

Electroencephalographic Motor Imagery Brain Connectivity Analysis for BCI: A Review

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Recent research has reached a consensus on the feasibility of motor imagery brain-computer interface (MI-BCI) for different applications, especially in stroke rehabilitation. Most MI-BCI systems rely on temporal, spectral, and spatial features of single channels to distinguish different MI patterns. However, no successful communication has been established for a completely locked-in subject. To provide more useful and informative features, it has been recommended to take into account the relationships among electroencephalographic (EEG) sensor/source signals in the form of brain connectivity as an efficient tool of neuroscience. In this review, we briefly report the challenges and limitations of conventional MI-BCIs. Brain connectivity analysis, particularly functional and effective, has been described as one of the most promising approaches for improving MI-BCI performance. An extensive literature on EEG-based MI brain connectivity analysis of healthy subjects is reviewed. We subsequently discuss the brain connectomes during left and right hand, feet, and tongue MI movements. Moreover, key components involved in brain connectivity analysis that considerably affect the results are explained. Finally, possible technical shortcomings that may have influenced the results in previous research are addressed and suggestions are provided.

1 Introduction ---

Brain-computer interface (BCI) is a state-of-the-art technology that translates neuronal activities into user commands. It provides a communication and control channel between the brain and external environment that does not depend on the brain's normal output pathways of peripheral nerves

and muscles so that it offers effective help for those with motor disabilities (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). BCIs are of great value to rehabilitation engineering and assistive technology in which the use of prosthetics, robots, and other devices fully controllable by mental intentions have become a reality (McFarland & Wolpaw, 2008). These systems not only have a direct positive impact on users with disabilities in terms of life quality and communication with their environment, but also offer new modes of human-machine interaction for both disabled and healthy users such as music generation (Miranda, 2010) and computer game control (Finke, Lenhardt, & Ritter, 2009). An increasing number of systems allow control of more sophisticated devices, including orthoses, prostheses, robotic arm, and mobile robots (Graimann et al., 2008; Leeb et al., 2007; Millan, Renkens, Mouriño, & Gerstner, 2004; Müller-Putz & Pfurtscheller, 2008; Pfurtscheller, Müller, Pfurtscheller, Gerner, & Rupp, 2003; Velliste, Perel, Spalding, Whitford, & Schwartz, 2008).

In recognition of the great importance of BCI, there have been remarkable advances in recent decades. In this area, noninvasive BCI has been enhanced in terms of usability, information transfer, and robustness by virtue of modern machine learning and signal processing technology. Generally BCIs measure neurophysiological signals, process them, and produce control signals that reflect the user's intent. Among all neuroimaging techniques, BCIs based on electroencephalogram (EEG) are well accepted for practical applications because they are inexpensive, lightweight, portable, noninvasive with minimal clinical risks, user friendly, and comparatively easy to apply. BCI based on EEG sensorimotor rhythms is known as motor imagery (MI) BCI, a type of endogenous EEG-based BCI that refers to the act of imagining a specific action without actually executing it. MI has been defined as the conscious mental simulation of actions involving our brain's motor representations, similar to when we actually perform movements (Jeannerod & Decety, 1995). This has led to the suggestion that MI and motor execution rely on similar neural structures and processes (Jeannerod & Decety, 1995; Munzert, Lorey, & Zentgraf, 2009). MI can affect neuroplasticity changes after a period of training in healthy subjects (Bakker et al., 2008) and in stroke patients (Cicinelli et al., 2006), which is likely to facilitate functional gains during stroke rehabilitation (Dunsky, Dickstein, Ariav, Deutsch, & Marcovitz, 2006; Dunsky, Dickstein, Marcovitz, Levy, & Deutsch, 2008). In MI-BCI, subjects are asked to haptically imagine movements of certain limbs, for example, the left or the right hand. Then, in order to produce the commands, the operator switches voluntarily between corresponding mental tasks in either synchronous (cue-paced) or asynchronous (self-paced) mode. It is shown that EEG rhythms and their propagation can provide valuable evidence concerning the mechanisms of information processing in the brain (Kus, Ginter, & Blinowska, 2005). Previous studies have indicated that when the subject performs or even imagines limb movement, specific frequency components of EEG such as

the mu and central beta rhythms are (de)synchronized over the contralateral (ipsilateral) sensorimotor area (Neuper & Pfurtscheller, 2001a, 2001b; Wolpaw, McFarland, & Vaughan, 2000). Thus, early studies on MI movement pattern discrimination were based on quantification of event-related synchronization/ desynchronization (ERS/ERD) using bandpower (BP).

A typical signal processing pipeline for such MI-BCI includes preprocessing, feature extraction, and classification stages. In the preprocessing stage, signals are filtered in the spatial or spectral domain, or both, or they are decomposed into the main components in order to remove electrooculogram and electromyogram artifacts. Spatial filters generally unmix the existing signal channels; common methods consist of bipolar derivations (Ofner, Müller-Putz, Neuper, & Brunner, 2011), Laplace filters (Qin, Ding, & He, 2004), independent component analysis (ICA) (Wang, Miao, & Blohm, 2012), and common spatial patterns (CSP) (Ramoser, Muller-Gerking, & Pfurtscheller, 2000). The data are then processed in the feature extraction step. Most noninvasive BCIs have employed single-channel features such as amplitude values like autoregressive (AR) model coefficients, frequency-based features like BP, and time–frequency maps of cortical activity at specific regions (Lotte, Congedo, Lécuyer, & Lamarche, 2007). To classify the features, a number of linear and nonlinear algorithms with different complexity and efficiency have been proposed to discriminate different brain states or MI tasks. A very good review on different algorithms of each BCI processing step can be found in (Bashashati, Fatourechi, Ward, & Birch, 2007).

This review is organized as follows. Section 2 presents the common challenges and limitations observed in conventional MI-BCI systems, followed by a short overview of brain connectivity analysis. Then a comprehensive review on EEG-based brain connectivity analysis during MI movement is presented. In the following section, brain topography analysis during left hand, right hand, feet, and tongue MI movements is discussed. In addition, key components involved in brain connectivity analysis that have considerably affected the results are argued. Finally, we propose suggestions on the shortcomings that may have influenced the results of previous work.

2 Challenges and Limitations of Conventional MI-BCI

Although promising results and achievements have been reported in the literature using the processing pipeline already noted, there remain many challenges and barriers to use this technology easily and effectively for the intended beneficiaries: those who require an alternative means of communication and control, such as people with neuromuscular deficiencies due to disease, spinal cord injury, or brain damage.

It has been shown that the motor imagery responsive frequency bands are not consistent for inter- and intrasubjects (Kam, Suk, & Lee, 2013), which indicates the instability of such BCIs. ERD/ERS analysis for

different subjects has proven to be complex, as ERD/ERS occurs in different parts of the cortex, at different frequencies, and during different time intervals, which leads to difficulty when extracting features for classification (Asensio-Cubero, Gan, & Palaniappan, 2013). As EEG data are often of low amplitude and noisy, there is no consistency in the patterns among different subjects and the patterns that arise can change within a session for the same subject (Asensio-Cubero et al., 2013).

It has been reported that activity invoked by imagination of limb movements is located on the contralateral side of somatosensory cortex, and only a few electrodes have been employed (C3, C4, Cz) to capture the corresponding EEG patterns in such areas (Lal et al., 2004; Spiegler, Graitmann, & Pfurtscheller, 2004). However, other studies have shown that somatosensory stimuli suppressed mu rhythms at both the contralateral and the ipsilateral somatosensory cortex (Nikouline et al., 2000; Yuan, Doud, Gururajan, & He, 2008). In addition, the positions of ERDs are not necessarily beneath electrodes C3 and C4 (Pfurtscheller & Neuper, 2001). Several EEG studies also confirmed the notion that MI can activate primary sensorimotor areas (Beisteiner, Höllinger, Lindinger, Lang, & Berthoz, 1995; Lang, Cheyne, Höllinger, Gerschlagel, & Lindinger, 1996; Pfurtscheller & Neuper, 1997). Other researchers have tended to show that during the performance of cognitive tasks, many different parts of the brain are activated and communicate with one another, thus making it difficult to isolate one or two regions where the activity takes place (McEvoy, Smith, & Gevins, 1998). For instance, it has been demonstrated that the supplementary motor area (SMA), prefrontal area, premotor cortex, cerebellum, and basal ganglia are activated during both movement execution and imagery (Deiber et al., 1998; Erslund et al., 1996; Roland, Larsen, Lassen, & Skinhoj, 1980). Moreover, the role of primary motor cortex (M1) has been widely reported in numerous brain imaging studies explored by EEG (Beisteiner et al., 1995; Lang et al., 1996; Pfurtscheller & Neuper, 1997), functional magnetic resonance imaging (fMRI) (Dechent, Merboldt, & Frahm, 2004; Lotze et al., 1999; Michelon, Vettel, & Zacks, 2006; Porro et al., 1996; Roth et al., 1996), magnetoencephalogram (MEG) (Lang et al., 1996; Schnitzler, Salenius, Salmelin, Jousmäki, & Hari, 1997), positron emission tomography (PET) (Boecker et al., 2002; Malouin, Richards, Jackson, Dumas, & Doyon, 2003), and near-infrared spectroscopy (Miyai et al., 2001; Wriessnegger, Kurzman, & Neuper, 2008).

