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Synchronization of Slow Cortical Rhythms During Motor Imagery-Based Brain–Machine Interface Control

Juan A. Barios*,§, Santiago Ezquerro*, Arturo Bertomeu-Motos*,
Marius Nann†, Fco. Javier Badesa*, Eduardo Fernandez*,
Surjo R. Soekadar†,‡ and Nicolas Garcia-Aracil*

*Biomedical Neuroengineering Research Group (nBio)
Systems Engineering and Automation
Department of Miguel Hernández University
Avda. de la Universidad s/n 03202 Elche, Spain

†University Hospital of Tuebingen, Applied Neurotechnology Lab
Department of Psychiatry and Psychotherapy
Calwerstr. 14, 72076 Tuebingen, Germany

‡Clinical Neurotechnology Laboratory
Neuroscience Research Center (NWFZ)
Department of Psychiatry and Psychotherapy
Charite University Medicine Berlin, Berlin, Germany
§jbarios@umh.es

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Modulation of sensorimotor rhythm (SMR) power, a rhythmic brain oscillation physiologically linked to motor imagery, is a popular Brain–Machine Interface (BMI) paradigm, but its interplay with slower cortical rhythms, also involved in movement preparation and cognitive processing, is not entirely understood. In this study, we evaluated the changes in phase and power of slow cortical activity in delta and theta bands, during a motor imagery task controlled by an SMR-based BMI system. In Experiment I, EEG of 20 right-handed healthy volunteers was recorded performing a motor-imagery task using an SMR-based BMI controlling a visual animation, and during task-free intervals. In Experiment II, 10 subjects were evaluated along five daily sessions, while BMI-controlling same visual animation, a buzzer, and a robotic hand exoskeleton. In both experiments, feedback received from the controlled device was proportional to SMR power (11–14 Hz) detected by a real-time EEG-based system. Synchronization of slow EEG frequencies along the trials was evaluated using inter-trial-phase coherence (ITPC). Results: cortical oscillations of EEG in delta and theta frequencies synchronized at the onset and at the end of both active and task-free trials; ITPC was significantly modulated by feedback sensory modality received during the tasks; and ITPC synchronization progressively increased along the training. These findings suggest that phase-locking of slow rhythms and resetting by sensory afferences might be a functionally relevant mechanism in cortical control of motor function. We propose that analysis of phase synchronization of slow cortical rhythms might also improve identification of temporal edges in BMI tasks and might help to develop physiological markers for identification of context task switching and practice-related changes in brain function, with potentially important implications for design and monitoring of motor imagery-based BMI systems, an emerging tool in neurorehabilitation of stroke.

Keywords: Slow rhythms; synchronization; EEG; coherence; motor imagery; BMI.

§Corresponding author.

1. Introduction

Brain–Machine Interfaces (BMI) translate neuronal information, usually recorded by electroencephalography (EEG), into control signals of external devices. Several types of oscillatory activity in the brain can be used: evoked oscillations (e.g. steady-state-visually-evoked potentials), event-related potentials (e.g. P300 response), or task-related modulation of spontaneous EEG oscillations. In the past few decades, the main topic in BMI research was communication, specially in severely disabled patients. Recently, BMI-based applications in rehabilitation have attracted great attention, specially in stroke, where promising results have been reported.[1–4]

A successful BMI paradigm has been mainly focused on changes of sensorimotor EEG rhythms, modulated during motor imagery.[5–7] Sensory, cognitive and motor processing can result in changes of the ongoing EEG in form of an event-related desynchronization (ERD) or event-related synchronization (ERS). Unilateral voluntary upper limb movement is accompanied by an ERD in the alpha (originally, the ERD term was coined in this frequency) and beta bands localized over the contralateral sensorimotor area. Both phenomena are time-locked but not phase-locked to the event and they are highly frequency-band specific,[8] facilitating real-time detection in BMI systems.

Slow cortical oscillations in δ frequency, classically associated with slow-wave sleep and anesthesia,[9] also play a relevant role in wake cognitive processes (for review, see Refs. 10 and 11), mainly in decision-making and attentional processes, both in animal[12,13] and humans.[14–16] Slow rhythms are also related to task-switching and general preparation processes, showing different spatial activation and time courses.[17]

Interest in slow cortical rhythms is renewing in the BMI field, although, in fact, cortical slow rhythms have been used for BMI control[18,19] for a long time now. Since Kornhuber and Deecke (1964) discovered the Bereitschaftspotential (Readiness Potential) preceding volitional movements in humans, a number of studies investigated the physiological and functional substrates of cortical slow rhythms involved in movement preparation, and were described in early descriptions of EEG activity before volitional movements[20,21] that later became summarized under the term movement-related cortical potentials (MRCP).[22] However, the physiological significance of each identifiable MRCP component has not been fully understood yet,[20,23] and a better understanding of the underlying mechanisms of MRCP will be important for improving single-trial BMI paradigms.[24–26] Information obtained from phase and synchronization of slow rhythms during motor tasks might be useful for BMI control,[27] because phase of cortical slow rhythms may contain relevant movement-related information,[26,28–31] and delta activity carries information about hand or arm kinematics (position and velocity).[32]

For extracting phase-based information from brain signals, providing information about timing of frequency-band-specific activity, several techniques are being used. Kolev *et al.*[33] used single-sweep wave identification histograms to analyze phase-locking. Tallon-Baudry *et al.*[34] defined a method called phase-locking factor, while a practical method for evaluation of spatial phase coherence was introduced by Lachaux.[35] Event-related phase consistency across trials is an important method allowing to see how phase information varies between trials. Delorme *et al.* introduced a method called inter-trial phase coherence (ITPC), implementing it in a freely distributed software.[36]

Experimental paradigms in BMI usually include several tasks that BMI-users have to complete sequentially, changing the state of movement and brain activity at temporal edges of the trials. Recently, phase locking in the δ–θ frequency bands related to the initiation of motor tasks has been described,[37,38] which might be a relevant mechanism of cortical function at temporal edges of a task.

