Recent advances of adoptability of EEG signals for application aimed at improving the life of disabled people

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Abstract **-** In the recent years affordable wireless commercial EEG headsets have become widely available, thus opening the possibility of mass EEG signal application for various tasks. With the help of these devices the life of disabled people that are not able to walk or talk can be vastly improved by measuring and recognizing certain brain patterns with their manifestation in EEG signals. In this paper we present a survey on the recent advances in the field for recognizing brainwaves like in the cases that EEG signals are to be used for directional movements that can be used to control a mechanized wheelchair, or for typing on virtual keyboard by presenting on a screen alphabet symbols and recognizing the p300 signal, that is a specific brain signal appearing when the right presented pattern like the right letter symbol emerges, thus enabling the disabled person to communicate easier with others. With this paper we aim to present what is currently done and what could be done in the near future to improve the life of disabled people.

Keywords **-** EEG, medical application

I. Introduction

IN the recent years electroencephalography is becoming a very viable option for brain-computer interface control. This is due to the mass production release of cheap wireless headsets with electrodes for electroencephalography signals (EEG) taken from the human scalp as representation of the brain activity with EEG as the Emotiv Epoc and Emotiv Insight. In this paper it will be presented what possible applications can be done of the mass produced EEG caps for applications aimed to improve the life of disabled people.

Before describing the different methods and techniques for analyzing the EEG signals it will be considered the basic types of existing EEG signals [1].

In the encephalography it uses a set of electrodes (usually from 8 to 20), which put on the human scalp by previously known order. Transmitted electromagnetic waves reflect the spontaneous bioelectrical activity of human's brain and register as waves with small amplitude. Depending on its frequencies' band they divide on gamma (γ), beta (β), alpha (α), theta (θ) and delta (δ) waves.

The amplitude of the respective wave is reciprocally connected with its frequency.

Gamma waves *(γ)* have a frequency in the range 35 - 100 Hz and amplitude up to 15 μV. These waves arise very rarely so they are not studied in details yet.

Beta waves have a frequency in the range 13 – 30 Hz and amplitude between 5 and 30 μV (see Fig. 1).

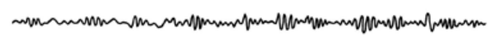

Fig. 1 Beta (β) EEG waves

Alpha waves have a frequency in the range 8 – 13 Hz (usually around the 10 Hz) and amplitude between 20 and 100 μV (see Fig. 2). The look like as a sequence of spindles. The length of the spindle is approximately 0.5 – 1 s.

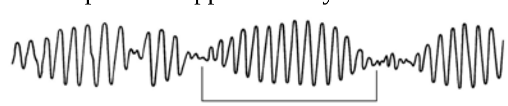

Fig. 2 Alpha (α) EEG waves

Theta waves have a frequency in the range 4 – 8 Hz and amplitude between 10 and 30 μV (see Fig. 3).

Fig. 3 Theta (Θ) EEG waves

Delta waves have a frequency in the range 0.5 – 4 Hz and amplitude between 50 and 500 μV (see Fig. 4).

Fig. 4 Delta (Δ) EEG waves

Alpha-waves detects predominantly from the occipital lobe during wakeful relaxation with closed eyes. They reduce when

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the eyes are opened or during the sleep or drowsiness state.

When the eyes are open the quantity of *alpha*-waves significantly decreases and it replaces with *beta*-waves. This process is known as a desynchronization.

Beta-waves origin in different points placed on the whole brain cortex in wakeful state and open eyes. They are appeared more strongly in the front part of the head, where they can be detect in closed eyes. In powerful intellectual activity and in psychically stress in EEG signals appear more β-waves and less α-waves even in closed eyes. The process when in closing eyes increases the α-rhythm is well-known as synchronization.

Theta-waves detect mainly in persons in active age in the first 3 phases in the sleep, but sometimes they origin in wakeful state and detect from the temporal or front part of the head during the violent emotion.

Delta-waves arise only during the deep sleep (in its 3-rd and 4-the phases).

