

Afferent and Efferent Activity Control in the Design of Brain Computer Interfaces for Motor Rehabilitation

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Abstract—Stroke is a cardiovascular accident within the brain resulting in motor and sensory impairment in most of the survivors. A stroke can produce complete paralysis of the limb although sensory abilities are normally preserved. Functional electrical stimulation (FES), robotics and brain computer interfaces (BCIs) have been used to induce motor rehabilitation. In this work we measured the brain activity of healthy volunteers using electroencephalography (EEG) during FES, passive movements, active movements, motor imagery of the hand and resting to compare afferent and efferent brain signals produced during these motor related activities and to define possible features for an online FES-BCI. In the conditions in which the hand was moved we limited the movement range in order to control the afferent flow. Although we observed that there is a subject dependent frequency and spatial distribution of efferent and afferent signals, common patterns between conditions and subjects were present mainly in the low beta frequency range. When averaging all the subjects together the most significant frequency bin comparing each condition versus rest was exactly the same for all conditions but motor imagery. These results suggest that to implement an on-line FES-BCI, afferent brain signals resulting from FES have to be filtered and time-frequency-spatial features need to be used.

I. INTRODUCTION

THE cerebro-vascular accident (CVA) caused by stroke, brain injury, or cerebral paralysis is one of the main causes of long-term motor disability worldwide and in more than 85% of the cases functional deficits in motor control occur [1]. In particular stroke is the leading cause of disability in western countries and the costs of care rose by 30% over the last 20 years due to aging society. Furthermore, the

predictions are indicating a tremendous growth in elderly population. Additionally, in the EU the percentage of the population over 65 years old will increase from 17.1% in 2008 to 30% in 2060. The percentage of persons over 80 years old will rise from 4.4% to 12.1% over the same period (EUROSTAT population projections). Incidence of a first stroke in Europe is about 1.1 million and prevalence about 6 million. Currently, about 75% of people affected by a stroke survive one year or more and this proportion will increase in the coming years due to enhancing quality in hyper-acute, follow-up acute and subacute care, and life-long treatment of these conditions. From all the stroke survivors showing no active upper limb motion at hospital admission 14% showed complete recovery, 30% showed partial recovery and 56% showed no recovery [2].

Physical therapy is the overall accepted method of rehabilitation for stroke patients. To promote the effects of physical therapy researchers and clinicians suggest various methods: intensive exercise and augmented feedback [3], constraint induced movement therapy [4], exercise in virtual environments with feedback to assist skills learning [5]; robotic assistive devices with sensory feedback for repetitive practice could provide therapy for long periods of time, in a consistent and measurable manner [6]–[8].

The interventions made possible with the development of robotic technology are based on stimulation of haptic and proprioceptive receptors [9], [10] and allow repetitive training which is essential for learning of movement schema (training of the brain). A variety of robots for the upper and lower limb have been used as an addition to physical therapy for the training of different components of the central nervous system (spinal circuits and the brain).

FES of muscles might enable movements not otherwise possible during the practice of tasks such as reaching to grasp an object [11]–[14]. Furthermore, studies have shown that FES can be used to reconstruct skills needed for movements in daily living activities, such as standing up, walking, and cycling [15]–[17].

Both, the FES and the robot based motor rehabilitation therapies have demonstrated positive results assessed by common motor impairment scales for stroke patients such as the Fugl Meyer scale [18].

The hypothesis behind the augmented movement therapy by the FES and robots assumes that recovery happens partly due to the peripheral mechanisms, but mostly due to cortical

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plasticity [19]. This hypothesis has been confirmed in motor training tasks with physiological tests involving transcranial magnetic stimulation (TMS) [20]–[24] and imaging based on functional resonance imaging (fMRI) [25].

It is well known that plasticity effects and thereby possible functional recovery depend on coherence between afferent and efferent neural activity [26]. The role of the intentional efforts or efferent activity for the recovery has been demonstrated for example with the motor imagery alone or combined with computer feedback when used as a rehabilitation therapy [27], [28].

