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Neurofeedback training of alpha-band coherence enhances motor performance

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Highlights:

- New brain-computer interface approach with training of coherence between target areas
- Healthy subjects and stroke patients can learn to enhance coherence
- Training of alpha-band coherence between motor cortex and rest of brain leads to improved motor performance after stroke

Abstract

Objective: Neurofeedback training of motor cortex activations with brain-computer interface systems can enhance recovery in stroke patients. Here we propose a new approach which trains resting-state functional connectivity associated with motor performance instead of activations related to movements.
Methods: Ten healthy subjects and one stroke patient trained alpha-band coherence between their hand motor area and the rest of the brain using neurofeedback with source functional connectivity analysis and visual feedback.
Results: Seven out of ten healthy subjects were able to increase alpha-band coherence between the hand motor cortex and the rest of the brain in a single session. The patient with chronic stroke learned to enhance alpha-band coherence of his affected primary motor cortex in 7 neurofeedback sessions applied over one month. Coherence increased specifically in the targeted motor cortex and in alpha frequencies. This increase was associated with clinically meaningful and lasting improvement of motor function after stroke.
Conclusions: These results provide proof of concept that neurofeedback training of alpha-band coherence is feasible and behaviorally useful.
Significance: The study presents evidence for a role of alpha-band coherence in motor learning and may lead to new strategies for rehabilitation.

1 Introduction

The technology of brain-computer interfaces (BCI) enables the monitoring of brain activity and the generation of a real-time output about specific changes in activity patterns. The recorded subject receives a feedback about the neural activity associated his/her efforts and can thus learn to voluntarily modulate brain activity (Kamiya, 1969). This has been shown in particular for the sensorimotor rhythm (SMR). The SMR corresponds to activity of neuronal groups in the sensorimotor cortex in alpha and beta frequencies (~8-30 Hz), which is suppressed by real or imagined movements (Arroyo et al., 1993; Pfurtscheller et al., 2006). The ability of humans to voluntarily modulate the SMR has led to the development of BCI for motor substitution, i.e., for controlling prosthetic and robotic devices (Galan et al., 2008; McFarland et al., 2008). A more recent application of BCI technology consists in training brain patterns with feedback. In neurorehabilitation, the interest of neurofeedback lies mainly in its potential for improving recovery of patients with brain lesions (Birbaumer et al., 2007; Daly et al., 2008). Neurofeedback for motor rehabilitation mostly aims to train SMR modulation (Buch et al., 2008; Broetz et al., 2010; Caria et al., 2011; Ramos-Murguialday et al., 2013) and thus can be seen as a support for motor imagery training (Mattia et al., 2012).

Here, we propose a new approach for enhancing motor performance with neurofeedback, which does not target circumscribed neural activations related to movements. Instead it is based on a resting-state network correlate of motor performance.

The brain is a complex network of dynamic systems with abundant functional interactions between local and more remote brain areas (Varela et al., 2001). Interregional neural communication is thought to be accompanied by a synchronization of oscillations between different brain regions (Fries, 2005). This interregional synchronization can be quantified with the concept of *functional connectivity* (FC) which is a measure of the stastistical dependency between activity in different brain regions.

Synchronization has also been observed in the resting brain with different imaging techniques including fMRI (Greicius et al., 2003), magnetoencephalography (He et al., 2008; Brookes et al., 2011), and EEG (Guggisberg et al., 2011; Guggisberg et al., in press). Moreover, a linear correlation has been described between FC at rest and performance in motor and cognitive tasks, in healthy people (Fox et al., 2007; Wang et al., 2010; Hipp et al., 2011; Koyama et al., 2011; Schlee et al., 2012; Wang et al., 2013) and in stroke patients (He et al., 2007; Carter et al., 2010). Particularly, FC in the EEG alpha band (8-12 Hz) between a brain area and the rest of the brain was significantly correlated with performance in tasks depending on this area. For instance, the more the primary motor cortex of stroke patients was functionally connected to the rest of the brain in the alpha band, the better patients were able to perform motor tasks (Dubovik et al., 2012; Dubovik et al., 2013). Based on this observation, we hypothesized that a treatment capable of increasing alpha-band FC between the motor cortex and the rest of the brain should have beneficial effects on motor performance. Recent studies have indeed shown that traditional neurofeedback training of SMR modulation improves motor cortex FC as a marker of recovery (Várkuti et al., 2013; Sugata et al., 2014). Here, we developed a neurofeedback system where EEG FC is trained directly (Sacchet et al., 2012). This study aimed to provide proof of principle that such a network variant of neurofeedback training is feasible and that it is behaviorally useful.

