



The influence of central neuropathic pain in paraplegic patients on performance of a motor imagery based Brain Computer Interface [☆]



A. Vuckovic ^{a,*}, M.A. Hasan ^{a,b}, B. Osuagwu ^a, M. Fraser ^c, D.B. Allan ^c, B.A. Conway ^d, B. Nasserolelami ^{d,e}

^a Biomedical Engineering Division, University of Glasgow, Glasgow, UK

^b Department of Biomedical Engineering, NED University of Engineering and Technology, Karachi, Pakistan

^c Queen Elizabeth National Spinal Injuries Unit, Southern General Hospital, Glasgow, UK

^d Department of Biomedical Engineering, University of Strathclyde, Glasgow, UK

^e Academic Unit of Neurology, Trinity College Dublin, Dublin, Ireland

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HIGHLIGHTS

- Motor imagery based BCI-classifier built on EEG data of paraplegic patients, gives higher classification accuracy in patients with central neuropathic pain compared to patients with no chronic pain.
- Higher BCI classification accuracy in paraplegic patients with central neuropathic pain is accompanied with stronger event related desynchronisation during motor imagery.
- BCI classification accuracy between feet and a hand was comparable with classification accuracy between hands, in all three groups of participants.

ABSTRACT

Objective: The aim of this study was to test how the presence of central neuropathic pain (CNP) influences the performance of a motor imagery based Brain Computer Interface (BCI).

Methods: In this electroencephalography (EEG) based study, we tested BCI classification accuracy and analysed event related desynchronisation (ERD) in 3 groups of volunteers during imagined movements of their arms and legs. The groups comprised of nine able-bodied people, ten paraplegic patients with CNP (lower abdomen and legs) and nine paraplegic patients without CNP. We tested two types of classifiers: a 3 channel bipolar montage and classifiers based on common spatial patterns (CSPs), with varying number of channels and CSPs.

Results: Paraplegic patients with CNP achieved higher classification accuracy and had stronger ERD than paraplegic patients with no pain for all classifier configurations. Highest 2-class classification accuracy was achieved for CSP classifier covering wider cortical area: $82 \pm 7\%$ for patients with CNP, $82 \pm 4\%$ for able-bodied and $78 \pm 5\%$ for patients with no pain.

Conclusion: Presence of CNP improves BCI classification accuracy due to stronger and more distinct ERD. **Significance:** Results of the study show that CNP is an important confounding factor influencing the performance of motor imagery based BCI based on ERD.

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1. Introduction

Spinal cord injury may cause paralysis leaving a person highly dependent on their caregivers for most basic activities of daily liv-

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* Corresponding author at: School of Engineering, James Watt Building (South), University of Glasgow, G12 8QQ Glasgow, UK. Tel.: +44 141 330 3251; fax: +44 141 330 4343.

E-mail address: Aleksandra.Vuckovic@glasgow.ac.uk (A. Vuckovic).

ing (Field-Fotte, 2009). Therefore various assistive devices have been used to improve patients' independence and quality of life (Poduri and Cesarz, 2009). In the recent years, assistive and rehabilitation devices based on Brain Computer Interface (BCI) have been intensively explored, due to their capacity to promote combined neurological and physical recovery (Dobkin, 2007; Roset et al., 2013).

Motor imagery (MI) has been a frequently used BCI strategy which can be applied for controlling assistive devices (Pfurtscheller et al., 2000; Kauhanen et al., 2006; Leeb et al.,

2007) and for rehabilitation of SCI patients with incomplete injury and stroke, that have partially preserved movements (Roset et al., 2013; Pfurtscheller et al., 2009; Daly et al., 2009; Tam et al., 2011; Onose et al., 2012). However, there are two major challenges in using MI-BCI in SCI patients: reduced brain activity and reorganisation of somatosensory-cortex (Kokotilo et al., 2009); both affecting the BCI performance. Several BCI studies (Pfurtscheller et al., 2000, 2009) showed that compared to the able-bodied, SCI patients have distinctive activation patterns and reduced event related desynchronisation during MI causing poor performance of a BCI classifier. Multiple imaging studies demonstrated the reorganisation of the sensory-motor cortex, causing the posterior shift of the maximum activity and modification of the level of cortical activity during imagined or attempted movements (Green et al., 1999; Tran et al., 2004; Kokotilo et al., 2009; Jurkiewicz et al., 2010; Vuckovic et al., 2014).

Within the BCI community it is widely accepted that the main cause of these changes is a disuse reorganisation of the cortex caused by paralysis (Kauhanen et al., 2006; Pfurtscheller et al., 2009). Although paralysis is the most obvious effect of the injury, SCI is a complex injury with multiple primary and secondary consequences (Field-Fotte, 2009). It is therefore possible that some secondary consequences of SCI which contribute to the reorganisation of the cortex also affect performance of MI based BCI. One of the most frequent secondary consequences of SCI is chronic pain. A very common subtype of the chronic pain, severely affecting around 40% of SCI population, is central neuropathic pain (CNP) (Siddall et al., 2003; Watson, 2008). CNP is caused by an injury to the somato-sensory system (Haanpaa et al., 2011) but can appear months or years post-injury. An explanation for the origin of CNP is the thalamo-cortical dysrhythmia following the injury (Sarnthein and Jeanmonod, 2008), suggesting that CNP is generated in the brain rather than in the body (Apkarian et al., 2009; Haanpaa et al., 2011; Henderson et al., 2013). Although the origin of CNP is within the central nervous system, it is perceived as coming from the paralysed limbs (Haanpaa et al., 2011). In SCI patients CNP is manifested as a chronic pain below the level of the injury, described as burning, tingling stabbing, shooting or aching sensation (Siddall et al., 2003; Baastrup and Finnerup, 2008). A thermosensory inhibition hypothesis (Craig, 2002), explains CNP as a thermoregulatory dysfunction, that is further supported by a burning sensations, often reported by patients with CNP.

CNP equally affects patients with complete and with incomplete SCI injury (Siddall et al., 2003). It also affects other groups of potential BCI users like stroke patients (8%) (Andersen et al., 1995) and is very frequent in amputees (80%) (Flor, 2002), patients with multiple sclerosis (27%) (Osterberg et al., 2005) and Parkinson's disease (10%) (Beiske et al., 2009).

Evidence for correlation between CNP and reorganisation of the sensorimotor cortex has been shown by many studies (Flor, 2002; Gustin et al., 2010a; Wrigley et al., 2009) where, due to sensory loss caused by the injury, the affected cortical somatotopy undergoes re-mapping or reorganisation, proportional to the intensity of pain. On the contrary, Makin et al. (2013) showed that in persons who suffer from CNP due to amputation, the sensory-motor cortex undergoes less reorganisation than in amputees with no pain. This result indicates that it is possible to distinguish between the effects of sensory loss and pain initiated by trauma leading to sensory loss.

