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SENSORY THRESHOLD ELECTRICAL STIMULATION ENHANCES CLASSIFICATION OF MOTOR IMAGERY

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ABSTRACT: Non-invasive brain-machine interfaces (BMI) based on motor imagery (MI) of body limbs have been largely studied. However, a non-negligible percentage of users do not produce sufficient discriminable MI brain patterns. It has been suggested that this limitation could be explained by the non-congruency of the delivered feedback with the attended MI task. Following this theory, we propose for the first time the use of sensory threshold neuromuscular electrical stimulation (St-NMES) during MI task to enhance kinesthetic strategies. We hypothesized that St-NMES would foster subjects MI performance without any EEG artefactual contamination by NMES. In this offline study, five naïve healthy subjects were recorded over two different days using either a visual or St-NMES guidance during MI or resting exercises. Results showed how, St-NMES led to enhanced MI discriminability and classification accuracy. Our findings indicate that St-NMES is a promising support for future online MI-BCI performances.

INTRODUCTION

Perirolandic μ and β rhythms modulations in response to motor actions, are a common input control signal for brain-machine interfaces (BMI) for healthy and paralyzed users [13, 2]. In particular, motor imagery (MI) is among the most common tasks to control devices via a BMI. MI is defined as a mental representation of body actions based on internal sensation of movement [10, 17]. However, in practice it can be very challenging for some subjects, especially naïve ones, to generate discriminable MI brain patterns [10]. A possible explanation to this large inter-subject performance variability is that the strategy used to perform MI plays a key role in the accuracy of MI production. It has been proven that the most efficient strategy to perform MI is based on kinesthetic imagery (internally feeling the movement) preferred over visual imagery (internally visualizing the movement) [17]. Indeed, contrary to visual imagery, only kinesthetic imagery activates sensorimotor brain networks, which are similarly observed during motor imagery and motor execution [17, 7, 8]. Thus, the difference between these two kinds of imagery is crucial to improve BMI efficiency, as pointed out by previous works. In particular, several studies already remarked the importance of emphasized users' kinesthetic experiences instead of visual representations during MI [6, 12]. However, despite it is currently well known that we have to brief users how to perform kinesthetic imagery, BMI remains poorly reliable and users' performance is still limited. Furthermore, most BMI systems are currently based on a visual feedback, although other types of feedback could possibly be more effective to help subject perform kinesthetic MI. The choice of the feedback modality could then have an important impact on the accuracy of the BMI.

Instead of simply delivering the outcome of the movement imagery as is common use for visual feedback, one possible solution is the use of somatosensory afferences in order to deliver kinesthetic information and to help subjects to focus on the sensation of the movement. Recent studies have already implemented continuous somatosensory feedback, such as robotic orthosis, vibrotactile stimulation or neuromuscular-electrical stimulation (NMES) to improve MI performance. Among them, Vukelić et al. showed that subjects were able to better modulate β oscillatory rhythms with a proprioceptive feedback delivered by a robotic orthosis [18]. Reynolds et al. demonstrated that NMES during MI induces a larger desynchronization of the sensorimotor rhythm compared to motor imagery supported only by visual feedback [15]. However, the main drawback of the proposed approaches is that the use of somatosensory feedbacks alone (such as passive movement of the joint [18], muscular contraction [15] and even vibrotactile stimulation [5, 6, 9] may also activate similar sensorimotor networks [4, 11, 1], even without any voluntary motor imagery performed by the subject. Thus, it is not yet clear how to provide such rich kinesthetic feedback for online experiments or kinesthetic guidance for offline MI tasks, without interfering with the voluntary modulation of brain activity, limiting their usability for online applications.

In this paper we propose a novel guidance modality to guide subjects during MI performance, based on sensory threshold neuromuscular electrical stimulation (St-NMES). This stimulation conveys natural proprioception by depolarizing sensory and motor nerves, yet without eliciting muscular contraction [15]. The purpose of this offline study is to understand the possible impact of this new approach on MI classification compared to a standard visual guidance. We hypothesize that St-NMES guidance does not interfere with EEG detected brain

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patterns, fosters MI and enhances the discriminability of EEG patterns during MI.

MATERALS AND METHODS

Experimental design

Five right-handed healthy subjects (2 females, age 25.6 ±1.67) naïve in motor imagery practice, took part voluntarily in the experiment. The study was approved by an internal ethical protocol and participants gave their written informed consent before participation.