The electromagnetic waves, transmitted from the human brain, detects from so called "Emotiv devices" which structure and operation will be described in the next section of the paper. In this Section 2, in briefly it will be stressed on the essence of p300 signals on which base are manufactured robots assisting the people with paralysis. Some of existing at the moment techniques for processing the EEG signals and synthesis the models movement control will be discussed in Section 3. The more detail explanation of main features and characteristics of classifiers for EEG signals will be made in Section 4. The paper will finish with conclusion remarks about the advantages and the disadvantages of the existing approaches for EEG signal processing on which logic are based the devices built-in the wheelchairs for improving the life of disabled people.

II. Structure and Functionality of Emotiv devices

The p300 EEG signal is a positive event-related potential. When the signal is recorded by electroencephalography, it surfaces as a positive deflection in voltage with a latency. It is a brain response directly resulted from a perception or a thought. This signal mostly occurs when the human detects some target, in a sense the p300 wave occurs only when the subject is engaged actively in tasks of target detection. While the p300 is elicited in many different ways, the most common factors influencing it are two stimulus-discrimination tasks presented to the subject in an unknown fashion. One occurs infrequently (i.e., target) and the other frequently (i.e., non-target). The p300 has been shown to be fairly stable in locked-in patients. The amplitude of p300 varies with the improbability of the targets. It also has latency and it varies with the difficulty of discriminating the target stimulus from the standard stimuli. The p300 component refers to the wave peaking around 300 ms after some task-relevant stimulus [2, 3]. Usually it is represented with typical peak latency when some young adult subject makes a simple discrimination and is around 300 ms starting from 250ms and up to 500ms. For P300 the spatial amplitude distribution is highest in the occipital region of brain and is symmetric around central

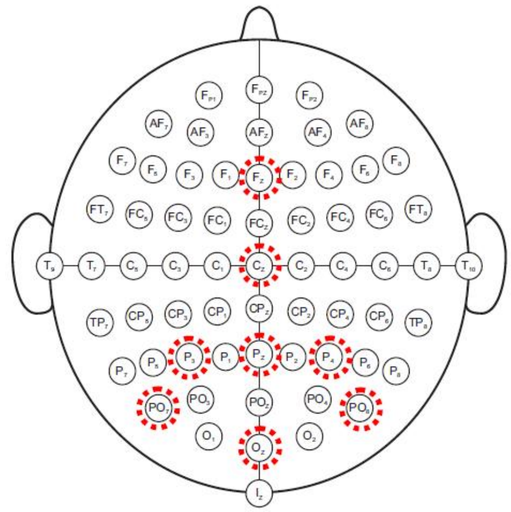

Fig. 5 Recoding of EEG based on 10-20 system and location of the electrodes typically used for p300 detection

location Cz recorded based on the 10-20 international system [Fig. 5].

In terms of temporal pattern, p300 wave amplitude is typically in the range of 2 to 5 μV. Measurements of p300 from humans with decreased cognitive ability shows that, the p300 is smaller and later than in age-matched normal subjects. Even now the intracerebral origin of the p300 signal wave is not known and the role it plays in cognition not clearly understood and is a topic of ongoing research, because p300 may be generated from multiple intracerebral clusters, with the hippocampus and various association areas of the neocortex all contributing to the scalp-recorded potential. The p300 wave may represent the transfer of information to consciousness, a process that involves many different regions of the brain.

The p300 is proven to have two subcomponents [3]. The subcomponents are the novelty P3, or named P3a, and the classic p300, that was renamed to P3b. The P3a is having a positive-going amplitude that displays maximum amplitude over frontal/central electrode sites with a peak latency in the range of 250 to-280 ms. The P3a is associated with brain activities that are related to the engagement of attention and orientation and the process of novelty processing. The P3b signal have a positive-going amplitude, obtained usually to a reference behind the ear or the average of two such references, peaking at around 300 ms. In P3 the peak varies in latency from 250-500 ms or more depending upon the cognitive task. The amplitudes of the extracted EEG signals are typically highest on the scalp over parietal brain areas. The P3b can be used for measurements of how some demanding task is influencing on cognitive workload.

III. Approaches for processing the EEG signals

Method for analysis the behavior of the living organisms divide on 2 basic classes: invasive and non-invasive. In essence the second type of methods based on the experiments on the living organisms, which guarantee completely preserving their physical and psychically health. Taking account of the physical nature of the people, the possibilities for implementing the experiments over them, which don't change their living conditions and normal existence, are rather limited than the animals. For this reason the persons' behavior analyses only by some non-invasive methods.

