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Comparing Common Average Referencing to Laplacian Referencing in Detecting Imagination and Intention of Movement for Brain Computer Interface

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Abstract. Brain-computer interface (BCI) is a paradigm that offers an alternative communication channel between neural activity generated in the brain and the user's external environment. This paper investigates detection of intention of movement from surface EEG during actual and imagination of movement which is essential for developing non-invasive BCI system for neuro-impaired patients. EEG signal was recorded from 11 subjects while imagining and performing right wrist movement in multiple directions using 28 electrodes based on international 10-20 standard electrode placement locations. The recorded EEG signal later was filtered and pre-processed by spatial filter namely; Common average reference (CAR) and Laplacian (LAP) filter. Features were extracted from the filtered signal using ERSP and power spectrum and classified by *k*-nearest neighbour (*k*-NN) and quadratic discriminant analysis (QDA) classifiers. The classification results show that LAP filter has outperformed CAR with respect to classification. Classification accuracy ranged from 63.33% to 100% for detection of imagination of movement and 60% to 96.67% for detection of intention of actual movement. In both of detection of imagination and intention of movement k-NN classifier gave better result compared to QDA classifier.

1 Introduction

Neurological disorders such as amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies and multiple sclerosis impair the neural pathway that control the muscle and /or the muscle themselves [1]. Patients loose voluntary control over their body due to these diseases and are driven to live an isolated, discriminated and restricted life in the long run. Their motor and sensory disabilities unable them to live a normal independent daily life.

Despite of losing their voluntary control over their body due to such neurological disorders, which is often a permanent effect, neuro-impaired patients can still communicate with outside world through brain-computer interface (BCI). BCI decodes the brain activities from electroencephalogram (EEG) signal and translates the user's intentions into commands [2] to control and/or communicate with the augmentative and assistive devices without activating any muscle or peripheral nerve.

In the past decades, number of BCI studies has been conducted in order to build successful interface that applies real-time EEG signal as command to control and /or communicate with the outside world [1]. Most of the studies aim to improve the speed and the accuracy of these interfaces by using improved EEG signal processing techniques and feature selection. One of the approaches that can be considered in signal processing techniques is implementing spatial and temporal filtering methods. The most often used spatial filtering methods in BCI studies to enhance the signal-to-noise ratio of EEG signal are Common average reference (CAR) [3, 4, 5] and Laplacian filter (LAP) [6, 7, 8].

In this paper we present the comparison of detecting motor imagery and intention of movement using 2 different spatial filters namely CAR and LAP. Our aim was to investigate which spatial filter would produce better results in detecting motor imagery and intention of movement.

The rest of the paper is structured as follow: Section 2 defines the implementation of experiment protocol and data analysis procedure. Section 3 presents the results of the experiment and the paper ends with a conclusion of the findings in section 4.

2 Method

2.1 Signal Enhancement by Spatial Filtering Methods

EEG recordings are usually contaminated by several sources of artefacts produced by the subject (for example any minor body movement, electromyogram (EMG), electrocardiogram (ECG), eye movements, sweating). Also, technical glitches (for instance, power line, impedance fluctuation, cable movement, broken wire contact or excessive electrode paste/ dried pieces) add to the noise levels of the EEG signal [9]. Thus, it is important to remove any existing noise and artefact from the recorded EEG signal before implementing any further signal processing analysis. In this paper the EEG signal was filtered by spatial filter namely CAR and LAP.

CAR is one of the reference-free techniques that is not affected by problem associated with an actual physical reference [9]. In CAR, the potential at each electrode is measured with respect to the average of all

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electrodes. The CAR was computed using (1) given below [10]:

$$V_i^{CAR} = V_i^{ER} - \frac{1}{n} \sum_{j=1}^{n} V_j^{ER} \quad (1)$$

Where V_i^{ER} is the potential between i th electrode and the reference and n is the number electrodes in the montage.

LAP serves as a high pass filter that enhances localized activity while suppressing the diffusion activity [8]. LAP is obtained by subtracting the sum of weighted potential of the surrounding electrodes from the current electrode potential where the weight is electrode distance dependent. The LAP was computed using (2) and (3) given below [10]:

$$V_i^{LAP} = V_i^{ER} - \sum_{j \in Si}^{n} V_j^{ER} g_{ij} \quad (2)$$

Where

$$g_{ij} = \frac{1}{d_{ij}} / \sum_{j \in Si}^{n} \frac{1}{d_{ij}} \quad (3)$$

Si is the set of surrounding electrodes of the i th electrode and *dij* is the distance between electrodes i and j (where j is a member of *Si*).

2.2 Experimental Recording Setup

EEG signals were recorded from 11 subjects (9 males and 2 female) and the experimental procedure had been approved by the Departmental Ethics Committee of the Biomedical Engineering Department, University of Strathclyde.

