New set of cognitive tasks in EEG based Brain Computer Interface

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***Abstract* - A set of new mental tasks that can be used with Brain Computer Interface systems are introduced. New mental tasks are natural to perform for controlling a cursor on a computer screen to select icons. With the help of three healthy subjects, performance of new mental tasks was evaluated and compared with that of popular motor imagery mental tasks. Three subjects who participated in this study showed better or equally good performance with new mental tasks as compared to motor imagery mental tasks.**

***Keywords* - Brain Computer Interface (BCI), Machine Learning, Electroencephalography (EEG)**

I. INTRODUCTION

A Brain–Computer Interface (BCI) is a direct technological interface between a human brain and a computer not requiring any motor input from the user [1] - [3], [18]. It is a system that utilizes electric, magnetic, or metabolic brain signals to control external devices such as switches, wheelchairs, computers, or prosthesis [2] - [6]. BCI is an invaluable tool for severely handicapped people to interact with outside world. However, it has also wide range of applications in virtual reality, rehabilitation, multimedia communication, and entertainment or relaxation which are useful for healthy individuals [7], [22] - [24].

EEG based BCI employs electrical signals generated on the scalp of the human brain for detecting thoughts or intensions of the user [11] - [16]. General scheme of EEG based BCI system consists of the following steps,

i. Cognitive tasks (mental tasks) of the subject initiate activities in the cerebral cortex.
ii. Activities in the cortex alter the EEG signals recorded from the scalp.
iii. EEG signals are then amplified and digitized.
iv. These digitized signals are read by a computer as time series data.
v. Data will be analyzed with the help of Digital Signal Processing methods.

User can control EEG based BCI system by producing already known brain electrical activity patterns which could be identified by the system and translated them into commands. Signal processing step mentioned above consists of preprocessing of EEG data, feature vector construction, and classification [9], [20] – [21]. In the preprocessing stage, unnecessary frequencies and contamination presented in the raw EEG data are usually eliminated by filters or some other means. At the feature extraction step, the dimensionality of EEG signal is reduced while keeping the important features of the original signal intact. Once the signals are cleaned and feature vectors are constructed, they will be classified according to the mental tasks. Classification of EEG signal enables the computer to take actions according to preprogrammed instructions.

In BCI research community, it is known that certain mental activities can alter EEG signals up to a level where it can be detected by signal processing methods. Some of the mental tasks which are known to alter EEG signals consist of, Multiplication (Solve non-trivial multiplications), Letter Composing (Mentally compose of a letter), Geometric Figure Rotation (Instructed to find the possible rotation of a imaginary geometric figure), Visual Counting (Mentally visualize numbers being sequentially written on a board) and Imaginary hand or leg moments (Imagination of hand movement or foot movement) [8] - [10].

In this paper we present preliminary results on new set of cognitive tasks which can be used in BCI systems for controlling cursor movements on a computer screen in a natural manner.

II. NEW MENTAL TASKS

Motor imagery mental tasks are the most heavily used and successfully implemented mental tasks in BCI [10], [17], [25] - [27]. This may be due to the fact that they can produce distinct signals corresponding to individual motor movements which are less susceptible to noise. Motor imagery mental tasks are generated in the motor cortex by motor actions activated within working memory without any explicit motor output (e.g. imagination of hand or foot movements). These changes in the motor cortex due to motor imagery mental tasks can be detected on the scalp with EEG. However, it has been observed that, even though, some severely paralyzed patients could control BCI using motor imagery mental tasks effectively, right after losing their motor abilities, over the time, they become less effective in controlling BCI through motor imagery mental tasks [8], [19], [28]. As a result it would be very useful to have new mental tasks which are as effective as imagery motor movements but will not deteriorate the effectiveness over the time. The main aim of the present investigation is to find such mental tasks which could be used in BCI. In this study following criteria were implemented for finding new mental tasks.

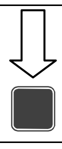
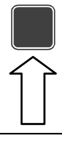
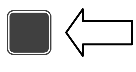
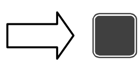
(a) should be able to perform easily and continually
(b) require no prior training
(c) should be able to use in BCI systems for controlling cursor movements on a computer screen in a natural manner.
(d) should be able to perform consistently

In this paper we present a new set of mental tasks which satisfies above criteria and performs better than motor imagery mental tasks by untrained subjects. The new set of mental tasks is named “Visualization of Arrow Movements” and consists of four mental tasks (Table I).