Another observed limitation is that foot movement imagery invokes activity over Cz, and a distinction between left and right foot movement is not possible because the corresponding cortical areas are too close (Graitmann, Allison, & Pfurtscheller, 2010). Similarly, ERD/ERS patterns of individual fingers cannot be discriminated (Graitmann et al., 2010). It was concluded that to produce detectable patterns, the cortical areas involved have to be large enough so that the resulting activity is sufficiently prominent compared to the remaining EEG. Hand areas, foot areas, and the tongue area

are comparatively large and topographically different. Therefore, current MI-based BCIs are limited in imagination of only four movements: left hand, right hand, feet, and tongue (Schlögl, Lee, Bischof, & Pfurtscheller, 2005). However, it is still challenging to design an effective and flexible BCI system for complex controls in practical applications since the number of control commands in the BCI systems is strictly limited, particularly for simultaneous commands (J. Li et al., 2013). More control commands would provide BCIs with more degrees of freedom.

Study evidence of stroke patients revealed their ability to perform MI despite chronic or severe motor impairments (Johnson, 2000; Malouin, Richards, Durand, & Doyon, 2008), but patients with lesions in the parietal and frontal cortices have difficulty performing MI (Johnson, 2000; Sirigu et al., 1996). These studies showed that the portion of the brain responsible for generating ERD/ERS in MI-BCI could be compromised. Hence, the issue remains whether stroke patients are practically capable of operating MI-BCI effectively. Although some promising findings have shown the reliability of MI-BCI in stroke rehabilitation (Ang et al., 2011; Broetz et al., 2010; Caria et al., 2011), there is a lack of long-term evidence to support its clinical relevance. In addition, no successful communication has been established through BCI with a completely locked-in subject (Birbaumer & Cohen, 2007; Kübler & Birbaumer, 2008). Kübler and Birbaumer (2008) reported that BCI technology has been unable to restore basic communication in patients who were in a complete locked-in state at the beginning of the training. However, these patients showed ERP responses to one or more complex cognitive tasks, thus indicating partially intact processing stages despite a reduced general arousal (Hinterberger, Birbaumer, & Flor, 2005). Therefore, the most challenging part in MI-based BCI research is communication with such patients, for which the reason is still unknown. Cognitive deficits in completely locked-in patients cannot be ruled out at present as the cause of this failure. It could be from abnormal brain activities in patients with severe disabilities, such as in late stages of amyotrophic lateral sclerosis (Kotchoubey, Lang, Winter, & Birbaumer, 2003). It might be possible that intentionally induced BP changes in the electric field of the brain are reduced in these subjects (Grosse-Wentrup, 2009). It was suggested that users should enter BCI training before the beginning of the total locked-in phase (Kübler & Birbaumer, 2008).

One of the most likely and inevitable reasons for the weaknesses and limitations of MI-based BCI noted is the use of temporal, spectral, and spatial EEG features from individual channels for discriminating different MI patterns because they may not provide enough information. Consequently, a better understanding of brain neural dynamic patterns behavior is essential for providing more useful and informative features for BCIs. It is well known that the execution of even simple motor or cognitive tasks by the brain requires the participation of multiple cortical regions that are mutually interconnected and exchange their information via plastic long-range

synapses (Cona, Zavaglia, Astolfi, Babiloni, & Ursino, 2009). Hence, knowledge of brain connectivity has become an essential aspect of modern neuroscience, especially for understanding how the brain realizes its basic functions and what the role of different regions is. Accordingly, it is expected that different cognitive tasks like MI of different limbs are associated with different connectivity patterns between brain regions. Therefore, a promising approach for solving the limitations is to consider the relationships among interchannels or sources of brain signals, measuring the connectivity of spatially distributed regions during MI movements.

3 Brain Connectivity Analysis

It is well established that neurons do not function as isolated units (John, 2002). Large groups of neurons distributed along the cortex can quickly become associated or disassociated, thus giving rise to transient assemblies (Triesch & von der Malsburg, 2001). The emergence of specific neural assemblies is thought to provide the functional elements of brain activity that execute the basic operations of informational processing (Finger, 2001; Varela, Lachaux, Rodriguez, & Martinerie, 2001). The assembly as a whole has emergent properties that do not exist at the level of individual neurons (John, 2002). Accordingly, physiologically speaking, brain connectivity is the communication of neurons within an assembly through the synchronous activity of the participating neurons (Nunez, 2000; Singer, 1993; Varela et al., 2001). The ultimate goal of brain connectivity analysis is to find such connections, whether direct or indirect, as well as their strength (Lang, Tomé, Keck, Górriz-Sáez, & Puntinet, 2012). Researchers tend to study both normal and pathological brain function in order to find variations in activation and interactions among brain regions (Sakkalis, 2011). In this context, EEG-based brain connectivity analysis plays a dominant role because the brain acts as a dynamic system in which certain physiological parameters change over time and since the transient synchronization of neuronal systems is essential for brain operation, a temporal resolution in the order of milliseconds is of special interest (Fingelkurts, Fingelkurts, & Kähkönen, 2005).

Brain connectivity analysis can be divided into neuroanatomical (structural), functional, and effective connectivity among which functional and effective connectivity can be applied for BCI. In the following sections, we provide a short overview of functional and effective connectivity. Before that, we explain one of the most challenging issues that significantly influence EEG-based brain connectivity analysis: the volume conduction (VC) effect.

3.1 Volume Conduction Effect. The goal of connectivity analysis in EEG recordings is to estimate interactions among different brain regions. Unfortunately, EEG recordings do not offer direct access to brain signal sources. Instead, each EEG electrode measures a linear and instantaneous

superposition of EEG sources within the brain (Nunez & Srinivasan, 2006). In other words, EEG recordings are spatially diffused while traversing from the source regions to the sensors by a process called VC. Due to VC, a deep source of electrical potential can influence many sensors on the scalp surface; that is, the signal measured from an EEG electrode does not exclusively represent the activity of one local neural source but, rather, the superposition of the activity of several active sources throughout the brain. In addition, neuroelectric signals recorded at the scalp are principally distorted by the effects of the skull, scalp, and other intervening conductive tissues. This distortion, the VC effect, acts as a spatial low-pass filter that causes the potentials at the scalp to appear blurred (Le, Menon, & Gevins, 1994). VC can give rise to spurious instantaneous correlations between scalp EEG signals and potentially leads to misinterpretation of sensor-space EEG analysis (Nunez et al., 1997). The fact that VC has to be accounted for in EEG-based brain connectivity studies is receiving more and more attention (Gómez-Herrero, Atienza, Egiastian, & Cantero, 2008; Nolte et al., 2004, 2008). To address this problem, various techniques have been proposed: (1) applying connectivity measures designed to suppress instantaneous effects (Kus, Kamiński, & Blinowska, 2004; Nolte et al., 2004, 2008; Omidvarnia et al., 2014), (2) inclusion of an instantaneous term in vector autoregressive (VAR) models (Erla, Faes, Tranquillini, Orrico, & Nollo, 2009; Faes & Nollo, 2010; Hamed, Salleh, Ting, Samdin, & Mohd Noor, 2015; Hyvärinen, Zhang, Shimizu, & Hoyer, 2010; Samdin, Ting, Salleh, Hamed, & Mohd Noor, 2014), and (3) modeling the EEG as a mixture of sources (Baillet, Mosher, & Leahy, 2001; Delorme et al., 2011; Gómez-Herrero et al., 2008).

3.2 Functional Connectivity. Functional connectivity is defined as the temporal dependency of neuronal activation patterns of anatomically separated brain regions. This concept relies on statistical measures that are highly time dependent and fluctuate on multiple timescales ranging from milliseconds to seconds (Lang et al., 2012). Computational methods to quantify functional connectivity can be grouped as linear, nonlinear, and information-based techniques. It must be noted that the absence of one of these statistical measures between two processes does not mean the absence of any interaction between them at all (Fingelkurts et al., 2005) (more information is provided in Bullock et al., 1995; Kaplan, Fingelkurts, Fingelkurts, Ivashko, & Darkhovsky, 1997).

Linear brain connectivity was primarily measured using cross-correlation of pairs of EEG signals as an amplitude measure. Higher correlations indicate stronger functional relationships between the related brain regions (Adey, Walter, & Hendrix, 1961; Brazier & Casby, 1952). In the frequency domain, linear connectivity is computed using magnitude squared coherence (MSC) or coherence (Coh) (Pfurtscheller & Andrew, 1999). Coh is a measure of synchronization between two signals based mainly on phase consistency; that is, two signals may have different phases but high Coh

occurs when this phase difference tends to remain constant (Bendat & Piersol, 2011; Srinivasan, Winter, Ding, & Nunez, 2007). Coh is sensitive to both changes in power and phase relationships (Bendat & Piersol, 1980). This measure has been widely employed to quantify synchronization brain processes (Nunez et al., 1997; Sarnthein, Petsche, Rappelsberger, Shaw, & Von Stein, 1998). Correlation is independent of amplitude and sensitive to phase and polarity (Sakkalis, 2011).

Nonlinear methods are designed to detect the dynamics of EEG signals (Lorenz, 1963). Synchronization is at the forefront of nonlinear neural connectivity measures, which is based on interacting chaotic oscillators (Pecora & Carroll, 1990; Pikovsky, 1984). This measure is principally denoted by the concepts of the phase and generalized synchronization (Sakkalis et al., 2009). It provides an amplitude-free measure of connectivity between cortical regions and is thus less susceptible to the effects of artifacts and inter-trial/intersubject amplitude variability (Truccolo, Ding, Knuth, Nakamura, & Bressler, 2002). Phase synchronization (PS) is often observed in gamma frequency large-scale oscillations that enter into precise phase locking over a specific period of time during cognitive tasks (Lachaux, Rodriguez, Martinerie, & Varela, 1999). Phase locking value (PLV) is a major statistical measure of PS strength (Pereda, Quiroga, & Bhattacharya, 2005; Sakkalis et al., 2009). It was first described for MEG as phase coherence (Hoke, Lehnertz, Pantev, & Lütkenhöner, 1989) and then introduced in EEG as PLV (Lachaux et al., 1999) and later in the fields of cognitive neuroscience and epilepsy research (Mormann, Lehnertz, David, & Elger, 2000). It has also been employed in various research kinds of (Bhattacharya, Petsche, Feldmann, & Rescher, 2001; Lachaux et al., 1999; van Putten, 2003) and as a feature in BCI applications (Song, Gordon, & Gysels, 2005). The neuroscience literature suggests that phase as a time-domain synchronization measure may be more discriminative than amplitude and is a sensitive measure due to its relevant change in synchrony (Gonuguntla, Wang, & Veluvolu, 2013). In addition, when dealing with nonstationary signals, PLV is the best choice (Sakkalis, 2011). Compared to Coh, PLV offers better results as it is more restrictive, easier to compute, and requires fewer data for a given time resolution (Gysels & Celka, 2004; Gysels, Renevey, & Celka, 2005). More details on these measures can be found in Sakkalis and Zervakis (2009).