Each subject faced a LCD monitor screen while being seated on a wheelchair at a distance of 1 meter from the screen. Subjects were attached to a manipulandum on to their right side. EEG and EMG recordings were acquired using Curry Neuroimaging Suite 7.0.8 XSB Software and NeuroScan™ Synamps² amplifiers from electrodes at 28 scalp locations and 4 bipolar electrodes (Figure 1). During the data recording process, subjects were required to hold the manipulandum and attempt, perform and imagine (kinesthetic imagery) performing right wrist movement (burst, point to point center out movement) towards multiple direction (3,6,9,12) triggered by a visual cue.

The subject had to move the manipulandum rapidly in order to correspond to the cue direction shown in the monitor. On reaching the cue position, subjects had to hold the manipulandum at the cue position for as long as the cue remained visible on the screen and later reposition the manipulandum to the neutral position (0) according to the cue.

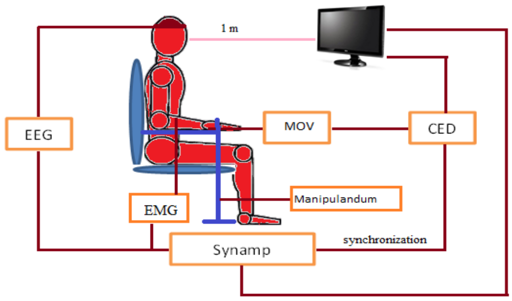

Figure 1: Experimental Recording Set Up.

The visual cue was displayed on the LCD monitor screen which consisted of 5 squares initially placed at the center of the screen whilst the subject held the manipulandum in the neutral position (0). The cue then randomly switched to different directions (3, 6, 9, 12) with a time interval of 10 seconds in between any 2 consecutive cues [11] (Figure 2).

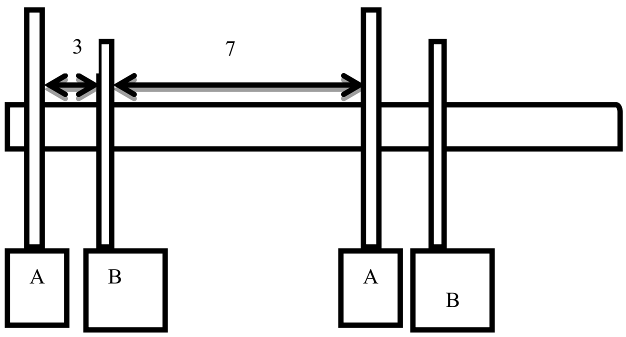

Figure 2: Timeline of Visual Cue Presentation.

In Fig. 2, during phase A, subjects were asked to move or imagine (kinesthetic imagery) moving the manipulandum from neutral position (0) to one of four directions (3, 6, 9, 12) and hold it in that position until the cue was visible on the screen; in phase B, subjects then repositioned the manipulandum back to the neutral position (0) as per the cue. While in the neutral position, subjects were instructed to stay calm and relaxed.

All the participants completed all the trials by imagining the movement and performing the actual movement based on external cue provided to them. Each experiment comprised of a total of 200 trials of both movement and imagery of movement towards 4 different directions, thus, establishing 50 repetitions per direction.

2.3 Data Recording Set Up

EEG, EMG and movement signals were recorded simultaneously during the experiments. EEG signal was recorded from 28 scalp locations located according to international 10-20 system (earlobe reference) using high density montage (Figure 3). EMG signals were recorded from flexor carpi radialis, extensor carpi ulnaris, extensor carpi radialis brevis and extensor carpi radialis longus muscles. The EMG signal was recorded in order to make sure that there is no movement during experiment of imagery of movement. Both EEG and EMG were recorded by Curry Neuroimaging Suite 7.0.8 XSB software using NeuroScan™Synamps² at sampling frequency of 2 KHz.

The movement signal was recorded from 2 precision servo potentiometers that are attached to the manipulandum in order to detect the onset of a movement. The signal recorded using Spike2 software through CED I401 (Cambridge Electronic Design, United Kingdom) at a sampling frequency of 100Hz.

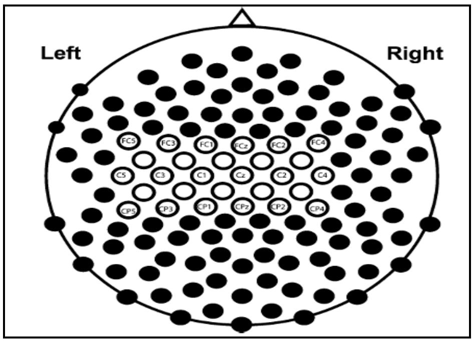

Figure 3: EEG Recording Montage.

