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# EEG Motor Imagery Applications in Brain Computer Interface based Wheelchair Control

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Abstract: Principally, this study gives an overview about the Neuronal oscillations appear throughout the nervous system in structures as well as, the range of frequencies of clinical and physiological interests for motor imagery EEG signal. In addition, a brief description about MI paradigm which is also known as movement imagery, which is a mental process through which a person imagines a physical action, such as jumping, or moving hands. In particular, event-related desynchronization (ERD) and synchronization (ERS). Finally, a set of studies have been listed towards highlights the advantages of using BCI Competition dataset which is a public dataset that have been widely used in the analysis of the EEG motor imagery signal methods and technique.

Keywords: EEG, Motor Imagery, Brain Computer Interface, Wheelchair

### 1. Neural Oscillations

Neuronal oscillations appear throughout the nervous system in structures as diverse as the cerebral cortex, hippocampus, subcortical nuclei, and sense organs [1]. EEG can measure and classify these oscillations according to their frequency. In general, frequency ranges have been defined according to the distribution over the scalp or biological importance [2]. For example, the range of frequencies of clinical and physiological interests is between 0.3 and 30 Hz. This range can be classified approximately in a number of frequency bands as follows[3]:

- Delta (0.3/4 Hz): delta rhythms are slow brain activities preponderant only in deep sleep stages of normal adults. Otherwise, they suggest pathologies.
- Theta (4\_/8 Hz): this EEG frequency band exists in normal infants and children as well as during drowsiness and sleep in adults. Only a small amount of theta rhythms appears in the normal waking adult. The presence of high theta activity in awake adults suggests abnormal and pathological conditions.
- Alpha (8\_/13 Hz): alpha rhythms exist in normal adults who are relaxed and mentally inactive. The amplitude is mostly less than 50 mV and appears most prominent in the occipital area. Alpha rhythms are blocked by opening the eyes (visual attention) and other mental efforts, such as thinking.
- Beta (14\_/30 Hz): beta activity is mostly marked in the front central region with a lower amplitude than that of alpha rhythms. It is enhanced by expectancy states and tension.
- Gamma (\_/30 Hz): gamma rhythms have a high-frequency band and usually are not of clinical and physiological interests and therefore often filtered out in EEG recordings.

## 2. Motor Imagery

Motor imagery (MI) is one of the most common methods used in BCI-based EEG control systems [4, 5]. MI which is also known as movement imagery, which is a mental process through which a person imagines a physical action, such as jumping, or moving hands. In particular, event-related

desynchronization (ERD) and synchronization (ERS) structures caused by MI will be analyzed [6].

Several research findings suggest that alpha and/or beta rhythms can be good signs to be used in BCI systems, as they are associated with cortical areas that are directly linked to brain motor activity [7]. Furthermore, it has been verified that sensorimotor rhythms (SMR) occurring in an imagined movement may help people with severe disabilities to perform tasks by merely using such a movement Essentially, SMR is created by the primary sensory and motor cortices, which can be divided based BCI into two, namely event-related synchronization(ERS) and eventrelated desynchronization (ERD), which are detected as mu rhythm and beta rhythm [9]. One of the most promising paradigms in BMI is motor imagery paradigm in which the alpha (8-13 Hz) and beta rhythms (14-30 Hz) of the sensorimotor cortex are used. The oscillations of the mu and beta rhythms of the sensorimotor cortex decrease when a movement is being initiated or when a movement has begun and this process is called event-related desynchronization (ERD). After a movement has occurred, the oscillations and this process is called event-related synchronization (ERS). If a person imagines moving his or her left hand, a strong ERD occurs at the right side of the sensorimotor cortex. On the other hand, if that person imagines moving his or her right hand, ERD occurs at the left side of the sensorimotor cortex [10]. Essentially, eventrelated Synchronization and Desynchronization (ERS and ERD, respectively) are the EEG patterns characterized by meaningful changes in the signal energy in specific frequency bands. As such, an energy increase is associated with an ERS, while an energy decrease is associated with an ERD .The frequency band used to detect these patterns is the alpha band (8-13 Hz), and digitized signal is filtered by a finite impulse response (FIR) filter with a pass band filter [11]. Given that MI does not require any voluntary muscle movement, it can be used effectively for people with severe disability [12]. Recently, EEG-based MI signals have been used in various types of applications, such as sports, psychology, neuroscience, and rehabilitation technology, as well as wheelchair control [6, 13]. Such wide applications are attributed to the fact that users do not have to gaze or

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focus when moving on a wheelchair. In addition, MI-based BCI signals provide a rapid response [14]. Therefore, these signals support the dynamic movements of an electrical wheelchair when making a turn and crossing a path during navigation [15, 16].

Table 1: MI Two Class BCI Competition Dataset

Table 1. Wil 1 wo Class Bel Competition					tasci
BCI Competition	Dataset			No. of Participant	Study uses dataset
		Classes	Chamieis	Farticipant	uataset
BCI Competition	Dataset-	2	3	1	[1]
II	III				
BCI Competition	Dataset-	4	60	3	[2]
III	III-a				
BCI Competition	Dataset-	2	2	3	[3]
III	III-b				
BCI Competition	Dataset-	2	110	5	F13
III	IVa	2	118	5	[1]
BCI Competition	Dataset-	2	118	1	[2]
III	IVc	_	118	1	[2]
BCI Competition	Dotogot I	2	64	7	[2]
IV	Dataset-1	2	04	/	[3]
BCI Competition	IIa	4	22	9	F11
IV					[1]
BCI Competition	Dataset-	set-	3	9	[2]
IV	IIb				[2]

MI-based BCI signals will be of particular interest to users in shared and complex navigation because they can offer continuous control of BCW with few low-level commands (e.g. forward, backward, stop, and turn left and right) [17]. BCI Competition dataset is a widely used dataset by researchers to test their methods and technique on this dataset. Table 1 shows the two classes of EEG-MI BCI competition dataset, which are publicly available in the BCI competition database.

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