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Developing Brain Computer Interface for Motor Imagery Mental Commands

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***Abstract* — In this study we propose how to design and develop brain computer interface for motor imagery (MI) where the training is based on action observation of a robot's body parts and MI activities in terms of electroencephalogram (EEG) signals are featured and classified by Support Vector Machines. As the classification process is binary, most relevant features under study are based on statistical changes. The portable brain-aware device Emotiv EPOC is used to track and transmit EEG signals while the human is focusing and following positional directions, which are translated into navigation commands for the robot. The designed by us EEG-based portable Brain-Computer Interface (BCI) measures and features the brain electrical activity for an observation/execution matching system. The electrodes in the parietal lobe, the area involved in transforming visual information into motor commands, together with "smart artifacts" induced in the raw EEG signals are used for classifying the type of the mental command.**

***Keywords* — Brain-computer interface, Motor imagery, Human-robot interaction, Pedagogical rehabilitation for children with SEN, SVM.**

I. INTRODUCTION

Our past experience in spatial orientation with children with Special Educational Needs (SEN) has shown that their basic skill is far below expected, which in turn means they need a different and task engagement approach for repetitions using their mind power and learning by imitation [1]. The Mirror Neuron System (MNS) [2] is believed to provide a basic mechanism for social behaviors such as action recognition and imitation. Thus, exploiting socially assistive robots for repetition by imitation we design brain-robotic scenarios how to create habits for orientation in space.

All human behaviors involve motor functions, from walking to simple picking up a glass of water, where the brain has not only to contract the muscles but has to estimate, execute and plan other factors, such as the volume of the water, the shape of the glass, the trajectory, etc. In this study we used the electroencephalogram (EEG) signals correlated with all mental activities underlying the motor imagery (MI) to identify observation/execution matching. Motor imagery is defined as the cognitive process of imagining the movement of your own body part without actually moving that body part [3]. Since self-cognition is difficult for children with SEN, to obtain consistency in mind training and, consequently, use of this training in terms of mental commands, we propose a new model for training – a Brain-Computer Interface (BCI) training by action observation for imagining the movements of the robot's body part.

Novel approaches in HCI include the use of information technologies and, specifically, the use of brain aware devices and Brain-Computer Interface which bypasses the conventional channels of communication, i.e. muscles, and provides direct communication and control between the human brain and the physical devices. BCI translates different patterns of brain activity into commands in real time [4]. Recently, portable, non-invasive and affordable EEG commercial devices for "gaming" or "well-being sustainability" have emerged [5]. They record the brain activity and measure the change in brain pulse voltage by electrodes on the scalp. We use low resolution devices "EPOC" or "INSIGHT" (Fig.1.) by EMOTIV bioinformatics company [6]. The electrode locations (INSIGHT ones are discriminated by red circles) are shown on Fig.1.a according to the 10-20 international EEG system (Fig.1.b), recommended by the International Federation of Societies for Electro-encephalography and Clinical Neurophysiology [7]. Although both devices have low resolution and are with a few electrodes, they provide high-quality output neural signals [8]. More electrodes are positioned around the frontal and prefrontal lobes and they pick up signals from facial muscles and the eyes. The frontal sensors induce noise in EEG signals - however we also use these signals to classify which muscle groups are responsible for the artifacts. These so-called "smart artifacts" induced in pure EEG signals are diverted and classified to map the activation in different muscle groups and eye movement into events and we used them for detecting the motor imagery activities.

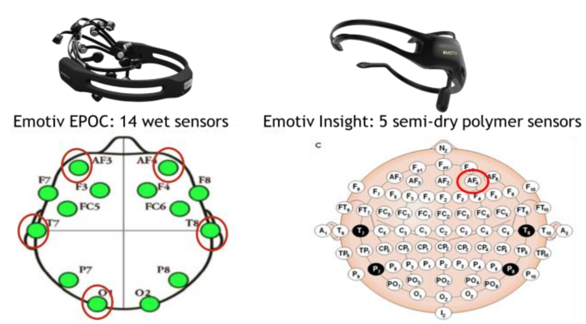

Fig. 1. EMOTIV BCI technologies and electrode locations according to the 10-20 international EEG system.

