Joint EEG - EMG Signal Processing for Identification of the Mental Tasks in Patients with Neurological Diseases

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***Abstract*—Correlation size together with Lyapunov exponents estimated from both electroencephalography (EEG) and electromyography (EMG) signals, are the crucial variables in the classification of mental tasks using an artificial neural network (ANN) classifier for patients suffering from neurological disorders/diseases. The above parameters vary according to the status of the patient, for example: depending on how stressed or relaxed the patient is and what mental task is executed. The signals were acquired from patients with Parkinson disease, while they performed four different mental tasks. The performed mental states, detected with high specificity and accuracy, can help a completely paralyzed person (locked-in) to communicate with the environment through the brain waves, leading to increasing their quality of life.**

Keywords-Artificial Neural Network, Biomedical Signal Processing, EEG, EMG, Mental Tasks, Neurological Diseases

I. INTRODUCTION

There are many neurodegenerative diseases such as multiple sclerosis (MS) or Parkinson disease (PD). Those suffering from such diseases often develop both physical and mental disorders and disabilities. MS, for example, is an autoimmune disease, a chronic illness, and involves inflammation and degeneration of the central nervous system, whose causes are not fully known and for which there is no definite treatment. The disease often begins in the age of between 20 - 30 years.

The data submitted on the European Platform of MS located Romania in 27th place out of 33 states in Europe regarding the medical services [1]. The same worrying statistics, which include those of Romania, affect the peripheral neuropathies. In these cases, however, the risk factors are traced at early ages and are related to living style: excessive consumption of alcohol, deficiencies in food, exposure to toxic substances, etc. For Parkinson's, the age at which this might occur has decreased in the last few years. Annually at the global level, 10 out of 100,000 people are diagnosed with this disease, being the second neurodegenerative affection after the Alzheimer disease. Although most often it is considered that this disease predominantly affects the persons over 60 years, some around the age of 20 years have also been affected [1]. Sedentary lifestyle disrupted feeding, foods rich in carbohydrates and saturated fats may cause or accelerate the neurodegenerative diseases [2]. The initial symptoms may vary, with tremor being the most common motor symptom in patients, in which the diagnosis of PD has been verified post-mortem [1]. A recent community-based study in 358 patients identified tremor as initially the leading symptom in approximately half of the patients. Some 44% showed an akinetic-rigid phenotype and only 7% presented with a leading gait disturbance. Interestingly, the akinetic-rigid presentation was more pronounced in younger patients, while tremor and gait disturbance, as initial symptoms, increase with age [3]. The characteristic tremor is a low-frequency (4-6 Hz) resting tremor, but other tremor forms, such as action or postural tremors may occur as the disease progresses [4]. Previous studies for activity recognition of PD patients mostly use the accelerometer and occasionally gyroscope sensors attached to various parts of patients' body [3], [4]. In [3] a robust technique for identification of the Parkinsonian tremor from the EEG, using a constrained robust singular spectrum analysis approach is presented.

The acquisition, pre-processing and processing of the jointly recorded EEG and EMG signals are presented in this paper. The signals were acquired from 22 patients with Parkinson disease, while performing a number of four different mental tasks. The feature vectors obtained for classification include the features from both recording modalities. The classification results are then effectively used to distinguish the mental activities carried out by the patient. Accurate classification and identification of a number of mental states can be used in mobilizing an assistive technology system which enables completely paralyzed persons (locked-in) to communicate with the environment through the brain waves, leading to the improvement of the life quality of people with disabilities.

II. Methodology

Combined signal processing and machine learning have been used in this paper for classification of the mental tasks from both EEG and EMG signals.

A. Data Collection

Joint EEG and EMG signals from 22 patients (16 men and 6 women of 62 years in average) have been acquired by applying the following mental tasks:

1. **Cortical activity**: the subject is instructed to relax as much as possible and to run some simple lifting and moving of a light object (Task 1);
2. **Eye blinking**: the subject is required to blink regularly to calibrate the EEG (Task 2);
3. **Lifting and placing an object with open eyes**: the subject is required to lift and place a light object (a plastic bottle) on a box located in front of him at a distance of 15-20 cm (with open eyes) (Task 3);
4. **Lifting and placing an object with eyes closed**: Task 3 is repeated with eyes closed. This is to include the effect of visual feedback within the process (Task 4).