In the current study, we decided to evaluate whether analysis of phase information from cortical slow rhythms during a motor imagery-based BMI control paradigm, in basal conditions and under sensory modulation, might increase our knowledge about EEG-correlates of task switching and about temporal structure, e.g. onset and ending of the trials. These objectives might aid in developing valuable measures to improve reliability and safety of BMI control, and for improving BMI-based tools for neurorehabilitation of stroke.

2. Material and Methods

2.1. *Study design*

2.1.1. *Participants*

A total of thirty healthy volunteers participated in this study. EEG human recordings used in this study were approved by the ethics committee of the Miguel Hernández University of Elche, Spain. All participants gave written informed consent before the session. Subjects were naive for BMI systems and right-handedness, because the motorized orthosis was designed for the right hand, so left-handedness or with some alteration of the comprehension subjects were excluded.

2.1.2. *Description of the experiments*

Participants were invited to collaborate in 1-h experimental sessions, in the context of a BMI project with objectives including the design and implementation of an inexpensive and simple to use BMI-controlled motorized exoskeleton. Sessions were distributed in two independent experiments with different subjects (experiments I and II). Experiment I (20 subjects) was performed in a 1-h unique session and included only the Visual task. Experiment II (10 independent subjects) included 1-h sessions in five successive training days. All the sessions began with Visual task, and in days 4 and 5 also included Haptic and Auditory tasks performed in random order. The motorized orthosis used in experiment II has been developed by the Biomedical Neuroengineering research group (*nBio*) at the Miguel Hernández University[39] 1).

2.2. *Description of the tasks*

After a 15 min guided relaxation session, a detailed explanation of the experiment, and the attachment of the electrodes, participants were instructed to use visuo-kinesthetic motor imagery (MI) of moving their right hand to generate contralateral ERD (CLOSE task) or rest (RELAX task) following a visual cue (a white text label on a black screen, saying RELAX or CLOSE, respectively) displayed on a computer screen. Subjects were asked to avoid blinking during the trial, intending to gaze at the center of the screen. Visual indications were separated by inter-trial-intervals (ITIs) of 5 s.

Visual task: Composed of 20 trials (10 RELAX, 10 CLOSE, in randomized order). In this task, two cues appeared, *Close*, indicating onset of motor imagery, or *Relax*, where the participants were instructed to keep quiet. A *Pacman* animation appeared on the black screen acting as a visual feedback of SMR (the mouth of animation kept opening while the online BMI system detected an ERD; see Fig. 1(c)). This task was performed in experiments I and II. For this task, that was always performed before the other two, we considered that first session of experiment II (10 subjects) and unique session of experiment I (20 subjects) were analogue: subjects were of similar age, setup and tasks were identical, basal condition of the subjects were also the same (naive), and statistical differences in studied parameters were not found, so results of the 30 subjects were pooled for the visual task.

Haptic task: Same setup than Visual task, but SMR feedback was indicated only by movement of the motorized orthosis attached to right arm, without animation in the screen, asking to the subject to avoid looking to the arm. After the end of the CLOSE trials, motorized orthosis had to reopen again, passively moving the hand to the subject during 1-2 s. This task was performed only in experiment II.

Auditory task: Same setup than Visual task, but SMR feedback was indicated by noise produced by a buzzer in the motorized orthosis, situated outside the visual field of the subject. After the end of the CLOSE trials, motorized orthosis had to open again, producing an audible sound for 1–2 s. This task was performed only in experiment II.

2.3. *EEG recording*

Subjects sat in a comfortable chair, facing a computer monitor that displayed the trial-based paradigm. Because of the objectives of the ongoing project, oriented to the design and implementation of a simple to use BMI system, only SMR brain oscillatory activity of contralateral hemisphere to the orthosis was obtained, so EEG was recorded only from five conventional EEG recording sites (F3, T7, CZ, C3 and P3 according to the international