While the areas of the brain involved in processing of pain normally do not involve the primary motor cortex (Apkarian et al., 2009; Jensen, 2010), fMRI studies demonstrated that the presence of CNP in SCI patients causes an increased activation of the primary motor cortex during imagination of movements (Gustin et al., 2010a; Wrigley et al., 2009). EEG studies of spontaneous brain activity also showed the increased power of the theta band and a shift of the dominant alpha peak frequency towards the theta band

in paraplegic and other groups of patients suffering from CNP (Boord et al., 2008; Sarnthein et al., 2006; Stern et al., 2006; Jensen et al., 2013; Vuckovic et al., 2014). Evidence of correlation between CNP and the level of the brain activity has been shown in our previous study (Vuckovic et al., 2014): we defined spontaneous and dynamic EEG signatures of CNP by comparing responses of paraplegic patients with CNP, paraplegic patients with no CNP and able-bodied people in relaxed state and during cue-based MI task. Results of that study showed that patients with CNP had strongest and spatially distinctive event related desynchronisation (ERD) during MI in the theta, alpha and beta frequency bands, with maximum activity shifted posteriorly. Theta band desynchronisation during motor imagination was a singular feature of patients with CNP. Patients with no CNP had weakest ERD, that has spatial topography comparable to those of the able-bodied group.

Given the previously mentioned evidence regarding the role of CNP, there is a possibility that performances of a MI-based BCI, which uses ERD based features, may not only vary between paralysed and able bodied people, but importantly between paralysed people with and without CNP. It should be noted that in previous reports (Gustin et al., 2008, 2010b) the effect of motor imagery on CNP was not analysed for the purpose of BCI, so the effect of CNP on BCI performance is unknown. From a BCI perspective increased cortical activity during MI in patients with CNP is a desirable feature as it implies that better classification accuracy might be achieved. However, a study on SCI patients with CNP who practiced motor imagery for several weeks showed that prolonged imagination of movements of a painful part of the body worsens pain, i.e. MI is able to produce painful sensation without a peripheral input (Gustin et al., 2008, 2010b). Equally important is to question whether MI as practiced for BCI has an adverse effect on CNP.

The aim of this EEG-based study was to test whether the presence of CNP in paraplegic patients influences the performance of MI based BCI. We compared performances of BCI classifiers and the accompanying ERS/ERD responses between three groups: able bodied people, paraplegic patients with no pain and paraplegic patients with CNP. These results are potentially also relevant for other patient groups suffering from CNP, e.g. stroke patients, who are typical BCI candidates.

2. Methods

2.1. Participants

Three groups of age-matched adults (age between 18 and 55) were recruited. The groups were:

1. Ten paraplegic patients (3F, 7M age 46.2 ± 9.4), with diagnosed CNP below the level of injury, referred to as Patients With Pain (PWP),
2. Nine paraplegic patients with no chronic pain (2F, 7M age 43.8 ± 9.1), referred to as Patients with No Pain (PNP),
3. Nine able bodied volunteers with no chronic pain (3F, 6M age 39.6 ± 10.2) referred to as Able Bodied (AB).

The neurological level of SCI was determined using the American Spinal Injury Association (ASIA) impairment classification (Marino et al., 2003). Injury level A means the loss of motor and sensory functions while level B means the loss of motor function with some sensations preserved. All SCI patients were at least 1 year post injury and had a spinal lesion at or below T1. The inclusion criteria for patients with CNP was a positive diagnosis of CNP, reported pain level ≥ 5 on the Visual Numerical Scale (VNS ranging from 0 to 10, 0 meaning no pain and 10 meaning worst pain imaginable) and a treatment history of CNP for at least 6 months. The

general exclusion criteria for all three groups were a presence of any chronic (non CNP) or acute pain at the time of the experiment; brain injury or other known neurological condition that would affect EEG interpretation or would prevent patients from understanding the experimental task. Prior to the experiment patients were asked to fill out the brief pain inventory (Daut et al., 1983) to assess the intensity (based on a VNS) and location of pain. Information on Patients With Pain (PWP) and Patients with No Pain (PNP) is shown in Tables 1 and 2. The exact location of perceived pain in each patient is shown in Fig. 1. All patients had pain under the level of injury, that was bilateral in 8 out of 10 patients. In some patients pain was also present over the lower abdomen and buttock. In all patients pain was present in shanks and feet.

The ethical approval was obtained from the University of Strathclyde Ethical Committee for the able-bodied group and from National Health Service Ethical Committee for Greater Glasgow and Clyde for patients' groups. Informed consent was obtained from all participants. The same groups of patients were used in our previous study to describe dynamic signature of CNP (Vuckovic et al., 2014).

2.2. Recording equipment

EEG was recorded from 61 channels using the Synamps², (Neuroscan, USA) system. Electrodes were placed according to standard 10-10 locations (ACNS, 2006) using an ear-linked reference and AFz ground. Electrooculogram (EOG) was recorded from 3 channels around the right eye. All channels were sampled at 1000 Hz. Individual electrode impedances were below 5 k Ω . In addition, electromyograms (EMGs) were recorded from the right and the left wrist extensor muscles and right foot dorsiflexor using the bipolar inputs to the Synamps² device. The purpose of EMG recording was to check for the absence of any evidence of voluntary movements when subjects attempted MI.

2.3. Experimental procedures

An experimental protocol that instructed participants to imagine hand or lower limb movements was devised using visual cues. Participants were seated at a desk, approximately 1.5 m in front of a computer monitor. Participants were instructed to look at the centre of the monitor and were instructed to respond to a sequence of visual cues. The cues comprised at $t = -1$ s, a readiness cue (a cross +) which remained on for 4 s (Fig. 2). At $t = 0$ s an initiation cue, presented as an arrow, was displayed for 1.25 s, pointing to the left \leftarrow , to the right \rightarrow or down \downarrow and corresponded to imagination of the left hand waving (LH), right hand waving (RH) and tapping with both feet (F), respectively. Participants were asked to continue to perform imaginary movements until the cross disappeared from the screen (3 s after the initiation cue appeared). This is a standard experimental paradigm for discrimination between imagined movements between different limbs (Pfurtscheller

et al., 2006, 2009; Blankertz et al., 2007). Separate imagination of the left and right feet is typically not performed, due to the anatomical location of the motor areas of left and right feet, which lie in close proximity, deeper in the central sulcus and would therefore be hard to distinguish using a classifier (Bear et al., 2007).

In PNP group, RH and LH were non-paralysed parts of the body while F were paralysed. None of the limbs were painful. In PWP group, RH and LH were non-paralysed and non-painful parts of the body while F were both a paralysed and painful part of the body.

In total 60 trials of each movement type (180 trials in total) were collected from the subjects with randomised cue sequences. The whole session consisted of 6 sub-sessions with rest periods in-between. In each sub-session 10 trials of each type (30 trials in total) were presented to subjects. We collected relatively a small number of trials (60 for each limb) because of PWP group who could not successfully concentrate on a longer experiment.