The FES, as well as the robot movements, activates sensory channels that provide maximal afferent inflow to the brain. If this inflow is coherent with the motor activity outflow we would be able to close the motor control loop. Recently some groups explored the potential of Brain Computer Interfaces (BCIs) in promoting functional recovery following the previously described principle [29], [30].

In all brain computer interface systems the main problem is to extract the signals of interest in presence of massive biological and externally induced artifacts. In the case of integration of two technologies (BCI and FES or Robotics) brain signals are contaminated with electrical noise and with neural correlates of muscle contractions (FES) and movements (FES and robot), but also other voluntary motor activity. The *artificial* neural contamination comes from the afferent activities due to the muscle contraction and/or limb movement which activate regions habitually used as a source of information for the BCI. This could therefore be understood as a physiological artifact in the integrated system that could either bias or reinforce an online SMR based BCI. In this paper we analyze the different issues concerning the online afferent brain activity influencing motor areas in order to design an on-line FES-BCI.

II. METHODS

A. Experimental Design

Five right handed healthy volunteers were involved in the study. The subjects were seated in a comfortable chair facing a computer screen located 1m apart from the chair. The experiment was divided in two separate blocks: the *hand fixed block* (A) having the subjects hand fixed to a robotic hand orthosis and the *hand free block* (B) in which the hand of the subject was not attached to the orthosis (See Table I). In both

TABLE I. Experimental Design

A. Hand Fixed Block				B. Hand Free Block		
1	2	3	4	1	2	3
Motor Imagery	sFES	Passive	Rest	Voluntary	FES	Rest

There are two separate blocks: four conditions for Hand Fixed Block (A) and three conditions for Hand Free Block (B). Hand openings were targeted in all the conditions other than the condition, ‘Rest’ and ‘sFES’ (sFES: FES below motor threshold)

blocks, the hand starting position and range of motion were controlled to be the same. In the hand fixed block the position of the right hand was controlled defining the maximum and minimum finger extension of the robotic orthosis, while in the hand free block a mechanical structure restricted the movements (See fig. 2).

The hand fixed block consisted of 4 different tasks to the right hand: A1) kinaesthetic motor imagery of opening the hand, A2) FES using a below motor threshold stimulation intensity, A3) passive extension of the fingers and A4) rest. During A2 no movement was produced due to the FES. The hand free block consisted on 3 different tasks to the right hand: B1) voluntary movements, B2) FES-driven hand opening and B3) rest. In task B1, the subject was asked to open the hand and maintain it opened until the end cue appears. In task B2 the hand was passively opened using FES while the subject was asked to relax.

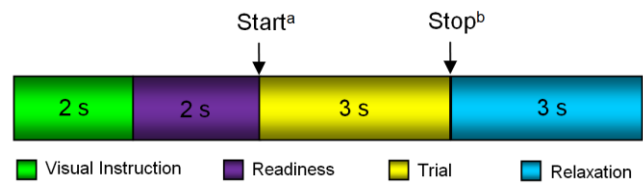


Fig. 1. Time course of a single trial. Subjects were visually informed of the upcoming condition for 2 seconds following 2 second readiness period and then the trial period occurred for 3 seconds. ^aMotor imagery (A1) and voluntary movement (B1) start with auditory cue, “Go”, but the other conditions have no cue signal. ^bTrials for all the conditions stop with “End” signal.

In both blocks the subjects were presented with 2 seconds long visual cues on the screen indicating the upcoming task (time 0 s). In Tasks A1 and B1, two seconds after the visual cue disappeared (time +4 s), an auditory *GO* cue indicated the beginning of the task (see fig. 1). In the remaining tasks no auditory cue was presented since all of them involved passive actions and were either initiated automatically by the orthosis or the FES, or consisted of resting. All the tasks lasted 3 seconds until an auditory and visual *END* cue was presented (time +7 s). The inter-trial interval was constant and lasted for 3 seconds. The cues indicating the tasks were presented to the subject in random order to minimize anticipatory attention. Each task was repeated 50 times during the experiment (n=50). The experimental protocol was approved by the ethics committee of the University of Tübingen, Medical Faculty.



Fig 2. A mechanical structure restricted the range of finger movements for the hand fixed block. The extension of each finger was controlled by this.