As the effect of VC, time series that are recorded from nearby electrodes are likely to pick up activity from the same sources, which gives rise to spurious correlations between these time series (Stam, Nolte, & Daffertshofer, 2007). As mentioned, each EEG signal is generated by a superposition of many brain current sources; the contribution of each source depends on source and electrode locations and the spread of current through the head volume conductor (Nunez & Srinivasan, 2006). Geweke (1982) showed that total connectivity is a sum of instantaneous and true components. Since Coh and PLV measure connectivity, they are very sensitive to VC effect so

they are not suitable to assess electrode-space functional connectivity. As a better alternative, it was shown that the imaginary part of coherence (iCoh) can diminish the effects of volume conduction (Mima, Matsuoka, & Hallett, 2000; Nolte et al., 2004). The idea here is that only the real parts of the cross-spectrum and related quantities are affected by instantaneous effects. Thus, by using only the imaginary part, many traditional coupling measures can be made robust against VC (Nolte et al., 2004, 2008). In 2007, phase lag index (PLI) was proposed, which reflects the strength of the coupling and less sensitivity to the influence of common sources and amplitude affects (Stam et al., 2007). This measure is based on the idea that the existence of a consistent, nonzero phase lag between two time series cannot be explained by VC from a single strong source and therefore renders true interactions between the underlying systems. In simulations, PLI performed better than iCoh in detecting true changes in PS and was less sensitive to the addition of volume-conducted noise sources (Stam et al., 2007). Still, PLI's sensitivity to noise and VC may be hindered by the discontinuity in this index, as small perturbations turn phase lags into leads and vice versa, a problem that becomes more serious for synchronization effects of small magnitude (Vinck, Oostenveld, van Wingerden, Battaglia, & Pennartz, 2011). Weighted phase lag index (WPLI), which is based on the imaginary component of the cross-spectrum, was then introduced to better detect true changes in PS and reduce the influence of common noise sources, as well as changes in the phase of the coherency (Vinck et al., 2011). The WPLI extends the PLI by weighting the contribution of observed phase leads and lags through the magnitude of the imaginary component of the cross-spectrum, which leads to alleviating the discontinuity mentioned above.

Information-based measures are another group of functional connectivity techniques that can detect both linear and nonlinear interactions between two signals. The cross-mutual information (CMI) method computes the mutual dependence between two signals by quantifying the amount of information obtained about one signal from measuring the other as a function of delay between them (Sakkalis, 2011). The main strength of CMI is that it detects high-order correlations as it is based on probability distributions. This method has been used for diagnosing schizophrenia and Alzheimer's disease (Jeong, Gore, & Peterson, 2001; Na, Jin, Kim, & Ham, 2002). As another method, minimum description length is based on the degree of predictability of each of the two signals as a function of the other (Sakkalis et al., 2009).

3.3 Effective Connectivity. Effective connectivity describes the influence one neuronal system exerts on another, thus reflecting causal interactions between activated brain areas (Lang et al., 2012). In other words, effective connectivity represents the direction and strength of the information flow between different brain areas (Astolfi, Cincotti et al., 2007). This type

of connectivity can be measured by means of model-based, data-driven, and information theory-based approaches.

Model-based effective connectivity is based on theoretical models that describe how brain areas interact and influence each other (Sakkalis, 2011). Dynamic causal modeling (DCM) is the most popular method for measuring nonlinear interactions that assume a bilinear state-space model (Friston, Harrison, & Penny, 2003). The key to DCM is that a dynamic system response can be modeled by a network of discrete but interacting neuronal sources described in terms of neural-mass (Da Silva, Hoeks, Smits, & Zetterberg, 1974; Moran et al., 2007) or conductance-based models (Morris & Lecar, 1981). This method was introduced for fMRI (Friston et al., 2003) and was later extended to EEG and MEG (Daunizeau, Kiebel, & Friston, 2009; Kiebel, Garrido, Moran, Chen, & Friston, 2009). DCM requires knowledge about the input to the system because this input is modeled as modulating the interactions of the parts of the system (Friston et al., 2003). It also requires a certain amount of a priori knowledge about the network of connectivity under investigation since DCM ultimately compares the evidence for several competing priori models with respect to the observed data (Vicente, Wibral, Lindner, & Pipa, 2011). This a priori knowledge on the input to the system and on the potential connectivity may not always be available or accurate—for example, in studies of the resting state and neurodegeneration. Therefore, DCM may not be optimal for exploratory analysis (Vicente et al., 2011). Moreover, application of neural mass models to estimate effective connectivity is a difficult task due to the number of parameters involved and the presence of nonlinear terms, which preclude the use of analytical solutions (Cona et al., 2009).

Data-driven methods do not assume any particular underlying model or prior knowledge concerning spatial or temporal relationships (Sakkalis, 2011). Granger causality (GC), one such method, assumes that causes precede their effects in time, and it uses a linear stochastic model for the intrinsic dynamics of the signal and a linear interaction (Vicente et al., 2011). If a signal can be predicted by past information from a second signal better than the past information from its own signal, then the second signal can be considered causal to the first one (Granger, 1969). This relation between time series is not necessarily reciprocal; $X(n)$ may cause $Y(n)$ without $Y(n)$ causing $X(n)$. This lack of reciprocity allows the evaluation of information flow direction between elements (Fallani, Astolfi, Cincotti, Babiloni, & Colosimo, 2008).

GC in the frequency domain was developed in 1982 and allowed the analysis of coupling between EEG frequency bands, which is significant in biomedical signal analysis (Geweke, 1982). Later, the concept was improved from bivariate to multivariate signals (Geweke, 1984; Hosoya, 2001). Multivariate spectral techniques directed transfer function (DTF) (Kaminski & Blinowska, 1991) and partial directed coherence (PDC) (Sameshima & Baccalá, 1999) were proposed to determine directional influences between any

given pair of channels in a multivariate data set. These estimators are able to characterize the direction and spectral properties of the brain signals simultaneously, requiring only one multivariate autoregressive (MVAR) model to be estimated from all the EEG channel recordings. As Kuś et al. (2004) have stressed, the multivariate approach avoids the problem of the estimation of spurious functional links, which is very common with conventional bivariate approaches. DTF was applied successfully to localize epileptic foci (Fraszczuk & Bergey, 1998) and investigate EEG propagation in different sleep stages (Kamiński, Blinowska, & Szelenberger, 1997). In 2001, a time-varying extension of DTF, short-time DTF (SDTF), was developed to investigate the dynamics of brain activity (Kamiński, Ding, Truccolo, & Bressler, 2001) and has been employed in evaluating motor task experiments (Ginter, Blinowska, Kamiński, & Durka, 2001). DTF is robust in respect to noise (Kuś et al., 2005); it correctly identifies the propagation in the presence of noise that is several times higher than the signal itself and is insensitive to constant phase disturbances (Kamiński et al., 2001). VC involves propagation of the electromagnetic field with the light velocity; hence there are no delays between channels—it is zero phase propagation. DTF effectively discriminates against VC since it detects the differences of phases (Kuś et al., 2005). Other extensions of these measures that have been used in the BCI context are generalized partial directed coherence (GPDIC), partial directed coherence factor (PDCF), and full-frequency DTF (ffDTF) (Billinger, Brunner, & Müller-Putz, 2013). The MVAR estimators have already been applied to high-resolution EEG signals in order to achieve connectivity networks during motor and cognitive tasks (Astolfi, Cincotti et al., 2007; Astolfi, De Vico Fallani et al., 2007).

Information theoretic-based technique is another successful approach to measure the effective connectivity. Transfer entropy (TE) is the best-known method in this area, which naturally incorporates directional and dynamical information because it is inherently asymmetric and based on transition probabilities (Vicente et al., 2011). It does not require a priori information of the type of interaction; it is able to detect frequently observed types of purely nonlinear interactions; it can detect effective connectivity even if there is a wide distribution of interaction delays between the two signals; and it is robust against linear cross-talk between signals (Vicente et al., 2011). Furthermore, for continuous processes, it is invariant under coordinate transformations (Kaiser & Schreiber, 2002). Importantly, this entails invariance with regard to scaling of the random processes. This technique has been employed in Grosse-Wentrup (2009) and Vicente et al. (2011) for EEG and MEG connectivity analysis, respectively.

4 EEG-Based Motor Imagery Brain Connectivity Analysis _____

This section reviews previous studies that have investigated the EEG-based brain network of healthy subjects and connectivity analysis during different

MI movements. Although great efforts were made to find related studies, only a few have been found, which indicates the short tenure but rapid growth of this research field. In this review, research that highlighted the differences of brain network during both real movement and its imagination are also considered; however, only the results for MI movements of different conditions are taken into account and reported here.