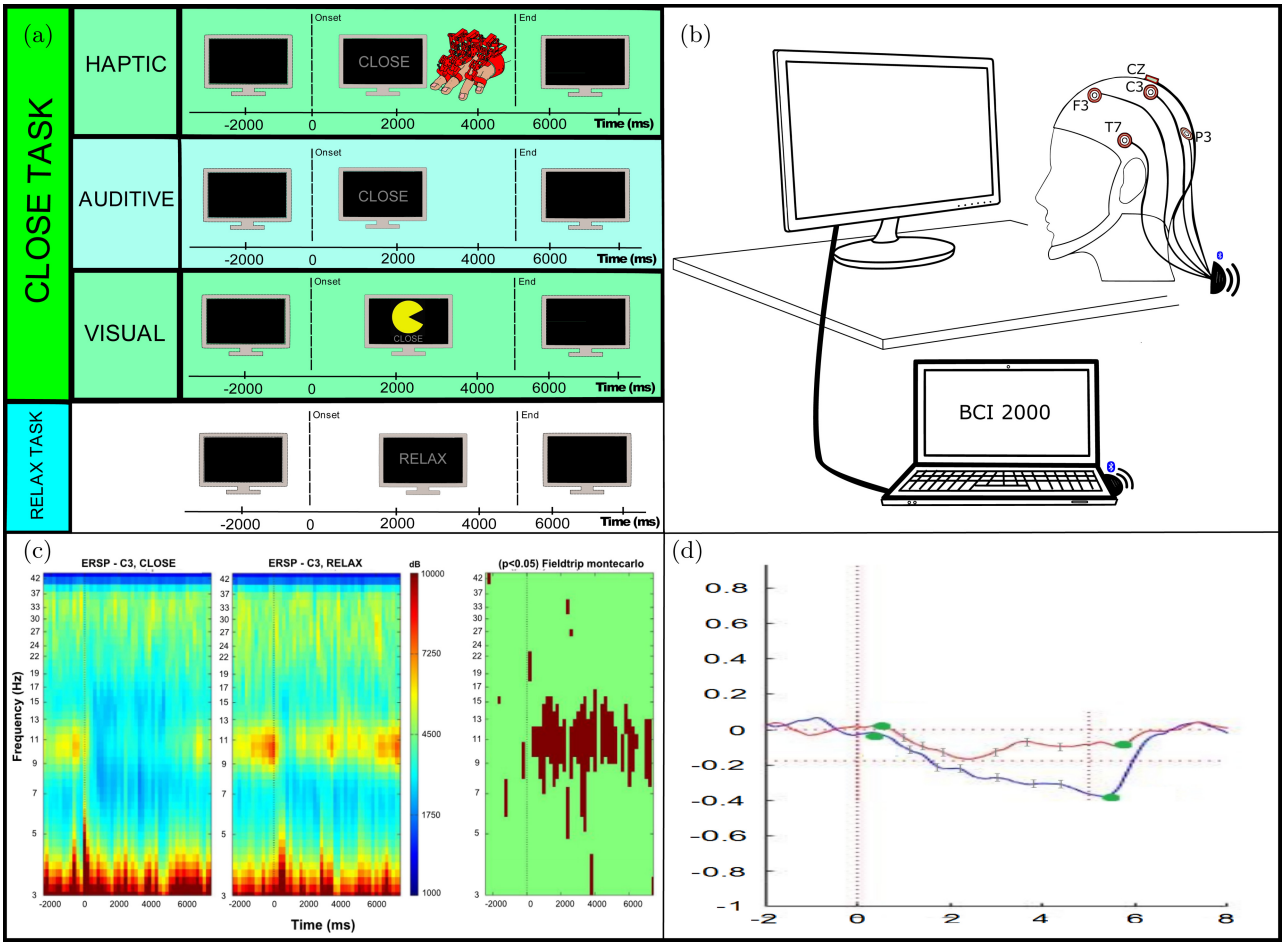

Fig. 1. Graphical summary of the experimental setup. (a) Graphical description of the tasks and stimulation modalities. (b) Elements used in the experiments. (c) Example from a subject of event-related desynchronization (ERD) of electroencephalographic (EEG) sensorimotor rhythm activity (SMR, 8–15 Hz) during a CLOSE (left part) and RELAX trial (right part). (d) Calculation of threshold.

10/10 system) using an EEG neoprene cap (Enobio, Neuroelectrics, Barcelona, Spain) with a reference electrode placed at Fz. Skin/electrode resistance was kept below 12 kOhm. EEG was recorded at a sampling rate of 200 Hz, bandpass filtered at 0.4–70 Hz and pre-processed using a small Laplacian filter. Horizontal eye movements were recorded by electrooculography (EOG) in accordance to the standard EOG placement at the left and right outer canthus 1. For EOG calibration, participants were asked to look to the left or right in analogy to Soekadar *et al.*[7]

2.4. *Description of the BMI system*

Biosignals recorded by EEG and EOG were used to control the SMR-based BMI system during all the experiments. A real-time system was implemented using BCI2000, a freely distributed software platform that consists of four modules (source, signal processing, user application, and operator interface) and incorporates customizable signal filtering as well as extraction of signal features for translation into device control signals. Computation of ERD involved the power spectrum estimation (an autoregressive model of order 16 using the Yule-Walker algorithm implemented by signal processing module of BCI2000) of the ongoing EEG signal associated with the specified SMR rhythm frequency range (1114 Hz) during the tasks, calculated from C3 electrode. Based on the maximum values for basal ERD, a subject's individual motor imagery and EOG discrimination threshold were set at two-standard deviations above average SMR-ERD variance at rest, and used for later online BMI control, calculated

after the end of the calibration task. Calibration of the BMI system and calculation of threshold was performed once at the beginning of the session and kept unvaried for the rest of the session. Through the use of an interface that the user controlled using EOG, the system controlled several external devices: an animation in a computer monitor, a buzzer, and a robotic hand exoskeleton.[39]

2.5. *Processing of recordings*

A number of pre-processing steps were performed after recording and storing of EEG data. First, after band-pass filtering in the frequency band 0.5–48 Hz (to avoid aliasing artifacts), EEG was down-sampled from 500 to 128 Hz. Next, the raw EEG data were visually inspected for paroxysmal and muscular artifacts not related to eye blinks so that noisy portions of the EEG signal were excluded from further analysis. In the next step, the EEG recordings were segmented to single trials, i.e. they were subdivided into intervals of 11 s, from 3 s before the visual cue marking the onset of task to 8 s after, and 3 s after the second visual stimulus marking the end of the task. The length of the EEG epochs (−3 to 8 s) encompassed time points beyond the period of interest in order to include sufficient data before and after the edges of the period of interest (0 and 5 s related to the onset of the task). The reference point (time zero) was assigned to the start of the visual stimulus (text label on screen). In this way, both conditions (RELAX and CLOSE) could be compared. The length of the intervals before and after the reference point was chosen such as to take the length (approx. 2 s) of the MRCP. After subdividing the data into single trials, they were further corrected for artifacts. All trials with an amplitude larger than 100 uV in any of the recorded channels or showing a drift that exceeded 75 uV over the whole interval (abnormal drift) were automatically rejected. Trials with other artifacts (blinks, eye movements, muscle activity, and infrequent single-channel noise) were identified and trials rejected by means of visual inspection of data aided by simultaneous presentation of results obtained by the EEGLAB plugin *adjust*, an algorithm that identifies artifacts-containing components combining stereotyped artifact-specific spatial and temporal features of ICA.[40] ICA was calculated with the Info-Max ICA algorithm implemented in EEGLAB. Finally, the trials were baseline-corrected taking the first 500 ms of each interval as baseline. In order to improve the spatial resolution and to eliminate the influence of distortions due to the reference electrode, we used the *common average* montage.[41,42]