- *FES*

Before starting the experiment FES parameters were adjusted for each individual. Two FES unipolar electrodes were placed on the *extensor digitorum communis* (EDC) for finger extension following physical landmarks. We fixed the stimulation frequency to 20 Hz and the pulse width to 300 μ s varying the intensity to detect the motor threshold. We used a stimulator from UNAFET, Belgrade, Serbia to provide the FES. We defined two levels of stimulation: S1) the subject feels the stimulation but no movement is evoked and S2) crossing the motor threshold using the minimum intensity producing finger extension. The subjects were instructed not to move their fingers against or together with the FES-driven movements.

- *Orthosis*

Each finger can be moved individually using a DC-Motor M-28 from Kaehlig Antriebstechnik GmbH, Hannover, Germany with worm gear head from the same company for each finger. Each motor drives via cogwheel and cograil a bowden cable. A finger holder is mounted on the other side of each bowden cable. Near this finger holder an optical position sensor is mounted to detect the finger position independent of the bowden cable tolerance and elasticity. The power electronics is made as a linear regulation to prevent artifacts from switching devices influencing the EEG.

B. Signal Acquisition

EEG data were acquired using 2 BrainAmp amplifiers of 32 channels each from Brainproducts GmbH, Munich Germany. An ActiCap 64-channel EEG cap (modified 10-20 system) from the same company was used for EEG data acquisition, referenced to the nasion, and grounded anteriorly to Fz. EMG data was acquired using 8 bipolar Ag/AgCl electrodes from Myotronics-Noromed (Tukwila, WA, USA) and placed on antagonistic muscle pairs; one close to the external epicondyle on the extensor digitorum (forearm extension), other on the flexor carpi radialis (forearm flexion) other on the external head of the biceps (upper arm flexion) and the last one placed on the external head of the triceps (extension upper arm). The EMG electrode impedance was always kept under 20 kohm.

C. Signal Processing

Data of five healthy volunteers were acquired excluding the entire data set of one participant due to excessive movement related artifacts. To observe the influence of the different afferent stimulation in Online BCI control, an R-square statistical analysis was performed. The “Rest” condition was used as reference for the analysis comparing it to the other classes (FES, passive movement, motor imagery, active movement and below motor threshold FES). The analysis was done using the Offline-Analysis tool from the BCI2000 platform [www.bci2000.org] obtaining a value for each channel and frequency bin (2Hz) combination from 0 to 60 Hz (See Fig. 4).

In each R2 plot, the most significant difference between conditions was determined by the frequency bin and EEG channels combination with the highest R-square values. Since some influences of the electrical noise were observed during FES conditions as seen in fig. 4(e), the stimulation frequency and its harmonics were excluded from our analysis in FES conditions. Since in motor imagery based BCI systems the sensory motor rhythms are commonly used we decided to focus our analysis on frequencies between 6 and 35 Hz. No further artifact rejection was used in order to simulate online conditions.

- *Common Spatial Patterns*

CSP is a technique to analyze multichannel data based on recordings from two classes (tasks). It yields a data-driven supervised decomposition of the signal $x(t)$ parameterized by a matrix W that projects the signal from the original sensor space to a surrogate sensor space [32].

$$x_{csp}(t) = x(t)W \quad (1)$$

Each column vector of W is a spatial filter. CSP filters maximize the variance of the spatially filtered signal under one task while minimizing it for the other task. Since the variance of a band-pass filtered signal is equal to band-power, CSP analysis is applied to band-pass filtered signals to obtain an effective discrimination of mental states that are characterized by ERD/ERS (event related desynchronization/synchronization) effects. In this study the bands and time intervals were individually optimized for each user. The patterns were computed between class Rest vs Motor Imagery, Rest vs sFES and Motor Imagery vs FES and they serve to show that it would be possible to find meaningful patterns between these combinations to perform on-line experiments.