As training FC may require different mental efforts than activations of the motor cortex, we first tested whether healthy participants need particular instructions to be able to modulate cortical FC. In a second experiment, we demonstrated that most healthy subjects can voluntarily enhance alpha-band FC of their motor cortex in a single session of neurofeedback. In the third experiment, a patient with chronic stroke learned to enhance alpha-band FC of his affected primary motor cortex in 7 neurofeedback sessions applied over one month. This was associated with clinically meaningful improvement of his motor function.

2 Methods

All procedures were approved by the University Hospital of Geneva Ethics Committee and subjects gave informed written consent for their participation in the study. Healthy subjects were paid for participation.

2.1 Experiment 1

The purpose of this experiment was to test whether particular instructions can facilitate the voluntary modulation of FC.

2.1.1 Participants

Seven healthy subjects participated. Data from two subjects were excluded because of abundant EEG artifacts. The participants had a mean age of 28 years ranging from 26 to 33 years old, five were females, and two subjects were left-handed.

2.1.2 Task

Three different mental imagery tasks were performed by the subjects, and each was repeated once for the left side and once for the right side. They were chosen based on previous work suggesting that they might be associated with modulations of alpha-band coherence in the motor cortex. In the first task the subjects had to imagine the space or distance separating the fingers of their hand. Mental imagery of space was reported to induce a consistent increase in alpha-band coherence in pioneering studies on neurofeedback (Fehmi, 2003). In the second task the subjects had to imagine a movement of their hand without actually moving it (Andrew et al., 1996). In the third task, the subjects simply received the instruction to increase the neural synchrony in their brain hemisphere.

Before these tasks, subjects were recorded during a resting-state condition of the same duration.

2.1.3 Data acquisition

EEG was recorded with a 128-channel Biosemi ActiveTwo EEG-system (Biosemi B.V., Amsterdam, Netherlands) at a sampling rate of 512 Hz. Artifacts like eye movements, muscular contractions and electrode artifacts were excluded by visual inspection of the data leaving between one and three minutes of clean data for each condition. Channels containing artifacts over prolonged periods were completely excluded from further analyses.

2.1.4 Functional connectivity analysis

The detailed procedures for EEG source connectivity analyses have been described previously (Guggisberg et al., 2011). Artifact-free data was divided into segments of 1 s duration, re-referenced against the average of all included electrodes, and bandpass filtered between 1 and 20 Hz. A spherical head model with anatomical constraints (SMAC) with 10 mm grid spacing (~1000 solution points) (Spinelli et al., 2000) was created based on the Montreal Neurological Institute (MNI) standard brain (Mazziotta et al., 2001). An adaptive spatial filter (scalar minimum variance beamformer) was used to estimate grey matter source time series from the sensor data (Sekihara et al., 2004). Computation of the spatial filter **w** used a lead-potential **L** as well as the channel covariance **R** of recorded data:

$$\mathbf{w}(r) = \frac{\mathbf{R}^{-1}\mathbf{L}(r)}{\mathbf{L}^{\mathrm{T}}(r)\mathbf{R}^{-1}\mathbf{L}(r)}, \tag{1}$$

where r represents each solution point. Dipole orientations were fixed such they yielded maximum output signal-to-noise ratio at each solution point (Sekihara et al., 2004; Guggisberg et al., 2011).