2.5.1. *Calculation of ITPC*

An important indicator of the phase dynamics between trials is the ITPC. ITPC is a frequency-domain measure of the partial or exact synchronization of activity at a particular latency and frequency to a set of experimental events to which EEG data trials are time locked. The measure was introduced in Ref. 34 and termed as phase locking factor', a concept related to the extent to which a distribution of phase angles at a time point is non-uniformly distributed in polar space.[43] The ITPC measure takes values between 0 and 1. A value of 0 (not expected in practice based on a finite number of epochs) represents absence of synchronization between EEG data and the time-locking events; a value near 1 indicates their perfect synchronization (i.e. near perfect EEG phase reproducibility across trials at a given latency). For calculation, instantaneous phase and power for each frequency were calculated applying a complex Morlet wavelet analysis to the EEG epochs time locked to the cue onset. Then, a complex vector of amplitude = 1 and phase $\phi(t)$ of the signal is first averaged across all the trials $(1 \ldots \mathrm{Tr})$ and then normalized as follows

$$\mathrm{ITPC}(t) = \mathrm{Tr}^{-1} \left\| \sum_{1}^{\mathrm{Tr}} e^{i\phi(t)} \right\|.$$

Thus, ITPC measures the degree of intertrial variation in phase between the responses to stimuli and thereby quantifies phase locking of the oscillatory activity irrespective of its amplitude. Band-power and ITPC were computed for all recorded channels (electrodes) in the frequency range from 2 to 48 Hz. For preprocessing and analysis of the EEG data, we used the EEGLAB toolbox[36] and in-house scripts developed in Matlab R2016b (MathWorks Inc.).

2.6. *Statistical procedures*

All statistical analyses were performed using the *R* package[44] and statistic methods included in

EEGLAB. All results are reported as the mean ± SD, and considered significant if $p < 0.05$. For evaluation of significant differences between groups, Wilcoxon rank sum test was used. For comparison of bandpower in EEG, permutation methods with Bonferroni correction were used, as implemented in EEGLAB toolbox.

3. Results

3.1. *Classification accuracy*

Average classification accuracy in CLOSE trials for the three experiments (a two-choice task) was 72.4 ± 0.46. In experiment II, we also compared performance between session 1 and 4 (in session 5, some subjects would have already used the exoskeleton, what might modify basal conditions) and we did not find significant differences (72.4 ± 0.4 and 72.3 ± 0.4 respectively, $p = 0.78$).

3.2. *Amplitude dynamics*

First, we investigated the amplitudes (power) of the wavelet transforms near the onset of the task. Our results match with previous reports on ERD during motor imagery[6] (see Fig. 2), and as was expected we