2.4. Data pre-processing

For pre-processing of spontaneous EEG, a high-pass filter (IIR, 12 db cut off frequency) was set to 1 Hz and a notch filter (IIR, 12 db cut off frequency) was applied between 48 and 52 Hz, to remove line noise at 50 Hz. Filtering was applied forwards and then backwards to avoid phase shift. Signals were then down-sampled to 250 Hz. EEG was visually inspected and epochs containing EOG artefact and other types of noise (amplitude exceeding approximately 100 μ V over all channels) were manually removed. After removing heavily contaminated epochs, signals were exported to EEGLAB (Delorme and Makeig, 2004). Independent Component Analysis (ICA) was performed using the infomax algorithm (Bell and Sejnowski, 1995) implemented in EEGLAB for advanced noise removing purposes. ICAs representing noise was detected based on their power spectral density, time distribution, scalp maps and dipole localisation. In this way excessive EEG removal from a limited number of trials was avoided, as no more than 2 (out of 60) trials had to be removed per dataset of a single

Table 2
Information about Patients with No Pain (PNP group).

| Nr | Level of injury | ASIA | Years after injury |
|----|-----------------|------|--------------------|
| 1 | T7 | A | 7 |
| 2 | T7 | B | 7 |
| 3 | T12 | A | 7 |
| 4 | L1 | A | 6 |
| 5 | T2 | A | 2 |
| 6 | T5 | B | 15 |
| 7 | T11 | A | 11 |
| 8 | T4 | A | 9 |
| 9 | T7 | A | 15 |

Table 1
Information about patients with CNP (PWP group).

| Nr | Level of injury | ASIA | Years after injury | Pain VNS | Years with pain | Medications |
|----|-----------------|------|--------------------|----------|-----------------|-----------------------------------|
| 1 | T5 | A | 7 | 7 | 7 | Baclofen Carbamazepine Gabapentin |
| 2 | T5/6 | A | 11 | 6 | 11 | – |
| 3 | T5 | A | 7 | 8 | 7 | Pregabalin Gabapentin |
| 4 | L1 | B | 15 | 7 | 15 | Gabapentin |
| 5 | T7 | B | 6 | 8 | 5 | – |
| 6 | T6/7 | B | 25 | 10 | 24 | Gabapentin |
| 7 | T1 | A | 25 | 5 | 10 | Pregabalin |
| 8 | T5 | A | 14 | 5 | 13 | Amitriptyline, Baclofen, Diazepam |
| 9 | L1 | B | 5 | 5 | 4 | – |
| 10 | T8 | B | 11 | 1 | 10 | Pregabalin |

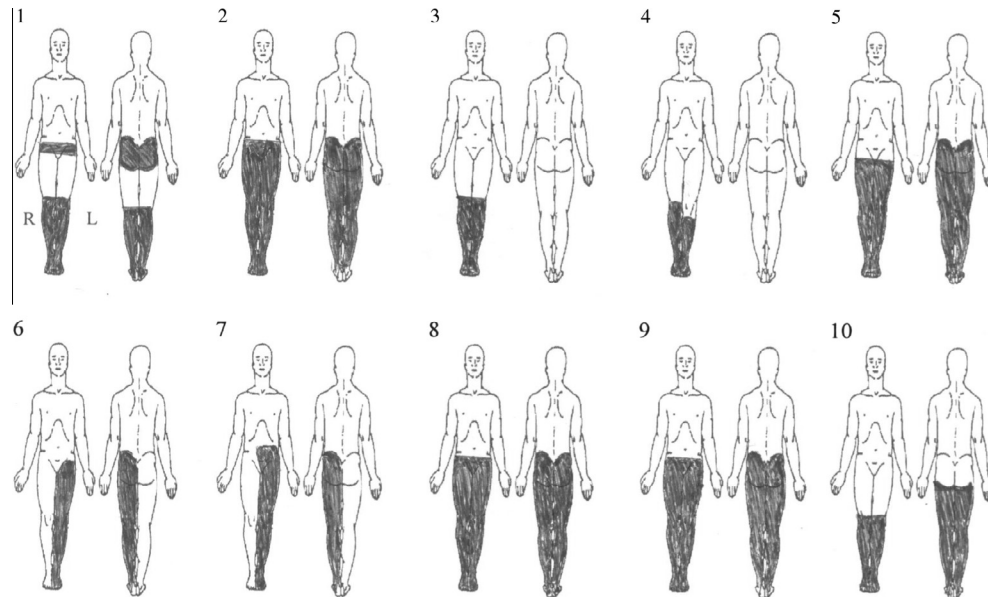


Fig. 1. Body maps showing perceived location pain in patients in PWP group.

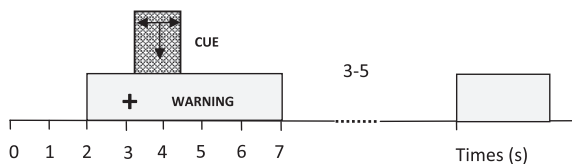


Fig. 2. The experimental paradigm for a motor imagination task.

limb. After noise removal data were converted back to EEG domain for further analysis.

2.5. Classification of motor imageries

We performed classification between the following two tasks: right hand vs left hand, right hand vs feet and left hand vs feet. We used bipolar montages and common spatial patterns (CSPs) montages. All montages were derived from the original 61 electrodes recorded with respect to the ear-linked reference. A simple bipolar montage consisted of three bipolar electrodes located over the centro-parietal cortex. Common spatial patterns were calculated over two different set of electrodes, namely CSP1 and CSP2. CSP1 consisted of 23 electrodes covering mainly the sensory and motor areas (Fig. 3, dark circles) and CSP2 consisted of 44 electrodes (Fig. 3, dark and grey circles) covering a wider cortical networks involved in pain processing. The number of CSPs in CSP1 varied from 2 to 22 to test the influence of the number of CSPs on the classification accuracy and on a difference in classification accuracies across three groups of participants. While we expected that increasing the number of electrodes used for BCI classifier will improve its classification accuracy we wanted to test whether this improvement will increase proportionally across all three groups.

2.6. Bipolar montage feature selection and classification

Three bipolar montages were derived: C3–P3, C4–P4 and Cz–Pz. A slightly posterior location was chosen because it is known that SCI causes a posterior shift of the area of strongest activity during MI (Kokotilo et al., 2009).

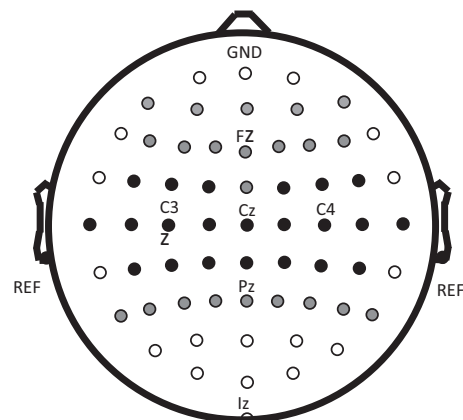


Fig. 3. Location of a smaller set of electrodes used to build a CSP1 classifier (black dots only) and a larger set used to build a CSP2 classifier (black and grey dots). All 61 electrodes (including the ones with white circles) were included when creating ERS/ERD scalp maps.