2.4 Data Pre-processing

The recorded data from both of the experiments were processed offline. EEG was epoched using EEGLAB software version 12 [12] based on the type of experiments and categorized according to the type of the direction (3, 6, 9, 12). For instance, in experiment of external cue movement, the EEG signal was epoched 3 seconds before and 3 seconds after the onset of the movement (the movement initiation time) whereas, for the experiment where the subjects imagined the movement, the EEG signal was epoched 3 seconds before and 3 seconds after the initiation time (visual cue presentation time).

A Notch filter was applied to the epoched EEG to remove 50Hz power line interference [13] and then a Chebyshev type 2 bandpass filter was used [14]. CAR and LAP methods were applied before the features were extracted.

2.4 Features Extraction and Classification

The features of the interest were Event Related Spectral Perturbation (ERSP) and average of Power Spectrum in alpha (α, 8-12 Hz), beta (β, 13-30 Hz) and gamma (γ, 31-50 Hz) frequency bands. ERSP is a generalization of Event Related Desynchronization (ERD)/Event Related Synchronization (ERS) which helps visualize the entire spectrum in form of baseline-normalized spectrogram. ERSP is computed where each epoch is divided into a number of overlapping windows and spectral power is calculated for each window. The calculated spectral power is then normalized (divided with the baseline spectra calculated from the EEG immediately before each event) and averaged over all the trials. The whole process was performed by EEGLAB [12]. Power Spectrum indicates the distribution level of the signal power in frequency. Average of Power Spectrum in α, β and γ frequency bands were computed using code adapted from the EEGLAB.

Features were extracted from neutral condition and motor imagery/ intention of movement condition for direction of 3, 6, 9 and 12 respectively. For neutral condition, features were extracted 500ms before the subject imagined/performed the wrist movement. On the other hand, for motor imagery, features were extracted 500ms after the initiation time (t=0) whereas for intention of movement features were extracted 500ms prior to the onset of the movement (t=0) [15, 16]. The extracted features of the epoched EEG were spilt into training data set (70%) and testing data set (30%) [19,21]. The training data set and testing data set are randomly [19,23] selected by using Matlab function 'crossvalind' and fed to *k*-Nearest Neighbors (*k*-NN) [17,18] and quadratic discriminant analysis (QDA) [19, 20] classifier for pattern recognition classification. For *k*-NN classifier, '*k*' was set to 8 [22].

3 Results

3.1 Results of Event Related Spectral Perturbation (ERSP)

Figure 4,5,6 and 7 show the ERSP results for detection of motor imagery and intention of movement for direction 3, 6, 9 and 12 at channel C3 using CAR and LAP filters respectively. The results are obtained from subject 1 for both of experiments.

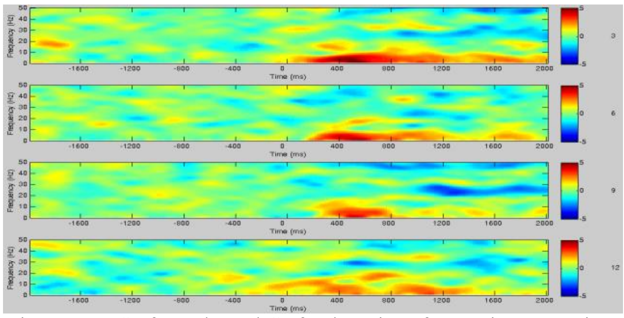

Figure 4: ERSP from channel C3 for detection of motor imagery using CAR Method.

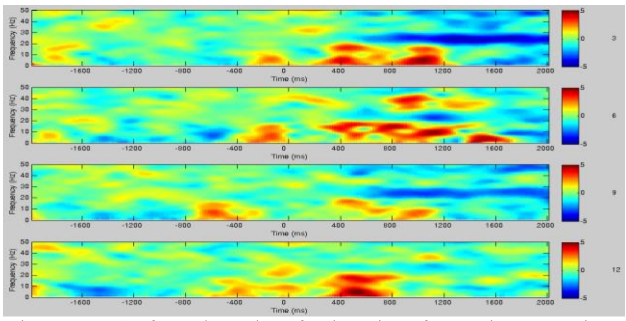

Figure 5: ERSP from channel C3 for detection of motor imagery using LAP Method

From Figures 4 and 5, ERSP using LAP method show more significant result when compared to CAR method in detection of motor imagery towards direction 3, 6, 9 and 12. The decrease in power spectrum as shown by the ERD (blue colour) 400ms after the initiation time (t=0) for all directions. ERD was evidently detected in β

(direction 3, 6, 9 and 12) and γ band (direction 3, 6 and 9).

Also from Figure 6 and 7, ERSP using LAP method again shows more significant result compared to CAR method in detection of intention of movement towards direction 3, 6, 9 and 12. In this paper, intention of movement refers to 500ms prior to the onset of the movement (t=0). ERD was clearly detected in α (6, 9 and 12) and γ band (12, 9 and 3).