The experiment (Fig. 1) was composed of two days of recordings during which all subjects were asked to perform continuous kinesthetic motor imagery (MI) of closing their dominant hand (day 1: n = 60 trials, day 2: n = 40 trials) or a resting task (same amount of trials). For both days subjects randomly started with one guidance modality (St-NMES or visual guidance) then with the other one (visual or St-NMES guidance). During the second day, a control condition was also recorded during which subjects received St-NMES whereas no MI was performed. For all 3 conditions (St-NMES, visual, control) each trial started with the preparation cue (3s), then a cue indicating the type of trial (MI or rest, 1s), followed by the task (MI or resting, 4s) and finished with the appearance of the stop cue. Inter-trial intervals lasted between 3 and 4.5 s.

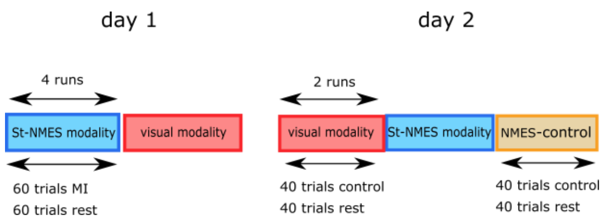

Figure 1: Schema of the experimental design. The order of the guidance modality was randomized across subjects.

St-NMES guidance modality

NMES electrodes were placed on the *Flexor digitorum superficialis* muscle at the anterior face of the forearm. Amplitude of the sensory threshold stimulation (St-NMES) was fixed for each subject before each recording (but keeping the same for both days), and was on average 5±1 mA. With sensory threshold stimulation subjects felt tingling sensation in their palm and forearm but they did not elicit any muscular contraction. The frequency of stimulation was fixed to 30 Hz for all subjects. Subjects received sensory threshold NMES during the MI task and control trials. No stimulation was delivered during resting trials. No visual guidance was provided during the St-NMES condition.

Visual guidance modality

We compared our new approach to the standardly used cursor paradigm moving in a screen for MI [3] [14] [20]. Subjects were instructed to perform kinesthetic MI while seeing a bar going up (for MI trials) or going down (for resting trials).

EEG acquisition and trials extraction

EEG signal was recorded at 512 Hz using a gHiAmp system (gTec, Austria) from 60 channels equally distributed over the scalp following the 10/10 International System. EEG was filtered within the [1,100] Hz (zero-phase Butterworth 4th order), re-referenced to linked ears, then common-averaged referenced. Noisy channels (detected post-experiment by visual inspection) were manually replaced by the mean of the orthogonal neighboring channels. Trials were epoched and concatenated per condition (St-NMES, visual, control), and composed of a baseline from [-3s 0s] and a task time window [1s 5s]. Trials with a filtered EEG signal above 100 μV were considered artefactual and discarded.

Features analysis

We evaluated the discriminability of MI EEG patterns with both guidance modalities (St-NMES, visual) with single-sample classification. First, power spectral density (PSD) for the 16 channels covering the sensorimotor regions (Fz, FCz-1-3-2-4, Cz-1-3-2-4 and Cpz-1-3-2-4) were computed using the Welch method with 5 internal Hanning windows of 500ms (75% overlap). We extracted all the features from μ and β frequency bands for all channels, then fed them to principal component analysis (PCA). We evaluated the accuracy of each guidance modality (St-NMES vs rest, visual vs rest) using a linear discriminant analysis (LDA) as a function of the number of components retained from PCA (from 1 to 20). Each classifier was trained with data from day 1 and tested with data from day 2.

Additionally, we investigated the impact of guidance modality by plotting the first two principal components extracted from 4 pairs of tasks: St-NMES MI vs rest; visual MI vs rest; visual MI vs St-NMES MI; and St-NMES MI vs control.

Classification analysis

We further evaluated the LDA classification performance from the following pairs of tasks St-NMES-MI vs rest, visual-MI vs rest, and control vs rest. Every classifier was trained with data from day 1 using the first 8 principal components (optimal number of features, see below) and tested with data from day 2. For the control condition the classifier was trained with data from St-NMES-MI vs rest from day 1 and tested with the control data from day 2. Statistical significance of classification was defined from a binomial cumulative distribution assuming equal priors (p=0.5) and the number of trials available (n = 80) leading to a chance level of 0.60.