Signal was filtered in 8–12 Hz and 16–24 Hz bands using an IIR Butterworth filter of the 5th order. Signal was then squared and smoothed/averaged over one second window. The logarithm of the resulting signal was obtained and used for classification. This provided 6 features in total used to build a BCI classifier. Each trial, from $t = 0$ s (an arrow, i.e. the initiation cue appears) till $t = 3$ s (a cross, i.e. the readiness cue disappears) was split into smaller segments of 0.4 s.

Feature classification was performed using a Fisher's Linear Discriminate Analysis (LDA) (Duda et al., 2001). A leave-one-out cross validation procedure was adopted because of a relatively small number of trials. Initial classification was performed on each of the 0.4 s segment to estimate the best performing segment across the trials. LDA classifier was then computed using a training set from the chosen segment. Each trial was assigned a class by classifying each time point in the trial using the LDA classifier. A true positive rate (the ratio of correctly classified trials to the total number of trials) was adopted as a measure of the classification accuracy. Signal processing was performed using the BioSig open source toolboxes (Vidaurre et al., 2011) in MATLAB (Mathworks Inc., USA).

2.7. Common spatial patterns

Before computing CSPs, the recorded signal was band-pass filtered using an IIR Butterworth filter of the 5th order filter between 8 and 30 Hz. The CSP method projects multi-channel EEG data into a low-dimensional spatial sub-space in such a way that the variances of the filtered time series are optimal for discrimination (Müller-Gerking et al., 1999). After computing the spatial filters and using it to filter the signal, the variance of the resultant signal was computed for every time segment of 70 samples (approximately 30 ms) over the whole 3 s trial. Classification was performed in the manner described in methods for bipolar arrangement.

2.8. Statistical analysis of classification results

For each classifier, a two factor 3×3 ANOVA was used to compare classification results between three groups; this was followed by an unpaired *t*-test. The two factors were 'motor imagery types' RH, LH and F and 'groups' were PWP, PNP and AB. A statistical significance was set at $\alpha = 0.05$.

2.9. EEG analysis of motor imagery

Before performing the analysis, EEG data were re-referenced to the average reference. A 'Study' structure was designed in EEGLAB to allow EEG analysis on a group level. 'Groups' were PWP, PNP and AB and 'Conditions' were motor imagery of LH, RH and F.

An extension of the ERS/ERD (Pfurtscheller and da Silva, 1999), called Event Related Spectral Perturbation (ERSP), based on sinusoidal wavelets rather than on filters (Makeig, 1993), was used to allow more precise time–frequency analysis. For calculating the ERS/ERD of each single volunteer a reference period from -1.9 to -1.1 s (before the cross) was adopted, time–frequency decomposition was performed in a frequency range 3–55 Hz using a sinusoidal wavelet with minimum 3 wavelet cycles per data window at lowest frequencies. Overlapping Hanning tappers windows were applied. Signal processing was implemented in EEGLAB.

In order to find regions of significant ERS/ERD for each condition (on a single electrode site), a significance level was set to $p = 0.05$ and nonparametric bootstrapping procedure ($N = 2000$ randomisation) (Blair and Karinski, 1993) was performed, comparing ERS/ERD maps between groups, applying the False Discover Rate (FDR) correction (Benjamini and Yekutieli, 2001). ERS/ERD maps for a single electrode were analysed for the central areas only.

ERS/ERD scalp maps over the whole scalp (61 electrodes in total) were created for three frequency bands: theta (4–8 Hz), alpha (8–12 Hz) and beta (16–24 Hz). Comparison between scalp maps of different groups or conditions was performed based on a permutation statistics ($p = 0.05$), a Monte Carlo method. A correction for multiple comparisons was performed using the FDR. All procedures were implemented in EEGLAB. Spatial analysis was limited to electrode locations defined by 10–10 system (ACNS, 2006).

3. Results

3.1. BCI classification accuracy for bipolar montage

When classification was performed with 3 bipolar channels, the classification accuracies in all groups except PWP was low, just reaching the chance level of 65%. This increased chance level, higher than 50% was adopted to compensate for a small number of trials (Mueller-Putz et al., 2008).

The classification accuracy of AB group was $65 \pm 4\%$, of PNP group was $66 \pm 5\%$ and of PWP group was $70 \pm 7\%$ (Fig. 4a). The ANOVA analysis showed a statistically significant difference for a

factor 'groups' ($p = 0.0188$) and no statistically significant difference for a factor 'motor imagery type' ($p = 0.6302$). There was no statistically significant interaction among these factors ($p = 0.8188$). A *t*-test between groups showed a statistically significant difference in the classification accuracy between PWP and PNP group ($p = 0.0211$) and between AB and PWP group ($p = 0.009$) but no statistically significant difference between AB and PNP group ($p = 0.7413$).

3.2. BCI classification accuracy for CSP montages

Classification was performed with CSPs based on two different numbers of electrodes. Classifier CSP1 was based on 23 electrodes and a variable number of CSPs. A classifier CSP2 was based on 44 electrodes and 20 CSP; the number of CSPs was chosen to maximise the overall classification accuracy.

For CSP1 a detailed analysis showing classification results between each pair of limbs for each subject was performed on two representative CSPs, CSP1A (4 CSP) and CSP1B (14 CSP). CSP1A was based on 4 CSP which is a configuration often used for BCI (Müller-Gerking et al., 1999) while CSP1B was based on 14 CSP, which is a configuration that achieved the highest overall classification accuracy. Classification results are shown in Fig. 4b for CSP1A and in Fig. 4c for CSP1B.

When classifier was based on a configuration with only 4 common spatial patterns (Fig. 4b), the average BCI classification accuracy for PWP group was $74 \pm 9\%$ which was comparable with the average classification accuracy for AB group of $74 \pm 7\%$ and was higher than the classification accuracy for the PNP group of $69 \pm 8\%$. The ANOVA analysis showed a statistically significant difference for the factor 'groups' ($p = 0.433$) and no statistically significant difference for a factor 'motor imagery type' ($p = 0.878$). There was no statistically significant interaction among the two factors ($p = 0.682$). A *t*-test between groups showed a statistically significant difference in the average classification accuracy between PWP and PNP group ($p = 0.0335$) and between AB and PNP group ($p = 0.0343$), but no statistically significant difference between AB and PWP group ($p = 0.808$).