FC was quantified as the absolute imaginary part of coherence (IC) (Nolte et al., 2004), representing lagged coherence, between voxel pairs. The advantage of IC over other measures of FC is that it is not subject to biases arising from volume conduction or spatial leakage of the inverse solution (Sekihara et al., 2011). Imaginary coherence was calculated for the frequency band between 8 and 12 Hz by tapering non-overlapping 1 s epochs with a Hanning window and performing a discrete Fourier transform with 1024 frequency bins *f*. The complex Fourier coefficients **F** at all electrodes were projected into the source space:

$$\mathbf{G}(f) = \mathbf{w}^{\mathrm{T}}\mathbf{F}(f), \tag{2}$$

where T indicates the matrix transpose. We could then compute IC from the Fourier transformed source time series **G** from each voxel to all other voxels resulting in a full all-to-all voxel connectivity matrix.:

$$\mathbf{IC}(f) = \left| \operatorname{Im} \frac{\mathbf{G}(f)*\mathbf{G}(f)}{\operatorname{diag}\left(|\mathbf{G}(f)|^{\mathrm{T}}|\mathbf{G}(f)|\right)\operatorname{diag}\left(|\mathbf{G}(f)|^{\mathrm{T}}|\mathbf{G}(f)|\right)^{\mathrm{T}}} \right|, \tag{3}$$

where * denotes the complex conjugate, Im the imaginary component, and diag(**M**) the vertical vector formed by the diagonal entries of the matrix **M**. IC at the alpha band was obtained by summing the cross- and auto-spectra across the corresponding frequency bins.

Individual voxel connectivity was computed as the average of its coherence with all other voxels. We thereby obtained a measure of global FC in the alpha band of each voxel during each condition (Dubovik et al., 2012). Our calculation of global coherence to the entire brain corresponds to the graph theoretical measure of node degree in weighted networks (Newman, 2004). Hence, it can be seen as an index of the overall importance of an area in the brain network (Stam et al., 2012).

2.1.5 Statistical analysis

The FC map of each task was compared to the pre-session resting state map in a voxel-wise manner. Differences were averaged across subjects and tested against the null-hypothesis of zero change with statistical non-parametric mapping (SnPM) at each voxel. A correction for testing multiple voxels was obtained by defining a cluster-size threshold based on the cluster size distribution obtained after 10’000 random reversions of original data (Singh et al., 2003). In addition, differences between conditions were tested in the primary motor cortex region-of-interest with paired t-tests as well as voxel-wise across the entire cortex with SnPM.

2.2 Experiment 2

This experiment investigated whether healthy subjects can modulate alpha-band coherence between the motor cortex and the rest of the brain in a single neurofeedback training session.

2.2.1 Participants

Ten healthy subjects participated. They had a mean age of 27.4 years ranging from 25 to 31 years; 6 were females and 2 left-handed.

2.2.2 Neurofeedback

EEG was acquired with a 128-channel Biosemi ActiveTwo EEG-system (Biosemi B.V., Amsterdam, Netherlands). Channels containing artifacts were excluded from further analysis. At the beginning of each session, 5 minutes of artifact-free data during an eyes open resting-state condition were acquired. An adaptive spatial filter (scalar minimum variance beamformer) was computed based on a SMAC head model created from the individual MRI and the channel covariance of the resting-state data. A region with radius 20 mm centered on the hand notch was defined as target area for visual feedback. Six subjects (1 left-handed) trained the left motor cortex, four (1 left-handed) the right.

Data was then made available for real-time analysis through the FieldTrip buffer at a sampling rate of 512 Hz (Oostenveld et al., 2011) and was simultaneously recorded for offline analysis. Real-time analysis was updated every 300 ms. At each update, a data segment of 500 ms was average referenced and bandpass filtered between 1 and 20 Hz with a 4th-order butterworth filter. The signal was then projected to the gray-matter voxels with the adaptive spatial filter computed at the beginning of the session. Global functional connectivity in the alpha band (8-12 Hz) between the voxels in the target region and the rest of the brain was calculated. In order to obtain a more stable feedback of current alpha-band coherence, the global FC was averaged over the last 15 overlapping segments (last 4.7 seconds). Coherence magnitudes can be influenced by changes in signal-to-noise ratios. To minimize this potential confound, we normalized local IC magnitude by calculating z-scores (Dubovik et al., 2012). This was achieved by subtracting the mean IC value of all voxels of the subject from the IC values at target voxels and by dividing by the standard deviation over all voxels. The mean normalized IC of voxels in the target region was then used for visual feedback.

