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Multimodal approach for polysensory stimulation and diagnosis of subjects with severe communication disorders

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Abstract

An experimental multimodal system, designed for polysensory diagnosis and stimulation of non-communicative subjects, with severe brain injuries is presented. The user interface uses an eye-tracking device and EEG monitoring of the subject. The system is evaluated on 9 patients, data analysis methods are described, and experiments of correlating Glasgow Coma Scale with extracted features describing subjects performance in therapeutic exercises exploiting EEG and eyetracker are presented. Performance metrics are proposed, and k-means clusters used to define concepts for mental states related to EEG and eyetracking activity. Finally, it is shown that the strongest correlations are between the number of detected mental states and GCSe score, and between maximal length of mental state and GCSm. Weaker correlations are reported as well. Moreover an approach to classification of real and imaginary motion of limbs is presented and discussed. Classifiers based on SVM, Artificial Neural Networks, and Rough Sets were trained and accuracy reaching 91% for the real, and up to 100% for the imaginary type of motion was observed. Assessments of communication skills and therapy is possible with the system, already employed in long-term care facility.

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1. Introduction

Each year in Europe approx. 300 people for every 100,000 people suffer from traumatic brain injury (TBI), usually due to traffic accidents[1]. It is estimated that 1 in 8 subjects with severe brain injury fall into a long-term coma or a vegetative state. From diagnostic and rehabilitation points of view, the key problem is the lack of communication with such patients, in up to 40% cases leading to erroneous diagnosis[2]. The multimodal stimulation and diagnosis system developed at the Gdańsk University of Technology, is an innovative solution for diagnosis and rehabilitation of subjects considered to be in a vegetative state. This system integrates different technologies: eye-gaze tracking, EEG analysis, and scent emission for stimulating purposes. The paper presents this multimodal approach and preliminary experiments in human-machine communication. It is organized as follows. Sec. 2. describes developed and implemented multimodal system for patient stimulation and monitoring, Sec. 3 presents results of patients performance assessment and correlation with their Glasgow Coma Scale scores, Sec. 4 documents a methods and results of EEG analysis and classification aimed at recognizing intent of motion, dedicated to HCI user interface. Sec. 5 concludes the paper.

2. Multimodal stimulation and monitoring setup

The developed system assumes various phases of operation: first an objective testing of hearing, then monitoring of brain activity and user gaze, and finally visual and aromatic stimulation. Auditory evoked potentials (ABR - Auditory Brainstem Response) were chosen for their advantages: it is objective and non-invasive, and requires the subject only to stay relaxed, e.g. during sleep. The examination could last hours, so it is the main disadvantage. Test duration depends on the number and types of test signals, longer for precise measurement of hearing threshold, enabling personalized adjustment of signal levels. ABR uses EEG with defined number and arrangement of electrodes and signal acquisition parameters in a dedicated setup (Fig. 1a, 1b).

EEG typically uses 5 to 20 electrodes arranged symmetrically on the head. In the current research, following EEG devices were used: ENOBIO8 by Neuroelectronics with 8 electrodes, and EPOC and INSIGHT models by Emotiv (Fig. 1c) with 14 and 5 electrodes, respectively. Non-professional EEG might be inaccurate because of large area covered by a single electrode, however, for diagnostic and multimedia applications simple devices can be used, determining concentration of the subject, and overall activity in different brain areas.

EyeX Controller is an eye-tracker for monitoring user attention and reaction to visual stimuli presented on a screen. It records the gaze fixation point x, y coordinates in the monitor screen plane, 60 samples per second[3].

Dedicated software applications developed by our team, incl. therapist's application for managing training; database of anonymized subjects results; player application, used as a polisensory interface for the subject, providing an interaction between user's action (gaze fixation point, EEG reaction) and the elements visible on the screen, the reproduced sound, and the emitted scent. In typical session subject activity is monitored with the use of EEG, eyetracker, and video cameras for a reference. The therapist controlling the session could report events by clicking buttons in his application (the exercise beginning and ending, entrance of random person to the room during the session, pain felt by the subject, movement of the subject, and others). Events are automatically logged in the data file of the eyetracker and are linked with current position of the fixation point. Such events may be tracked later on in the post-processing and then visualized along with the gaze position and EEG signals features.