In 2004, for the first time, the phase coupling of sensorimotor rhythms in different motor areas during tongue-MI was investigated on three right-handed subjects using PLV (Spiegler et al., 2004). EEGs in channels C3, C4, and Cz were filtered between 1 Hz and 50 Hz and local average reference derivations were computed in order to obtain reference-free EEGs. Then the signals were transformed into the time-frequency domain through Morlet wavelets, PLV measures were calculated between each electrode pair, and the significant PLVs were kept by the use of 95% confidence level. Results reported an increase in amplitude around left and right hand region mu rhythms while imagining tongue protrusion. Phase coupling of 10 Hz oscillations was also increased between the primary sensorimotor hand representation areas (C3 and C4) and the premotor area (Cz). No particular changes in phase coupling were found between mu rhythms in both hemispheres at electrodes C3 and C4.

The usefulness of interaction between EEG signals was examined for classifying mental tasks in the BCI framework (Gysels & Celka, 2004). Using 32 channels, we recorded EEGs from five right-handed volunteers during imagination of repetitive self-paced left hand (LH) and right hand (RH) movements and imagination of words that begin with the same letter. PLV and Coh were measured from sliding 1 second windows, eight times per second within 8 Hz to 30 Hz. The power spectral densities (PSDs) in the α (8–12 Hz), β_1 (13–18 Hz), β_2 (19–30 Hz), and λ (8–30 Hz) bands were computed by means of the Welch's averaged PSD. Several subsets of features were made based on the extracted features and fed to support vector machine (SVM) for classification. Pairs of feature subsets were compared with each other to examine significant differences. Generally the results provided evidence of high-variable classification performance within subjects on different days. Classification results indicated that PLV considerably outperformed Coh. α and λ features were better than β_1 for two subjects and β_2 in the case of all subjects. Low-frequency features performed better than higher-frequency ones. For very short time windows, PLV distinguished different intervals of common activity, though with high inconsistency, while Coh was unable to make any distinctions at all. Moreover, α and λ meaningfully outperformed Coh and PLV. All cognitive tasks were successfully recognized when PLVs and PSD were combined.

Determination of electrical brain activity propagation in beta and gamma band in sensorimotor areas during LH-MI and RH-MI movements was studied on three right-handed participants (Ginter et al., 2005). SDTF measures were estimated where a MVAR model was fitted to 10 EEG signals

with model order 5 and 0.4 second window length, which was shifted by 10 samples over the whole epoch. Their results showed a gap in the propagation in alpha and beta bands for electrodes overlying primary motor-sensory area in seconds 3 to 5 (including pre- and perimovement) and bursts of gamma activity in about the same time. A decrease of propagation in beta band was not always accompanied by the increase in gamma; sometimes both components fluctuated in a similar way. Investigation on difference of flows in gamma and beta bands after the cue showed that between 3.0 and 3.7 seconds for both hands, the most characteristic feature was the activity in the left hemisphere. For RH, it was the contralateral side, and for LH, where it was the ipsilateral side, the gamma propagation from around C4 was also observed. In epoch 3.7 to 4.2 seconds, for RH, the propagation in gamma band mainly came from primary sensorimotor area (electrode C3) and the locations posterior to it. This activity was mainly directed toward frontal structures. For LH, there was still strong propagation at the ipsilateral side; however, the contralateral side became more active, especially in the area underlying C4 and electrodes located closer to the midline. For epoch 4.2 to 5.0 seconds, for RH, the beta-gamma spread from the regions close to C3 and posterior to it (more toward midline) and was directed to the front and to Cz. For LH, this situation was mirrored. For both hands, flows were also observed in more posterior locations at the ipsilateral side.

The pattern of EEG activity propagation in beta and gamma band was also investigated during imagination of lifting up left and right hand index finger (LHF and RHF) movements (Kuś et al., 2005). EEG signals were recorded from nine right-handed volunteers using 30 electrodes. To examine the dynamics of brain activity, signals from 18 channels were analyzed by means of a nonnormalized SDTF based on a MVAR model with model order 5, window size with 400 msec, and sliding window with 80 msec of length. The statistical significance of flow changes related to the subject's action was then found using a bootstrap technique. The results demonstrated the bigger dynamics of outflows from the primary motor cortex area in comparison to outflows from other areas in beta band. In the same band, the activity was increased after cue onset, and it decreased during MI and a subsequent rebound. For imagination of RHF, 0 to 0.5 seconds after cue onset, the strongest outflow was observed in the left hemisphere. However, this increase was not obvious for LHF in the same period. A short and weak decrease of outflow of beta activity was localized on the right hemisphere around electrode C2, 0.3 to 1.5 seconds after cue onset for LHF. For RHF, the decrease was observed in both hemispheres; however, it was more pronounced for electrode Cp3. After the task (1–3 seconds after cue), an increase of outflow was seen mainly at the electrodes at the mid-central and frontal areas. In the gamma band, activity outflow started 1.0 to 1.1 seconds after the cue onset, and big areas of brain, especially around Cz, were engaged in activity emission. In this band, the propagation often started in more posterior areas, which indicated more involvement of the

sensory areas. In case of LHF, the gamma activity started to propagate in the right hemisphere (0.4–0.8 seconds after the cue onset), after which the flow was observed with a delay of about 0.7 to 0.8 seconds in the symmetrical locations of the left hemisphere. For the RHF, the results were less consistent in more cases where the flow started in the contralateral hemisphere. Another characteristic feature was the propagation from the central areas of the head (electrodes Cz, Fz, Fc1, Fc2) overlying the SMA, especially for RHF from Fc1 and for LHF from Fc2.

Song and associates (2005) proposed an MI-BCI based on phase synchrony rate (PSR). PSR, computed from binarized PLV, described the number of discrete synchronization events within a window. This study was carried out on data set IVa of BCI competition III (five subjects participated) for RH and foot MI movements. Spatial resolution of raw EEGs was improved by using a Laplacian filter. Then filtered EEGs were split into 6 sliding windows of length 100. Each window was further divided into 76 microwindows (with size 25 and overlap by 24). PLVs were then computed using Hilbert transformation and binarized for each microwindow. Averaging the 76 binarized PLVs resulted in the PSR. As a whole, 6 PSRs were computed for each electrode pair in a trial. PSRs from all electrode pairs were passed to statistical tests and further used as features for classification by linear SVM. Statistical nonparametric tests showed that PSRs contained significant differences between two types of motor imageries. Generally the error of the PSR method was higher than those of the PLV method. The qualitative similarity between the PSR and PLV method suggested that phase was more discriminative than amplitude within the first 1.5 to 2.0 seconds.

An online BCI system based on ongoing phase coupling quantified by the PLV of EEG channels was presented in Brunner, Scherer, Graimann, Supp, and Pfurtscheller (2006). In offline study, EEG signals were recorded from six subjects during imagination of LH, RH, foot, and tongue movement using 22 electrodes. A feature set was formed through a number of PLV features by using signals from seven channels; 21 different electrode pairs were constructed. For each pair, PLV features in 12 frequency bands were calculated—namely, 11 nonoverlapping narrow bands (width 2 Hz) between 8 and 30 Hz plus a broadband (8–30 Hz)—yielding 252 different PLV features. These features were fed into a sequential floating forward feature selection (SFFS) algorithm to choose at most eight features and finally served to linear discriminant analysis classifier. It was shown that for most of the subjects, the feature subsets selected by the SFFS contained several PLV values that had been filtered in the broad frequency band between 8 Hz and 30 Hz. Therefore, broad-banded features were chosen to be used in online experiments. Offline topographical analysis indicated that interhemispheric electrode pairs were rarely selected; couplings within one hemisphere were dominant in all subjects. Moreover, couplings involving the frontal electrode location occurred more often than the occipital region.

Consequently, online study was conducted with only the four pairs and three classes (LH, RH, and foot). The online sessions revealed that all subjects were able to control three mental states with single-trial accuracies between 60% and 66.7% throughout the whole session. Another offline experiment was carried out in order to find out if classification performance can be improved when using PLV features in addition to BP features. Results showed that BP features performed better than phase features; when they were combined, the resulting classification accuracy was higher compared to using only one feature type.

The neural coupling level in the mu rhythm during imagination of LH and RH movement was studied using PLV among EEG electrodes in primary motor area (M1) (local scale) and between M1 and SMA (large scale) (Wang, Hong, Gao, & Gao, 2006). EEG signals were captured from six right-handed volunteers by means of 32 channels. Signals instantaneous phase was achieved through the analytic signal using Hilbert transform, and the corresponding phase difference in each signal pair was computed. For large-scale synchrony investigation, PLV was computed between the three pairs FCz-C3, FCz-C4, and C3-C4. For local-scale synchrony, four electrodes around FCz, C3, and C4 were joined to make a five-electrode group, and PLV was computed by averaging over all 10 combinations of electrode pairs from the five electrodes. For single-trial classification, three local-scale and three large-scale PLV features were obtained and fed to a Fisher discriminant analysis (FDA) classifier. Results indicated that large-scale PLV was bigger for RH over C3-FCz, as well as the left M1 area, while the PLV of the LH had a higher value over C4-FCz and within the right M1 area. In addition, PLV indicated a low level of synchrony between left and right hemispheres, and there was no meaningful difference between LH and RH. No significant difference was observed between LH and RH for local-scale synchrony in the SMA area. Classification results showed 84.70% and 77.08% accuracy for large-scale and local-scale synchrony, respectively. A higher accuracy (87.02%) was achieved for the combination of two-scale synchronies, and the best performance (96.13%) was gained when large-scale synchrony and power features were combined.