2.2.3 Task

Subjects received visual feedback on their current alpha-band coherence on a scale made of 12 white horizontal stacked bars. Subjects were instructed to raise the bar as high as possible. Given the result of experiment 1, no particular strategy was proposed. The scale of the feedback was adapted for each participant such that the value of the top bar was reached during about 10% of the feedback trial time.

One session of neurofeedback training consisted of 40 neurofeedback trials lasting 45 seconds each for a total duration of 40 minutes. A longer pause between trials was offered every five minutes.

2.2.4 Offline analysis

We assessed the effect of feedback training on the brain by investigating the change in alpha-band FC over time. Artifacts like eye movements, muscular contractions and electrode artifacts were excluded by visual inspection of the data. Trials were then grouped into four blocks of 10 trials each. Each block represented ten minutes of neurofeedback training. Alpha-band FC of the target voxels was calculated as described above for each of the four blocks.

The evolution of FC during the neurofeedback session was estimated at each voxel by computing the linear regression (least-square minimization) slope over the 4 blocks. This produced new maps with the slope in alpha-band FC at each voxel. Images were flipped along the midsagittal plane in subjects who trained the right motor cortex such that all trained voxels were on the left side of the brain. The average FC evolution slope was then computed at each voxel.

2.3 Experiment 3

This experiment tested the feasibility and usefulness of our network variant of neurofeedback in a patient with chronic stroke.

2.3.1 Participant

One 57 years old, right-handed male patient participated 40 months after a first ischemic stroke in the left internal capsule. The stroke produced severe right sided hemiparesis, right sided hypoesthesia and Broca aphasia for which the patient had benefited from intensive rehabilitation. At the time of the experiment, he had reached a stable clinical state of moderate impairement without significant changes for more than a year. He had recovered the ability to walk without aid, but the right upper extremity was not functional and not used for activities of daily living. He had maintenance physical therapy once every two weeks.

2.3.2 Neurofeedback

The real-time analysis was similar as for experiment 2 with the following exceptions. A realistic boundary element model (BEM) with 10 mm grid spacing was used based on the individual MRI and electrode positions digitized with a Polhemus Fastrak system. Target area for alpha-band FC training was the left (ispilesional) hand motor cortex. The average of the last 12 overlapping segments (3.8 seconds) was used for feedback. Sessions were composed of 50 neurofeedback trials of 45 s each for a total duration of 50 minutes. The patient trained twice a week over one month for seven neurofeedback sessions. He did not receive particular instructions other than to raise the feedback bar as high as possible.

2.3.3 Offline analysis

The neural effects of neurofeedback training were investigated similarly as in experiment 2. Trials were grouped into five blocks. Each block represented ten minutes of neurofeedback training. A normalized global alpha-band FC map was calculated for each of the five blocks.

At each voxel, the evolution of normalized FC during one neurofeedback session was estimated by computing the linear regression slope (least-square minimization) over the five blocks. In order to look for changes in alpha-band FC within each of the 7 sessions, we tested against the null hypothesis of 0 slope across blocks with a one sample t-test performed at each voxel. The evolution of FC across sessions during the month of training was investigated voxelwise through a linear regression slope computed with the seven FC values of the pre-training resting states.

In additon, a spectrogram of the FC evolution slope during the session, as calculated above, was computed between 1 and 20 Hz.

Power evolution during one neurofeedback session was estimated analogously by computing the linear regression slope over the five blocks.

2.3.4 Clinical assessment

To assess the clinical effect of our resting-state neurofeedback training, a trained physical therapist performed standardized tests of motor function 3 days before the first training session, as well as one day and 6 weeks after the last training session.

Upper limb motricity was measured using the Fugl-Meyer motor assessment for the upper extremity with a maximal score of 66 points (Fugl-Meyer et al., 1975). The grip strength was evaluated with a Jamar dynamometer (Schmidt et al., 1970) and a Nine Hole Peg test was performed for dexterity assessment (Kellor et al., 1971; Gladstone et al., 2002).

We also investigated changes in somatosensory function. Light touch perception was quantified with monofilaments on the thumb and index finger pulp as well as on the hypothenar and forearm.