In the current study we have developed a BCI to be used in pedagogical scenarios, mediated by socially assistive robots. BCI measures and features in real time the brain electrical activity behind the mental commands for spatial orientation by motor imagery of the robot head, arms or legs. The robots are controlled by BCI and this integration of both technologies engages the spatial orientation of children with SEN by action observation and reinforces their attention. First, they have to create personally a mental command for each direction. Creating "Mental Commands" is a process to train the BCI system to recognize human background mental state from imagining the consequences of the command. In order to recruit and facilitate the imagination during the training phase, we bound the mental commands to different robot movements by analogy to the Emotiv EPOC Control Center [9] that supports animations of a 3D cube (or a car) during the training for PUSH, PULL, LIFT, DROP, LEFT, etc. This induces artifacts form eye movements and we use these "smart artifacts" complementary to the pure EEG signals placed on the temporal, parietal and occipital lobes. The BCI-Robot framework, developed in the frame of the CybSPEED project [10], contains EMOTIV brain headset for tracking, processing and translating EEG data into mental commands, as it is illustrated on Fig.2.

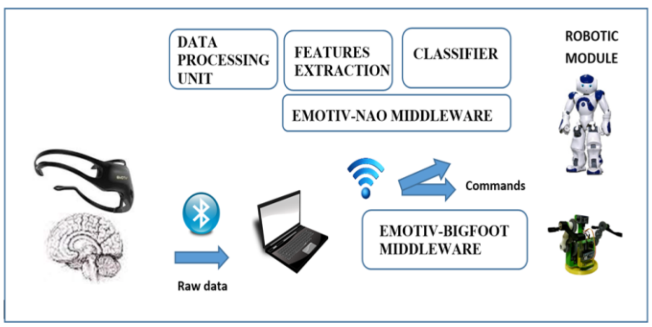

Fig. 2. BCI-Robot wireless framework for training and control

A research protocol, describing how the motor imagery mental commands, can be tracked by physiological (neural data) observations and how data will be recorded and used, was submitted to the Ethics Committee for Scientific Research (ECSR) of the Institute of Robotics, Bulgarian Academy of Sciences (IR-BAS) and approved in October, 2018.

The paper is organized as follows: Section II presents related work about neuroscience implications for motor imagery and a review for signal processing techniques for motor imagery BCI. Section III presents the used materials and methods. Section IV presents the classification results and the conclusion follows.

II. Related Works

A. Neuroscience implications for the motor imagery

A neuropsychological interpretation how the brain structures participate in mental simulation of motor behavior can be found in [11]. According to the anatomy of movement all human behaviors involve motor functions, from walking to simple picking up a glass of water, where the brain has to contract the muscles and their sequence for grasping the glass, however also has to estimate and execute the force needed to pick up the glass. Planning of other factors, like the volume of water and the material the glass is made from, also influence the brain calculations. Therefore, many anatomical regions need to be involved in motor tasks and the main regions of the motor cortex involved in the planning, control, and execution of voluntary movements are shown on Fig.3. The motor cortex is an area of the frontal lobe located in the posterior precentral gyrus immediately anterior to the central sulcus.

The primary motor cortex (PMC) is a brain area located in the frontal lobe and its role is to generate brain impulses that control the execution of movement by activating skeletal muscles. Left hemisphere controls the right side of the body and vice versa. Other regions of the cortex involved in motor function are the premotor cortex, posterior parietal cortex and the supplementary motor area (SMA). *The posterior parietal cortex is involved in transforming visual information into motor commands.*

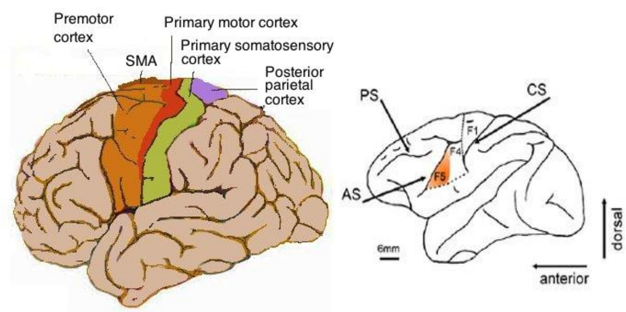

Fig. 3. Main regions of the motor cortex (adapted from Wikipedia). https://en.wikipedia.org/wiki/Motor_cortex, accessed January, 2020.