2.1. System evaluation

The system is validated with the participation of 10 persons with Traumatic Brain Injury from Neurorehabilitation Center, Department of Rehabilitation Medical Center "EPIMIGREN" in Osielsko, Poland. Subjects 01-09 are males, subject 10 is a female, the average age of the subjects was 44.2 years, their Glasgow Coma Scale points 11, 10, 6, 7, 10, 7, 8, 9, 9, 8. The GCS is one of the most popular methods of assessing consciousness of subjects with brain injuries, consisting in evaluation of eye opening, the best verbal answer and the best motor reaction caused by the external stimuli[4]. The hearing of all persons was evaluated by ABR, in 9 cases was proven to be correct, and those took part in exercise sessions with the therapist. The subject is encouraged to look at the image specified by the therapist or to fill a gap in the sentence with one of three words provided on the screen and chosen by gaze.

The brain activity of subjects was monitored and eyetracker and EEG data were further analyzed with the use of data clustering algorithms. Mental states classifications fused with subject performances are a valuable source of information for the therapist deciding about further treatment.

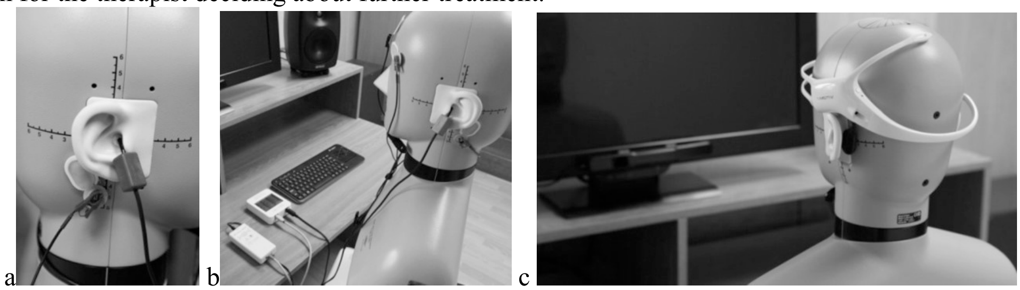

Fig. 1. Used equipment: (a) Echodia Elios ABR electrode mounted on the right mastoid and in-the-ear earpiece, (b) left-side electrodes, main unit beside the keyboard, (c) EEG Emotiv INSIGHT with 5 electrodes, and eyetracker mounted below the monitor screen.

3. Patient performance data analysis

39 therapeutic sessions data was collected and analyzed. The data consisted of EEG records, eyetracker data, events log. EEG data was processed in a following manner. Independent component analysis (ICA)[5] was used to blindly estimate unknown original signals related to brain functioning, assumed to be mixed and observed as the electrode signal. The number of estimated signals is equal to the number of electrodes. Estimations were then split into 512 samples frames, each analyzed by discrete wavelet transformation (DWT)[6]. Six types of wavelets of given level were used for the calculation: coiflets 1, 2, daubechies 1, 2, 9, and symlet 9 – selected upon a literature review[6]. Mean values and variances in each decomposition level were calculated, and finally clustered with k-means algorithm. Each cluster represented a group of frames of the time-domain EEG signal. Therefore, for any EEG frame a single closest cluster can be found, which is a way of classifying given frame to a 'mental state' concept. The number of clusters has to be specified arbitrarily, in our research set to 15. It's worth mentioning that generated clusters are related to actual mental activity but also to impulse-like artifacts and electrode contact loss due to person movement. EEG frame assignment to one of clusters can be visualized as segmented time plot of the signal. Such plot may be treated as estimation of subjects' mental states during the exercise (Fig. 2).

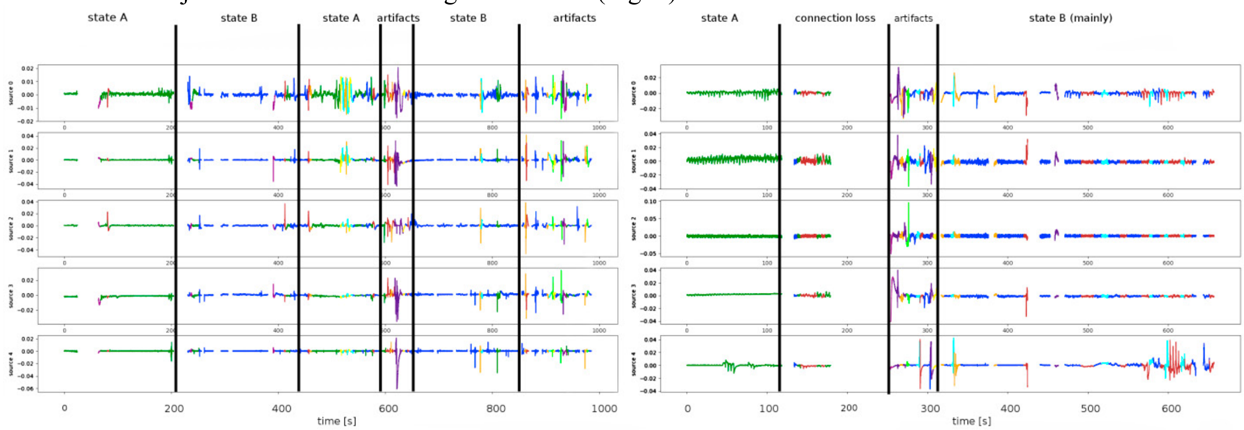

Fig. 2. Results of EEG clustering: segments denote detected mental states, comprised of individual clusters of DWT coefficients. Some states last for more than a couple hundred seconds, other only for a few seconds.