3 Results

3.1 Experiment 1

All task instructions produced an increase in alpha-band coherence between the medial parietal cortex and the rest of the brain as compared to resting-state (Figure 1). No significant change was observed in the motor cortex ($p>0.15$). The global pattern of FC difference was similar between the different tasks and no significant difference in lateralization was found between the left and right homologous tasks nor between different tasks ($p>0.05$, corrected).

3.2 Experiment 2

Seven out of the ten subjects (5/6 training the left, 2/4 training the right motor cortex) were able to enhance alpha-band coherence between the target motor cortex (Figure 2A) and the rest of the brain during a single neurofeedback session. On average across all patients, FC increased primarily in the motor and posterior regions of the brain (Figure 2B).

In contrast to traditional neurofeedback training of *mu* desynchronization, our approach did not require movement imagery and none of the subjects reported to use such a strategy. There was therefore no reason to suspect confounding EMG activation. In order to further exlude the possibility of muscle activitations, we analyzed EMG root mean square values of thumb abductor and digit extensor muscles during the neurofeedback in 2 subjects. No increase of muscle activity could be observed compared to rest periods ($p>0.22$), confirming that participants used pure mental activity for this neurofeedback task.

3.3 Experiment 3

The patient learned to significantly increase alpha-band FC between the target area (Figure 3A) and the rest of the brain within each training session ($t_6=3.8$, $p=0.009$) (Figure 3B). This also led to a progressive increase of resting-state global alpha-band FC before each session, as confirmed by a linear regression analysis across sessions ($\beta=0.17$, $R^2= 0.6$, $t_5=2.8$, $p=0.040$). This increase was specific to the trained region with a significant positive slope only around trained voxels (Figure 3C). Moreover, the FC increase in these voxels was specific to the alpha band (Figure 3D). Conversely, FC training did not induce significant change in alpha power at the target area ($t_6=-0.4$, $p=0.71$).

Clinically, the patient improved his right upper limb motor function with an increase of seven points in the Fugl-Meyer score from the pre-training to the post-training session. This improvement was maintained until the third follow-up evaluation 6 weeks later. Dexterity as measured with the nine hole peg test and somatosensory function measured with monofilaments improved as well (Table 1). The patient also reported a subjective improvement and started to use his affected upper limb for activities of daily living. In fact, he became able to participate in a modified contrained-induced movement therapy protocol (Shi et al., 2011) which started about 2 months after the neurofeedback training sessions. Constrained-induced movement therapy had not been possible before our neurofeedback therapy because of insufficient ability to use the affected arm for activities in daily living.

4 Discussion

Our study proposes a new strategy for neurofeedback training. Rather than enhancing local neural activations relevant for task execution, our BCI system trains resting-state network correlates of behavioral performance. This proof-of-principle study confirms that this approach can induce region and band-specific enhancement of network synchrony, in agreement with other recent reports (Sacchet et al., 2012; Koush et al., 2013). Furthermore, this study provides first evidence that network training can translate into lasting clinical improvement of stroke-induced handicap.

The first experiment revealed that several mental imagery tasks enhance alpha-band coherence even without any feedback or training. Hence, typical strategies used for voluntary modulation of brain rhythms are associated with immediate increases in alpha-band coherence. However, this increase was observed mainly in medial parietal regions, but not in the motor cortex. Interestingly, the medial parietal region is part of the so-called default-mode network, which is known to be activated during tasks requiring inward attention to the own body or self, but deactivated during tasks requiring outward attention to external events or objects (Raichle et al., 2001; Cavanna et al., 2006). Since all tested instructions required attention to the own body, it would be possible that they all implicated the default-mode network. This might be associated with a corresponding increase in alpha-band coherence between its nodes and the rest of the brain. Our results do not exclude that some more specific instructions might have more immediate impact on motor cortex alpha-band coherence. For instance our movement imagery condition did not include specific instructions with regards to the aspects of the movement that subjects had to imagine. Previous studies have suggested that imagery of kinesthetic aspects have greater effect on cortico-spinal excitability than visual movement imagery (Stinear et al., 2006) and that it might lead to modulation of alpha-band coherence between the motor cortex and fronto-parietal areas in a neurofeedback environment (Vukelic et al., 2014).