A 'motor' theory of social development and its relation to mirror neurons (MNs) is first proposed by Rizzolatti [2]. A set of F5 neurons ("mirror neurons", n = 92) became active both when one is performing a given action and when one is observing a similar action performed by an experimenter. Many research efforts have been involved in motor theories of cognitive and social development in humans by providing a potential neural mechanism underlying an action observation/execution matching system [12, 13, 14]. It has been proposed that this system plays a fundamental role in the development of complex social and cognitive behaviors such as imitation and action recognition.

Children with ASD often exhibit early difficulties with action imitation possibly due to low-level sensory or motor impairments [12]. EEG activation displays differences in the pre-motor cortex and supplementary motor area between normal individuals and individuals with high and low traits of autism [14]. Children with ASD exhibit greater beta-ERD than their control peers but post-movement beta rebound (PMBR) is absent [12]. Typically developing adolescents exhibited adult-like patterns of motor signals, e.g., event-related beta and mu desynchronization (ERD) before and during the movement and a post-movement beta rebound (PMBR) after the movement. In contrast, those with ASD exhibited stronger beta and mu-ERD and reduced PMBR. Behavioral performance was similar between groups despite differences in motor cortical oscillations.

B. Review for signal processing techniques for motor imagery brain computer interfaces

Motor Imagery Brain Computer Interface provides a non-muscular channel for communication to those, who are suffering from neuronal disorders [15]. An example for a system with BCI for MI has been reported to be effective for stroke rehabilitation [3]. Authors in [15] discuss existing challenges in the domain of motor imagery brain-computer interface and suggest possible research directions. The designing of an accurate and reliable MI-BCI system requires the extraction of informative and discriminative features. Common Spatial Pattern (CSP) has been potent and is widely used in BCI for extracting features in motor imagery tasks. The classifiers translate these features into device commands. Many classification algorithms have been devised, among those Support Vector Machine (SVM) and Linear Discriminate Analysis (LDA) have been widely used. In recent studies deep neural networks for classification of motor imagery tasks are used. The research paper [15] provides a comprehensive review of dominant feature extraction methods and classification algorithms in BCI for motor imagery tasks.

More studies, using EEG signals and features of motor imagery to identify different imagery activities can be found in [16], where the authors propose similar to our approach: Emotiv EPOC is used to extract EEG features about MI based on electroencephalogram signals. They use only AF3, AF4, FC5 and FC6 to capture EEG signals. A feature vector of EEG signals is transferred by a Wavelet transform. The four classified actions are analyzed through SVM algorithm with the Gauss kernel function. However, we consider that these 4 electrodes are not enough to identify neural activities underlying the MI by action observation, because more electrodes need to be analyzed in the parietal lobe, the area involved in transforming visual information into motor commands. We studied the electrodes positioned at the posterior parietal cortex and supplementary motor area during action observation and our feature extraction involves the neural activities underlying the "Observation–execution matching system".

III. MATERIALS AND METHODS

A. Hypothesis and relevance of the materials and methods

Our hypothesis is the following: 1) Spatial orientation of children with SEN will be increased by practicing navigation skills by imitation, mediated by socially assistive robots in an entertaining and playful environment. 2) A non-intrusive monitoring and assessment by BCI will provide EEG evidence for the presence of an "observation–execution matching system" in these children.