III. RESULTS

As we can see in fig.3, the identified as most relevant frequency per condition changes from subject to subject in accordance to previous literature [33]. For subjects 1 and 2 the most significant frequencies comparing motor imagery and passive movement versus rest was the same. Subject 1 shared

Subject \ Task [Hz]	1					2					3					4					Grand Average				
	P	S	M	A	F	P	S	M	A	F	P	S	M	A	F	P	S	M	A	F	P	S	M	A	F
7-10																									
10-13																									
13-16																									
16-19																									
19-22																									
22-25																									
25-28																									
28-31																									
31-34																									

Fig. 3. Frequency bins with the highest R-square values for individual subject and for the grand average among subjects comparing Rest versus the 5 different conditions: Passive (P, ■), below motor threshold FES (S, ■), motor imagery (M, ■), Active (A, ■), and FES (F, ■).

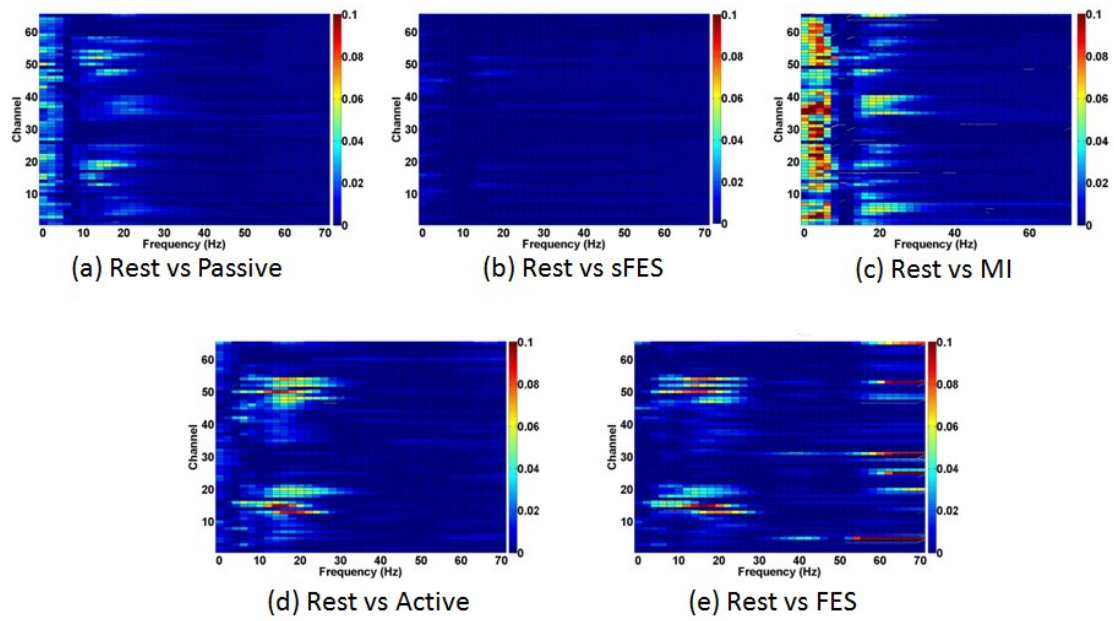


Fig 4. R-square plots of the grand average for the five conditions: (a) Rest vs Passive, (b) Rest vs sFES, (c) Rest vs MI, (d) Rest vs Active, and (e) Rest vs FES. All the conditions had the highest R-square value in the 13-16 Hz bin except one condition, MI. The Rest vs MI had the highest R-square value in the 19-22 Hz.

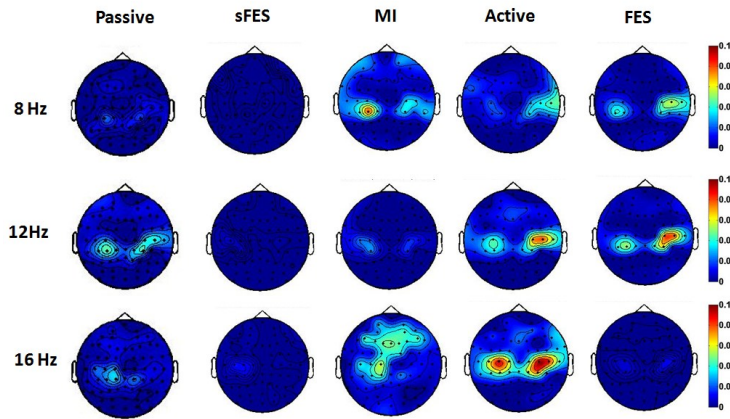


Fig 5. Topography of R-square values for tasks sharing relevant frequencies at three different frequencies (8, 12, and 16 Hz) in columns for all five conditions.