In experiment 2 and 3, we observed that voluntary enhancement of coherent alpha oscillations is also possible in other brain regions such as the motor cortex, but these modulations seem to require at least one session of neurofeedback learning.

Most importantly, the voluntary enhancement of oscillation synchrony between a target area and the rest of the brain was behaviorally useful in our stroke patient. This may be surprising given the large literature on the importance of intensive, task-specific exercises for recovery (Kwakkel et al., 1999; Langhorne et al., 2011). Our patient trained resting-state interactions of the brain without specific motor exercises which are useful for daily living. Yet, he still experienced clinically significant improvements. This adds to growing body of evidence that human behavior in general (Fox et al., 2007), and clinical recovery after stroke in particular (Westlake et al., 2011; Westlake et al., 2012), do not depend only on task-induced brain activation, but also on synchronous intrinsic brain activity at rest. Moreover, while previous studies showed mostly correlational evidence for the importance of resting-state oscillation coherence in behavior, this study shows that manipulation of resting-state alpha-band coherence with neurofeedback leads to behavioral changes. Similarly, transcranial theta-burst stimulation can modulate resting-state alpha-band coherence and this leads to corresponding changes in behavioral performance (Rizk et al., 2013).

Our neurofeedback system trained alpha-band coherence between the target area and the whole brain. This choice was based on our previous observation that these interactions correlated best with performance (Dubovik et al., 2012). Training other frequencies or more specific connectivity patterns would in principle be possible, but the definition of these parameters should be based on evidence for their behavioral usefulness.

Our network variant of neurofeedback has the advantage that it takes into account the massive interconnections in the human brain (Sporns et al., 2004; Stam et al., 2012). Cortical regions are interconnected in a specific topography that ensures efficiency. Brain disease typically affects not only local neural function, but also remote areas and interactions between them (Alstott et al., 2009). The reorganization of connections is thus an important process in post-stroke recovery (Rehme et al., 2011) and training task-induced activations of circumscribed brain areas may therefore not be the most efficient way for repairing the intrinsic brain architecture.

Another advantage of our approach is that it uses a general marker of performance that is not limited to motor function. Alpha-band coherence is also associated with performance in other domains such as language, spatial attention, and memory, both in patients with brain disease and in healthy participants (Dubovik et al., 2012; Dubovik et al., 2013; Rizk et al., 2013). Hence, our approach may also be useful for improving aphasia, executive dysfunction, neglect, and memory disturbances, or even for enhancing performance in healthy subjects. The improvement of somatosensory function seen in our patient might be a good indicator of such potential.

In order to obtain reliable coherence values, the network approach requires acquisition of at least 3-4 seconds of data. This could lead to feedback delay which could hinder learning (Weinberg et al., 2012). However fMRI based neurofeedback has been proven possible for controlling activations (Weiskopf, 2012) and FC control (Koush et al., 2013) while also presenting a delay of several seconds due to haemodynamic response properties and processing time.

Our findings will need to be confirmed in more patients and with a valid control group. Yet, our chronic patient had received intensive standard therapy for three years and reached a stable clinical state before entering the study. Furthermore, he did not receive additional physical training during the study other than his usual maintenance therapy every two weeks. This reduces the risk for non-specific effects. In clinical practice, a combination with intensive physical therapy can be offered which might further enhance the clinical benefits.