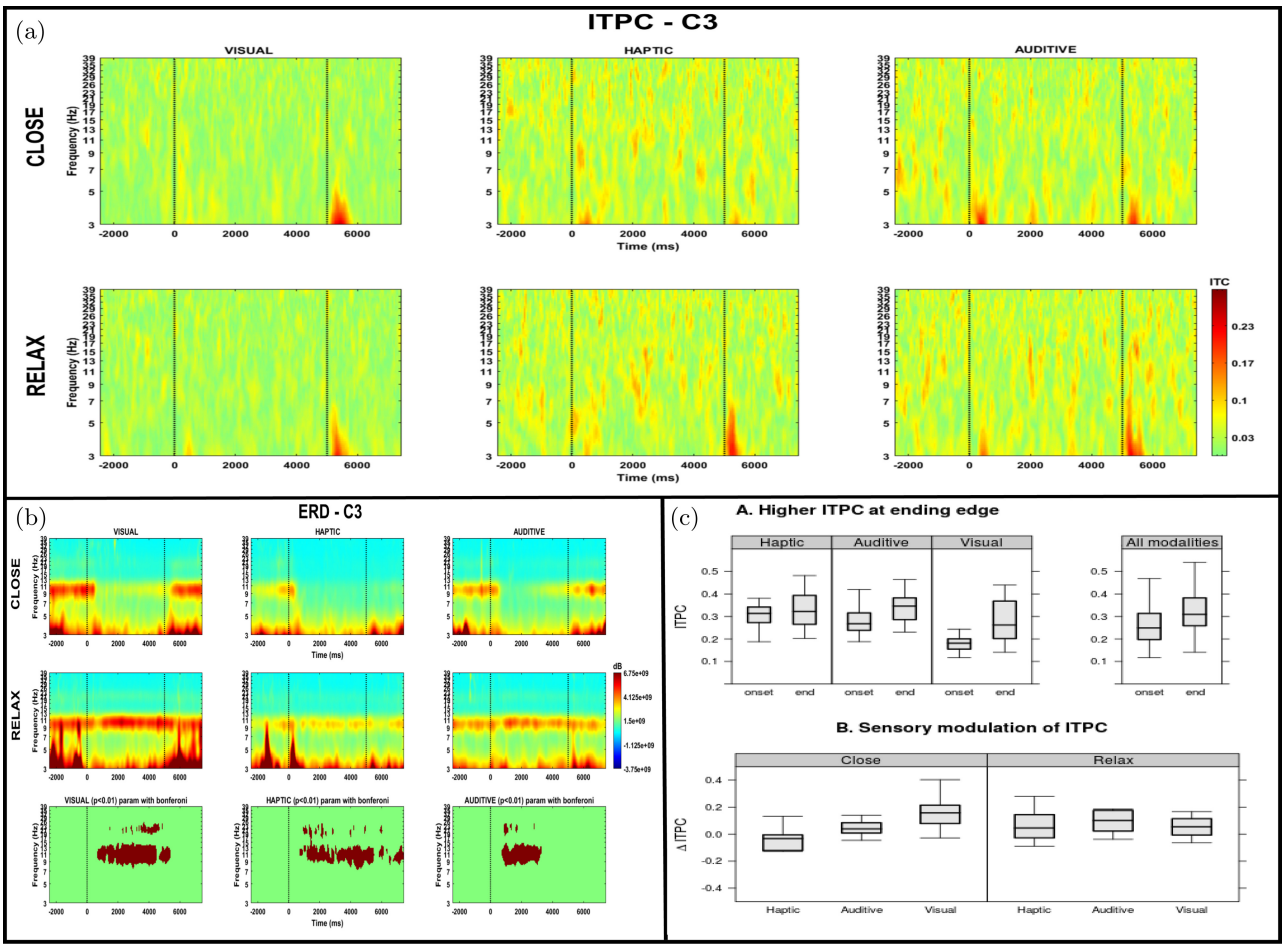

Fig. 2. (a) Group average of the time-frequency representation of ITPC in experiment II ($n = 10$) is displayed for the CLOSE (upper) and RELAX (lower) trials, in the three sensorial modalities (visual, haptic, auditive), showing ITPC changes related to temporal edges of BMI task. Amplitude of ITPC changes was reduced at the end of somatosensory task in CLOSE task; Up:CLOSE task, Down:RELAX task; C3 derivation is shown. (b) ERD during tasks. From left to right, each column presents results from Haptic, Auditory and Visual task. Upper row, CLOSE task. Middle row, RELAX task. Lower row, statistical significance of differences between RELAX and CLOSE task(green means $p > 0.05$). Notice that, 0–2 s after end of close trials, a significant ERD is observed in Haptic task. Averaging of 10 subjects (experiment II), two sessions by subject, C3 derivation is shown. (c) ITPC modulation by sensory input and temporal frame was found (see Results).

found a significant modulation of power in EEG in the alpha (mu) band. Interestingly, slow frequencies did not show any task-specific power modulations. In the right part of the figure, statistical significance of the differences between both tasks is presented. Note that, 0–2 s after end of CLOSE trials, a significant ERD is observed only in Haptic task, during the re-opening of the motorized orthosis.

3.3. *Phase dynamics*

We found that ITPC of slow EEG frequencies consistently increased during task switching in the context of a BMI motor imagery paradigm, both at the onset and at the end of trials, independent of the content of the task (closing and relaxing tasks); the magnitude of the changes was similar in RELAX and CLOSE tasks. From inspection, and as statistical analysis confirms, ITPC is higher at the end than at the onset of the task (see Fig. 2(c)).

Although our main analysis was centered in central EEG derivations, where motor-related EEG modulations are usually studied, the same phenomenon also appeared in other derivations. In Fig. 3(b), derivations C3, F3, P3 and T7 are also studied. It is shown that ITPC increases in δ