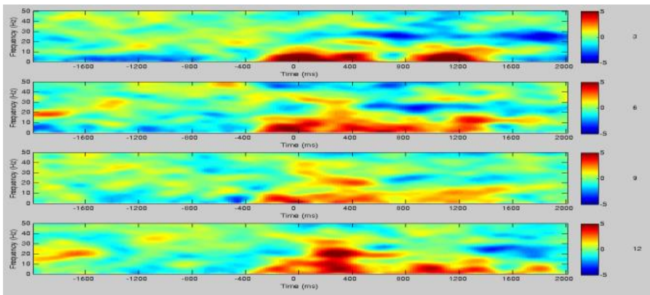

Figure 6: ERSP of channel C3 for detection of intention of movement using CAR Method.

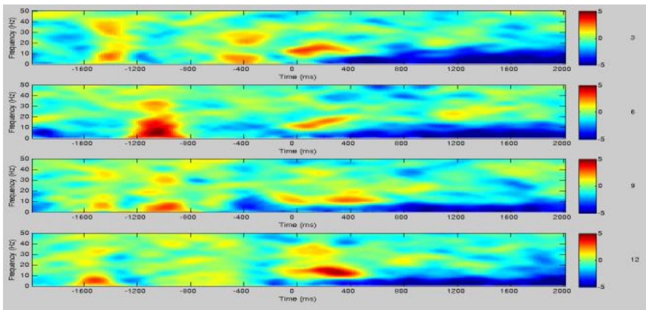

Figure 7: ERSP of channel C3 for detection of intention of movement using LAP Method.

3.2 Results of Power Spectrum

The results for detection of motor imagery are presented in Table 1 and Table 2, while results for detection intention of movement are tabulated in Table 3 and Table 4. The extracted features using CAR method and LAP method for direction toward 3, 6, 9 and 12 in detection of motor imagery and intention of movement are classified using *k*-NN and QDA classifier. In each of the table presented the maximum classification accuracy (Acc), channel of the maximum classification accuracy (Ch), true positive rate (TPR) and false positive rate (FPR).

TABLE 1: Classification results of detection of motor imagery for direction toward 3, 6, 9 and 12 using *k*-NN classifier on average of Power Spectrum in alpha (α), beta (β) and gamma (γ) band feature.

Subject	Parameter	Maximum Classification Accuracy, True Positive Rate (TPR) and False Positive Rate (FPR) for direction 3, 6, 9 and 12 (%)							
		Direction 3		Direction 6		Direction 9		Direction 12	
		CAR	LAP	CAR	LAP	CAR	LAP	CAR	LAP
S1	Acc	73.33	**83.33**	76.67	**80.00**	76.67	**86.67**	76.67	**80.00**
	Ch	CCP3	FC5	FCZ	C3	CCP4	CFC5	CP2	CFC1
	TPR	66.67	**80.00**	93.33	93.33	80.00	80.00	93.33	66.67
	FPR	20.00	13.33	40.00	33.33	26.67	6.67	40.00	6.67
S2	Acc	83.33	**90.00**	86.67	**93.33**	83.33	**93.33**	83.33	**96.67**
	Ch	CFC1	CFC1	CFC1	CFC1	CFC1	CCP4	CFC1	CFC1
	TPR	73.33	86.67	80.00	93.33	66.67	86.67	73.33	93.33
	FPR	6.67	6.67	6.67	6.67	0	0	6.67	0
S3	Acc	83.33	**86.67**	73.33	**80.00**	**83.33**	76.67	73.33	**76.67**
	Ch	C4	FC5	CP4	CFC2	C4	CFC4	FC1	CCP3
	TPR	86.67	93.33	53.33	80.00	86.67	73.33	73.33	73.33
	FPR	20.00	20.00	6.67	20.00	20.00	20.00	26.67	20.00
S4	Acc	73.33	**80.00**	76.67	**80.00**	80.00	**83.33**	76.67	**93.33**
	Ch	CZ	C3	CP4	C3	CZ	FC5	FC4	FC4
	TPR	80.00	73.33	66.67	66.67	60.00	80.00	66.67	93.33
	FPR	33.33	13.33	13.33	6.67	0	13.33	13.33	6.67
S5	Acc	73.33	**96.67**	73.33	**80.00**	76.67	**80.00**	83.33	**86.67**
	Ch	FC4	CFC4	FC3	CCP1	CP1	CCP1	FC3	CFC2
	TPR	60.00	93.33	66.67	73.33	66.67	100	86.67	80.00
	FPR	13.33	0	20.00	13.33	13.33	40.00	20.00	6.67
S6	Acc	70.00	**80.00**	73.33	**86.67**	73.33	**80.00**	73.33	**90.00**
	Ch	CP4	C4	FCZ	CCP3	CCP2	CCP3	C3	CP3
	TPR	66.67	86.67	66.67	80.00	66.67	80.00	80.00	80.00
	FPR	26.67	26.67	20.00	6.67	20.00	20.00	33.33	6.67
S7	Acc	70.00	**83.33**	70.00	**93.33**	73.33	**96.67**	73.33	**93.33**
	Ch	CP3	CFC3	CP3	FC2	CCP4	CP3	CCP3	FC3
	TPR	80.00	93.33	80.00	100	66.67	93.33	66.67	93.33
	FPR	40.00	26.67	40.00	13.33	20.00	0	20.00	6.67
S8	Acc	73.33	**93.33**	70.00	**100**	73.33	**90.00**	70.00	**90.00**
	Ch	CFC5	CP2	C3	FC1	C4	CP3	CPC3	FC5
	TPR	73.33	93.33	73.33	100	86.67	100	80.00	80.00
	FPR	26.67	6.63	33.33	0	40.00	20.00	40.00	0
S9	Acc	73.33	**76.67**	73.33	**76.67**	73.33	**83.33**	73.33	**76.67**
	Ch	CP5	CFC5	FC1	CP5	FC1	CCP5	CFC3	CFC5
	TPR	60.00	80.00	53.33	80.00	86.67	86.67	53.33	80.00
	FPR	13.33	26.67	7.14	26.67	31.58	20.00	6.67	26.67
S10	Acc	70.00	**90.00**	83.33	**86.67**	70.00	**86.67**	73.33	**90.00**
	Ch	CP1	C3	C4	CCP5	CCP5	FC3	CCP5	C3
	TPR	73.33	86.67	100	73.33	60.00	100	73.33	86.67
	FPR	33.33	6.67	33.33	0	20.00	26.67	26.67	6.67
S11	Acc	70.00	**90.00**	76.67	**83.33**	70.00	**93.33**	76.67	**83.33**
	Ch	C2	CP5	CPZ	FC5	C2	CP4	CFC3	CZ
	TPR	80.00	93.33	66.67	86.67	66.67	86.67	100	86.67
	FPR	40.00	13.33	13.33	20.00	26.67	0	46.67	20.00