When the number of common spatial patterns increased to 14 (Fig. 4c), the average BCI classification accuracy for PWP group was $78 \pm 9\%$ which was comparable with the average classification accuracy for AB group of $76 \pm 5\%$ and was higher than the classification accuracy for the PNP group of $73 \pm 7\%$ (Fig. 4c). The ANOVA analysis showed a statistically significant difference for the factor 'groups' ($p = 0.02$) and no statistically significant difference for a factor 'motor imagery type' ($p = 0.8621$). There was no statistically significant interaction among the two factors ($p = 0.682$). A *t*-test between groups showed a statistically significant difference in the average classification accuracy between PWP and PNP group ($p = 0.0018$) and between AB and PNP group ($p = 0.0286$), but no statistically significant difference between AB and PWP group ($p = 0.1927$).

When CSPs were computed with CSP2 (44 electrodes, 20 CSP filters), including the frontal and the parietal cortex, the classification accuracy increased in all three groups but previously observed difference across groups remained. A classification accuracy of $82 \pm 7\%$ for PWP group was very similar to the classification accuracy of $82 \pm 4\%$ for AB group and was higher than the classification accuracy of $78 \pm 5\%$ for PNP group (Fig. 4d).

The ANOVA analysis showed a statistically significant difference for a factor 'groups' ($p = 0.0118$) and no statistically significant difference for a factor 'motor imagery type' ($p = 0.6774$). There was no statistically significant interaction among the two factors ($p = 0.3576$). A *t*-test between groups showed a statistically significant difference in a classification accuracy between PWP and PNP groups ($p = 0.0135$) and between AB and PNP groups ($p = 0.0030$).

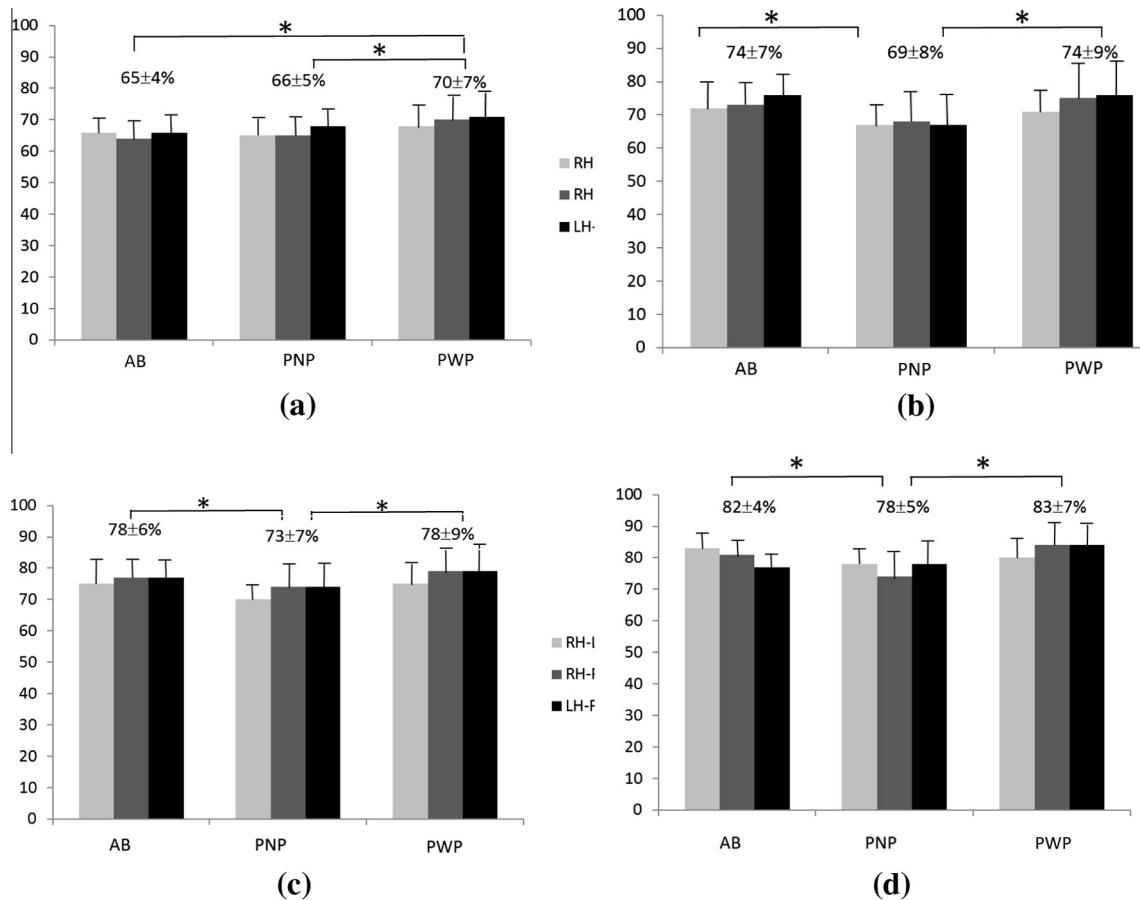


Fig. 4. Classification accuracy (mean \pm STD) between two different limbs for all three groups of volunteers using bipolar montage (Fig. 3a), CSP1A (Fig. 3b), CSP1B (Fig. 3c) and CSP2 (Fig. 3d). The numbers above bars show mean values for a single group. Abbreviations: RH: right hand; LH: left hand; F: feet; AB: able bodied; PNP: patients with no pain; PWP: patients with central neuropathic pain.

and no statistically significant difference between AB and PWP groups ($p = 0.713$).

To further investigate the consistency between classification accuracies of PWP and PNP groups, a graph is produced showing classification accuracies for all three groups for CSP1 based on 23 central electrodes (Fig. 5) for the variable number of common spatial patterns ranging from 2 to 22. Results show that the overall maximal classification accuracy for all three groups is achieved for 14 CSPs. Statistically significant differences between classification accuracies of PNP and PWP group was achieved for 8 out of 11 CSPs configurations while statistically significant difference between AB and PNP group was achieved for 9 out of 11 CSPs. None of the 11 classifiers showed a statistically significant difference in classification accuracy between AB and PWP groups.

To summarise, for all classifiers PNP group had significantly lower classification accuracies than the other two groups. There was no statistically significant difference in classification accuracy of MI of different limbs.

Two patients from PWP group reported increased pain in their legs and one patient from PNP group reported an unpleasant tingling sensation (i.e. paraesthesia) in their legs. The exact pain level was however not measured, as this was an unexpected result at the time of the experiment.