The impact of the guidance modality during the training phase of the classifier on the final accuracy was assessed by comparing accuracies of classifiers with equivalent guidance between the training and testing set to different guidance (e.g. training with St-NMES and testing with St-NMES versus training with visual guidance and testing with St-NMES guidance).

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RESULTS

Features analysis

Figure 2 shows the classification accuracy of MI compared to rest as a function of the number of selected features. We chose to use eight features as no discernable improvement was observed with more features. The averaged mean of accuracy across subjects was higher for the St-NMES (0.78±0.1) compared to the visual modality (0.69±0.1). Despite this improvement was not significant (Wilcoxon ranksum test, $p=0.31$), the power of the statistical analysis was low (0.5) and more subjects will be needed to draw further conclusions.

Representative cases

Figure 3 shows the representative case of one subject (s1) with larger discriminability with St-NMES compared to visual guidance; and another example of a subject (s3) who had low performances with both guidance modalities. S1 showed discriminable MI patterns with St-NMES guidance but not with visual guidance. The discriminable EEG patterns were induced by MI performance and not by the device itself, since the control condition, where the subject received St-NMES without performing MI, was poorly discriminable from rest. On the other hand, s3 showed no clear dissociation between distributions during St-NMES and poorly separable EEG patterns during the visual condition.

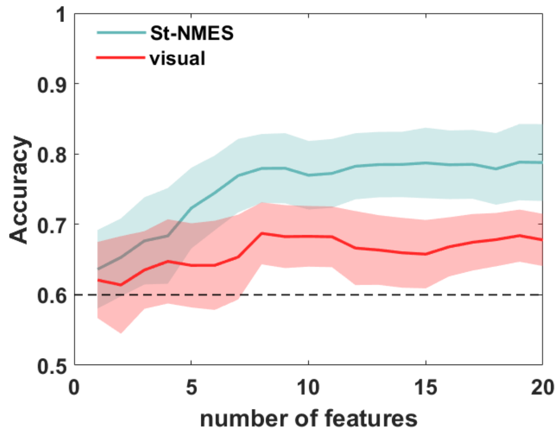

Figure 2: Classification accuracy between MI and rest as a function of the number of features selected, for both guidance modalities. The line (shade) represents the mean (standard error of the mean) of accuracy across subjects. The dashed line represents the chance level estimated at 0.60.

Classification accuracy

Figure 4 represents the accuracies of each subjects for each guidance modality (St-NMES and visual) as well as the classification of a possible bias induced by the St-NMES itself (control). On average, the accuracy for the St-NMES guidance was higher than for the visual guidance (accuracies: 0.78 and 0.69, respectively). Importantly, the control condition showed no significant classification of the St-NMES itself compared to rest