Tabulated data in Table 1 shows the classification results of direction toward 3, 6, 9 and 12 for detection of motor imagery, dwell within the range of 70.00% to 100.00%. Maximum classification accuracy for these four directions are obtained from different electrodes, namely CFC4 with classification accuracy of 96.67% (direction toward 3), FC1 with classification accuracy of 100.00% (direction toward 6), CP3 with classification accuracy of 96.67% (direction toward 9) and CFC1 with classification accuracy of 96.67% (direction toward 12). In all four directions, features extracted using spatial filter LAP contributed for the maximum classification results.

TABLE 2: Classification results for detection of motor imagery for direction toward 3, 6, 9 and 12 using QDA classifier on average of Power Spectrum in alpha (α), beta (β) and gamma (γ) band feature.

ubject	Parameter	Maximum Classification Accuracy, True Positive Rate (TPR) and False Positive Rate (FPR) for direction 3, 6, 9 and 12 (%)							
		Direction 3		Direction 6		Direction 9		Direction 12	
		CAR	LAP	CAR	LAP	CAR	LAP	CAR	LAP
S1	Acc	73.33	73.33	66.67	**70.00**	66.67	**83.33**	73.33	**80.00**
	Ch	CP1	C3	FC1	CCP1	C4	CFC5	CFC4	CFC1
	TPR	93.33	86.67	86.67	53.33	86.67	80.00	53.33	80.00
	FPR	46.67	40.00	53.33	13.33	53.33	13.33	6.67	20.00
S2	Acc	83.33	**93.33**	86.67	**96.67**	83.33	**93.33**	83.33	**93.33**
	Ch	CFC1	CFC1	CFC1	CFC1	FCZ	CFC1	FC2	CFC1
	TPR	73.33	100	86.67	100	73.33	100	80.00	86.67
	FPR	6.67	13.33	13.33	6.67	6.67	13.33	13.33	0
S3	Acc	76.67	**90.00**	**76.67**	73.33	73.33	**76.67**	73.33	73.33
	Ch	CFC5	CFC5	CP4	CFC4	FC2	CFC4	CFC2	CFC4
	TPR	86.67	80.00	73.33	53.33	80.00	60.00	66.67	60.00
	FPR	33.33	0	20.00	6.67	33.33	6.67	20.00	13.33

