Multimodal Brain-Computer Interface Based on Artificial Intelligence for Rehabilitation of People with Motor Disorders

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This paper describes a work in process of developing a solution for quality of life improvement for people with severe movement deficit after stroke and brain injuries. The solution is a multimodal brain-computer interface system for motor rehabilitation, which performs real-time decoding of brain and body signals using artificial intelligence methods. The project aims to develop a safe, affordable and portable system, which has the potential to become the key technology for neuro-rehabilitation of patients with severe movement disorders

Keywords— Brain-Computer interface, neuro-rehabilitation, motor imagery, EEG, Inertial Measurement Unit, Machine Learning;

I. INTRODUCTIONS:

There are millions of people with movement disabilities, however, modern medical and technical solutions have very limited capability to restore lost motor skills [1]. Therapists in the field of neuro-rehabilitation are in great need for new technological solutions. The objective of the project is to develop a novel, safe and reliable solution that improve the quality of life of people with severe movement deficits (after stroke, spinal cord injury, and traumatic brain injury) and aid in restoring lost motor abilities. The solution is a multimodal brain-computer interface (BCI) system for rehabilitation, which performs real-time decoding of brain and body signals using artificial intelligence methods.

Several clinical studies have showed evidence for the feasibility and positive effect of BCI-based neurofeedback systems for motor post-stroke recovery [2,3]. It is conjectured that this efficacy of BCI systems on motor rehabilitation is due to the underlying mechanism of synaptic plasticity [4,5,6]. The initiation of any muscle's movement can be seen in unique electric patterns on the sculp, using electroencephalograph (EEG). Similar patterns can also appear even when muscles do not contract – by imagined movements or in cases such as paralysis or amputation [7]. Hence, we focused on developing a comprehensive system to record and quickly analyze EEG data from subjects. This online analysis aims to allow prediction of the intended movement, based solely on EEG data.

Moreover, most of the target users can still make small residual movements, e.g. movements of shoulders. These residual movements can serve as the first targets for intervention.

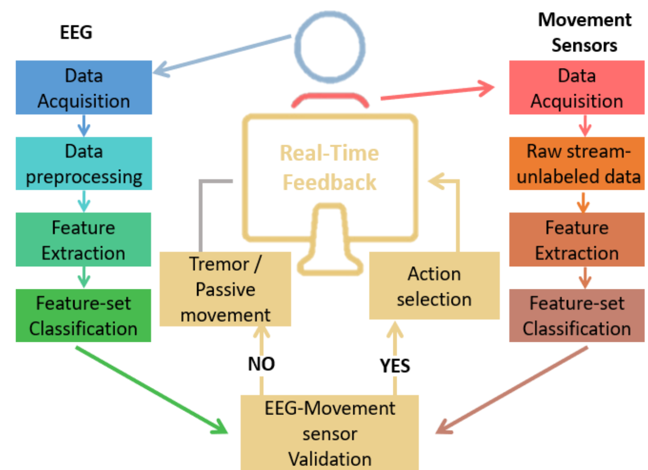

Fig. 1 | A parallel process of data - aquesition, preprocessing, feature extraction and classification that merges to predict user's intention of movement. The two data sources are brain signals recorded with EEG and limb movement as recorded by two small wireless motion sensors worn on the body. The closed loop circuit was shown to posess theraputic advanteges using neurofeedback methods.

In our research, we are developing a system that acquire and analyze data from the two modalities. The structure of the multimodal BCI is based on parallel acquisition and decoding of EEG, for neural patterns data, and Inertial Measurement Unit (IMU) signals for actual limbs movement recording. The system (Fig. 1) will performs, in parallel, the following main steps: (1) real time acquisition of EEG and IMU signals; (2) signal preprocessing; (3) advanced feature extraction, including principal component analysis (PCA), spectrum analysis and wavelet transform; (4) automatic feature selection; (5) decoding of motor commands by means of classifiers based on machine learning; and (6) feedback platform.

The basic principle of the multimodal system is to use mutual validation of motor command decoding obtained from both movement sensors and EEG pattern recognition. If one classifier recognizes the pattern corresponding to a motor command, the other classifier has to validate it, with minimal time delays, before sending the appropriate feedback.

In order to build a multimodal system, two separate development efforts were taken. The first is the development of

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a system for movement classification using data from motion sensors. The second effort was aimed at developing classification model for EEG data that was recorded from the sculp during cued motor task. The aim of this study was to validate that both methods achieve significant classification accuracy.

II. Methods

A. Movement data analysis:

. For movement data acquisition, two IMU sensors were placed on two shoulders inside special bracelets. Four types of shoulder movements and rest were recorded. Filtering, time-series analysis and PCA were performed on the 14-dimensional data to decrease its dimensionality to two dimensions. Descriptive features, such as kinematic landmarks and velocity peaks, were extracted from the first principal component for each IMU. Linear discriminant analysis (LDA) classifier was trained and tested for each subject (5-fold cross validation was used to test the accuracy of the developed classifier)

The training and testing of the system used the same experimental design: the movement sequence consisted of 20 movements, 5 of each type, in a random order. Ten subjects participated in two types of experiments – “Lab Conditions” and “Day to Day Usage” groups. In "Lab Conditions" experiment participants trained the system and immediately tested it. In "Day to Day Usage" experiment, a previously trained classification model was tested.

B. EEG data analysis:

EEG was recorded during the “training” protocol, where subjects moved (or imagined movement) at cue. Raw EEG data was transformed into the power-frequency domain. Then, frequency features were selected using statistical methods and were used to train a Support Vector Machine (SVM) classifier. Once a classifier was trained, new unlabeled EEG segments could be classified by it in real-time.

Nine subjects completed 27 minutes training protocol, instructing subjects to move one or two shoulders at cue or imagine the movement. The sequence was random for the side of movement (Left/Right/Both). For each side, the first three cues were for real shoulder movements and the last three cues were for imagined movement of the same side.

EEG data was collected using 19 head electrodes and 2 ear-reference electrodes. Two subjects repeated the experiment twice with two months interval. For all 11 datasets, offline re-referencing was performed (Averaged weighting and current source density – montages). All 33 datasets were used for the analysis and training of a classification algorithm.

III. Results

. In the movement data analysis, the "Lab Conditions" experiment showed a mean classification accuracy for actual shoulder movement of 98±2%, whereas in "Day to Day Usage" the mean accuracy was 89±3%. The main reason for decline of average accuracy in the "Day to Day Usage" experiment was changes in location of the sensors and in the posture of the participant, which were significantly different in training and testing. As chance level for 4 classes classification is, in average, 25%, Both results prove to be significantly accurate.

In EEG classification, parameter adjustment had led, in some subjects, to 90% accuracy of classification (by training on 80% of the data and testing on 20% unseen trials). Further development of automated parameters adjustment and incorporating other signal analysis techniques is in progress. However, results indicate moderately good accuracy level.

IV. Discussion

Preliminary results indicate that the system can learn to decode a subject specific movement profile accurately in real time, using both movements in space and brain activation that relate to these movement. The solution is aimed at allowing people with movement disabilities to perform multimodal rehabilitation training, with feedback that is based on both actual movements and intentions of the user.

An emphasis in development was given on creating a non-invasive, portable, intuitive and personalized system, by selecting which part of the body to place the IMU sensors, and which corresponding EEG patterns to use for control. Repetitive motor tasks with a paretic limb that is done while receiving neurofeedback based on decoding of brain signals related to these movements, can facilitate motor function recovery [3].

V. References

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