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Legends

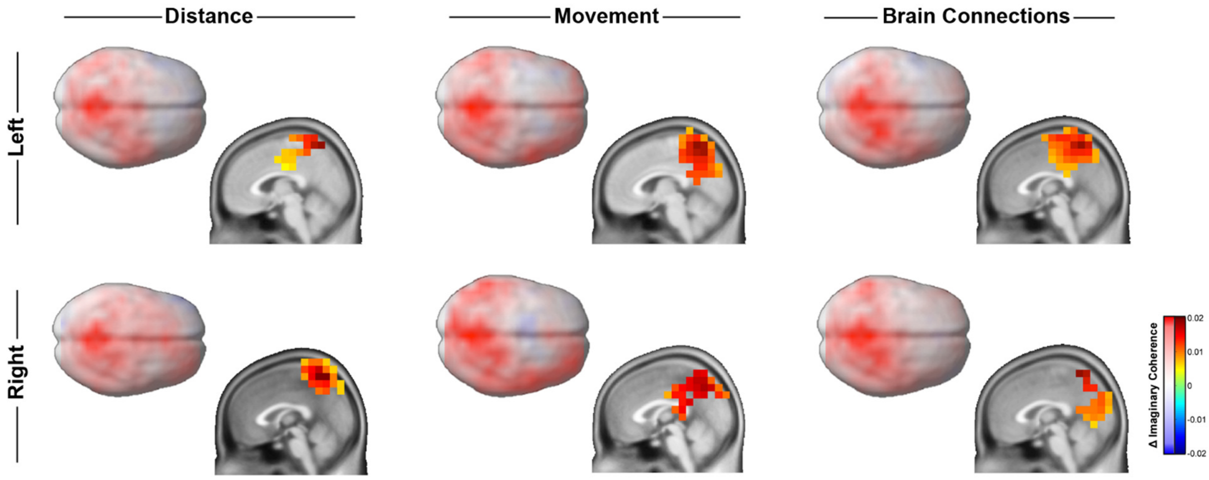

Figure 1. Different tasks of mental imagery without feedback induce similar changes in alpha-band coherence. Alpha-band coherence between red/yellow areas and the rest of the brain increased during mental imagery tasks as compared to rest (unthresholded in 3D renderings, thresholded at $p<0.05$ cluster corrected in sagittal cuts). In the *Distance* task, subjects imagined the space between their fingers. In the *Movement* task, they imagined movements of the corresponding hand. In the *Brain Connections* task, they visualized synchronous activity in the corresponding hemisphere.

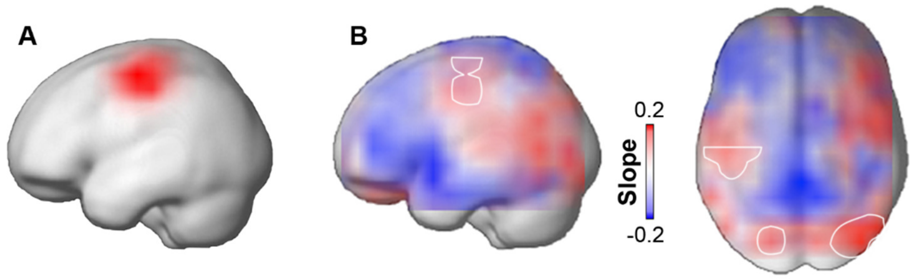

Figure 2. Mean slope of alpha-band coherence evolution during neurofeedback training of 10 healthy subjects. Subjects tried to volontarily enhance alpha-band coherence between the left or right hand motor cortex and the rest of the brain in a single session. Subjects with right target are flipped to left for visualization. **A** The target area is marked in red. **B** Red color indicates regions which global alpha-band coherence increase during the feedback session, blue regions which coherence decrease. Increases occurred relatively specifically in the target area. Maps are unthresholded, significant areas ($p<0.05$, uncorrected) are marked with white contour lines.