S4	Acc	70	**76.67**	73.33	73.33	76.67	**80.00**	80.00	**86.67**
	Ch	CP5	CCP5	CP4	C3	CP2	FC1	FC4	C2
	TPR	53.33	80.00	60.00	53.33	66.67	80.00	80.00	80.00
	FPR	13.33	26.67	13.33	6.67	13.33	20.00	20.00	6.67
S5	Acc	76.67	**90.00**	73.33	73.33	70.00	**86.67**	76.67	**80.00**
	Ch	C4	CFC3	CFC1	CCP1	FC4	CCP1	C3	FC3
	TPR	60.00	86.67	53.33	66.67	66.67	93.33	66.67	80.00
	FPR	6.67	6.67	6.67	20.00	20.00	20.00	13.33	20.00
S6	Acc	63.33	**80.00**	70.00	**80.00**	70.00	**76.67**	73.33	**83.33**
	Ch	FC1	C2	CPZ	FC5	CFC4	CFC1	CCP1	CFC1
	TPR	66.67	73.33	53.33	80.00	60.00	66.67	86.67	86.67
	FPR	40.00	13.33	13.33	20.00	20.00	13.33	40.00	20.00
S7	Acc	63.33	**80.00**	70.00	**80.00**	70.00	**76.67**	73.33	**83.33**
	Ch	FC1	C2	CPZ	FC5	CFC4	CFC1	CCP1	CFC1
	TPR	66.67	73.33	53.33	80.00	60.00	66.67	86.67	86.67
	FPR	40.00	13.33	13.33	20.00	20.00	13.33	40.00	20.00
S8	Acc	70.00	**90.00**	70.00	**96.67**	76.67	**90.00**	70.00	**83.33**
	Ch	C1	FC1	CCP1	CP3	C4	CP2	C2	CP3
	TPR	86.67	86.67	80.00	93.33	86.67	86.67	86.67	73.33
	FPR	46.67	6.67	40.00	0	33.33	6.67	46.67	6.67
S9	Acc	70.00	**76.67**	70.00	**76.67**	70.00	**80.00**	73.33	**73.33**
	Ch	CFC3	FC1	CP3	CP5	CFC3	CFC1	FC3	CCP1
	TPR	80.00	73.33	73.33	80.00	53.33	66.67	60.00	80.00
	FPR	40.00	20.00	33.33	26.67	13.33	6.67	13.33	33.33
S10	Acc	70.00	**93.33**	86.67	**93.33**	70.00	**90.00**	70.00	**96.67**
	Ch	CCP5	C2	CP3	CCP5	CFC5	C2	CCP5	CCP5
	TPR	66.67	93.33	86.67	93.33	93.33	86.67	66.67	100
	FPR	26.67	6.67	13.33	6.67	13.33	6.67	26.67	6.67
S11	Acc	73.33	**96.67**	70.00	**83.33**	70.00	**86.67**	70.00	**83.33**
	Ch	FC5	CPZ	CPZ	CFC3	CZ	CP2	CFC1	CFC3
	TPR	100	100	60.00	80.00	73.33	80.00	80.00	93.33
	FPR	33.33	6.67	20.00	13.33	33.33	6.67	40.00	26.67

Referring to Table 2, the classification results toward four directions for detection of motor imagery lie within the range of 63.33% to 96.67%. Maximum classification accuracies for direction toward 3, 9 and 12 were obtained from electrode CFC1 with classification accuracy of 93.33%. On the other hand, maximum classification accuracy for direction toward 6 was obtained from electrodes CP3 and CFC1 with classification accuracy of 96.67%. The features extracted using spatial filter LAP contributed for the maximum classification results in all direction.

TABLE 3: Classification results of detection intention of movement for direction toward 3, 6, 9 and 12 using *k*-NN classifier on average of Power Spectrum in alpha (α), beta (β) and gamma (γ) band feature.