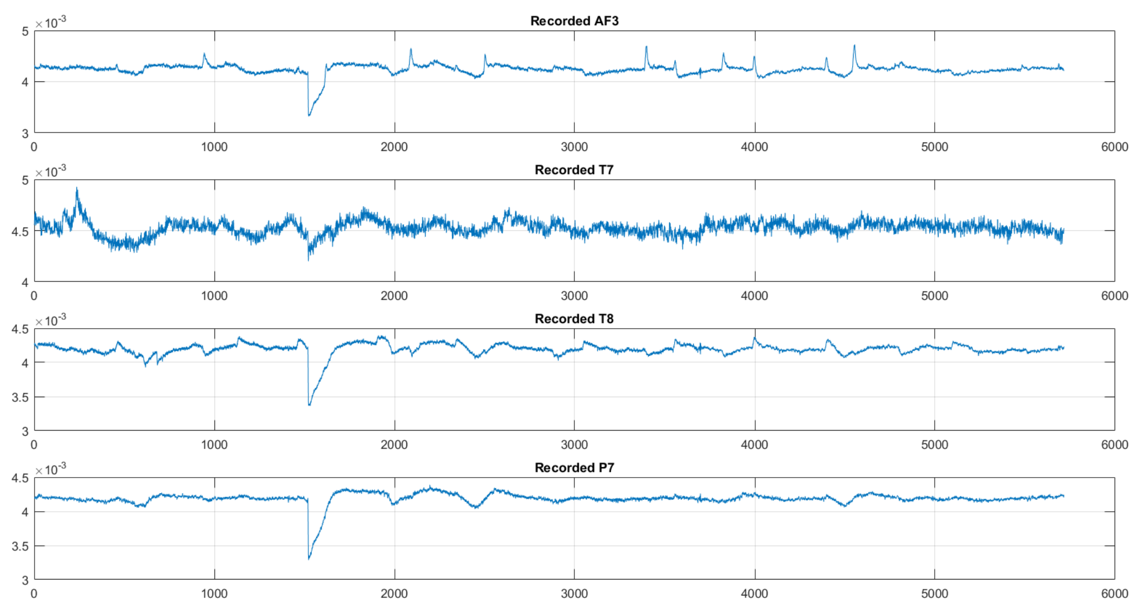

Fig. 4. Some representative signals of the recording sequence : Rest-Right-Left- Right- Right- Right- Left- Left- Left- Right-Left

Materials: Assistive robots: humanoid robot NAO or non-humanoid Arduino-based robot, especially designed to not scare the kids. The intelligent sensors used for measuring the EEG correlated to motor imagery – the brain-aware headset EMOTIV EPOC. This headset is harmless wearable device complying with the requirements of the Low Voltage Directive 2006/95/EC, the EMC Directive 2004/108/EC, the R&TTE Directive 1999/5/EC, and carries the CE and C-Tick marks accordingly [12].

B. Methods

The experimental conditions for testing the proposed brain-robotic intervention scenarios are described in detail in a research protocol. During the training and testing that are involved in the classification and detection of the left / right eye imagery movements, the human made a set of left and right looks, and the corresponding EEG signal is recorded in training and testing sessions.

To better understand the association between EEG activities and the eye movement responses, several factors have been intensively investigated, which are as follows:
1) number of electrodes; 2) types and numbers of features; 3) types of classifier.

After a series of recording and analysis sessions of the obtained signals, we noticed that MI and artifacts, induced from the movement of the eyes, did not affect all EEG data: Only AF3, AF4 and P7 signals (see Fig.4) are capable to provide reliable information for a classification task.

B.1. Signal preprocessing and features extraction

Since the recorded EEG data is very noisy, it was first preprocessed to make it smoother and to minimize the influence of the artifacts. A median filter of order 5 is then used to eliminate outlier values. The average value of each signal must then be eliminated in order to highlight only the ocular changes.

Before extracting the left and right eye patterns, a separate recording of each pattern is required to allow its identification (Fig.5). The two signals are differentiable by their phase oppositions.