From the eyetracking data the timeseries of x, y screen point coordinates were collected to create heat maps for determining points where the eye gaze fixation occurred most frequently.

The Pearson correlation between GCS coma score and features of both EEG signal clusters and eyetracker maps (Tab. 1). In total for 10 pairs of features the Pearson correlation factor is greater than 0.3, for 3 pairs greater than 0.4, however only the maximum correlation 0.493 for GCSe and n_{LS} is statistically significant if two-sided Student's t-test with significance level of 0.8 is concerned.

Table 1. Pearson correlation factor calculated for pairs of GCS score (employing both: general and partial components) and features of EEG and eye gaze: kurtosis of projection of heat map over the x and y screen axes, maximal length of mental state determined by k-means ($t_{ms\ max}$), mean duration of the state ($t_{ms\ mean}$), number of detected mental states (n_{LS}), and number of areas where eye gaze fixation occurred most frequently (n_c) calculated by meanshift with parameters q = 0.1, 0.2, and 0.3

Cross-correlation between features:	Kurtosis x	Kurtosis y	$t_{ms\ max}$	$t_{ms\ mean}$	n_{LS}	n_c (q=0.1)	n_c (q=0.2)	n_c (q=0.3)
GCS	0.0502	**-0.397**	0.296	**0.332**	**0.313**	0.129	**0.338**	0.295
GCSe	-0.094	-0.262	-0.064	-0.050	**0.493**	0.219	**0.408**	0.204
GCSm	0.2208	-0.102	**0.397**	**0.448**	0.106	0.027	0.176	**0.353**
GCSv	0.0070	**-0.365**	0.288	0.296	-0.086	-0.038	0	0

4. Motion intent EEG signals classification

The classification of EEG signals is mandatory for the brain-computer interface (BCI) application[7]. Applying a dedicated method of signal processing to EEG recordings allows for determining emotional states, mental conditions, and motion intents. Numerous experiments of imagined motion recognition deal with unilateral, i.e. of left or right hand motion. Such a classification is useful for locked-in-state or paralyzed subjects, and is successfully applied in controlling computer applications[8] or a wheelchair[9]. The synchronous motion intent classification uses a flashing visual cue (an icon) on the screen in timed intervals, and it verifies user's focus and reaction by means of the P300 potential[10]. The asynchronous approach is suitable for self-paced interaction, it first requires detection of action, and then determining its type[11]. In our work the classification of left and right, and up and down motion intents is performed.

The EEG signals are parameterized in frequency bands associated with mental and physical conditions: delta (2-4Hz, consciousness, attention), theta (4-7Hz) and alpha (8-15Hz, thinking, focus). Electrodes over motor cortex are used for assessing activity of the cortex related to motion intent. It was repeatedly observed that real and imagined motion are reflected by similar neural activity[8], particularly a decrease of alpha wave power in a motor cortex on the hemisphere opposite to the movement side. This is justified by event-related de-synchronization phenomena (ERD). The research approach presented in this paper employs classification with Rough Sets, SVM, and ANN.

For the experiment reported in this paper a large EEG database was used: EEG Motor Movement/Imagery Dataset[12]. This database includes 106 persons and exceeds the amount of data collected by Authors' themselves up to date, thus is better suitable for training and examining classification methods over a large population.

The dataset contains recordings of 4 tasks: real movement of left or right hand; real movement of upper or lower limbs; imagined left or right hand; and imagined upper or lower limbs. 64 electrodes were used located following a 10-20 standard, sampling rate 160 Sa/s, with timestamps denoting start and end of particular movement. Among the available channels, we used only 21 from motor cortex: $FC_{Z,1,2,3,4,5,6}$, $C_{Z,1,2,3,4,5,6}$, $CP_{Z,1,2,3,4,5,6}$.