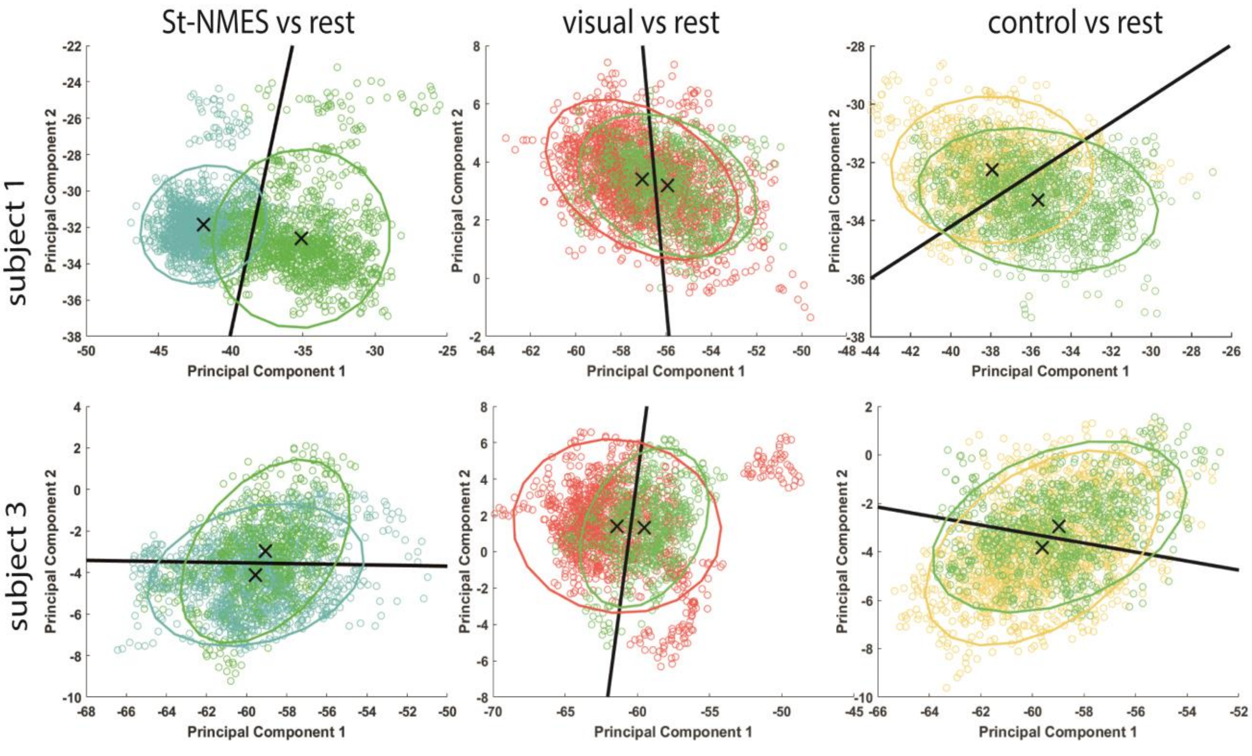

Figure 3: PCA analysis between the 4 pairs of tasks St-NMES (blue), visual (red), rest (green) and control (yellow). Representation of the two first principal components of each pairs of tasks. Each dot represent a sample. The ellipsoids represent the covariance matrix of the distriutions and the cross the mean of the distribution. The black line represents the hyperplane computed from an LDA classifier.

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(accuracy: 0.59). For 3 subjects over 5 (s1, s4 and s5) the accuracy increased with the St-NMES compared to the visual guidance by 35%, 27% and 26% respectively.
One subject (s2) had similar accuracy with both modalities (St-NMES: 0.84, visual: 0.85), and one subject (s3) had better accuracy with the visual modality (St-NMES: 0.61, visual: 0.69). Importantly, for every subjects except subject 1, the St-NMES itself (control condition) did not induce significant detectable EEG artefacts. In the case of subject 1, the St-NMES induced some discriminable patterns, but they did not explain completely the results obtained during MI with St-NMES.

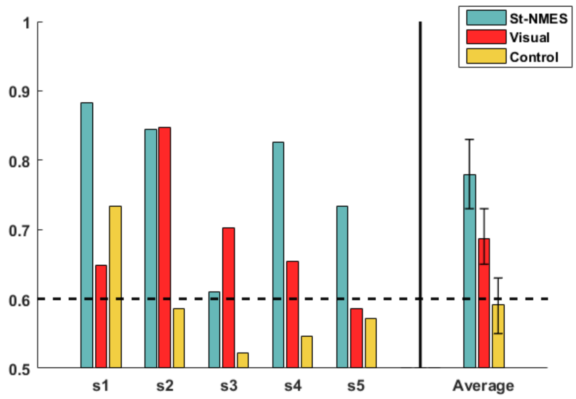

Figure 4: Classification accuracies for each individual subject according to the guidance modality and the control condition. The averaged accuracy across subjects (with the standard error of the mean) is represented on the right part of the figure. The dashed line highlights the chance level.

Impact of the guidance modality of the training data set on classification accuracy
Previous classification analyses were based on equivalent guidance modalities between the training data set and the testing data set. However, as illustrated in Figure 5, the guidance of the training set had an impact on the classification accuracies. Indeed, if the guidance modality of the training data set was different than the testing set the accuracy was decreased (St-NMES—St-NMES: 0.78±0.1, visual—St-NMES: 0.69±0.1 and visual—visual: 0.69±0.1, St-NMES—visual: 0.61±0.1).

DISCUSSION

In this work we show that St-NMES guidance enhanced discriminability of MI pattern and substantially increased classification accuracy without interfering with the recorded EEG signal. EEG pattern during MI were probably enhanced and stronger with the support of the St-NMES which led to a better classification. A plausible explanation of the obtained results is that St-NMES helped subjects to emphasize and focus on kinesthetic imagery.