To ensure the adequate and impartial assessment of the results from the analysis with non-invasive methods is sufficient to formulate the reliable criteria for assessment the people's reactions. Thus it is made by the following approaches for implementing the observations:

- *Controlled observation* – it creates the situation with the preliminarily known conditions, when studies the reactions of the people.
- *Longitudinal observations* — it traces out the changes in the behavior of a group of observed persons for different periods of time (months, years and etc.).
- *Populations' observations* – it observed a big amounts of people, which satisfy a general criteria (for example: type of eating, religion, place of living, family background, social environment and etc.).
- *Clinical observations* – it analyses the mentally diseased persons and in parallel it implements the analysis of the neural system and the brain activity of the individuals, which increases the adequateness of the observations.

All mentioned above types of observations are related basically with completely analysis of the physical condition of the person from the medical point of view. Current survey is devoted to the different approaches for classification of the EEG signals, which can be divided in different groups according to the using mathematical tool for processing the input information.

Because of the non-linear and dynamic nature of the EEG signals, it is very difficult to effectively decipher the subtle changes in them by visual inspection and by using linear techniques. Therefore, non-linear methods are more suitable to analyze these signals.

3.1. Classifiers of EEG signals, based on the probabilistic neural networks (PNN) employing Lyapunov's exponents [4]

In this approach the final decision takes on two stages. First, it calculates the Lyapunov's exponential functions as a separately vectors and next these vectors feed to the PNN for training and future classification of the analyzed EEG Signals.

3.2. Classifiers of EEG signals, based on the recurrent neural networks (RNN) employing Lyapunov's exponents [5]

In this approach the final decision again takes on two stages. First, it calculates non-linear functions, similar to the exponential Lyapunov's functions and then the data feed to the Elman's RNN. Litter trains by the Levenberg–Marquardt's algorithm. The essence of this approach consist of the fact that EEG signals discussed as a chaotic signals. The accuracy of the classification by RNN is bigger than the respective one, made with the classical neural networks, based on the back-propagation. The results from this classification show that it is a reliable tool for analyzing slow EEG signals (i.e. theta and delta waves), serving as an early diagnostics of the failures in electroencephalography.

3.3. Classifiers of EEG signals, based on the wavelet neural network employing wavelet feature extraction

In this approach the final decision again takes on two stages. First, the EEG signals decompose to the σ, β, α, θ and δ waves applying Wavelet Transformation (WT), and next they feed to the neural network (NN) for recognition.

In [6] is proposed a method, where first EEG signals decompose in frequency domain using *discrete wavelet transform (DWT)*, and next the resulting harmonics feed as an input to the NN, based on the *double-loop Expectation-Maximization (EM)* algorithm, which is built in the standard NN on type *Mixture of experts (ME)*. This NN has 2 outputs, finding normal condition and condition with faults. To improve the accuracy of the classification, the outputs of the NN are calculate by introducing the local weight coefficients, so called "gating" functions. Invariant transformations of the functions of the probability density in ME neural network include permutations of the expert levels and translations of the parameters of the "gating" functions. The results of classification with this method is higher that the respective one, made with the standard ME neural networks.

In [7] is suggested a method, where again first EEG signals decompose in time-domain and frequency-domain using DWT, and then the data approximates with the most appropriate distribution. These results feed to the NN, which realize in 2 types – one and double layers. To improve the accuracy if the classification in two-layers NN the outputs of the 1-st layer use as an inputs for the 2-nd layer of the network. This model is used for testing the 3 types of patients – clinical healthy and awake with open eyes and epileptic diseased in normal condition and in collapse, respectively. The accuracy of this method is 94.83 %. In general, it guarantees the classification accuracy which is bigger than the standard stand-alone NN.

Analogically as [7] in [8] are tested the same 3 types of patients; again firstly is applied the DWT transformation the EEG signals, but here it is uses *Multi-Resolution Analysis (MRA)*. Then it applies the Parseval's theorem for data approximation with the most appropriate distribution. The results from the approximation feed to the NN for future recognition. The accuracy of this method is higher than the respective ones gotten by other analogous classifiers.