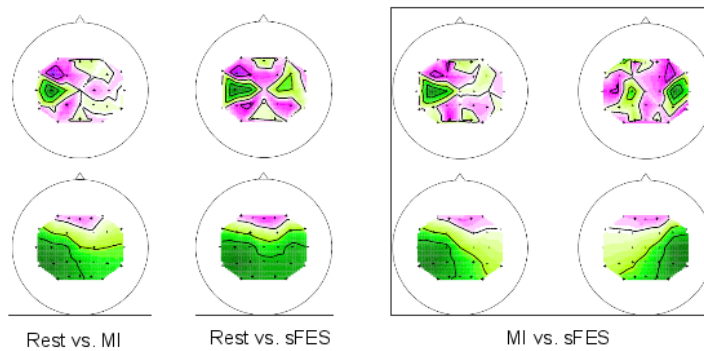


Fig 6. Patterns obtained for the three conditions: Rest vs. MI (8-18Hz), Rest vs. sFES (8-14 Hz), and MI vs. sFES (8-18 Hz).

the same frequency bin with highest R-square values when comparing rest versus Passive and MI. For the contrary Subject 2 presented similar frequencies for the highest R-square values comparing sFES and Active movement versus rest. Subject 3 showed very similar patterns in all conditions and Subject 4 presented the same frequency bin for passive and FES with the highest R-square values.

For the grand average among the subjects, all the conditions besides motor imagery showed the exact same frequency bin to be the most significant one when compared to rest. However, the spatial patterns of the R-square values vary in terms of frequency and electrode locations and among subjects. When observing the grand average data similar patterns were elicited during active and FES in mu and beta bands in terms of spatial distributions presenting high R-square values on top of the motor areas on both hemispheres (see fig. 5). However higher R-square values were found on the ipsilateral hemisphere in both conditions. During the FES without producing muscle contraction and therefore movement (sFES), the highest R-square values were found on the contralateral hemisphere motor regions. During sFES the R-square values were significantly lower compared to the obtained for FES and active movement implying skin mechanoreceptors afferent flow. Afferent brain activity influences more sensorimotor rhythm if a movement is involved although the simple skin sensation elicits as well some desynchronization as previously described in the literature [34].

We computed CSP analysis between different conditions to find out whether meaningful filters can be extracted. Fig. 6 depicts the patterns obtained for the conditions Rest vs. MI (frequency band 8-18 Hz), Rest vs. sFES (8-14 Hz) and MI vs. sFES (8-18 Hz). We can observe that all patterns extracted confirm the results previously described. The sFES presents more ipsilateral ERD than the condition MI, which is nicely represented by the weights around C4. This is however, not observable for the MI case. Additionally, it is possible to find patterns that distinguish between MI and sFES, one focused on the contralateral side and the other in the ipsilateral, to account for the strong ERD of sFES in both hemispheres.

IV. CONCLUSION

Despite the differences between subjects and conditions these data show that there is a clear overlap in terms of the most significant differences between conditions and rest. A classifier for a motor related BCI would use the most significant difference between a condition and rest in order to decode an intention to move (motor imagery in this paper), therefore it is necessary to control for the feedback influence (provoked movement by FES or orthosis) on the brain activity if this can alter the feature used for the classifier. In this paper we demonstrate that in the case of a BCI providing online haptic feedback of any kind it is necessary to differentiate

efferent and afferent brain activity. As well as frequency, spatial distributions are similar between conditions and a further comparison between efferent and afferent spatial and frequency patterns is necessary to avoid haptic feedback related bias in the BCI system. While we illustrated with one example that in principle it is possible to extract subject optimized patterns to distinguish between conditions, we need to still test whether both conditions can be correctly classified when they occur simultaneously. In that case the spatial distribution of a single frequency bin might not be enough to differentiate efferent and afferent motor related brain activity. Further analysis with more subjects needs to be done. Including time as an extra feature or parallel multi-frequency CSPs might serve as a proper solution for the afferent efferent differentiation.