3.3. Analysis of ERS/ERD maps

Fig. 6a shows ERS/ERD maps at the electrode location C3 for MI of the right hand, at Cz for MI of the feet and at C4 for MI of the left hand. These electrodes are located approximately over the primary

motor cortex, as being most representative for a chosen limb, though a single EEG electrode might record the electrical activity of several sources. The column on the right shows the areas of statistically significant differences among the groups. The largest differences among 3 groups can be noticed for MI of the right hand in the alpha band, sustained over the whole periods of MI. Fig. 6b shows the areas of statistically significant differences between each pair (AB vs PNP, AB vs PWP and PWP vs PNP). This widely adopted presentation method does not however show which group has stronger activity, so its interpretation requires simultaneous observation of ERS/ERD maps (Fig. 6a). Largest differences, spread over a range of frequency bands, can be noticed between PWP and PNP group across the theta, alpha and beta band for all three types of MI. These differences are caused by stronger ERD in PWP group (Fig. 6a). Differences between PWP and AB group, caused by stronger ERD in PWP group, could be noticed two distinctive bands (alpha/theta and higher beta). A smaller difference, mostly in the alpha band (stronger in AB group) can be noticed between AB and PNP; being most pronounced for MI of the left hand.

Fig. 7a shows scalp maps during MI of feet in the theta, alpha and beta (16–24 Hz) band, averaged over the period of maximum ERD from $t = 0.4$ to 0.8 s post cue. Fig. 7b shows the spatial distribution of statistically significant differences between ERS/ERD of different groups during MI for maps shown in Fig. 7a. Location of the dots in Fig. 7b correspond to 10–10 electrode location used in the study, where only statistically significant differences between groups are shown by bold dots. PWP group had the largest and spatially distinctive ERD in all three frequency bands. They

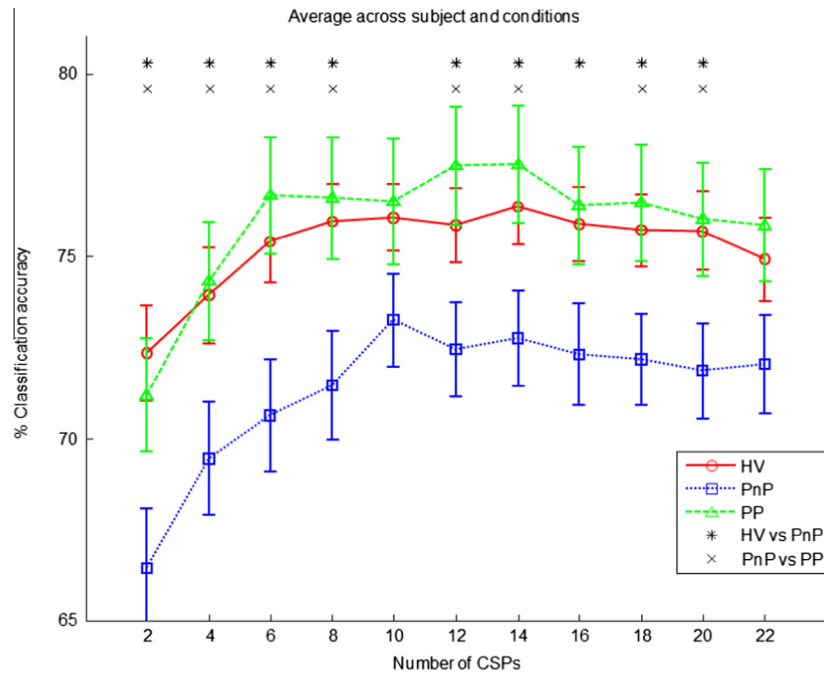


Fig. 5. Averaged classification accuracy for all combinations of limbs (mean \pm SE) for CSP1A (23 electrodes) with the variable number of CSP. *Abbreviations:* AB: able bodied; PnP: patients with no pain; PWP: patients with central neuropathic pain.

had significantly stronger ERD than PnP group in the theta and alpha band, the later being restricted to the centro-parietal region (Fig. 7b). Compared to AB group, PWP group had a statistically significant difference in ERS/ERD scalp maps in the alpha and beta band at several electrode locations at the central, frontal and parietal cortex. No surface cortical region showed statistically significant differences between AB and PnP groups in any band.

4. Discussion

This study investigated the influence of central neuropathic pain on the performance of a MI based BCI classifier in patients with spinal cord injury and the relationship between BCI classifier performance and the intensity of ERD during MI. Central neuropathic pain increased event related desynchronisation during motor imagery and also improved BCI classification accuracy.

4.1. Classification results

For classifiers based on CSPs, PWP group had a comparable level of classification accuracy with AB group, independent of the number of EEG channels or the derived CSPs. For a configuration with only three bipolar channels PWP had a better classification accuracy than the other two groups. PnP group had lowest classification accuracy of all three groups for all classifiers. Of interest is a result that PWP group had a significantly higher classification accuracy than PnP even when only three centrally placed bipolar channels were used. This indicates that the area of largest differences between PWP and the other two groups is located in the centro-parietal region of the cortex as this was the only cortical area included in both CSP and in a bipolar montage. That was also confirmed by ERD analysis (Fig. 7b) which showed largest differences between PWP and PnP groups in the alpha band in the centro-parietal region.

In a detailed ERS/ERD study performed on same three groups of participants (Vuckovic et al., 2014) we showed that PWP group, that had strongest ERD, had the largest number of electrodes loca-

tion with a statistically significant difference in ERD between three MI tasks. As a consequence, in this study when we applied a BCI classifier, PWP group had better classification accuracy than PnP group, in particular with CSP which can select optimal electrode location.

Increasing the number of electrodes improved classification accuracy but did not influence a difference in classification accuracy across groups. We used two sets of electrodes to cover both the sensory and motor cortex, because pain as a sensory phenomenon was expected to influence primarily the sensory area. However results showing a relation between classification accuracy among three groups are independent of the number of electrodes and of the number of CSP used for classification.

Our classification results obtained with PnP group based on CSP1A (with 4 CSP) are comparable with results of a study by Pfurtscheller et al. (2009) who used CSP to classify imaginary movements in chronic paraplegic patients. In the current study, a classification accuracy increased with the increasing number of CSP only up to a certain number of common spatial patterns, after which classification accuracy decreases with increasing the number of CSP. By definition, the first few CSP are the most discriminable between groups (Müller-Gerking et al., 1999). Too large number of CSP possibly resulted in 'over fitting' the classifier to the training set, reducing its ability to generalise classification on data from the testing set.