In the literature exists other class mathematical models, based on the decomposition the initial EEG signals as a separately harmonics and feeding to the specific class neural networks (adaptive NN) for their recognition [9, 10]. These adaptive NN use fuzzy logic in classification. Here the final solution also takes on 2 stages. The training of this adaptive NN based on the back-propagation technique in combination with the least squares method, which ensure the higher accuracy of the classification. Testing is made on 5 types of EEG signals, which recognize on the output of the first NN. To increase the accuracy of the classification it is added 6-th classifier, on which input feeds the outputs of the 5-th outputs of the previous NN. This guarantees the adaptively of the suggested NN with respect to the input data. The performance of this classifier is estimate with regard to the time for training the NN and the accuracy of the recognition. The results show that this mathematical model ensure higher classification accuracy of EEG signals than the respective one, gotten by using the standard NN with determine coefficients.

The proposed model of classifier in [11] is analogous of these which are suggested in [9] and [10], with the main difference consist of the fact that the decomposed EEG signals feed to the Artificial Neural Network (ANN), which makes the classification. Results show that this model guarantees enough high accuracy which gives a proof for its application as a reliable classifier.

In [12] is suggested new type of classifier, where the final conclusion makes by the decision tree method. The initial data processes by fast Fourier transformation (FFT) and the resulting harmonics feed to the tree structure for decision making and classification. This approach uses 5- and 10-fold cross-validation and the accuracies are 98.68 % и 98.72 %, respectively. This declares him as a reliable classifier.

3.4. Classifiers of EEG signals, based on the support vector machine (SVM) extraction

This approach bases on forming the eigenvector by existing energy levels in the energy spectrum of the initial EEG signal. SVM technique guarantees higher accuracy than other classifiers, because it uses so called structural risk minimization (SRM) principle, based on the mathematical induction principle. Here it searches the upper bound of the common error, presented as a sum of the error (formed during the training of the model) and the respective confidence interval.

In [13] is proposed relatively new classifier of EEG signals, based on SVM model, where it gives an account of the cross-correlation between the coefficients. The accuracy of classification of this method is 95.96 %.

The suggested in [14] classifier bases on the multiclass SVM model with error correlation, which appears as a difference between recognized and actual signal. Final decision also makes on two stages. First, the initial data decompose by using wavelet transformation (WT) and the respective harmonics approximates with exponential Lyapunov’s functions. Second, the litters feed to the SVM model for training and classification. The results from the classification are compared with analogous, by probabilistic neural network (PNN) and multy-layers NN, based on the perceptron. The conclusion of this comparison is that the new technique has a higher accuracy than the other two models.

The procedure for taking the final decision in [15] is the same as the respective one from [14] with only difference that analyzed EEG signals decompose by using Burg AR method, and then the separately harmonics feed to the SVM model, based on the least square method. The performance of this classifier estimates by the accuracy of recognition of the input data and Receiver Operating Characteristic (ROC), which is 99.56 %.

Usually EEG signals are noisy and likely to contain outliers which distort the information. The developed in [16] classifier suggest possibility for decreasing the influence of the noise added to the EEG signal, which guarantees the more exact classification. Here as an mentioned above methods of this group first it applies WT to the initials EEG signals and next the separately harmonics feeds to the neural network, which in this case is fuzzy VM (FVM) model with radial functional core for classification of the “parasitical” signals, where uses small part of the support vectors as a criterion for choosing the kernel parameter and the trade-off parameter, together with the membership parameter based solely on training data.

The classification of EEG signals in [17] makes by using SVM model with Gaussian (RBF) kernel. The accuracy of classification controls by two hyper parameters - the penalty parameter C and the kernel width σ which take very small or very large values. The results show that the hyper parameter space that leads to an efficient heuristic method of searching for hyper parameter values with small generalization errors. The analysis also indicates that if complete model selection using the Gaussian kernel has been conducted, there is no need to consider linear SVM.

In [18] is presented a new algorithm that automatically and reliably removes artifacts from EEG based on blind source separation and support vector machine. Performance on a motor imagery task is compared for artifact-contaminated and preprocessed signals to verify the accuracy of the proposed approach. The results showed improved results over all datasets. Furthermore, it is investigated the online applicability of the suggested algorithm.