Subject	Parameter	Maximum Classification Accuracy, True Positive Rate (TPR) and False Positive Rate (FPR) for direction 3, 6, 9 and 12 (%)							
		Direction 3		Direction 6		Direction 9		Direction 12	
		CAR	LAP	CAR	LAP	CAR	LAP	CAR	LAP
S1	Acc	76.67	**83.33**	76.67	**80.00**	80.00	80.00	76.67	**80.00**
	Ch	CCP4	FC1	CCP4	FC5	FC4	FC2	C3	C1
	TPR	80.00	66.67	86.67	73.33	86.67	80.00	60.00	73.33
	FPR	26.67	0	23.33	13.33	26.67	20.00	13.33	13.33
S2	Acc	90.00	**93.33**	**96.67**	90.00	93.33	93.33	90.00	**93.33**
	Ch	CP5	CFC5	CP5	CCP2	CP5	CCP5	CP5	CCP2
	TPR	80.00	93.33	93.33	93.33	86.67	86.67	80.00	100
	FPR	0	6.67	0	13.33	0	0	0	13.33
S3	Acc	80.00	**83.33**	70.00	**80.00**	73.33	**83.33**	73.33	**76.67**
	Ch	CZ	CP4	CP1	CCP5	CCP4	CFC4	CCP3	CFC1
	TPR	80.00	80.00	60.00	86.67	66.67	93.33	60.00	93.33
	FPR	20.00	13.33	20.00	73.33	20.00	26.67	13.33	40.00
S4	Acc	**90.00**	80.00	**80.00**	76.67	80.00	80.00	76.67	**86.67**
	Ch	FC5	CCP1	CFC3	C4	FC5	CFC5	FC5	CP2
	TPR	93.33	93.33	93.33	93.33	60.00	66.67	60.00	73.33
	FPR	13.33	33.33	33.33	40.00	0	0	6.67	0
S5	Acc	83.33	**93.33**	76.67	**90.00**	80.00	**96.67**	76.67	**96.67**
	Ch	CCP1	CCP1	C1	C3	CFC1	C1	CZ	CFC3
	TPR	73.33	86.67	60.00	80.00	73.33	93.33	66.67	100
	FPR	6.67	0	6.67	0	13.33	0	13.33	6.67
S6	Acc	76.67	**90.00**	73.33	**93.33**	70.00	**83.33**	73.33	**96.67**
	Ch	C3	CP3	C4	CP1	FC3	CCP5	CP1	CP1
	TPR	66.67	80.00	60.00	100	40.00	73.33	60.00	100
	FPR	13.33	0	13.33	13.33	0	6.67	20.00	6.67
S7	Acc	73.33	**93.33**	76.67	**96.67**	73.33	**90.00**	76.67	**93.33**
	Ch	C3	CFC5	C5	C4	FC1	CCP5	C5	CFC5
	TPR	66.67	86.67	66.67	93.33	60.00	86.67	60.00	93.33
	FPR	20.00	0	13.33	0	13.33	6.67	6.67	6.67
S8	Acc	70.00	**83.33**	73.33	**93.33**	76.67	**96.67**	70.00	**100**
	Ch	FCZ	FC3	CP5	C5	CP2	CP2	CP3	FC3
	TPR	80.00	73.33	80.00	86.67	93.33	100	80.00	100
	FPR	40.00	6.67	33.33	0	40.00	6.67	40.00	0
S9	Acc	73.33	**90.00**	73.33	**86.67**	73.33	**93.33**	73.33	**90.00**
	Ch	FC3	FC1	CCP2	CFC5	CP3	FCZ	CP3	CP2
	TPR	86.67	86.67	66.67	80.00	53.33	86.67	60.00	86.67
	FPR	40.00	6.67	20.00	6.67	6.67	0	13.33	6.67
S10	Acc	70.00	**73.33**	73.33	**76.67**	73.33	73.33	70.00	**76.67**
	Ch	FCZ	FC5	CP5	CFC2	FCZ	FCZ	CZ	FCZ
	TPR	66.67	66.67	66.67	80.00	80.00	73.33	66.67	66.67
	FPR	26.67	20.00	20.00	26.67	33.33	26.67	26.67	13.33
S11	Acc	70.00	**80.00**	73.33	**83.33**	73.33	**80.00**	90.00	**93.33**
	Ch	CCP3	FC5	CCP5	CP2	FCZ	FC5	FC5	C5
	TPR	73.33	66.67	80.00	73.33	86.67	73.33	100	100
	FPR	33.33	6.67	33.33	6.67	40.00	13.33	20.00	13.33

From Table 3, the classification results of four directions for detecting intention of movement lie within the range of 70.00% to 100.00%. Maximum classification accuracy for these four directions are obtained from different electrodes, namely CFC5 and CCP1 with classification accuracy of 93.33% (direction toward 3), CP5 and C4 with classification accuracy of 96.67% (direction toward 6), C1 and CP2 with classification accuracy of 96.67% (direction toward 9) and FC3 with classification accuracy of 100.00% (direction toward 12). In all four directions, features extracted using spatial filter LAP contributed for the maximum classification results.

TABLE 4: Classification results of detection intention of movement for direction toward 3, 6, 9 and 12 using QDA classifier on average of Power Spectrum in alpha (α), beta (β) and gamma (γ) band feature.