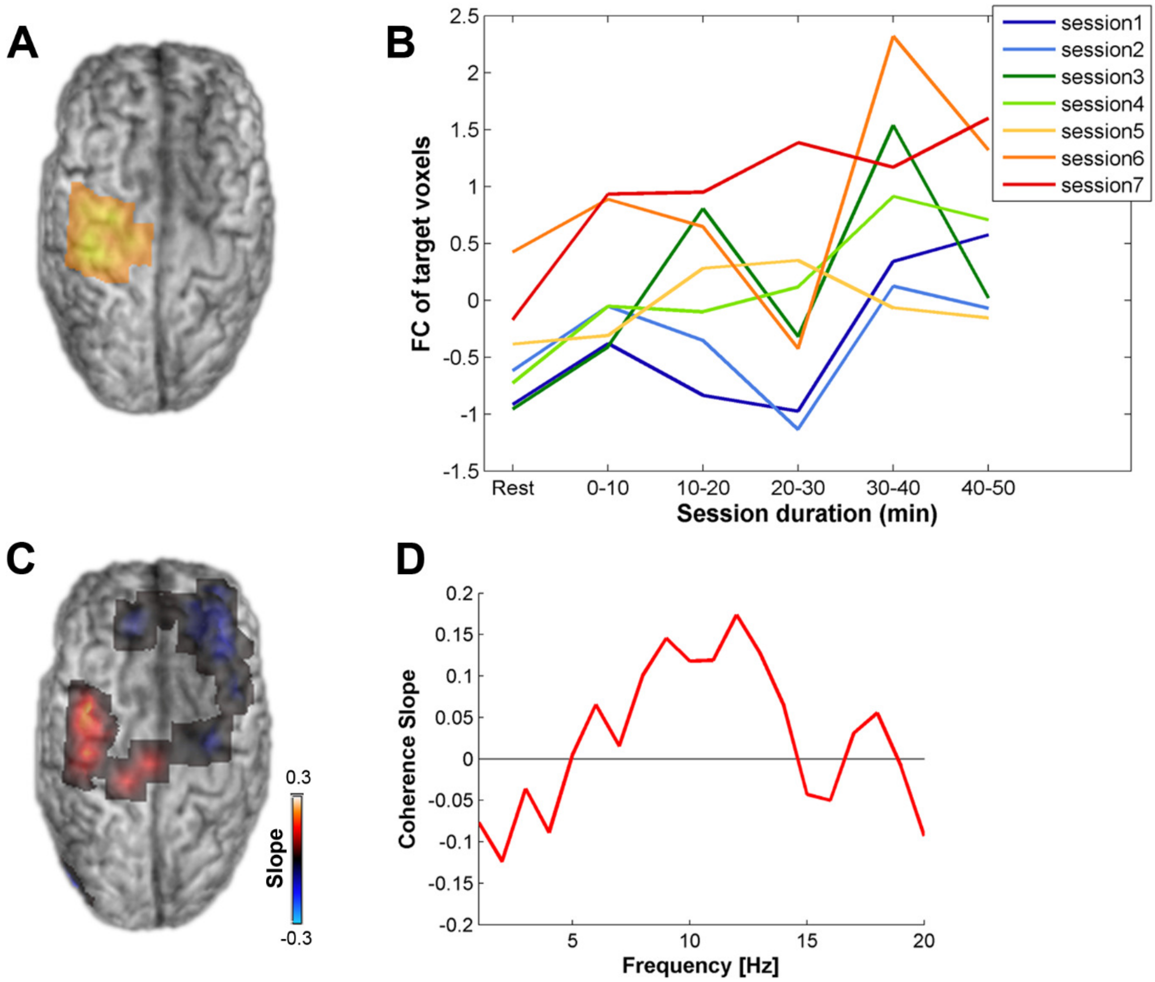

Figure 3. Alpha-band coherence training in a patient with chronic left hemispheric stroke and right hemiparesis. **A** Target area used for feedback. **B** Evolution of alpha-band coherence between the target area and the rest of the brain. The patient was able to enhance alpha-band coherence within and across training sessions. **C** This enhancement concerned specifically the targeted primary motor cortex ($p<0.05$, uncorrected). **D** The enhancement was specific to the trained alpha frequency band.

Table

Table 1. Clinical assessment of sensorimotor function of the right upper limb in the patient.

	3 days before training	1 day after training	6 weeks after training
Motor assessment			
Upper limb Fugl-Meyer Assessment	37/66	44/66	45/66
Jamar	11.5 kg	11 kg	10 kg
Nine Hole Peg Test	0 pegs placed in 2 minutes	6 pegs placed in 2 minutes	7 pegs placed in 2 minutes
Somatosensory assessment			
Pressure perception (nylon filament)			
D1 pulp	**0.6g**	**0.4g**	**0.4g**
D2 pulp	**0.4g**	**0.4g**	**0.4g**
Hypothenar	**0.6g**	**0.4g**	**0.4g**
Forearm	**0.6g**	**0.6g**	**0.6g**