With these four mental tasks user tries to move a square shape cursor on a computer screen by,

(1) *imagining an arrow hitting the cursor from above(to move it down)*
(2) *imagining an arrow hitting the cursor from below (to move it up)*
(3) *imagining an arrow hitting the cursor from right (to move it left)*
(4) *imagining an arrow hitting the cursor from left (to move it right).*

TABLE I
MENTAL TASK LABELS AND IMAGES OF ARROWS

Mental Tasks Labels	**Imagination**	**Image**
IMDAM	*Imagining a down arrow hitting a square from the top (to move cursor down)*	
IMUAM	*Imagining an up arrow hitting a square from the bottom (to move cursor up)*	
IMLAM	*Imagining a left arrow hitting a square from the right (to move cursor to the left)*	
IMRAM	*Imagining a right arrow hitting a square from the left (to move cursor to the right)*	

Four different mental tasks are labeled as Imaginary Down Arrow Movement (IMDAM), Imaginary Up Arrow Movement (IMUAM), Imaginary Left Arrow Movement (IMLAM), Imaginary Right Arrow Movement (IMRAM).

We have investigated performance of Visualization of Arrow Movements and compared it with that of Left Middle Finger Movement (LFM) and Right Middle Finger Movement (RFM) in motor imagery mental tasks. The major reason for comparing performance of Visualization of Arrow Movements with that of LFM and RFM is that currently motor imagery is the most heavily used mental tasks in EEG based BCI systems.

III. METHOD

Performance of Visualization of Arrow Movements and motor imagery is carried out with three healthy individuals. Two male, one right-handed and one left handed subjects and one female left-handed subject (ages 22-32 years) took part in this study. Ethical clearance (2009/EC/36) was obtained for recording of EEG from the volunteer subjects and the volunteers were paid an honorarium for their participation.

In order to record the EEG signals from subjects, the Mindset-24R amplifier system manufactured by NeuroPulse-Systems LLC was used [12]. To capture EEG signals from the scalp, ECI Electro-Cap electrode system II™ manufactured by Electro-Cap International Inc have been used [13]. In addition to 20 electrodes in the electro-cap, two ear electrodes have also been connected to the amplifier as reference electrodes. For measuring impedance of electrodes, we have used NPS impedance meter (model 1089NP) manufactured by NeroPulse Systems and the values of impedance between all EEG electrodes and reference electrodes were kept below 3 KΩ.

For recording EEG data, Mindmeld 24 Data acquisition software [29] was used. A program called *Alarm* was developed for informing the subject about the forthcoming mental task to be recorded and assisting the subject with when the recording starts and when it ends. Initially, to capture the EEG signals of Visualization of Arrow Movements , subjects were requested to be seated on an armchair looking at a black square pasted on a white blank screen which was placed approximately one and half meters away from the subject. They were asked to keep their arms and hands relaxed and to avoid eye movements while keeping his/her eyes open during the recordings. Each trial started with the alarm program informing the subject verbally what mental task should be imagined in the upcoming trial. A short beep is made to inform the subject to start the mental task and at the end of a fixed period another beep is produced to inform the subject to stop the mental task. If it is observed that eye blinks or eye moments occurred during the recording of the trial, data recorded in the trial is discarded and the trial is repeated. In motor imagery sessions we followed a similar procedure as for Visualization of Arrow Movements with few exceptions. In this setup the black square on the white screen was removed. The purpose of placing the white blank screen in front of the subject was to reduce distractions. They were asked not to pay any attention to the white board or any other objects but to concentrate on mental task they are performing.

IV. Signal Processing and Classification

For signal processing and classification of EEG data, software called "IMTE" (Identification of mental tasks through EEG) has been developed in the AI laboratory at Institute of Fundamental Studies using MATLAB® version 7.8.0.347 (R2009a). IMTE has a Graphical User Interface (GUI) with user friendly features and supports various signal processing techniques.

In this study, preprocessing of EEG data was carried out with band pass filtering. The lowest and the highest frequencies of the filter were determined such that classification performance is maximal. For feature vector constructions, three methods have been tried out; Bandpower, Down Sampling and Principal Component Analysis (PCA). It was found in the preliminary study that Bandpower outperformed the other two feature vector construction methods for both motor imagery and Visualization of Arrow Movements. Therefore, detail studies were only performed with feature vectors constructed with Bandpower. For classification of mental tasks, several classification methods were tested. They are,

(1) under Discriminant Analysis, Linear Discriminant Analysis, Diaglinear analysis, Quadratic analysis, Diagquadratic analysis, and Mahalanobis analysis,
(2) under Support Vector Machine, available options are Linear kernel or dot product, Quadratic kernel, Polynomial kernel, Gaussian radial basis function kernel (Rbf), and Multilayer perceptron kernel,
(3) k - Nearest Neighbor (kNN) classification.