Subject	Parameter	Maximum Classification Accuracy, True Positive Rate (TPR) and False Positive Rate (FPR) for direction 3, 6, 9 and 12 (%)							
		Direction 3		Direction 6		Direction 9		Direction 12	
		CAR	LAP	CAR	LAP	CAR	LAP	CAR	LAP
S1	Acc	70.00	**76.67**	**76.67**	73.33	**86.67**	83.33	73.33	**76.67**
	Ch	CCP4	FC2	CP5	CFC4	FC4	CFC4	C4	CCP1
	TPR	66.67	66.67	80.00	66.67	86.67	80.00	93.33	53.33
	FPR	26.67	13.33	26.67	20.00	13.33	13.33	46.67	0
S2	Acc	80.00	**96.67**	90.00	**93.33**	**96.67**	93.33	90.00	90.00
	Ch	CPZ	CCP3	CP5	CCP2	CP5	CCP2	CP5	CCP5
	TPR	100	100	93.33	86.67	93.33	86.67	80.00	80.00
	FPR	40.00	6.67	13.33	0	0	0	0	0
S3	Acc	**73.33**	70.00	66.67	**70.00**	60.00	**73.33**	66.67	**70.00**
	Ch	C2	CCP3	FC1	CCP5	CCP2	CZ	C4	CCP5
	TPR	66.67	66.67	60.00	73.33	40.00	86.67	40.00	66.67
	FPR	20.00	26.67	26.67	33.33	20.00	40.00	6.67	26.67
S4	Acc	76.67	**80.00**	73.33	73.33	**83.33**	80.00	86.67	**90.00**
	Ch	FC5	CFC5	FC3	C3	CP1	CFC5	C1	FC2
	TPR	80.00	86.67	73.33	86.67	73.33	73.33	80.00	86.67
	FPR	26.67	26.67	26.67	40.00	6.67	13.33	6.67	6.67
S5	Acc	86.67	**90.00**	76.67	**96.67**	83.33	**93.33**	76.67	**86.67**
	Ch	FC3	CCP1	CP1	CFC1	C1	CCP3	CZ	CFC3
	TPR	86.67	93.33	73.33	93.33	73.33	86.67	73.33	93.33
	FPR	13.33	13.33	20.00	0	6.67	0	20.00	20.00
S6	Acc	70.00	**90.00**	70.00	**96.67**	73.33	**83.33**	66.67	**96.67**
	Ch	CCP4	CP4	C4	FC4	FC3	CFC5	CFC3	C5
	TPR	53.33	100	73.33	93.33	66.67	86.67	73.33	93.33
	FPR	13.33	20.00	33.33	0	20.00	20.00	40.00	0

S7	Acc	80.00	**96.67**	73.33	**96.67**	73.33	**93.33**	73.33	**96.67**
	Ch	CP5	CCP5	C3	CCP5	CCP4	CFC5	CCP3	CCP5
	TPR	86.67	100	60.00	100	66.67	86.67	66.67	100
	FPR	26.67	6.67	13.33	6.67	20.00	0	20.00	6.67
S8	Acc	**73.33**	70.00	70.00	**93.33**	73.33	**93.33**	73.33	**93.33**
	Ch	CCP2	CP2	FCZ	CP1	CP4	FC2	CP1	CP3
	TPR	80.00	86.67	66.67	93.33	86.67	93.33	73.33	86.67
	FPR	33.33	46.67	26.67	6.67	40.00	6.67	26.67	0
S9	Acc	73.33	**86.67**	73.33	**86.67**	63.33	**90.00**	70.00	**80.00**
	Ch	CFC1	CP1	CCP1	CP2	C3	FCZ	C3	CP1
	TPR	53.33	100	73.33	80.00	73.33	80.00	60.00	80.00
	FPR	6.67	26.67	26.67	6.67	46.67	0	13.33	20.00
S10	Acc	70.00	70.00	70.00	70.00	70.00	**70.00**	66.67	**73.33**
	Ch	CFC2	CP4	FC1	CCP1	C4	CCP4	CZ	FC2
	TPR	60.00	60.00	60.00	53.33	66.67	73.33	80.00	60.00
	FPR	20.00	20.00	20.00	13.33	26.67	33.33	46.67	13.33
S11	Acc	70.00	80.00	70.00	76.67	63.33	66.67	93.33	96.67
	Ch	CCP5	FC3	CFC2	FC2	C2	C5	FC5	CFC5
	TPR	66.67	73.33	66.67	60.00	66.67	66.67	93.33	93.33
	FPR	26.67	13.33	26.67	6.67	40.00	33.33	6.67	0

Table 4 indicates the classification results of four directions for detecting intention of movement lie within the range of 60.00% to 96.67%. Maximum classification accuracy for these four directions are obtained from different electrodes, namely CCP3 and CCP5 with classification accuracy of 96.67% (direction toward 3),CFC1, CCP5 and FC4 with classification accuracy of 96.67% (direction toward 6), CCP3,CFC5 and FC2 with classification accuracy of 93.33% (direction toward 9) and CCP5 and C5 with classification accuracy of 96.67% (direction toward 12). In all four directions, features extracted using spatial filter LAP contributed for the maximum classification results.

4 Conclusion

In this paper we have demonstrated the feasibility of detecting motor imagery and intention of movement using right wrist movement in multiple directions namely, direction towards 3, 6, 9 and 12. This is significantly supported by ERSP results that evidently detected ERD and ERS in both intention and imagination of movement in all directions.

The classification results from this paper also highlights the comparison of using two type of spatial filters namely CAR and LAP, wherein the LAP filter outperforms CAR. This finding is supported by Ng and Raveendran (2007). In their study which based on motor imagery paradigm, LAP outperformed other spatial filter using ERD/ERS from different hemispheres. On the other hand our findings contradict the finding by Alhaddad (2012). In his work (based on P300 paradigm) CAR outperformed LAP. Nonetheless, both CAR and LAP referencing are superior to the ear reference [10]. Apart from that the classification results, the importance of implementation of high density electrodes is also highlighted.

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