LDA. TITR IS CALCULATED BASED ON MAXIMAL CLASSIFICATION ACCURACIES. VALUES ARE MEANS ACROSS SUBJECTS ± STANDARD DEVIATION.

Group	**EEG**			**EMG**			**COMB**		
	2-Class	***3-Class***	***7-Class***	***2-Class***	***3-Class***	***7-Class***	***2-Class***	***3-Class***	***7-Class***
Able-bodied	11 ± 7	7 ± 3	3 ± 1	52 ± 12	85 ± 16	166 ± 4	54 ± 9	88 ± 10	167 ± 4
SCI	10 ± 6	9 ± 5	5 ± 2	42 ± 18	82 ± 17	116 ± 49	44 ± 16	84 ± 16	118 ± 45

individuals is represented. When comparing the SCI and able-bodied subjects there was no difference. This may be explained by the presence of residual EMG in SCI individuals enrolled in the study. Despite this positive outcome, it should be noted that the results only apply for the subsample of tetraplegic SCI individuals having residual EMG. The HCI in this study relies heavily on the EMG, and in case there is no residual EMG or SCI individuals suffer from spasticity, the performance will be affected such that the user must rely on brain control if movement-related activity is decoded.

Although only three separate tasks were used in this study, i.e., flexion, extension and rest, different force levels were considered, i.e., 25%, 50% and 75% of MVC for flexion and extension. The maximal accuracies achieved for all classification difficulties using EMG and COMB, approached 100% for able-bodied, and >80% SCI subjects. These results suggest that force could be a distinguishable component to implement in an EMG or COMB based HCI, provided the users of the HCI are able to generate recordable EMG. Since this was achieved in this study with mostly complete SCI subjects, it may be possible to use an EMG-based HCI for some SCI patients.

The experimental protocol used in this study, consisted of a synchronous HCI paradigm, in which subjects were reliant on a cue to perform the tasks of the experiment (contraction of rest). In a real HCI application for control purposes, this methodology has proven to generate high ITRs when the EEG paradigm employed uses visually evoked potentials [15]. Using a synchronous HCI for control purposes with the tasks employed in this study may be inappropriate, as it would likely decrease the ITR and flexibility of the users control over external devices, at least when compared to other available synchronous systems [15]. However, for rehabilitation purposes, and when no residual EMG is present, a synchronous HCI based on the tasks employed in this study may be the most appropriate solution. This is partly due to ITR being less important in rehabilitation applications, and that movement-related activity is necessary to drive the Hebbian-mechanisms needed for rehabilitation [7], [49].

This study only considered offline analysis, which limits the applicability of these results for real EMG/COMB HCI application. Yet, using the tic-toc function in MATLAB 2019a on a laptop with an Intel® Core™ i7-6700HQ processor (2.6 GHz), it was calculated that the extraction and classification of features for a single epoch would take 0.075 s for the COMB, 0.036 s for EMG and 0.043 s for EEG. This processing time suggests that implementing the framework of this study for online use may be feasible.

C. Practical Considerations

The control signals used in this study were EEG and EMG and the combination of the two. As mentioned previously, the results indicate no reason to use EEG in addition to EMG if residual EMG is available. Even if the results had shown a significant difference between EMG and COMB, the additional gain in accuracy, latency or tITR should be considered in addition to the practicality of using EEG compared to EMG. EMG is relatively easy and quick to prepare for a caregiver/spouse (especially if dry electrodes are used). EEG is more time-consuming to prepare, requires more careful preparation to ensure high-quality signals, and requires the use of an EEG-cap and EEG-gel (if dry electrodes are not used) which may need to be applied over time and requires hair wash afterwards. According to Huggins et al. [14] only 65% of SCI individuals would accept a setup time for a BCI of 10-20 min, which may be possible using few EEG electrodes or dry electrodes. However, EEG remains a control signal, which may be utilized, even if the user has no residual EMG. Thus, EEG and EMG remain two options that are superior to one another for different SCI users.

V. CONCLUSION

The results of this study imply that if EMG is an option for use in an HCI, this is the simplest and most accurate solution. Additionally, there was no evidence of gain in accuracy by combining EEG and EMG using the framework of this study. Furthermore, force proved to be a viable control option for SCI subjects with residual EMG. In future studies, more SCI subjects should be included who have varying degrees of muscle activity and spasticity to investigate the feasibility and usability of using a HCI when less residual EMG is available.

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