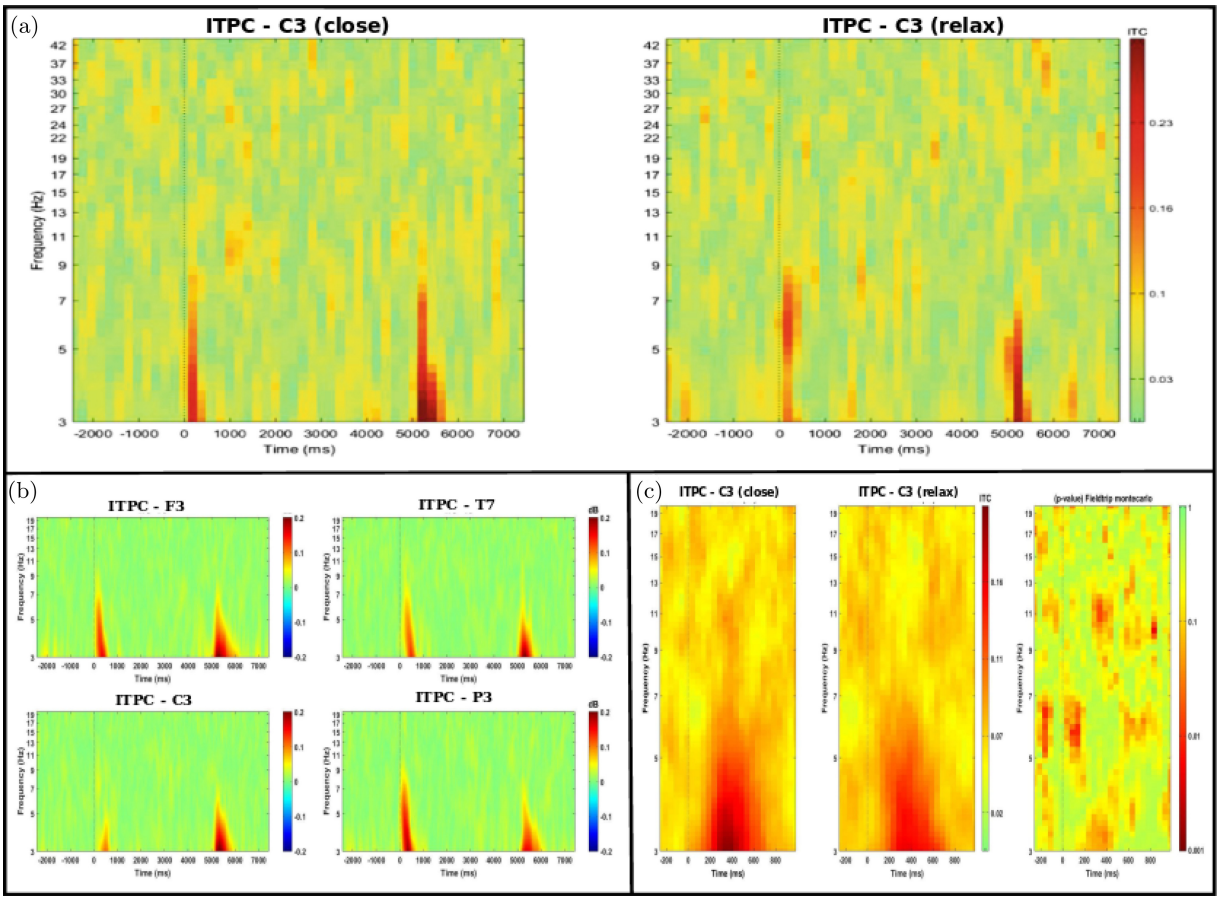

Fig. 3. (a) Group average of the time-frequency representation of ITPC over all participants ($n = 30$) is displayed for the CLOSE (left) and RELAX (right) trials, in Visual task, showing ITPC changes related to temporal edges of BMI task. Notice that amplitude of ITPC changes was similar in RELAX and CLOSE task, both at the onset and at the end of the task; Left:CLOSE task, Right:RELAX task; C3 derivation is shown. (b) ITPC increases can be found across several brain regions (frontal, central and parietal) indicating that ITPC increases at the temporal edges of BMI control trials is a brain phenomenon spanning several cortical areas; C3, CZ, P3, T7 derivations are shown, during CLOSE trials. (c) ITPC increases show different frequencies patterns in relax and close task (ITPC of θ frequency increases more and earlier in RELAX task), suggesting the presence of different physiological mechanisms in both tasks. Averaging across 10 subjects (experiment II); Left:CLOSE task, Right:RELAX task; CZ derivation is shown, where these changes were more prominent.