REFERENCES

- [1] M.C. Cirstea, A. Ptito, and M.F. Levin, "Arm reaching improvements with short-term practice depend on the severity of the motor deficit in stroke," *Exp. Brain Res.*, vol. 152, pp. 476-488, 2003.
- [2] H.T. Hendricks, J. van Limbeek, A.C. Geurts, and M.J. Zwarts, "Motor recovery after stroke: a systematic review of the literature," *Arch Phys Med Rehabil.*, vol. 83, no. 11, pp. 1629-37, 2002.
- [3] A. Sunderland, D.J. Bradley, E.L., et al., "Enhanced physical therapy improves recovery of arm function after stroke - a randomised controlled trial," *J. Neurol. Neurosurg. Psych.*, vol. 5, no. 7, pp. 530-35, 1992.
- [4] E. Taub, G. Uswatte, and R. Pidikiti, "Constraint-Induced Movement Therapy: a new family of techniques with broad application to physical rehabilitation-a clinical review," *J. Rehabil. Res. Develop.*, vol. 36, no. 1, pp. 237-51, 1999.
- [5] A.S. Merians, H. Poizner, R. Boian, et al., "Sensorimotor training in a virtual reality environment: does it improve functional recovery poststroke?" *Neurorehabil. Neural Repair*, vol. 20, pp. 252-67, 2006
- [6] C.D. Takahashi, L. Der-Yeghiaian, V. Le, et al., "Robot-based hand motor therapy after stroke," *Brain*, vol. 131, pp. 425-37, 2008.
- [7] B.T. Volpe, D. Lynch, A. Rykman-Berland, et al., "Intensive sensorimotor arm training mediated by therapist or robot improves hemiparesis in patients with chronic stroke," *Neurorehabil. Neural Re.*, vol. 22, no. 3, pp. 305-310, 2008.
- [8] B. T. Volpe, H.I. Krebs, N. Hogan, O. L. Edelstein, C. Diels, and M. Aisen, "A novel approach to stroke rehabilitation: robot-aided sensorimotor stimulation," *Neurology*, vol. 54, no. 10, pp. 1938-1944, 2000
- [9] S. Hesse, H. Schmidt, C. Werner, and A. Bardeleben, "Upper and lower extremity robotic devices for rehabilitation and for studying motor control," *Curr. Opin. Neurol*, vol. 16, pp. 705-710, 2003.
- [10] R. Loureiro, F. Amirabdollahian, M. Topping, B. Driessen, and W. Harwin, "Upper limb robot mediated stroke therapy," *Auton. Robot.*, vol. 15, pp. 35-51, 2004.
- [11] L.R. Sheffler, and J. Chae, "Neuromuscular electrical stimulation in neurorehabilitation," *Muscle and Nerve*, vol. 35, no. 5, pp. 562-90, 2007.
- [12] J. Cauraugh, K. Light, S. Kim, M. Thigpen, and A. Behrman, "Chronic Motor Dysfunction After Stroke: Recovering Wrist and Finger Extension by Electromyography-Triggered Neuromuscular Stimulation," *Stroke*, vol. 31, no. 6, pp. 1360-4, Jun. 2000.
- [13] C.L. Lynch, and M.R. Popović, "Functional electrical stimulation: Closed-loop control of induced muscle contractions," *IEEE Control. Syst. Mag.*, vol. 28, pp. 40-50, 2008.
- [14] J. Powell, D. Pandyan, M. Granat, M. Cameron, and D. Stott, "Electrical stimulation of wrist extensors in poststroke hemiplegia," *Stroke*, vol. 30, pp. 1384-1389, 1999.