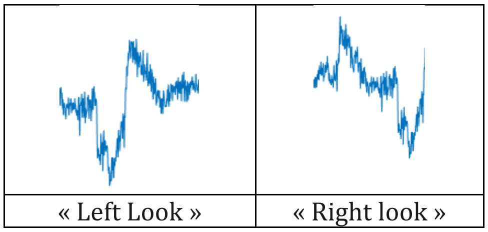

Fig. 5. Patterns representing left and right looks: Case of the P7 signal

To reflect the real case of an interactive class between the robot and the students, the recording is asynchronous. Pattern detection and its extraction from the recorded signal are then achieved through a visual inspection and analysis. The choice of features aims to describe one or more characteristics of the eye movement activity and will be used by a learning algorithm to establish a model for the Left Look-Right Look classes. Since the classification process is binary, the most relevant features under study are essentially based on the temporal, statistical and power changes. They are calculated and organized as follows:

TABLE I. LIST OF USED FEATURES

Feature	Designation	Role
mn	Mean value	measures the distribution of the pattern over time
vr	Variance	measure of the dispersion of values
sk	Skewness	the asymmetry measurement of the pattern
kr	Kurtosis	measure of the "tailedness" of the pattern
rms	Root mean square	quadratic mean
apwr	Average power	the power related to the pattern

Following this calculation approach, the original elements are neither redundant, nor correlated. This will allow a better understanding of the information, contained in each vector of functionalities, obtained without any additional processing.

For the recording sequence, shown in Fig. 4, the values of the calculated features for each pattern are represented in the following tables:

TABLE 2. CALCULATED FEATURES FOR EACH RIGHT PATTERN: CASE OF THE RECORDING REPRESENTED BY THE SIGNAL P7 IN FIGURE 4.

Features\Pattern	Right1	Right2	Right3	Right4	Right5
mn	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
vr	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
sk	*0.12*	*-0.04*	*1.11*	*0.27*	*1.47*
kr	*2.19*	*2.67*	*5.90*	*2.65*	*6.33*
rms	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
apwr	*1,7e-05*	*1,8e-05*	*1,6e-05*	*1,8e-05*	*1,8e-05*

TABLE 3. CALCULATED FEATURES FOR EACH LEFT PATTERN: CASE OF THE RECORDING REPRESENTED BY THE SIGNAL T8 IN FIGURE 4.

Features\Pattern	Left1	Left 2	Left 3	Left 4	Left 5
mn	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
vr	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
sk	*0.68*	*-0.13*	*1.64*	*0.86*	*0.54*
kr	*3.42*	*2.07*	*8.52*	*4.82*	*2.91*
rms	*0.004*	*0.004*	*0.004*	*0.004*	*0.004*
apwr	*1,8e-05*	*1,7e-05*	*1,8e-05*	*1,8e-05*	*1,8e-05*

According to the calculated values, the characteristics that have a large discriminatory effect are skewness and kurtosis.

B.2. Classification algorithm

The classifier used in this study is based on the supervised approach developed in the 1990s based on Vladimir Vapnik's theoretical considerations on the development of a statistical theory of learning - Support Vector Machines (SVM) [17].

B.2.1. Basic Theory of SVM

Given a training set of instance-label pairs (x_i, y_i); $i = 1,....l$ where $x_i \in R^n$ and $y_i \in \{1,-1\}^l$. The SVM [17] are used to find a hyperplane Wx+b=0 to separate the data with the maximum margin. They require the solution of the following optimization problem:

$$\text{minimize } \ M = \frac{1}{2} W^T W$$

Subject to

$$y_i(\ W^T \emptyset(x_i) + b) \geq 1 \tag{1}$$

Using a soft-margin instead of a hard-margin, we obtain the primal problem for SVMs:

$$\text{minimize } \ \frac{1}{2} W^T W \ + C \sum_{i=1}^{n} \xi_i \tag{2}$$

Subject to

$$y_i(\ W^T \emptyset(x_i) + b) \geq 1 - \xi_i \ ; \ \ \xi_i \geq 0 \tag{3}$$

where:

- $\{\xi_i\}$ are slack variables which allow for penalized constraint violation through the penalty function $F(\xi)$ defined by Equation 14:

$$F(\xi) = \sum_{i=1}^{n} \xi_i \tag{4}$$

- C is the parameter controlling the trade-off between a large margin and less constrained violation
- $\emptyset(\dots)$ represents the mapping from the input space to the feature space. However researchers prefer to use a kernel function K(.,.) given by the following expression: $K(x_i, x_j) = \emptyset(x_i)^T \emptyset(x_j)$. Practically, the most commonly used kernel functions are:
  - Linear: $K(x_i, x_j) = {x_i}^T x_j$
  - Polynomial: $K(x_i, x_j) = \ (\gamma {x_i}^T x_j + r)^d \ \ , \gamma > 0$
  - Exponential Radial basis function (ERBF): $K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^{\,2}), \gamma > 0$
  - Sigmoid: $K(x_i, x_j) = \tanh(\gamma {x_i}^T x_j + r)$

Here, γ, r and d are kernel parameters. Furthermore, a practical use and implementation of the SVM classifier is presented in [19].

B.2.2. Optimization of the classifier

We set the classifier parameters based on binary classification. Beyond the fundamental principle of parsimony in research, the SVM approach leaves, in practice, a number of options and settings to the user such as: the choice of the tuning parameter, and the choice of kernel type.

The kernel function:

The adopted kernel is the Exponential Radial Basis Function (ERBF) as it represents the best way to follow the non-linear decision surfaces.

For maximum robustness, instead of the basic equation, we use a structure that takes into account the number of learning elements [18]. The kernel function expression is given by (5).

$$k(x, y) = \exp\left(-\frac{\|x - y\|^2}{m\sigma^2}\right) \tag{5}$$

- m is the dimension of the observation vectors;
- σ represents the width of the Gaussian function. It is the main parameter that affects the complexity of decision surfaces. Optimization of the classifier involves determination of that parameter in order to maximize the performance and the feasible value is σ=0.5 [18].

Controlling parameters

As already mentioned, this coefficient controls the tradeoff between maximizing the margin of a class's separation and minimization of classification errors on the training set. It's a balancing parameter to set a priori, in order to make floppy the margin's SVM. The best practical results are usually obtained [19] using an adaptive value "C_{dat}"of that penalty parameter based on the number of « m » learning elements. Thus, C_{dat} is obtained according to the equation (6) wherein the kernel function $k(x_i, x_i)$ is defined by Equation (5).

$$C_{dat} = \frac{1}{\frac{1}{m} \sum_{i=1}^{m} k(x_i, x_i)} \tag{6}$$

IV. Classification Results

The recordings were made for several people and a database was built for training and testing of the classification model. In this last phase, a cross validation method was applied. With this approach, the generality of the established classification systems is tested and verified when the system has trained the characteristics of the studied EEG signals.

The procedure consists of starting the supervised learning process with the first database and later launching the test phase with the second and vice versa. The result of this test is given as a confusion matrix in the table below.

TABLE V. AVERAGE SVM BINARY CLASSIFICATION RESULTS (Left look vs. Right look)

SVM classifier : *« ERBF Kernel », σ=0.5 and C=C$_{dat}$*		*Estimated Patterns*	
		Left	***Right***
Real Patterns	***Left***	***65%***	*35%*
	Right	*38%*	***62%***

Although the overall result is correct, a binary classification based on supervised learning often leads to better precision: two reasons are possible:

1) The signal had to be cleaned well before the classification process.

2) Among the characteristics chosen, some calculated values have a low class separation power.

However, the use of the SVM classifier and its correct configuration made it possible to clearly distinguish the patterns under study.

In the future we intend to apply the proposed model for training and controlling social robots by mental commands correlated with the attention and emotional knowledge of children with special educational needs, in order to extend our past experiments [20]. We plan to test another brain-aware device – the Open BCI [21].

CONCLUSION

A new EEG-based brain-computer interface has been proposed for controlling body parts of a humanoid robot NAO or non-humanoid Arduino-based robot by motor imagery. To obtain consistency in BCI training and consequently use of personalized mental commands we propose a model for BCI training by action observation. The experimental results show that the BCI classification system for motor imagery that extracts features and translate those features into navigation robot commands is general enough to establish and classify other mental commands based on EEG signals.

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