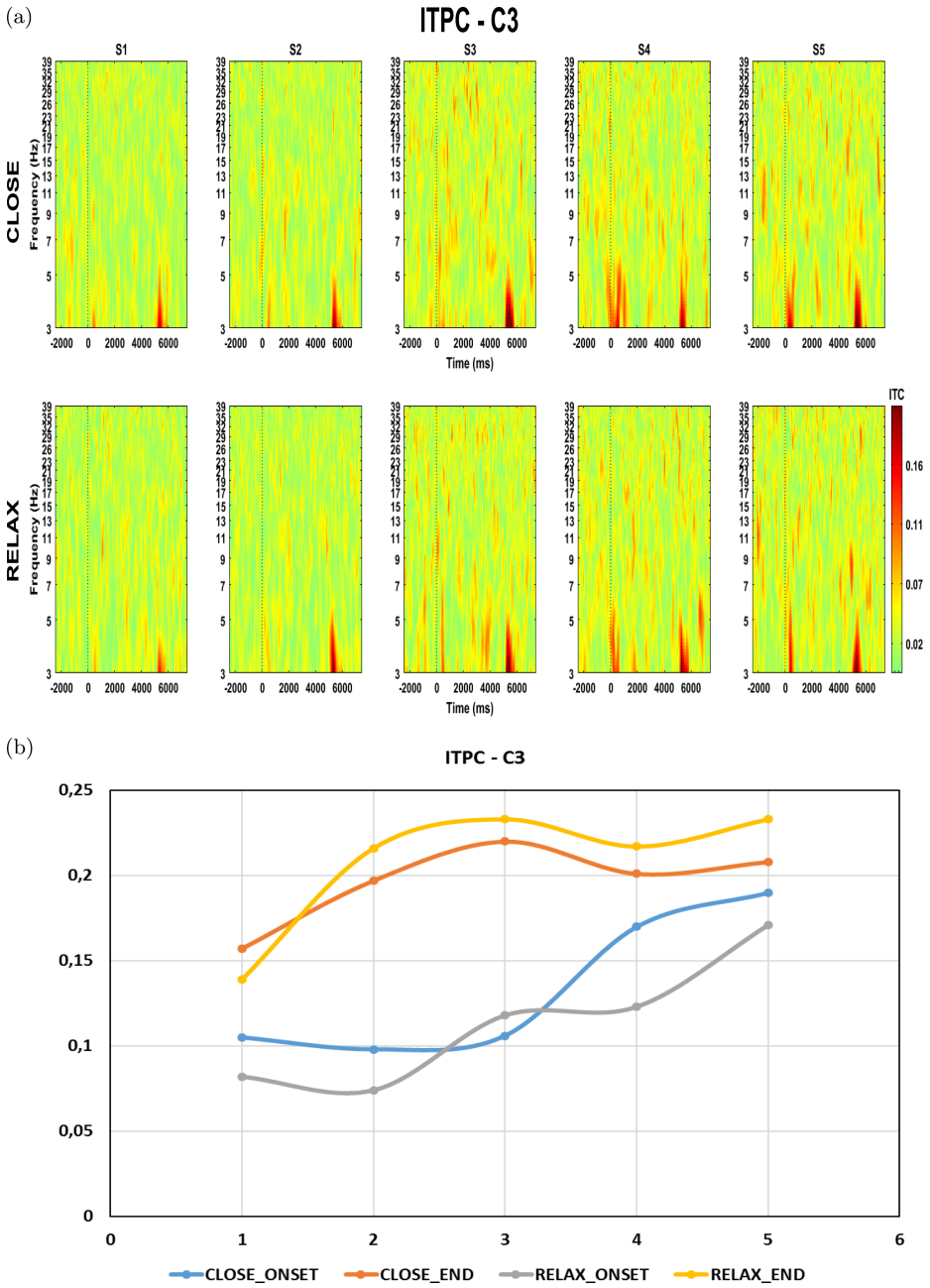

Fig. 4. Changes of ITPC in θ band (3–7 Hz) during CLOSE task (upper row) and RELAX task (lower row) along weekly training sessions. Notice the progressive increase of coherence at the onset and at the end of the task from session to session; C3 derivation is shown. In (a) grand average of 10 subjects (experiment II) is shown. In (b) numeric values are shown.

and θ band in several brain regions simultaneously, suggesting that ITPC increase during task switching is a brain phenomenon spanning several cortical areas.

To further elucidate the mechanisms underlying this finding, we investigated whether all slow frequencies share similar behavior. In Fig. 3(c), ITPC increases show different frequencies patterns in RELAX and CLOSE tasks (ITPC increase in θ band) occurs significantly earlier, and is more marked in RELAX task, suggesting that the physiological mechanisms underlying modulations of θ and

δ band coherence at the onset of the tasks states might be different depending on task content.

In subjects of experiment II, we also studied whether magnitude of slow-waves synchronization was affected by the modality of sensory feedback during BMI control. In CLOSE task, where sensory modulation is present (see Methods for description of sensory modality included on each task), ITPC amplitude at the ending edge of the task was significantly modulated by sensorial modality employed in the task, while during RELAX task no modulation was observed (Anova analysis, $p < 0.05$).

In experiment II, we also evaluated session-to-session differences in ITPC during BMI control (see Fig. 4), and we found a progressive increase of phase coherence at the onset and ending of the trials across BMI sessions.

4. Discussion

The main finding of this study is that cortical oscillations in δ and θ bands synchronize at the onset and at the end of a BMI task, independent of the content of the task (i.e. motor imagery versus relaxing). The magnitude of this synchronization is modulated by sensory modality of feedback received during the task, and it is also modulated by practice, further increasing along the BMI sessions.

Slow cortical oscillations in δ frequency are classically associated with anesthesia and slow-wave sleep.[9] Several generators of cortical δ oscillations in human brain exist, mainly pyramidal neurons through long-lasting hyperpolarizations,[9] but the role of glial cells is also being studied.[45] Delta oscillations are also present in subcortical regions, e.g. ventral pallidum and the brain stem.[10] Recently, superficial cortical layers seem to play a key role for generation of slow rhythms and integration of cortical activity.[46]

Delta oscillations in wake also play a relevant role in cognitive processes. Cortical slow rhythms of EEG are related to attention, both in animal[12] and humans,[10,14] and to decision making,[47] as research in monkeys also supports.[16] The role of δ oscillations during cognitive processes is also supported by several studies analyzing event-related δ oscillations of cognitively impaired patient groups during cognitive stimulation. This supports the idea that δ responses are involved in cognitive processes and could be a general electrophysiological marker for cognitive dysfunction. In several studies, cognitively impaired subject groups (mild cognitive impairment, Alzheimer's disease, schizophrenia, bipolar disorder) showed reduced amplitudes of δ oscillatory responses during cognitive paradigms (for a review, see Ref. 10). Reduction of δ responses during aging upon presentation of cognitive stimulation was also reported during visual oddball paradigms[48] and during go/no-go tasks.[49] On the other hand, elderly subjects showed higher δ coherence upon presentation of an auditory oddball paradigm.[50]

Phase synchronization between brain areas is a key mechanism for large-scale integration through synchrony, and constitute the basis for several broader considerations about brain dynamics as coordinated spatiotemporal patterns,[51–54] which has been extensively studied in attentional mechanisms. For example, phase-reordering by visual and auditory stimulation is an important mechanism in attention processes in the monkey brain,[13] which could also be called phase entrainment.[46,55]

One commonly accepted principle is that slow rhythms coordinate activity across widespread neuronal pools, whereas fast rhythms mediate local processing. Synchronization of cortical slow rhythms might be a marker of functionally relevant global coordination mechanisms. For example, delta oscillation phase changes have been reported for task-switching[56] and movement preparation.[37,38] The phase of cortical slow activity is reset by infrequent stimuli, supporting a primary role of superficial slow rhythms in generating the EEG and integrating cortical activity.[46] Delta phase entrainment also predicts behavioral performance.[57,58] The role of phase synchronization in motor control is also a well-known issue.[59,60]

Recently, ITPC increase during a volitional movement has been described,[37,38] interpreted as a phase locking in the δ–θ frequency band (2–8 Hz), a ubiquitous movement-related signal associated with movement execution across different movement initiation contexts, a suggestive interpretation that extends to the motor domain the emerging role of slower rhythms as a temporal framing for successive cognitive moments of synchronous assemblies.[51] These reports are in line with the main finding of the present work (partially presented in a preliminary report[61]), the presence of synchronization

of slow rhythms on temporal edges of a motor imagery-related task, supporting the hypothesis of the delta phase locking mechanism acting as a functional mechanism underlying the motor imagery, and assigning a key role for its function to the resetting of the slow waves by sensory afferences.