The previous study was extended by examining amplitude and phase coupling measures for feature extraction in an MI-based BCI (Wei, Wang, Gao, & Gao, 2007). Five right-handed participants were instructed to imagine RH and LH movement, and EEGs were captured with 32 electrodes over the primary sensorimotor area (SM1) and the SMA. The data were re-referenced by common average reference and filtered by spatial Laplacian filter. The connectivity between EEGs was quantified for the amplitude coupling by nonlinear regressive (NLR) coefficient and for the corresponding phase relationship using PLV. The coupling measures were based on five electrodes around C3 and C4 in each hemisphere and three electrodes in SMA: (1) coupling between any two electrodes around C3 and C4 (CW), (2) coupling between each electrode around C3 and each electrode around

C4 (CB1), and (3) coupling between each electrode around Fz and each electrode around C3 and C4 (CB2). Six feature vectors were achieved by using these coupling methods separately for computing the NLR and PLV. For single-feature vectors FDA and for a combination of two feature vectors, SVM techniques were applied for classification. In this study, the performance of NLR and PLVs was also compared to AR coefficients, which were estimated from single EEG signals using Burg algorithm. The best classification accuracy was obtained by CB2 for NLR (92.8%) and PLV (92.9%), and CW outperformed CB1 for both coupling measures. Wei et al. (2007) reported that although NLR features delivered slightly higher classification accuracy for CW and CB1, their computational cost was higher than PLV features. It was also shown that considering CW and CB1, AR provided a little higher classification accuracy (93.3%) than the best performance obtained by coupling measures. They finally indicated that a combination of coupling measures with AR coefficients increased classification accuracy.

Stavrinou, Moraru, Cimponeriu, Della Penna, and Bezerianos (2007) investigated the cortical activation and connectivity subserving imaginary rhythmic finger tapping using PS analysis. Three right-handed volunteers were instructed to imagine the kinesthetic of right index finger-tapping movement while EEGs were recorded by 60 channels. Active electrodes (20 electrodes) were selected based on the detection of maximum activity; 10 for the left and 10 for the right hemispheres. Laplacian filtering was employed to reduce the effect of VC, and a complex Morlet wavelet transform was used to quantify the oscillatory activity. They applied wavelet PS, taking the scale of the wavelet corresponding to the most reactive frequencies in the beta range. After extraction of phases, the degree of synchronization between any two of the selected electrodes was evaluated on a single trial basis by means of a PS index. Using a significance level of 5%, they reported the frontoparietal coactivation during MI movements and functional connectivity over the contralateral hemisphere. For prestimulus and poststimulus, the most reactive frequencies were in the range of 18 to 20 Hz. A clear decrease in the signal energy was revealed in electrodes C1 and FC3 after the stimulus presentation at the contralateral hemisphere (ERD). Afterward, energy power rebounded, and an ERS occurred. The significant synchronization values identified beta range synchronization between signals recorded at electrodes FCZ, C5; CPZ; and CP1.

EEG connectivity during MI of the LH and RH was investigated in a broad frequency range across the whole scalp by combining beamforming with TE (Grosse-Wentrup, 2009). EEG signals were captured from four subjects by 128 electrodes and re-referenced to common average reference. Beamformers were designed to extract those components of the EEG originating in the left and right motor cortex. Then model-based covariance matrices for EEG sources within the left and right motor cortex were computed. The extracted EEG sources, as well as the unfiltered data recorded at

each electrode, were then bandpass-filtered with sixth-order Butterworth filters in five frequency bands ranging from 5 Hz to 55 Hz in steps of 10 Hz. Then TE was computed from all EEGs at each sample point. Class-conditional BP changes (ERD/ERS) of extracted sources were computed in order to identify frequency bands with common modulations in BP and TE. Observed changes in TE were statistically significant at level 0.01 for all electrodes. Their results showed no distinct differences in TE between MI of the LH and RH. Instead, the strongest differences in TE were observed in rest versus MI of either hand. The amount of decrease in TE during MI relative to rest increased with higher frequencies and was most pronounced in the gamma band, 45 Hz to 55 Hz. Topographically, the strongest differences were observed in frontal, precentral, and postcentral areas.

Tsiaras, Andreou, and Tollis (2009) investigated the differences between the LH and foot (F) MI synchronization networks by comparing them with the average idle state (I) synchronization network characterized by modern graph theory. EEGs recorded from four participants were filtered by the CSP spatial filter, and PSD was computed by Welch's algorithm. The synchronization between all channel pairs for mu and beta frequency bands was computed by means of a robust interdependence measure (RIM) and PDC. Results showed that functional networks constructed from motor imagery EEG data were irrelevant to MI movements due to VC effect. Networks LH and F were also very similar. To eliminate redundant connectivities, network I was subtracted from networks LH and F. For two subjects, when networks were constructed by PDC, the network LH minus I had long edges that spanned both hemispheres and was associated with the MI task or occipital or parietal alpha activity. In network F minus I, the long edges were less obvious. When networks were constructed by RIM, the long edges between hemispheres of network LH minus I were mixed with other edges. Network I minus LH and I minus F had more edges close to the LH and F areas of the sensorimotor cortex, respectively. Intersubject variability was also observed in this study.

The interchannel connectivity of LH, RH, feet and tongue MI tasks for a noninvasive BCI application was studied in Chung, Kim, and Kim (2011). The goal was to find a spatiotemporal pattern of connectivity unique to each MI by studying the EEGs of two subjects. They considered a total of 6 seconds of data that contained 2 seconds preimagery and 4 seconds peri-imagery segments. A short-time window approach (1 second window length with step size of 0.1 second) was used to estimate connectivity by computing a linear correlation coefficient (CC) in each window. Their results showed clear differences among the four motor imageries. More positive CCs were obtained for LH and RH compared to feet and tongue. They observed contralateral connectivity for LH and RH in two subjects. CCs between frontal and parietal areas showed substantial difference between LH and RH at different time windows for different subjects. They observed the least number of significant connectivity in the tongue MI in

both subjects. They reported the central connectivity for both feet MI in one subject, while no significant channel connection was seen for the other subject.

Hoang, Tran, Nguyen, Huang, and Sharma (2011) proposed a bivariate feature that combined a short-window bivariate autoregressive (CSWB-VAR) model for classification of RH and LH motor imagery movements from one subject. Given the channels pair, they divided each of them into overlapping short windows and then estimated bivariate autoregressive (BVAR) parameters for each pair of windows. CSWBVAR was formed by combining extracted BVAR parameters together with a pre-defined overlapping window parameter. Finally, they fed the formed feature vectors into a linear-kernel SVM for classification. Their results showed that CSWB-VAR features improved classification accuracy up to 7% compared to the univariate one. This study also investigated the optimum parameters of CSWBVAR feature, window length, and moving step size. Higher accuracy was obtained with a window size of 128 data points and 50% overlapping step size. It was also reported that among the considered channel pairs, C3-C4 produced the most stable and best performance, which emphasized the important role of these two channels in MI problems.

Independent source-based causal connectivity brain network was proposed in Chen, Li, Yang, and Chen (2012) to classify LH and RH motor imagery for BCI applications. At first, scalp EEGs of one subject participated in BCI Competition IV, data set 2a were decomposed via ICA (FastICA algorithm) into maximally independent components. Independent components were then localized using forward and inverse models (equivalent current dipole), while adaptive VAR models were fitted to the time series to model transient information flow in the form of PDC measures. Statistically significant PDCs were obtained using bootstrap for the data set. Then a simple classification rule was defined based on source analysis results and causal connectivity brain network. For equivalent dipole analysis, the classification was correct if the equivalent dipole was located on the contralateral side with the imaginary hand. For causal relation analysis among independent components, the classification was correct if the quantitative feature of causal density and causal flow was related to the corresponding imaginary hand. Based on these two criteria, 86% and 92% classification accuracy was obtained for LH and RH respectively.

Athanasiou, Lithari, Kalogianni, Klados, and Bamidis (2012) inspected the efficiency of the effective connectivity for classifying foot and hand MI tasks, while EEGs were recorded by means of 17 electrodes from seven right-handed participants. EEGs were bandpass-filtered within 8 Hz to 15 Hz, and ICA was employed to get rid of ocular artifacts. Epochs were set from 800 msec prestimulus to 2200 msec poststimulus. A cortical current density (CCD) source model was used to recover the sources of scalp EEGs. These authors compared region of interests (ROIs)—primary hand and foot motor areas (M1), hand and foot sensory areas (S1), and SMAs—activation of

foot MI versus hand MI. Effective connectivity was estimated on the whole epoch using DTF derived from the fitted MVAR model. Results indicated that foot and hand MI movements were discriminated for five subjects. There was a stronger activation of SMAs during foot MI for all subjects. Study on the electrode plane revealed that in hand MI, the maximum information flow was from C1 toward FC2 and from FC1 toward C4. On the cortical surface, for hand MI, strong information flow was observed between primary hand motor areas, from the contralateral toward the ipsilateral. In addition, very strong flow was reported from the SMAs toward the ipsilateral primary hand motor area. For foot MI, information flow was from the SMAs toward the contralateral primary foot motor area. Moreover, there was a high bilateral information flow between the SMAs of both hemispheres.

The dynamic of interregional communication within the brain (functional connectivity) during the imagination of LHF and RHF tapping was examined as a control feature for BCI (Daly, Nasuto, & Warwick, 2012). EEG signals were captured via 19 electrodes from 15 subjects with the common average reference montage. Bandpassed-filtered data (0.1–45 Hz) were segmented into trials with 1 second length from cue presentation. The empirical mode decomposition phase-locking spectra was used to map PS levels between all channel pair combinations in each trial. The mean clustering coefficient was then used as a descriptive feature encapsulating information about interchannel connectivity. Hidden Markov models were applied to characterize and classify dynamics of the resulting networks. Their results showed that very high levels of classification accuracy were achieved in the frequency range of 5 Hz to 15 Hz. They reported that the proposed method achieved higher accuracies than the BP approach for all subjects.