Of interest is the observation that there was no statistically significant difference in classification accuracy between different limbs. While all three groups had functional arms and hands, PnP group had paralysed legs and lower abdomen while PWP group had paralysis combined with pain in their legs. PWP had increased ERD response for all three types of motor imagery, not only for MI of feet, that could explain why classification between feet and one of the hands was comparable to classification between both hands. PnP had weaker ERD responses for MI of all limbs. Previous studies on spinal cord injured patients with no pain (Pfurtscheller et al., 2009) and on able-bodied people (Pfurtscheller et al., 2006) showed slightly better classification between MI of feet and a hand than between MI of two hands. They

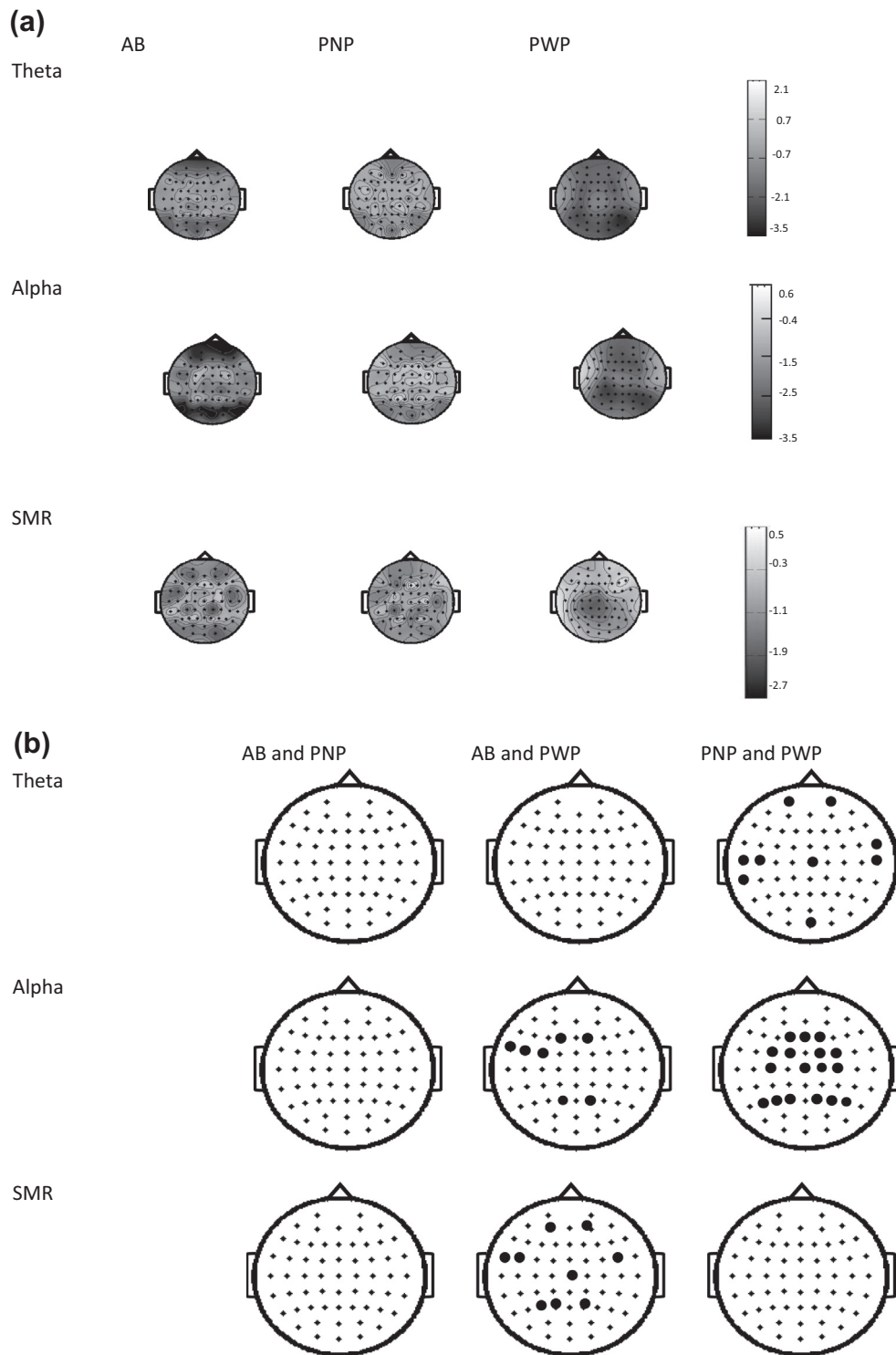


Fig. 6. ERS/ERD maps over the central cortical area during MI (a) ERS/ERD maps for motor imagery of different limbs over the electrode locations C3 for the right hand, Cz for feet and C4 for the left hand. Dashed lines at $t = -1$ s show a moment when a readiness cue appeared at the screen while a vertical solid line at $t = 0$ s shows a moment when the initiation cue appeared on the screen. Positive numbers are for ERS and negative for ERD. A column to the right shows areas of statistically significant differences among the groups. (b) Areas of statistically significant differences between ERS/ERD maps between different groups, shown in Fig. 5a.

explained it by ‘focal ERD/surround ERS’ phenomena, often noticed during imagined movement of feet (also noticed in Vuckovic et al. (2014)) that might facilitate detection of MI of feet. In addition to this, results from the literature (Tran et al., 2004; Boord et al., 2008; Jensen et al., 2013) showed that both paralysis and pain have global effect on EEG which spreads beyond the cortical presentation of the paralysed/painful limbs.

4.2. Event related synchronisation/desynchronisation

The analysis of event related desynchronisation showed that PWP has stronger ERD than the other two groups over the central electrode locations for MI of both painful and non-painful limbs. Results of ERS/ERD analyses support BCI classification results showing significantly higher classification accuracy in PWP than