Careful analysis of reported phase-locking of slow rhythms support the previously stated hypothesis. First, it seems related to a widely distributed cortical resetting of slow waves; as other reports previously have stated (see Refs. 37, 38 and 61, we did not find an increase of power in δ–θ frequencies (see Fig. 2(c)), but we found indeed a cortically-extended ITPC increase at the onset of the trials indicating a task-related phase alignment of θ and δ frequency bands (see Figs. 3(a) and 3(b)). Second, the increase of ITPC was also present at the end of the task (higher than the former, see Fig. 2), and was present, independent of the content of the task, both in active and relaxing trials. So, we suggest that ITPC of cortical slow rhythms might be not only related to movement planning, but to a more general mechanism related to task-switching. In fact, our subjects had to decide in each trial between motor imagery or suppression of motor imagery, which might be considered as a clear example of a GO/NO-GO task, where an increase of coherence in δ band between different cortical regions has been described earlier.[16,56,59,62]

We also report that somatosensory and, weakly, auditory stimulation, reduce the observed synchronization at the temporal edges of the task. Recent findings associated resetting of delta-band oscillations in individual cortical areas with attention.[12] In monkey primary visual cortex[13] and human motor cortex,[14] delta-band oscillations entrain to the rhythm of external sensory events in an attention-dependent manner, although specific studies about interaction between somatosensory areas and delta waves are lacking. A possible explanation of the reported somatosensory modulation of slow rhythms synchronization, that could be studied in future studies, is that sensorial input during the motor task is entraining or resetting cortical slow rhythms, reducing the possibilities of recording the phase-locking at the temporal edges after averaging multiple trials.

We also observed that ITPC increases show different frequency patterns at the onset of RELAX and CLOSE tasks (ITPC increase in θ band) occurs significantly earlier, and is more marked in RELAX task, see Fig. 3(c). This suggest that the physiological mechanisms underlying modulations of θ and δ band coherence at the onset of the tasks states might be different. Executive functions like cognitive control and monitoring of movements have been shown specifically associated with changes in θ power (4–8 Hz) in the lateral and medial frontal cortex and phase synchronization between frontal electrodes in the θ band,[63,64] while phase locking in the $\delta - \theta$ frequency band (2–8 Hz) might be more related to motor tasks.[37]

Our findings suggest some practical points related to the BMI field. The presence of significant ITPC changes at the end of the RELAX task suggests that participants, although asked to relax, were not "simply relaxing", i.e. in an idle state, but "actively relaxing", somehow performing a subtle cognitive task related to an expectation related event, as contingent negative variation experiments might suggest,[18] or related to suppressing motor imagery. Although more studies are needed, where onset and end of the task are not anticipated, we suggest that the ability to actively relax, which might be quantified by ITPC changes, plays an important role in BMI learning, an issue that should be considered in the design of BMI paradigms.

A desired characteristic for usability of BMI systems is a short training time. Motor-imagery based BMI systems usually show high performance from initial sessions of training,[65] and little or no improvements are usually reported during training. Changes in signal features related to practice, but not necessarily related to performance, are expected and have been reported previously. For example, modulation depth of beta power during movement increases with practice over sensory-motor areas in normal subjects but not in patients with Parkinson's disease, independent of performance.[66] We did not find significant differences in performance between first and last session of experiment II, but we found session-to-session changes of ITPC with a progressive increase over consecutive days, that might relate to brain changes related to BMI learning (see Fig. 4), an issue that should be investigated in future studies.

A third practical point is derived from modulation of phase-locking by sensory modulation. A main objective of stroke neurorehabilitation strategies, where BMI-based strategies are increasingly used, is the activation or inactivation of cortical areas

in different tasks to improve long-term function of brain. We have seen that somatosensory modulation is able to modify brain activity during the task, which suggests that the presence of absence of haptic feedback using passive or motorized orthesis might modify the results obtained by BMI-based strategies. This is a fact that might be relevant in the design of strategies for BMI-based neurorehabilitation systems.

Our study has some limitations, that should also be shortly discussed. As the onset and ending of trials were indicated visually, with the appearance or disappearance of a visual cue over a black screen, it cannot be excluded that ITPC increase is related to visual presentation of stimuli. This seems, however, unlikely due to the spatial distribution of ITPC increase that is not restricted to posterior (visual) areas, but also include signal changes in frontal areas (suggesting the presence of associated cognitive processing), and to the fact that another modality of stimulation (somatosensory), which occurs during the task (between temporal edges), is also able to modulate it. A second limitation is the reduced number of subjects in experiment II, related to the practical limitations derived from temporal following of the subjects. In spite of it, the use of non-parametric statistical methods allowed us to obtain statistically significant results.

5. Conclusion

In summary, we used phase-analysis of slow rhythms of EEG for investigating the structure of temporal edges in a motor imagery-based BMI session. We found that cortical slow rhythms synchronized at the onset and at the end of active and relaxing trials and that this synchronization, quantified by ITPC, was modulated by sensory feedback (sensory feedback reduced it) and progressively increased along day-to-day training sessions. These findings suggest that phase-locking of slow rhythms and resetting by sensory afferences might be a functionally relevant mechanism in cortical control of motor function. We also propose that information extracted from phase of slow cortical rhythms might improve identification of temporal edges in BMI tasks and might help to develop physiological markers for identification of context task switching and for evaluation of practice-related brain changes during motor imagery tasks. These are findings with potentially important implications for design and monitoring of motor imagery-based BMI systems, an emerging tool in neurorehabilitation of stroke.

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