Krusienski, McFarland, and Wolpaw (2012) inspected hand MI-based BCI performance when using power spectral, MSC and PLV, separately and in combination. EEGs were recorded through 64 channels, while only 9 channels of the right and left hemisphere hand areas of the motor cortex were chosen for feature extraction. Then fast Fourier transform (FFT), PLV, and MSC were calculated for each trial and pair of channels. Using the extracted features, seven linear regression models were constructed for classification: PLV, MSC, FFT, PLV + MSC, PLV + FFT, MSC + FFT, and PLV + MSC + FFT. The model weights were set by means of a stepwise linear discriminant analysis. Results showed that PLV performed better than only PLV + MSC, which was outperformed by FFT, PLV + FFT, and PLV + MSC + FFT. It was indicated that the FFT-based feature was at least as effective as the PLV and MSC features. Furthermore, inclusion of PLV and/or MSC in models with the FFT based did not improve the performance compared to the FFT based alone. It was concluded that PLV and MSC-based features did not offer more information than FFT-based features.

In 2013, the brain effective connectivity network was investigated to understand brain function and compare the network between RH-MI movement and rest state (Li, Ong, Pan, & Ang, 2013). EEG signals were recorded by 27 channels from eight subjects during MI of RH and rest state (mental counting). EEGs were bandpass-filtered 8 Hz to 35 Hz, and for each trial, time segments of 0.5 to 2.5 seconds after the cue were used for analysis. The MVAR model was built up based on raw EEGs; then PDC and DTF were calculated and integrated in the range of alpha band. A one-sided *t*-test was applied to compare the averaged PDC and DTF of each pair of connections between MI trials and rest trials. Results showed that one subject had very high information flow from the central motor cortex. Another subject showed high activation in the left motor cortex, although the significant sources were not concentrated around C3. They also observed the prominent source at FC4, sensorimotor area. For another subject, strong source activation was observed in the posterior left motor cortex. Cross-validation accuracy of around 70% was reported for the subjects. For the rest of the subjects, they noted that less significant influential sources were located in the left motor cortex.

Later, Billinger et al. (2013) extracted single-trial connectivity measures from VAR models of independent components for classification in a BCI setting. In this study, 45 channels were used to record the EEGs from 14 volunteers while performing hand and foot MI movements. At first, an extended Infomax ICA was used for extracting the source signals. Then, connectivity estimates were measured from all sources with a window length of 4.5 seconds. For further process, eight sources were chosen after being ranked based on the estimates. The final connectivity estimates were computed for these sources with window length 1.5 seconds. BP was calculated by FFT, and connectivity measures cross-spectral density, Coh, PDC, PDCE, GPDC, DTF, ffDTF, direct DTF (dDTF), and directed coherence were computed from VAR coefficients. Modified false discovery rate was then used to find statistically significant connectivities, and shrinkage linear discriminant analysis was employed for classification. Results showed that ffDTF, dDTF, and BP performed similarly while outperforming other measures. They reported that Coh and the unmodified DTF were not appropriate for BCI.

Gonuguntla et al. (2013) analyzed the network mechanisms related to LH and RH motor imagery tasks based on PLV in EEG alpha band. This experiment was performed on the eighth subject of BCI Competition IV data set 2a. They computed the difference of PLV between active and rest states for all electrode pairs in the range of 6 Hz to 14 Hz. The five most significant pairs (MSP) corresponding to the pairs with maximum difference PLV were selected for each task. MSPs were laid in the contralateral part corresponding to task—5 MSPs for the left side and 5 MSPs for the right side of the brain. MSPs were employed as features, and the difference in PLV level after cue was used for classification. Results showed that the PLV

magnitude increased during the imagination compared to rest state within the frequency band 9 Hz to 11 Hz. It was demonstrated that the (Cz,Cp3) pair was the most significant one for RH-MI, which was mostly seen during imagination. Similarly the (Fz,Cp4) pair was identified as MSP for LH imagery. Classification results indicated the potential of such methodology for BCI applications.

In 2014, Hu, Wang, Zhang, Kong, and Cao (2014) used scalp EEGs at Cz, C3 and C4 from data set 2b of BCI Competition IV to study causality flow during MI. They proposed a new causality (NC) in time and frequency domains using a time-invariant BVAR model. They found strong directional connectivity from Cz to C3/C4 during LH and RH motor imagery. During LH-MI, there was directional connectivity from C4 to C3, whereas during RH-MI, there was strong directional connectivity from C3 to C4, which was more clearly revealed by NC than GC. They concluded that NC in time and frequency domains was much better than GC to reveal causal influence between different brain regions.

5 Brain Connectome of Motor Imagery Movements

Brain topography analysis aimed to explore the brain connectome using either functional or effective connectivity during MI tasks. Investigation on the difference between LH and RH information flows in gamma and beta bands after the cue showed that for both hands, the maximum activity was in the left hemisphere (Ginter et al., 2005). At first, the sensorimotor areas were activated with the preponderance of the dominant hemisphere. Then the organization of the pattern started with the participation of both hemispheres, but the contralateral hemisphere became more involved in the initiation of flows. This was supported by PET and fMRI studies, where it was shown that MI activates various cerebral structures, including, at the cortical level, the SMA, the premotor areas, the primary sensorimotor areas (Decety et al., 1994; Porro et al., 1996; Roth et al., 1996), and the parietal and frontal regions of the brain (Hanakawa, Dimyan, & Hallett, 2008). In addition, EEG studies revealed an activation of the contralateral primary sensorimotor area during MI when one of the upper limbs was involved (Pfurtscheller & Neuper, 1997). It is therefore reasonable that in the case of RH-MI, the flow of gamma oscillations is focused on the left hand representation area and vice versa for LH-MI. Different bilateral distribution observed during movement imagery of the LH and RH corresponded to the activation patterns found in movement experiments of the dominant and the nondominant hand (Stancák & Pfurtscheller, 1996). The gamma flow pattern enhanced at the midcentral regions close to electrode Cz, which was supported by the increase of regional cerebral blood flow (rCBF) and metabolism in SMA during MI (Decety et al., 1994). For both MI tasks, the gamma flow pattern started over the left hemisphere during cue presentation, which was justified by the dominance of the left hemisphere.

Simultaneous with the enhancement of gamma flow, beta flow was decreased due to an increased synchronization of small groups of neuronal assemblies and consequent enhanced amplitude of gamma oscillations. This was explained as the result of a more widespread desynchronization of beta oscillations, accompanied by an attenuation or blockade of beta oscillations. Ginter et al. (2005) also observed a local increase of gamma flows concentrated in certain regions for a given time epoch. This finding was justified since gamma and beta rhythms may appear alternatively or coexist and gamma rhythms support robust synchronization over shorter distances than beta rhythms (Kopell, Ermentrout, Whittington, & Traub, 2000). For LHF and RHF motor imagery, a decrease of propagation from sensorimotor areas in the beta band and its following increase (Kus et al., 2005) corresponded well with the ERD and ERS described in Pfurtscheller, Graimann, Huggins, Levine, and Schuh (2003). It was stated that the outflow from a certain location need not be exactly correlated with the EEG amplitude. The increase of outflow of beta activity before the RH-MI from locations around the C1 electrode was not accompanied by an increase in amplitude of the beta rhythm in the corresponding locations. This was interpreted in terms of information exchange between structures involved in motor action and an increase in the level of attention before the tasks. Beta rhythm has been connected with attention (Wróbel, 2000). A small decrease of propagation in the beta band during imagination was explained as the need for a higher level of concentration and attention. The beta propagation after the movement from the more frontal location was observed in Ginter et al. (2001) and Kus et al. (2005) which was in agreement with results of an MEG experiment (Salmelin & Hari, 1994) indicating the existence of a source of beta activity in those areas. Kus et al. (2005) also reported a long increase of gamma outflow from large brain areas, in line with the imaging studies indicating involvement of several brain areas connected with motor function. It was shown that sensory motor areas were more involved in the propagation respect to the primary motor cortex (Kus et al., 2005), which was also found in a study of rCBF (Goldenberg, Podreka, Steiner, & Willmes, 1987). The role of SMA in MI was suggested in Deecke (1996). Mutual transmission in the gamma band between the locations overlying SMA and other sensory motor areas, especially the primary motor area, was observed in Kus et al. (2005). This was also detected in fMRI-based MI studies (Hallett, Fieldman, Cohen, Sadato, & Pascual-Leone, 1994; Porro et al., 1996; Rao et al., 1993). However, gamma activity involves small neural assemblies as suggested in Pfurtscheller, Graimann, et al. (2003) and is characterized by a small amplitude (Singer, 1993), so it does not consume a significant amount of energy; therefore, this activity may not be well reflected in fMRI. By considering the involvement of SMA as well as left and right M1 areas in hand MI movement (Dechent et al., 2004; Roland et al., 1980), Wang et al. (2006) studied the characteristics of local-scale and large-scale synchronies within and between these areas. They showed large-scale

PS between SMA and M1 (C3-FCz and C4-FCz) and a low synchrony level between both hemispheres (C3-C4). This was in line with the findings reported in Wei et al. (2007) that the long-range coupling between SMA and SM1 offered discriminative features between RH and LH motor imagery movements. No significant difference between LH and RH for local-scale synchrony in SMA area suggested that SMA might be activated for both MI movements, synchronized with the contralateral M1 area (Y. Wang et al., 2006). It has been argued that although long-range couplings do reflect cognitive processing, short-range couplings might be caused by the VC of nearby sensors (Lachaux et al., 1999). Stavrinou et al. (2007) showed strong connectivity between frontal and central areas (electrodes C5, FCZ) during the imagination of RHF that was supported by the coactivation of hand and midcentral areas (Lotze et al., 1999; Spiegler et al., 2004). Moreover, brain functional imaging studies have found a similar network in both the execution and imagination of a hand movement (Michelon et al., 2006; Stephan & Frackowiak, 1996). Grosse-Wentrup (2009) suggested that in order to fully exploit the capabilities of connectivity measures for BCIs and establish communication with completely locked-in subjects, gamma band oscillations should be considered. Hu et al. (2014) emphasized the strong directional connectivity from Cz to C3/C4 during LH and RH motor imagery. Moreover, directional connectivity from C4 to C3 was observed for LH-MI, and vice versa for RH-MI.