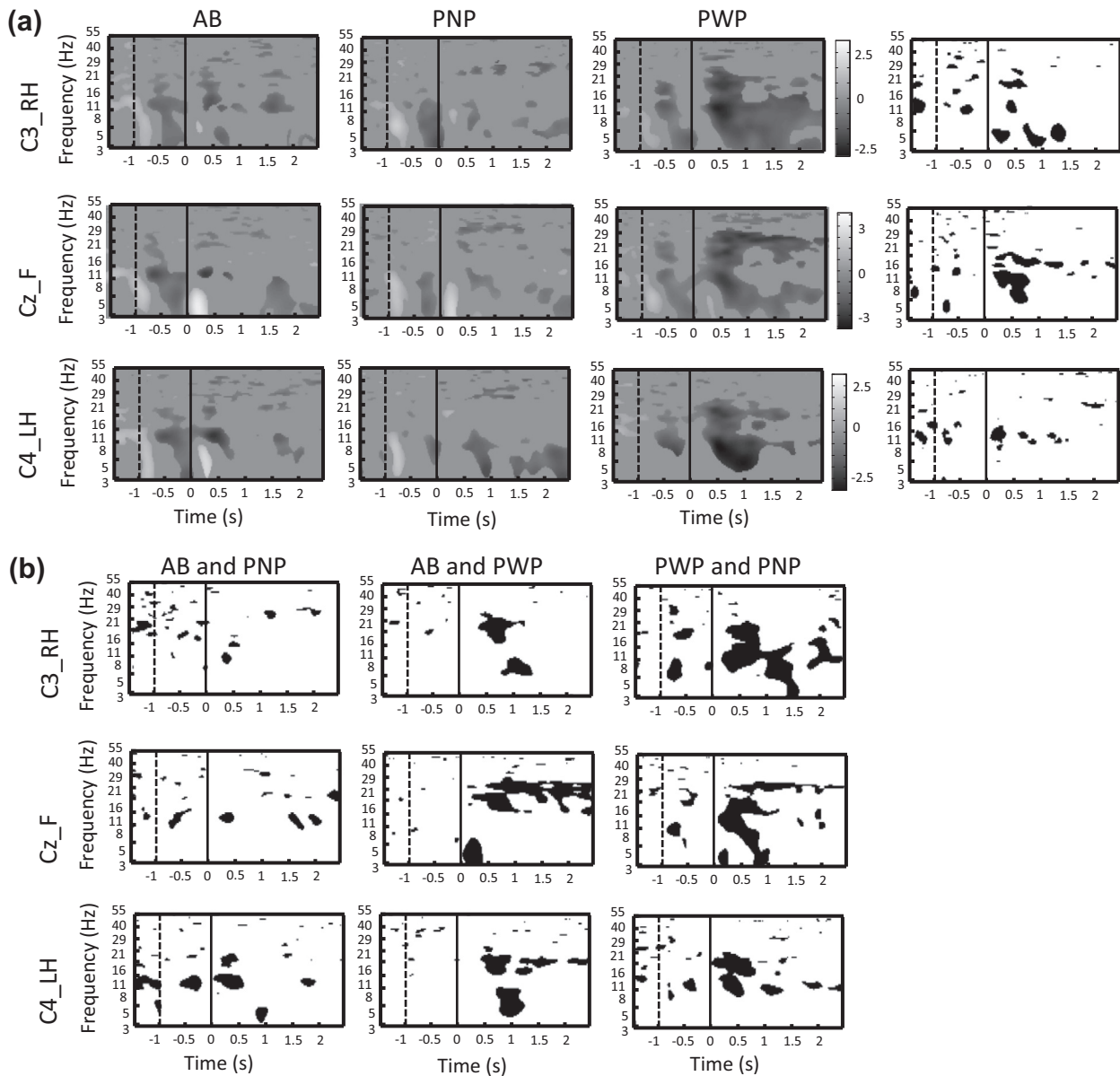


Fig. 7. Scalp maps of ERS/ERD during MI of feet for three groups of participants. (a) Averaged scalp maps over a period $t = 0.4$ s to 0.8 s post cue. Upper row is for the theta band, middle row is for the alpha band and the lower row is for the beta band. (b) Marked electrode locations shows areas of statistically significant differences between groups for three different frequency bands. *Abbreviations:* AB: able-bodied; PNP: patients with no pain; PWP: patients with central neuropathic pain.

in PNP group. In this study it was not possible to separate the effect of paralysis (including both sensory and motor impairments) and CNP, because all CNP patients were also paraplegic. However distinctive results in PNP and PWP groups suggest that brain signatures of CNP do not simply present the exaggerated brain signature of paralysis. This can appear contradictory to fMRI studies showing that in amputees and patients with spinal cord injury the extent of cortical reorganisation caused by the injury is proportional to the intensity of pain (Flor, 2002; Gustin et al., 2010a; Wrigley et al., 2009). Although the number of patients in this study was relatively small, results are more in favour of a recent hypothesis (Makin et al., 2013) that sensory-motor loss and CNP caused by that loss produce distinctive brain responses. We believe that this is observation that requires attention and further investigation on the larger number of patients, ideally involving a group of patients with CNP and no sensory-motor deficit.

Interestingly, although ERD in AB group seem to be of a comparable intensity to PNP and was weaker than of PWP group, all CSP

classifiers showed higher classification accuracy for AB than for PNP group. Results of bipolar classifier are in line with the analysis of ERS/ERP showing highest classification accuracy for PWP group. Classifiers in this study were limited to 8–30 Hz that covers both sensory-motor rhythms in able-bodied people (8–12 Hz and 16–24 Hz, Pfuertscheller and da Silva, 1999) and was previously used for building CSP in similar studies on paraplegic patients (Pfuertscheller et al., 2009). It is possible that more discriminative results between groups would be achieved if the theta band was also used, as both single electrode analysis and scalp maps analysis indicate significant differences between PWP and PNP group in this frequency band.

4.3. Influence of medication for treatment of CNP on baseline EEG

Most of participants in PWP group used antiepileptic or antidepressant drugs as a part of their pharmacological treatment of pain. Antiepileptic drugs are known to increase resting state EEG in the

theta band (Olbrich and Ams, 2013) while antidepressants increase EEG amplitude in the theta and higher beta (>20 Hz) range (Bauer and Bauer, 2005; Wauquier, 2005). This might influence the intensity of ERD during motor imagery, but for this study, theta band was not included in analysis, thus reducing the influence of the drugs on the results of the study. Therefore, although inclusion of the theta band, believed to be a signature of CNP, would potentially improve performance of BCI classifier in PWP group, it would be hard to distinguish to which extent this is due to pain and to which extent due to medications.

It is believed that increased theta band power is related to thalamo-cortical dysrhythmia (Sarnthein and Jeanmonod, 2008), and the shift of the dominant alpha frequency towards the theta band (Boord et al., 2008; Sarnthein et al., 2006; Stern et al., 2006; Jensen et al., 2013; Vuckovic et al., 2014). Patients with CNP who underwent a surgery involving a therapeutic lesion of the thalamus, reported reduction of pain that was accompanied with reduction of theta band power (Sarnthein et al., 2006).

Better classification accuracy in paraplegic patients with CNP might not directly imply that these patients are potentially better candidates for MI based BCI. In a study by Gustin et al. (2008) six out of seven tested patients with SCI and CNP reported increased pain after practicing of pressing an imaginary car gas pedal for a period of a week. Incidental finding of this study also indicate that some patients may experience discomfort already during first MI sessions.

CNP is related to the lack of sensory information coming from the body (Haanpaa et al., 2011) and occurs months or years after an injury (Siddall et al., 2003; Haanpaa et al., 2011). It is therefore likely that immediately after the injury patients would have minimal CNP symptoms. MI based BCI has been proposed as a rehabilitation therapy for SCI (Dobkin, 2007; Daly et al., 2009; Tam et al., 2011; Onose et al., 2012; Roset et al., 2013). A therapy based on MI BCI would aid improvement of the sensory-motor functions thus hopefully preventing CNP. Therefore MI based BCI might be a strategy better suited for rehabilitation, especially shortly after injury, than for communication and control in long term, later after injury.

At present, due to the lack of recognition of the correlation between CNP and the activity of the motor cortex, patients are typically not assessed for pain before being recruited for a BCI study. We suggest that in future pain status pre and post motor imagination may require monitoring.

5. Conclusion

Central neuropathic pain in SCI patients affects the performance of BCI classifiers and increases the amplitude of ERD over the sensory-motor cortex during motor imagery. Higher classification accuracy in paraplegic patients with pain compared to patients with no pain was independent on the type of classifier and on the number of recording electrodes used to create a classifier. Higher classification accuracy existed independently whether the classifier was based on MI of painful or non-painful limbs, indicating globally modified cortical activity.

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