Proposed in [19] classifier of EEG signals is realized with a recently developed machine learning algorithm referred to as Extreme Learning Machine (ELM). It classify five mental tasks from different subjects using EEG signals. Performance of ELM is compared in terms of training time and classification accuracy with a Backpropagation Neural Network (BPNN) classifier and also Support Vector Machines (SVMs). For SVMs, the comparisons have been made for both 1-against-1 and 1-against-all methods. Results show that ELM needs an order of magnitude less training time compared with SVMs and two orders of magnitude less compared with BPNN. The classification accuracy of ELM is similar to that of SVMs and BPNN. The study showed that smoothing of the classifiers' outputs can significantly improve their classification accuracies.

3.5. Classifiers of EEG signals, based on the analysis of the eigenvectors

Historically these classifiers apply for pattern recognition where very often requires extracting different features from “raw” data and their classification in separately groups according to appointed criterion. One of existing approach in this group is based on extracting eigenvectors, corresponding to the initial data and feed them to the expert system for their recognition. In last 10 years this techniques applies more and more frequency for classifying the EEG signals.

In [20] is presented the expert systems (mixture of experts - ME and modified mixture of experts - MME) for classifying EEG signals. Two models are benchmarked for their performance on the classification of the studied EEG signals.

Decision making is performed in two stages: feature extraction by eigenvector methods and classification using the classifiers trained on the extracted features and then the inputs of these expert systems composed of diverse or composite features were chosen according to the network structures. The results from analysis demonstrate that the MME trained on diverse features achieved accuracy rates which were higher than that of the ME.

In [21, 22, 23] the final decision makes on 2 stages: feature extraction by eigenvector methods and classification using the classifiers trained on the extracted features. The proposed approached in [21] uses multiclass SVM neural network, but the suggested technique in [22] and [23] based on the Probabilistic Neural Network and recurrent neural network, respectively. In all three cases the results from classification guarantee high accuracy of recognition, which implement them for reliable classification tool for EEG signal.

3.6. Classifiers of EEG signals, based on the autoregressive models

In [24] are proposed 2 models for classification of the EEG signals extracted during mental tasks. These methods use fixed autoregressive (FAR) and adaptive AR (AAR) models. Experiments are made by solving of 5 different tasks from 4 subjects, as each subjects solve 2 different mental tasks. It uses 4 different methods for classification: FAR coefficients computed with Burg’s algorithm, based on the 125 data points, without segmentation and with segmentation of 25 data points; AAR coefficients computed with Least-Mean-Square (LMS) algorithm using 125 data points, without segmentation and with segmentation of 25 data points and Multilayer Perceptron (MLP) neural network (NN) trained by the backpropagation (BP) algorithm. The best results are gotten for FAR - 92.70 %, while for AAR the accuracy is only 81.80 %. This indicates that FAR using 125 data points without segmentation give better classification performance as compared to AAR, with all other parameters constant.

In [25] is suggested a new time-varying autoregressive (TVAR) modelling approach for signal processing and power spectral estimation. It is based on the fact that the time-dependent coefficients of the TVAR model are represented using a novel multiwavelet decomposition scheme. Then the time-varying modelling problem is reduced to regression selection and parameter estimation, which can be effectively resolved by using a forward orthogonal regression algorithm. Two examples, one for an artificial signal and another for an EEG signal, are given to show the effectiveness and applicability of the new TVAR modelling method.

In [26], are proposed two fundamentally different approaches for designing classification models (classifiers); the traditional statistical method based on logistic regression and the emerging computationally powerful techniques based on artificial neural networks (ANNs). Logistic regression as well as feedforward error backpropagation artificial neural networks (FEBANN) and wavelet neural networks (WNN) based classifiers were developed and compared in relation to their accuracy in classification of EEG signals. In these methods it is used FFT and autoregressive (AR) model by using maximum likelihood estimation (MLE) of EEG signals as an input to classification system with two discrete outputs: epileptic seizure or nonepileptic seizure. By identifying features in the signal we want to provide an automatic system that will support a physician in the diagnosing process. By applying AR with MLE in connection with WNN, it is obtained novel and reliable classifier architecture. The network is constructed by the error backpropagation neural network using Morlet mother wavelet basic function as node activation function. The comparisons between the developed classifiers were primarily based on analysis of the receiver operating characteristic (ROC) curves as well as a number of scalar performance measures pertaining to the classification. The WNN-based classifier outperformed the FEBANN and logistic regression based counterpart. Within the same group, the WNN-based classifier has higher accuracy than the FEBANN-based classifier, and the logistic regression-based classifier.