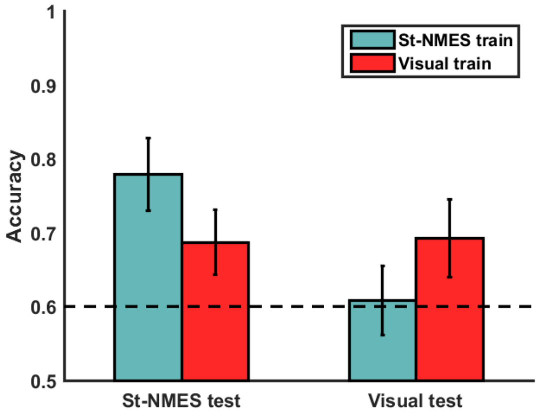

Figure 5: Classification accuracy based on the testing data set according to the guidance modality of the training data set. The dashed line represents the chance level.

As described in the literature kinesthetic imagery activates sensorimotor brain regions similarly to motor execution [15, 8]. Moreover, it is known that MI is based on body representation and on the internal focus of sensation of movement. Thus, we believe that our somatosensory support delivered by St-NMES guided subjects to bring their attention toward the feeling of the limb movement and less on the outcome of the task. On the contrary, the standard visual guidance did not deliver information through somatosensory afferences, which may make less natural for subjects to focus on the sensation of the movement. As a result, subjects may have performed suboptimal strategy during MI based on visual guidance. Our results could be explained then by more accurate kinesthetic focus which induced more discriminable EEG patterns.
Moreover, it has been shown that in the absence of somatosensory feedback, novice subjects were spontaneously less able to produce kinesthetic imagery [19], which can explain the lack of BMI reliability and accuracy [16, 6]. Our study shows that a somatosensory guidance appeared to be more suitable to support MI tasks and it could improve BMI classification. Importantly, our results show that the increase of classification accuracy was not due to a bias induced by the stimulation but by an improvement in MI task. Indeed, St-NMES during rest did not provide detectable sensorimotor network activations.
The representative cases highlighted further elucidated the differences in accuracy obtained. S1 was barely able to modulate sensorimotor rhythms modulations with visual guidance (accuracy: 0.65), but able to perform accurate MI with St-NMES (accuracy: 0.88). As a result, no discriminable patterns were obtained with visual guidance whereas St-NMES guided the user to generate more discriminable brain patterns. Our explanation is that the visual guidance and the instructions of the task were insufficient to guide our subject to perform

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appropriate MI strategy. In fact, this subject reported that it was easier to focus with St-NMES because he knew where to focus his attention (behavioral questionnaire, results not shown). However, for subject 3 no discriminable EEG pattern could be discerned during MI task even during St-NMES condition. Further studies will have to investigate the reasons of this remaining limitation.

Our results are in line with current opinions on motor imagery performance. Neuper et al. [12] already pointed the importance of emphasizing kinesthetic imagery to improve single trial EEG classification. Moreover, other studies also showed that a somatosensory feedback such as a robotic orthosis [18], vibrotactile stimulation [1, 6] or NMES [15] improves BMI classification and may induce stronger MI neural correlates. In this study, we also showed that results are only due to subjects' improvement and not biased by the feedback alone. On the contrary, a continuous robotic feedback which induces a passive movement of the joint may induce similar EEG patterns and thus, the detected EEG brain pattern will be biased by the passive movement and not due to an accurate MI. In a similar context, Chatterjee et al. [5] also proved that vibrotactile stimulation induces a significant bias in BMI MI features, and other studies showed that NMES eliciting muscular contraction cannot be used as a continuous feedback since it activates similar brain networks [11].

In sum, these results show that the choice of the guidance modality can have a significant impact on the induced EEG features and classification accuracy. Thus, future BMIs may benefit from the use of a continuous feedback that does not induce undesirable brain activations but that help subject to perform MI. Perhaps logically, this feedback should remain the same throughout the entirety of the sessions as results have shown that the transferability from one feedback to another leads to suboptimal performances.

CONCLUSION

MI-based BMI systems have become an interesting tool to induce motor recovery and motor learning. However, its applicability remains limited for an important amount of subjects. In this work, we propose a new kind of continuous guidance, St-NMES that has the potential to face some BMI limitations by delivering feedback congruent with the kinesthetic effort of the task without biasing the EEG recordings. Further analysis and online experiments will shed light on the applicability of the proposed feedback for online BMIs.

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