4.1. Features extraction and classification

All 21 signals were decomposed into the time-frequency domain: delta (2-4 Hz), theta (4-7 Hz), alpha (8-15 Hz), beta (15-29 Hz), and gamma (30-59 Hz), and subband envelopes were obtained by Hilbert transform, reflecting activity in the given frequency band. 615 various features of band filtered signal's envelopes were collected: the sum of squared samples of the signal envelope, mean, variance, minimum, and maximum of signal envelope values, the sum of envelopes differences for symmetrically positioned electrodes, showing asymmetry in hemispheres activities, all previously described[13]. Here we extend this attempt by applying and evaluating more classifiers. Four scenarios are considered: classification of rest/left/right hand real motion (LR_real), rest upper/lower limbs real motion (UD_real), and the same but imagined movements (LR_imag, UD_imag).

An SVM classifier with sequential minimal optimization algorithm was used. This method transforms nominal attributes into binary ones, normalizes all attributes. Multi-class problems, such as recognition between a rest, left motion, and right motion, in this case, are solved using pair-wise classification. Complexity parameter was C=1.0, tolerance L=0.001.

An artificial neural network trained by a backpropagation method was employed. The neuron activation function was a sigmoid, numbers of neurons in the input/hidden/output layers were set to 615/12/3, accordingly. The learning rate for weights updating was set to L=0.3, the momentum for weights values was M=0.2, number of epochs to train was N=100.

A classification method applying Pawlak's Rough Set theory[14] was employed. It uses maximum discernibility method for data discetization and selects a minimal set of attributes (a reduct) maintaining discernibility between different classes, by applying greedy heuristic algorithm[15]. A reduct is finally used to generate decision rules describing objects of the testing set, and applying these to the testing set.

EEG classification is hampered by personal biological and neurological differences, or other characteristics influencing EEG signal quality and features. Therefore each person is treated as individual classification problem, and thus classifiers customized for given subject are created.

All 3 classifiers were applied in a 10 cross-validation runs, with a training and testing sets selected randomly in a 65/35 ratio split. These sets contain 1228 and 662 signals for a single person performing a particular task of 3 different action classes (rest, up/left motion, and down/right motion). The process is repeated for every 106 persons, while achieved average classification accuracy records are collected. Data classification was performed in WEKA software package offering various data mining techniques[16], and in R environment[17] with RoughSets package[18].

4.2. Motion intent classification results

Obtained classification accuracies from 3 classifiers for all 106 persons are characterised in Table 2. It can be observed that Rough Sets are significantly more accurate in classification than SVM and ANN, both performing on a similar level. There are a few cases of very high accuracy > 0.9, but also few persons' action were impossible to classify (accuracy below 0.33 reflects inability to classify, i.e. results are random).

In each case the imagined motion classification is not as accurate as classification of real motion. This can be justified by persons' inability to perform a task restricted only to mental activity in a repeated way, and by subjects fatigue as well. Classification of real upper/lower limbs movement is the easiest one for every method.

Table 2. Real and imagined motion classification results, min, max and mean accuracy in [%] achieved during 10 cross-validation runs reported.

Task	SVM accuracy [%]				ANN accuracy [%]				Rough Set accuracy [%]			
	LR_rea	LR_ima	UD_rea	UD_ima	LR_rea	LR_ima	UD_rea	UD_ima	LR_rea	LR_ima	UD_rea	UD_ima
Min	30	30	38	29	36	36	34	30	38	47	47	44
Mean	54	50	60	50	55	51	58	51	68	65	68	63
Max	81	80	**94**	80	84	82	**90**	77	**91**	**91**	**100**	85

5. Conclusions

An approach for examination and interaction with persons with TBI was described, involving hearing assessment, and monitoring mental performance and eye gaze activity in exercises designed by a therapist. It was found, that some eyetracker and EEG signals features are correlated with the GCS score. More research to investigate applicability of these findings for predicting or for tracking GCS scores improvements over time. Number and length of stable mental states can be used for assessing participant focus, distractions, or fatigue, and repetitive brain activity patterns may reflect subject mental involvement in the process. Ability of gaze focusing on key elements on the screen also proves conscious activity.

A methodology of EEG signal pre-processing, parametrization, feature selection, and classification with selected methods was presented. Among applied algorithms a Rough Set, SVM and ANN achieved the highest accuracy. Rough Set was proven to be the best choice in terms of accuracy, and easy application of rules generated in this method, employing up to 7 parameters instead of all 615.

The presented method can be employed in a simple, yet practical system for motion classification by EEG signals analysis. It opens a possibility to develop computer applications to be interacted by performing actions of rest, left, right, up, and down motion intent. These five binary input controls are sufficient to perform complex actions as: selecting, confirming, and cancelling options in a graphical user interface. Tests with a larger group are planned. Further development may include other variants of blind separation, and applying several clustering algorithms e.g. self-organizing maps.

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