We have used similar settings, same recording parameters and same subjects for both sets of mental tasks (Visualization of Arrow Movements and Motor Imagery). Following parameters and settings were used in all the recording sessions (Table II).

During the detail investigation, performance was optimized while keeping number of channels in the analysis to be less than six and changing the parameters and EEG channels.

In the preliminary investigation, the classification methods in the discriminant analysis performed poorly except diaglinear and diagquadratic. With the exception of linear and polynomial kernels all the other kernels in the Support Vector Machine (SVM) classification methods performed very poorly (less than 65%). Further, the classifications carried out with certain combination of parameters for SVM linear and SVM polynomial did not converge. Throughout the studies kNN performed well compared to Diaglinear and Diagquadratic Discriminant analysis, and Linear and Polynomial SVM kernels in both preliminary and detail investigations.

Therefore in this paper we will be presenting the final results of the analysis carried out for Visualization of Arrow Movements and motor imagery with Bandpass filter for preprocessing, Bandpower for feature vector construction and kNN for classification.

TABLE II
Parameters and Settings Used in All the Recording Sessions

Channels used for recording	All 20 channels according to 10 - 20 system
Sample rate	256 samples per second
Block size	768 bytes per block per channel
Preparation period used in alarm program	7 seconds
Recording duration	9 seconds
Number of Subjects	03
Number of Test trials per mental task per subject	30 trials
Number of Train trials per mental task per subject	90 trials
Total number of mental tasks including Baseline(BL)	08
Total number of test trials per subject	240 trials
Total number of train trials per subject	720 trials
Total number of trials per subject	960 trials

V. Results

It was found in the preliminary investigation that, all the methods tested in this study could not identify the difference between Imaginary Right Arrow Movements (IMRAM) and Imaginary Left Arrow Movements (IMLAM) and similarly Imaginary Up Arrow Movements (IMUAM) and Imaginary Down Arrow Movements (IMDAM) (See Table III for details) could not be differentiated. The best performance of classification for IMRAM and IMLAM is less than 65% while for IMUAM and IMDAM it is less than 70%. Consequently the results presented below are for Baseline (BL), IMRAM, and IMDAM.

Performance of mental tasks of Visualization of Arrow Movements and motor imagery were calculated as percentages;

$$P = \frac{N_S}{N} \times 100 \qquad (1)$$

P – Performance
N_s – Number of successfully identified mental tasks
N – Total number of mental tasks

TABLE III

THE BEST PERFORMANCE OF TWO UNTRAINED SUBJECTS FOR IMRAM AND IMLAM, AS WELL AS IMUAM AND IMDAM FOUND IN THE PRELIMINARY STUDIES. NUMBER OF EEG DATA POINTS USED IN THE CALCULATION WAS 2048.

SUBJECT 1		
Mental Tasks	IMRAM & IMLAM	IMUAM & IMDAM
Channels	1, 2, 18, 19	1, 2, 18, 19
Preprocessing	Bandpass (1, 40)	Bandpass (1, 40)
Feature Vectors	BP (42)	BP (42)
Classification	kNN (k = 10)	kNN (k = 10)
Individual Performance	63%	57%
SUBJECT 2		
Channels	2, 11, 12	2, 11, 12
Preprocessing	Bandpass (1, 44)	Bandpass (1, 44)
Feature Vectors	BP (43)	BP (43)
Classification	kNN (k = 4)	kNN (k = 4)
Individual Performance	52%	70%

TABLE IV

OVERALL BEST PERFORMANCE OF UNTRAINED SUBJECTS FOR FIXED CHANNELS, METHODS AND PARAMETERS FOR BASELINE (BL) AND IMRAM, BASELINE AND IMDAM, AND IMRAM AND IMDAM. NUMBER OF EEG DATA POINTS USED IN THE CALCULATION WAS 2048.