Investigation on tongue (Spiegler et al., 2004) and foot (Neuper & Pfurtscheller, 1999) MI movements found the increase of hand area mu rhythm synchronization in both hemispheres, in line with oscillatory pattern during the execution of these movements (Pfurtscheller & Neuper, 1994). It was stated that different motor tasks may have a feature in common: specific networks within either the sensorimotor foot or the tongue area need to be activated. These findings supported the notion of the neural networks' antagonistic behavior called "focal ERD/surround ERS" (Suffczynski, Kalitzin, Pfurtscheller, & Da Silva, 2001). This notion is based on the observation that the ERD of 10 Hz rhythms at a particular brain area does not take place separately but can go along with an increase of ERS in nearby regions. Spiegler et al. (2004) indicated no meaningful changes in phase coupling during tongue MI between mu rhythms in both hemispheres at electrodes C3 and C4. This was consistent with the results in Suffczynski et al. (2001), where the networks within both hemispheres produce broadly independent mu rhythms. Phase coupling between hand and midcentral regions was increased during tongue MI in the same frequency band. Accordingly, Spiegler et al. (2004) hypothesized that at least two neural networks, one in the SMA and the other in the left or the right hand representation area, both with the same resonance-like frequencies in the alpha band, are phase-coupled with each other. Chung et al. (2011) showed no significant channel connection in the tongue MI quantified by a cross-correlation measure that might be caused by pairwise analysis, ignorance

of VC, and/or the low information provided by cross-correlation. Regarding foot MI movement, Chung and associates (2011) observed the central connectivity in only one subject, and Athanasiou et al. (2012) reported that the activation of SMAs varied and was intense for all subjects, with information flow from the SMAs to the contralateral primary foot motor area. In addition, high-output information exchange was detected between the SMAs of both hemispheres.

6 Discussion

Motor imagery is defined as a perception-like process in the absence of any external stimulus input (Annett, 1995; Farah, 1984; Kosslyn, Ganis, & Thompson, 2001). It has been studied in applied cognitive psychology and neurophysiology, and recently it has drawn researchers' attention in rehabilitation and neuroengineering, especially for brain-computer interfacing applications. Early studies on electrical brain activity revealed desynchronization of EEG in alpha and beta bands during imagery in the primary motor areas, followed by a beta activity increase (Pfurtscheller & Neuper, 1997). In particular, the μ -rhythm that is associated with the inhibition of the movement (Arroyo et al., 1993) has been identified as an effective EEG feature in MI studies (Pfurtscheller & Neuper, 1997). Generally μ -rhythm is examined using ERD/ERS, which provides spatially static neuroelectric information of activated brain regions during tasks. It was also shown that MI can enhance brain oscillations, for instance, over the ipsilateral hemisphere during unilateral hand movement imagination (Pfurtscheller & Neuper, 1997) or bilaterally over the hand representation area during foot movement imagination (Neuper & Pfurtscheller, 2001a).

As mentioned before, most MI-based BCI studies used features extracted from BP (Pfurtscheller & Neuper, 2001), AR model (Anderson, Stolz, & Shamsunder, 1998; Dornhege, Blankertz, Curio, & Müller, 2004; Huan & Palaniappan, 2004) or CSP (Müller-Gerking, Pfurtscheller, & Flyvbjerg, 1999; Ramoser et al., 2000). These methods are based on the individual signals dynamics and do not use the coupling information and causal influence between two EEG signals; thus, they cannot deliver the information of how different brain areas communicate with one another. However, brain signals exhibit such phenomena because cognitive tasks require the integration of different functional areas widely distributed over the brain and the communication among them (Rodriguez et al., 1999; Varela et al., 2001). It was also shown that brain functional networks are shaped by distributed spatiotemporal brain activity and provide significant neurophysiological information to understand brain functions and dysfunctions (Ioannides, 2007). In this context, brain functional/effective connectivity has played a major role in neuroscience to investigate the organized behavior of brain regions (Varela et al., 2001). This area has been recently focused to be applied in MI-BCI in order to find new types of features to enhance system

performance. However, very few studies have been recognized that investigated brain connectivity during MI movements in healthy individuals. In this section, the key components and factors in brain connectivity analysis that considerably affect the results are discussed, and potential technical shortcomings that might have influenced the results in the literature are addressed and suggestions are provided.

Very few studies analyze connectivity patterns revealed by EEG during MI. Some of them focused on differences in connectivity patterns between MI and motor execution, which is not of primary interest for research on BCIs (Athanasίου et al., 2012; Daly et al., 2012; Kuś et al., 2005; Stavrinou et al., 2007).

It has been suggested that the use of more channels can increase the EEG spatial resolution and thus may lead to more accurate results (Astolfi, Cincotti et al., 2007; Fallani et al., 2008). High-resolution EEG techniques for BCI application have been stressed (Cincotti et al., 2008). According to the literature, the number of channels considered was between 3 and 128. Thus, the results achieved by low-resolution approaches might be less accurate. The maximum number of channels was implemented in (Grosse-Wentrup, 2009); however, the results showed no distinct differences between MI of the LH and RH, which might be due to the applied method for connectivity estimation. Some other studies examined ROI-based brain analysis (Athanasίου et al., 2012; Wei et al., 2007) while using the average of channels for connectivity estimation; however, this may ignore interesting correlations as the actual part of the region containing a significant signal gets averaged out. Others have suggested using high-resolution EEG in conjunction with robust methodology for brain connectivity estimation to achieve more accurate spatiotemporal findings. However, high-resolution EEG contrasts with the ease of use (difficulty of installing the system without an expert and the time that the electrode preparation requires) and cost efficiency (high-resolution EEG needs more recording channels and expensive amplifiers) that are desired in practical BCIs. Therefore, depending on the application, a trade-off between EEG resolution, system complexity, and performance, as well as user friendliness, should be considered.

Data sets with different motor tasks or imageries were considered, among which MI movement of left or right hand was usually more focused in the BCI context, while tongue and foot had been less investigated. Although a higher number of MI movements can provide more flexible and applicable BCIs, the research indicates that a maximum of four MI movements have been furnished in this area (Chung et al., 2011; Gonuguntla et al., 2013). It has been shown that imagination of foot movement invokes activity over Cz, and a distinction between left and right foot movements is not possible because the corresponding cortical areas are too close (Graumann et al., 2010). Similarly, brain patterns of individual fingers have not been discriminated (Graumann et al., 2010). A distinction between other motor control or imagination tasks would substantially improve the reliability of BCIs in actual

applications. One possible way might be the use of high-resolution neuroimaging protocol, with an increment of electrode numbers. This would be helpful to discriminate the MI tasks with neighboring cortical areas like left and right foot movement or different individual fingers. Moreover, the development of more realistic mathematical techniques that can fit accurate models to different MI tasks may tackle this flaw.

Almost all studies have investigated brain connectivity only among different regions at either scalp or cerebral cortex, yet the roles of subcortical structures, as well as deep brain regions, have been neglected. However, it has been shown that cerebellum and basal ganglia (Chakravarthy, Joseph, & Bapi, 2010; Doya, 2000) are activated during both movement execution and imagination. Therefore, whole brain connectivity analysis is highly recommended to discover underlying brain functions and mechanisms during different MI tasks. This again requires high-resolution EEG recordings, as well as an accurate model for retrieving actual brain source signals from scalp EEG signals.

One of the most critical challenges for brain connectivity analysis is VC, which can give rise to spurious instantaneous correlations between scalp EEG signals and potentially leads to a misinterpretation of sensor-space EEG analysis (Nunez et al., 1997). Some studies have not taken this issue into account (Brunner et al., 2006; Chung et al., 2011; Daly et al., 2012; Gonuguntla et al., 2013; Gysels & Celka, 2004; Hoang et al., 2011; Krusienski et al., 2012; X. Li et al., 2013; Spiegler et al., 2004; Tsiaras et al., 2009; Wang et al., 2006). Athanasiou et al. (2012) applied an inverse method CCD to estimate the cortical source signals; however, it has been stated that a fully satisfactory inverse method does not exist (Sarvas, 1987). Any inverse method is based on prejudices about the underlying sources. If these prejudices are wrong (and sometimes even if they are correct), the separation of channel amplitudes into source amplitudes will be wrong (incomplete), and again it is likely that artifacts of VC will be misinterpreted as brain interaction. The literature reports that spatial filters surface Laplacian (SL) (Song et al., 2005; Stavrinou et al., 2007; Wei et al., 2007), beamforming (Grosse-Wentrup, 2009), and ICA (Billinger et al., 2013; Chen et al., 2012) have been used to unmix distorted EEGs into source signals. SL subtracts the average of its neighbors from the channel of interest, enhances the local activity from local sources, and widely reduces the distributed activity, including that from distant sources. It was demonstrated that SLs may remove genuine source coherence associated with widely distributed source regions along with VC contributions; that is, the SL spatial filter cannot distinguish between source and VC effects properly (Nunez & Srinivasan, 2006). Beamforming uses an array of sensors and combines the signals recorded at individual sites to increase the signal-to-noise ratio or resolution and to focus the entire array on a certain region in space (Van Veen, Van Drongelen, Yuchtman, & Suzuki, 1997; Ward, Jones, Bones, & Carroll, 1999). Beamformers try to find the magnitudes, locations, and directions of active electric currents flowing

inside the brain under a certain task. However, these require prior information on the source location, and it was shown that they are sensitive to the estimate of the depth of the sources, which might reduce the signal-to-noise ratio of the output signal (Ward et al., 1999). ICA is an unsupervised statistical blind source separation technique used for decomposing a complex mixture of signals into independent sources. It is able to extract the relevant information buried within noisy signals and allow the separation of measured signals into their fundamental underlying independent components (Wang & James, 2007). The fundamental assumption employed by ICA for source extraction is statistical mutual independence (Naeem, Brunner, Leeb, Graimann, & Pfurtscheller, 2006). DTF has been used (Athanasios et al., 2012; Ginter et al., 2005; Kuś et al., 2005; X. Li et al., 2013) to determine directional influences between any given pair of channels in multivariate data sets as this measure effectively discriminates against VC (Kuś et al., 2005). As Kuś et al. (2004) emphasized, the multivariate DTF avoids the problem of the estimation of spurious functional links and is robust in respect to noise (Kuś et al., 2005). Among the mentioned methods, blind source separation has been widely used as the most promising approach in the BCI context.