The suggested in [27] procedure for classifying the EEG signals is similar to this one, which is described 3.3, i.e. wavelet neural network employing wavelet feature extraction. Here introduces a multilayer perceptron neural network (MLPNN) as a final classifier. First, EEG signals decompose into frequency sub-bands using discrete wavelet transform (DWT). Second, the wavelet coefficients clustere using the K-means algorithm for each frequency sub-band. The probability distributions is computed according to distribution of wavelet coefficients to the clusters, and then used as inputs to the MLPNN model. The results based on the five different experiments for evaluation the performance of the proposed model in the classifications of different mixtures of healthy segments, epileptic seizure free segments and epileptic seizure segments. It is shown that the proposed model resulted in satisfactory classification accuracy rates.

In [28] is proposed a classifier of EEG signals, where the evaluation based on the combination of complexity analysis and spectrum analysis of the on EEG signals which can perform robust evaluations on the collected data. Principle component analysis (PCA) and genetic algorithms (GAs) are applied to various linear and nonlinear methods. The best linear models resulted from using all of the features without other processing. For the nonlinear models, applying PCA for feature reduction provided better results than applying GAs. The feasibility of executing the proposed methods on a personal computer for on-line processing was also demonstrated.

3.7. Classifiers of EEG signals, based on the Hilbert-Huang transformation models

The implementation and testing of the algorithm proposed in [29] is made in MATLAB environment. The analysis in question presents a classification of normal and ictal activities using a feature rely on Hilbert-Huang Transform. Through this method, information related to the intrinsic functions contained in the EEG signal has been extracted to track the local amplitude and the frequency of the EEG signal. Based on this local information, then the weighted frequencies are calculated and is performed a comparison between ictal and seizure-free determinant intrinsic functions. Used methods of comparison the t-test and the Euclidean clustering. The t-test results in a P-value < 0.02 and the clustering leads to accurate (94 %) and specific (96 %) results. The proposed method is also contrasted against the Multivariate Empirical Mode Decomposition that reaches 80 % accuracy. Finally the proposed approached is compared with the exiting similar classifiers with respect to the accuracy, fast response and easy use.

The presented in [30] classifier of EEG signals uses empirical mode decomposition (EMD) method. The intrinsic mode functions (IMFs) generated by this method can be considered as a set of amplitude and frequency modulated (AM–FM) signals. The Hilbert transformation of IMFs provides an analytic signal representation of the IMFs. The two bandwidths, namely amplitude modulation bandwidth (*BAM*) and frequency modulation bandwidth (*BFM*), computed from the analytic IMFs, have been used as an input to least squares support vector machine (LS-SVM) for classifying seizure and nonseizure EEG signals. This method provides better classification accuracy than the method adopted by Liang and coworkers in their study published in 2010 [17, 18, 26, 29].

3.8. Classifiers of EEG signals, based on the recursive analysis models

The main important feature of the epilepsy is that it is a common neurological disorder which is characterized by the recurrence of seizures. In [31] uses the recorded EEG signals in Recurrence Plots (RP) and it extracts Recurrence Quantification Analysis (RQA) parameters from the RP in order to classify these signals into *normal*, *ictal*, and *interictal* classes. Recurrence Plot (RP) is a graph that shows all the times at which a state of the dynamical system recurs. Studies have reported significantly different RQA parameters for the three classes. However, more studies are needed to develop classifiers that use these promising features and present good classification accuracy in differentiating the three types of EEG segments. The proposed method uses ten RQA parameters to quantify the important features in the EEG signals.These features were fed to seven different classifiers: Support vector machine (SVM), Gaussian Mixture Model (GMM), Fuzzy Sugeno Classifier, K-Nearest Neighbor (KNN), Naive Bayes Classifier (NBC), Decision Tree (DT), and Radial Basis Probabilistic Neural Network (RBPNN). The results show that the SVM classifier was able to identify the EEG class with an average efficiency of 95.6 %, sensitivity and specificity of 98.9 % and 97.8 %, respectively.