SUBJECT 1			
Mental Tasks	BL & IMRAM	BL & IMDAM	IMRAM & IMDAM
Channels	1, 2, 18, 19	1, 2, 18, 19	1, 2, 18, 19
Preprocessing	Bandpass (1, 40)	Bandpass (1, 40)	Bandpass (1, 40)
Feature Vectors	BP (42)	BP (42)	BP (42)
Classification	kNN (k = 10)	kNN (k = 10)	kNN (k = 10)
Individual Performance	75%	90%	93%
Overall	89%		
SUBJECT 2			
Channels	2, 11, 12	2, 11, 12	2, 11, 12
Preprocessing	Bandpass (1, 44)	Bandpass (1, 44)	Bandpass (1, 44)
Feature Vectors	BP (43)	BP (43)	BP (43)
Classification	kNN (k = 4)	kNN (k = 4)	kNN (k = 4)
Individual Performance	100%	98%	100%
Overall	99%		
SUBJECT 3			
Channels	6, 13 18	6, 13 18	6, 13 18
Preprocessing	Bandpass (1, 38)	Bandpass (1, 38)	Bandpass (1, 38)
Feature Vectors	BP (45)	BP (45)	BP (45)
Classification	kNN (k = 8)	kNN (k = 8)	kNN (k = 8)
Individual Performance	88%	77%	70%
Overall	78%		

TABLE V

OVERALL BEST PERFORMANCE OF UNTRAINED SUBJECTS FOR FIXED CHANNELS, METHODS AND PARAMETERS FOR BASELINE (BL) AND RFM, BASELINE AND LFM, AND RFM AND LFM. NUMBER OF EEG DATA POINTS USED IN THE CALCULATION WAS 2048.

SUBJECT 1			
Mental Tasks	BL & RFM	BL & LFM	RFM & LFM
Channels	2, 8, 12, 13	2, 8, 12, 13	2, 8, 12, 13
Preprocessing	Bandpass (1, 30)	Bandpass (1, 30)	Bandpass (1, 30)
Feature Vectors	BP (34)	BP (34)	BP (34)
Classification	kNN (k = 10)	kNN (k = 10)	kNN (k = 10)
Individual Performance	78%	65%	65%
Overall	69%		
SUBJECT 2			
Channels	1, 8, 11	1, 8, 11	1, 8, 11
Preprocessing	Bandpass (1, 30)	Bandpass (1, 30)	Bandpass (1, 30)
Feature Vectors	BP (43)	BP (40)	BP (40)
Classification	kNN (k = 3)	kNN (k = 3)	kNN (k = 3)
Individual Performance	97%	100%	63%
Overall	87%		
SUBJECT 3			
Channels	4, 5, 15	4, 5, 15	4, 5, 15
Preprocessing	Bandpass (1, 33)	Bandpass (1, 33)	Bandpass (1, 33)
Feature Vectors	BP (45)	BP (45)	BP (45)
Classification	kNN (k = 6)	kNN (k = 6)	kNN (k = 6)
Individual Performance	93%	90%	82%
Overall	88%		

In a real BCI system, channels, parameters and methods have to be the same for a given subject, but they can be different for different subjects. The Table (IV) below shows the best performance of each subject with the optimal channels, methods and parameters used for Visualization of Arrow Movements mental tasks. Note that in all the tables, *Bandpass*(f_1,f_2) indicates that allowed frequency range of the Bandpass filter is $[f_1,f_2]$ and *BP* (Δ) implies that Bandpower is calculated with band width Δ.

For motor imagery, we present the performance results in the same format as above to make comparisons (Table V) between motor imagery and Visualization of Arrow Movements easier.

VI. CONCLUDING REMARKS

It is evident from the results presented in this paper that compared to motor imagery, Visualization of Arrow Movements performed better or equally good as far as three subjects are concerned. Optimal performance was achieved with three EEG channels for two subjects while four EEG channels for the other. The Subject 2 achieved best performance of 100% for Visualization of Arrow Movements while 92% for motor imagery. On the other hand Subject 1 performed well (88% - 98%) for the mental tasks in Visualization of Arrow Movements, while performed poorly (75% - 80%) for motor imagery. Best performance of Subject 3 for Visualization of Arrow Movements was good (80% - 90%) while the same for motor imagery was much better (82% - 98%).

When we combine performances of all the subjects, new set of mental tasks (Visualization of Arrow Movements) introduced in this paper performed better than or equally well compared to the most widely used motor imagery. Compared to mental tasks such as multiplication, letter composing, LFM or RFM in motor imagery, mental tasks in Visualization of Arrow Movements (IMRAM and IMDAM) are very natural to perform for moving the curser to left or down, on the computer screen.

On the other hand, LFM and RFM can be used effectively to simulate clicking of left mouse button and right mouse button respectively. Therefore Hybrid system of motor imagery and Visualization of Arrow Movements is ideal for controlling computers through icons in real time BCI systems.

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