As another component, connectivity measures can be estimated through two general routines: bivariate and multivariate. It has been shown that bivariate methods for the assessment of causality (effective connectivity) are likely to give misleading results, no matter if they are based on phases of bivariate coherences or bivariate GC measure (Blinowska, Kuś, & Kamiński, 2004; Kuś et al., 2004). This is important since bivariate or pairwise analysis is likely to find spurious correlations in cases where one driver drives two responses. In this case, both responses may have a common driver even if the responses appear to be fully independent. Although multivariate measures derived from MVAR modeling of multichannel EEG signals have been proved as a superior method to estimate connectivity measures (Kuś et al., 2004), they can also suffer from spurious effects when all driving sources are not observed (Eichler, 2007; Kamiński et al., 2001). Therefore, more satisfactory results are expected from the studies that employed multivariate measures for effective connectivity analysis. In this regard, studies in the literature that used bivariate routine for estimating effective connectivity are suspected to have spurious connectivities (Grosse-Wentrup, 2009; Hu et al., 2014; Tsiaras et al., 2009).

Regardless of capability of the MVAR model in estimating the connectivity among neural processes in multivariate framework, it captures only the linear interactions among time series. However, many crucial neural processes like EEG have nonlinear characteristics. Examples are the regulation of voltage-gated ion channels, which correspond to a steep nonlinear step-function relating membrane potential to current flow (Sakkalis, 2011), and the arch-shaped mu rhythm in sensorimotor areas (Pfurtscheller, Stanek, & Edlinger, 1997). In order to interpret the amount of transmission of

nonlinear information between brain regions and its functional role, it is important to consider the physiological basis of the signal, which seems to be mainly nonlinear. Thus, nonlinear brain connectivity analysis may reveal hidden interactions and provide complementary information on brain neural networks during different motor tasks. However, most studies have investigated only the linear brain connectivity (Athanasίου et al., 2012; Billinger et al., 2013; Chen et al., 2012; Chung et al., 2011; Daly et al., 2012; Ginter et al., 2005; Hoang et al., 2011; Hu et al., 2014; Krusienski et al., 2012; Kuś et al., 2005; X. Li et al., 2013; Tsiaras et al., 2009). Some researchers have employed PLV (Brunner et al., 2006; Gonuguntla et al., 2013; Gysels & Celka, 2004; Song et al., 2005; Spiegler et al., 2004; Stavrinou et al., 2007; Wang et al., 2006; Wei et al., 2007) and TE (Grosse-Wentrup, 2009) to estimate nonlinear interactions using MI tasks. However, TE is computed in a bivariate framework, which potentially leads to misleading results. It must also be noted that PLV, TE, and their derivations work based on time-domain synchronization characteristics and mutual dependence between two signals; however, it has been widely reported that frequency-based connectivity estimators are more reliable for the analysis of EEG data because the activity of neural populations is often best expressed in this domain (Groß et al., 2001; Wang, Deng, & He, 2004).

Another important property of the brain is its dynamic (nonstationary) behavior during any task; thus, analyzing brain connectivity within a static framework (considering the whole signal as one epoch and computing connectivity) or stationarity assumption is incompatible with the well-known dynamical condition-dependent nature of brain activity and leads to misinterpreting the results. Therefore, caution should be taken into account while comparing any result with those reported in Athanasίου et al. (2012), Brunner et al. (2006), X. Li et al. (2013), Spiegler et al. (2004), Stavrinou et al. (2007), Tsiaras et al. (2009), Wang et al. (2006), and Wei et al. (2007). The drawback also influence the conventional MVAR model, where the connectivity measures computed by this technique are fixed over time. A number of algorithms have been proposed for fitting MVAR models to nonstationary signals known as adaptive MVAR (AMVAR) or time-varying MVAR (TV-MVAR). The most popular approaches include segmentation (overlapping sliding-window) approaches (Ding, Bressler, Yang, & Liang, 2000) and state-space approaches (Sommerlade et al., 2009). Although a segmentation technique produces MVAR coefficient matrices that describe the evolution of the MVAR process across time, the local stationarity for each window is still assumed, and this may not be able to detect rapid parameter changes of brain activity and interactions (Sommerlade et al., 2009). A state-space model (SSM) provides a general framework for analyzing deterministic and stochastic dynamic systems that are measured or observed through a stochastic process. Although SSM is a powerful technique for dealing with the nonstationarity of neurophysiological signals and estimating the cortical connectivity from noisy scalp recorded EEG (Cheung, Riedner, Tononi,

& van Veen, 2010; Chiang, Wang, & McKeown, 2012), no study has used SSMs for brain connectivity analysis during MI movements.

Different types of functional and effective connectivity measures have been considered for analyzing the brain network. Most of these studied only the mechanisms for functional relations of spatially distinct neuronal groups during particular tasks known as couplings, which are measured by functional connectivity measures. These kinds of measures, also called symmetric brain connectivity analyzers, find undirected interactions between EEG signals. However, these interrelations are expected to be asymmetric (Grosse-Wentrup, 2009), with certain brain regions exerting a stronger influence on other regions than vice versa. For this reason, asymmetric (effective) connectivity measures potentially provide more information and can find the hidden and ignored connectivities on cognitive processes more than symmetric measures can. The literature reports that asymmetric connectivity analysis on different MI movements has not been extensively studied. Much work has to be carried out in this area to better understand and enhance the performance of the MI-BCI.

In the field of connectivity analysis, sometimes the value of a functional or effective connectivity measure is not due to the existence of statistical or causal relationship between the EEG signals but is the result of some feature of the individual signals such as complexity and limited length of nonstationarity (Bhattacharya, Pereda, & Petsche, 2003; Pereda, Rial, Gamundi, & Gonzalez, 2001). Thus, when making inferences about functional or effective connectivity in the neural system, it is highly recommended to produce confidence intervals and statistically significant threshold for the estimator.

7 Conclusion

Conventional motor imagery EEG-based BCI systems rely on temporal-spectral features from single channels to distinguish between different MI patterns. Apart from the worthy achievements of these systems, they nevertheless have some barriers and limitations in practical applications. As an efficient tool of neuroscience, a promising alternative to provide more useful and informative features is to take into account the relationships between EEG sensor or source signals in the form of brain connectivity. In this review, we present the first survey of brain connectivity analysis during motor imagery movements used for BCI systems. We state the common challenges and limitations observed in conventional MI-BCI systems; provide a short overview of brain connectivity analysis; report the topographic analysis of brain during left hand, right hand, feet, and tongue MI movements; and discuss the key factors involved in brain connectivity analysis that have a significant influence on the results.

The results of this survey form a valuable cross-reference for methods used in the motor imagery brain connectivity analysis for BCIs. This survey shows which techniques have received more attention and which have not.

The information we have provided paves the way for newcomers to the field; they can now find out which methods have been used and what the potential improvements are. We hope that this study will deliver essential messages to those in the MI-based BCI community who seek to improve system performance for BCI designs within brain connectivity analysis framework.

Appendix A: Index of Terms

Term	Description	Term	Description
AIC	Akaike information criterion	MI	motor imagery
AR	autoregressive	MSC	magnitude squared coherence
BCI	brain-computer interface	MSP	most significant pairs
BP	bandpower	MVAR	multivariate autoregressive
BVAR	bivariate autoregressive	NC	new causality
CC	correlation coefficient	NLR	nonlinear regressive
CCD	cortical current density	PDC	partial directed coherence
CMI	cross mutual information	PDCF	partial directed coherence factor
Coh	coherence	PET	positron emission tomography
CSP	common spatial patterns	PLI	phase lag index
CSWBVAR	combined short-window bivariate autoregressive model	PLV	phase locking value
DCM	dynamic causal modeling	PS	phase synchronization
dDTF	direct DTF	PSDs	power spectral densities
DTF	directed transfer function	PSR	phase synchrony rate
EEG	electroencephalogram	rCBF	regional cerebral blood flow
ERD	event-related desynchronization	RH	right hand
ERS	event-related synchronization	RHF	right hand index finger
FDA	Fisher discriminant analysis	RIM	robust interdependence measure
ffDTF	full-frequency DTF	ROIs	region of interests
FFT	fast Fourier transform	SDTF	short-time DTF
fMRI	functional magnetic resonance imaging	SFFS	sequential floating forward feature selection
GC	Granger causality	SL	surface Laplacian
GPDC	generalized partial directed coherence	SMA	supplementary motor area
ICA	independent component analysis	SVM	support vector machine
iCoh	imaginary part of coherence	TE	transfer entropy
LH	left hand	VAR	vector autoregressive
LHF	left hand index finger	VC	volume conduction
MEG	magnetoencephalogram	WPLI	weighted phase lag index

Acknowledgments

This work is supported by Center of Biomedical Engineering, Universiti Teknologi Malaysia research university grant (R.J130000.7809.4F434) and funded by the Ministry of Higher Education.

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Received September 23, 2015; accepted January 31, 2016.