4. Main features and characteristics of EEG signals classifiers

Classifiers of EEG signals, based on the neural networks employing Lyapunov's exponents (see 3.1 and 3.2) are the earliest appeared methods for analyzing the EEG signals, but in spite of this fact they are reliable classifiers of these signals.

At this stage classifiers of EEG signals, based on the wavelet distributor and recognizing by neural networks (see 3.3) uses for prognosis of the epileptic crisis in the patients suffering from this disease.

SVM classifiers (see 3.4) mainly designs for binary classification and use for optimal data distribution in two classes for difference as the others classifiers which divides the analyzed EEG signals in three classes. This restrict their application.

From the beginning of 21-st century the classifiers, based on eigenvectors analysis (see 3.5), appear and are coming in increasingly as a new tool for recognition of the EEG signals.

EEG signals classifiers, based on the Hilbert-Huang transformation (see 3.7) are reliable tool for processing these signals to diagnose brain functionality abnormalities. They ensure fast and efficient diagnosis, high accuracy, good sensitivity and specificity, time saving and user friendly communication interface, as at the same time they are cheaper than other similar classifiers.

Classifiers, based on the recursive analysis models (see 3.8) are rather better than the other own types of counterparts, because in these models gives an account of recurrence nature of the EEG signals.

In [32] is presented a comparative analysis between existing methods for classifying the EEG signals. There uses multilayer perceptron neural network (MLPNN) architectures as basis for detection of electroencephalographic changes in EEG signals. Three types of EEG signals (EEG signals recorded from healthy volunteers with eyes open, epilepsy patients in the epileptogenic zone during a seizure-free interval, and epilepsy patients during epileptic seizures) are classified. The selected Lyapunov exponents, wavelet coefficients and the power levels of power spectral density (PSD) values obtained by eigenvector methods of the EEG signals are used as inputs of the MLPNN trained with Levenberg–Marquardt algorithm. The classification results confirm that the proposed MLPNN has potential in detecting the electroencephalographic changes.

The high-dimensional and noisy nature of EEG signals limits the advantage of nonlinear classification methods over linear ones. On this reason in [33] is presented the results from comparison between linear and non-linear classifiers of EEG signals. On one side, it is used a linear discriminant analysis, and on other side - two nonlinear classifiers - neural networks and support vector machines. It are solved five mental tasks, showing that nonlinear classifiers produce only slightly better classification results. As an addition it is discussed an approach to feature selection based on genetic algorithms is also presented with preliminary results of application to EEG during finger movement.

5. Conclusion

The reliable operation of brain-computer interfaces (BCIs) based on spontaneous electroencephalogram (EEG) signals requires accurate classification of multichannel EEG signals.

The significant part of discussed in Sections 3 and 4 approaches for classification of EEG signals are the most widely used in medicine and especially for detection the state of the epilepsy suffering people. All of them based on the analysis of the EEG signals, generated form their brain. The commonly for all proposed approaches consist of the fact that almost everyone technique (except Wavelet transformation –

see 3.3 – [6] and Support Vectors Machines – SVM – see 3.4 – [13, 14, 15, 16, 17, 18, 19]) classify the tested people in three basic groups – clinic healthy and epilepsy suffering (in normal state and in collapse). The final decision makes on two stages. First, the "raw" EEG signal decomposed on different harmonics, by using different mathematical processing. Next, these separately components feed to the different neural network for classifying the patients. Usually real detected EEG signals are noisy. Then the non-linear classifiers are better that linear ones. But the litter are faster and have more simple realization.

At the moment classifiers of EEG signals are applied only for diagnosis the abnormal functionality of the brain connected to the epilepsy suffering, but with the same success they can be applied for recognition of p300 signals and their control for improving the life of disable people. The classification results can be used for synthesis of control devices, which will be built-in the wheel-chairs of the disabled persons.

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