- [15] R. Riener, M. Ferrarin, E.E. Pavan, and C.A. Frigo, "Patient-Driven Control of FES-Supported Standing Up and Sitting Down: Experimental Result," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 4, pp. 523-529, 2000.
- [16] J. J. Chen, N. Yu, D. Huang, B. Ann, and G. Chang, "Applying fuzzy logic to control cycling movement induced by functional electrical stimulation", *IEEE Trans. Rehab. Eng.*, vol. 5, pp.158 - 169 , 1997.
- [17] J. Kojović, M. Đurić-Jovičić, and S. Došen, et al., "Sensor-driven four-channel stimulation of paretic leg: functional electrical walking therapy," *J. Neurosci. Meth.*, vol. 181, no. 1, pp. 100-5, 2009
- [18] N. Hogan, H.I. Krebs, B. Rohere, J.J. Palazzolm, L. Dipietro, S.E. Fasoli, J. Stein, R. Hughes, W.R. Frontera, D. Lynch, B.T. Volpe, "Motions or muscles? Some behavioral factors underlying robotic assistance of motor recovery," *J. Rehabil Res. Dev.* vol. 43, pp. 605-618.
- [19] D.B. Popović, and M.B. Popović, "Hybrid assistive systems for rehabilitation: Lessons learned from functional electrical therapy in Hemiplegics," *Proceedings of the 28th IEEE EMBS Annu. Int. Conf.*, pp. 2146-2149, 2006.
- [20] J. Classen, et al., "Rapid plasticity of human cortical movement representation induced by practice," *J Neurophysiol*, vol. 79, pp. 1117-1123. 1998.
- [21] T. Tazoe, et al., "Effects of remote muscle contraction on transcranial magnetic stimulation-induced motor evoked potentials and silent periods in humans," *Clin. Neurophysiol.*, vol. 118, pp. 1204-1212, 2007.
- [22] K. Kamibayashi, et al., "Facilitation of corticospinal excitability in the tibialis anterior muscle during robot-assisted passive stepping in humans," *Eur. J. Neurosci.*, vol. 30, pp. 100-109, 2009.
- [23] D.J. Kidgell, et al., "Neurophysiological responses after short-term strength training of the biceps brachii muscle," *J. Strength. Cond. Res.*, vol. 24, pp. 3123-3132, 2010.
- [24] F. Tyc and A. Boyadjian, "Plasticity of motor cortex induced by coordination and training," *Clin Neurophysiol.*, vol. 122, no. 1, pp. 153-62, 2011.
- [25] J. Liepert, "Evidence-based methods in motor rehabilitation", *J. Fur Neurologie, Neurochirurgie Und Psychiatrie*, vol. 11, no. 1, pp. 5-10, 2010.
- [26] D. O. Hebb, *The organization of behavior*. New York: Wiley & Sons, 1949.
- [27] C. Mercier, A. Aballea, C.D. Vargas, J. Paillar, and A. Sirigu, "Vision without Proprioception modulates cortico-spinal excitability during hand motor imagery," *Cereb. Cortex*, vol. 18, pp. 272-277, 2008.
- [28] J.J. Daly, N. Hogan, E.M. Perepezko, H.I. Krebs, J.M. Rogers, K.S. Goyal, M.E. Dohring, E. Fredrickson, J. Nethery, and R.L. Ruff, *J. Rehabil. Res. Dev.*, vol. 42, pp. 723-736, 2005.
- [29] E. Buch, C. Weber, L.G. Cohen, " Thing to move: a neuromagnetic brain-computer interface (BCI) system for chronic stroke," *Stroke*, vol. 39, pp. 910-917, 2008.
- [30] A. Ramos, S. Halder, and N. Birbaumer, "Proprioceptive feedback in BCI," *Neural Engineering*, 2009. *4th Int. IEEE/EMBS Conf.*, pp. 279-282.
- [31] G. Pfurtscheller, G. R. Müller-Putz, J. Pfurtscheller, and R. Rupp, "EEG-Based Asynchronous BCI Controls Functional Electrical Stimulation in Tetraplegic patient," *J. on Appl. Signal. Process.*, vol. 19, pp. 3152 - 3144.2005.
- [32] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. R. Müller, "Optimizing spatial filters for robust EEG single-trial analysis," *IEEE Signal Process Mag*, vol. 25, no. 1, pp. 41-56, 2008.
- [33] G. Pfurtscheller, C. Brunner, A. Schlögl, and F.H.L. daSilva, "Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks," *NeuroImage*, vol. 31, pp. 153-159, 2006.