The recording duration for each round of the object lifting and placing was approximately 2 minutes. The EEGs were recorded using *g.Nautilus* system [6], a new wireless biosignal acquisition system. This makes the recording fast, easy, and convenient. The device is attached to the EEG cap to avoid cable movements and to allow completely free movements. In combination with the active dry electrodes, we obtained EEG recordings from 32/16/8 channels within few minutes, providing clean EEG signals in almost any environment [6]. The device uses advanced active electrodes, high impedance amplifiers, a high sampling rate if necessary, and up-to-date technology to ensure top-quality recording. The system has a built-in lithium-ion battery, which allows continuous recordings of up to 10 hours.

The transmission of data is made via the 2.4 GHz band with an indoor operating range of about 10m [6]. The input sensitivity of all channels is adjustable and the sampling rate can be set to the conventional 250 Hz or 500 Hz for EEG recording. An electrode impedance check is performed automatically via software, and a 3-axis acceleration sensor provides online head movement information along with the signals.

In this paper, the standard EEG was used and the EEG signals have been bandpass filtered at 0.1 Hz and 100 Hz. The signals are then sampled at 250 Hz and digitized using a 12–bits converter.

B. Pre-processing

The acquired EEG and EMG signals from 22 patients have been pre-processed to alleviate the effect of noise and artifacts, such as eye-blink, and improve the EEG and EMG quality. In order to remove the blinking artifact two of the electrodes placed above the patient's eyes were effectively used during the calibration. The eye blinking artifact contributes to large negative peaks of over 10μV observed in a period of less than 10ms. The EEG signals are generally nonstationary. In order to apply the popular signal processing methods, the signals are segmented and the ten-second segments (or less) are processed separately. Within such interval, the signals are often considered stationary [7]-[10].

In principle, the duration within the signals are stationary may be estimated by trial and error or adaptive algorithms. In some studies, it is stated that the two-second segments of an EEG signal are "quasi-stationary" [7]-[10]. For the EMG signals, we have two channels and the third one is a reference electrode. We use the EMG Analysis software, a quality analysis program, that allows for implementation of a wide range of useful analysis methods such as fast Fourier transform (FFT), moving average envelope with adjustable window size, dual pass digital FIR filter, root mean square (RMS) estimator, zero crossing detection, power spectrum, amplitude distribution, and co-contraction correlation [11].

C. Feature extraction

EEG and EMG signals are non-stationary and non-linear, and it is difficult to analyze these signals using only statistical and time-frequency domain methods. The extracted features from the EEG signals include a set of autoregressive (AR) parameters.

The Yule-Walker Equations within MATLAB are used to calculate the AR coefficients. It is assumed that the prediction order is known a priori or fixed, though methods such as Akaike Information Criterion (AIC) [12] can be used to estimate the order. For the EEG signals, the prediction order of 10-12 is often sufficient. For the EMG signals, the prediction order can be higher as it has more noisy behavior. In addition, the signal amplitudes in the four major EEG frequency bands are measured and used as features. On the other hand, nonlinear features have been utilized to exploit the changes in the brain dynamics. The Chaos Date Analyzer (CDA) program has been used to measure the signal distribution, the power spectrum, the dominant frequencies, the largest Lyapunov exponent, the size of the correlation, the correlation function, and the Poincaré sections [13].

A first step in the nonlinear analysis is to draw the phase diagram, i.e. the representation of the derivation of the signal. If the signal is periodic, fault phase is represented by a closed curve. If the signal is chaotic, the representation is an open curve named "strange attractor" [14]-[17].

The EEG and EMG signals are analyzed by extracting features vector of Approximate Entropy, Correlation Dimension, Fractal (Capacity) Dimension and Largest Lyapunov Exponent. Estimation of the Lyapunov exponents involves a quantitative method that shows the level of the chaos in the system. The Lyapunov exponents have proven to be the most useful dynamical diagnostic for chaotic systems.

The Lyapunov coefficients represent the average of the exponential divergence of trajectories from the two closed points, represented in the phase space. The Lyapunov exponent is positive, which highlights the fact that the trajectories are divergent, causing an attractor specific to a chaotic system. In practice, the Lyapunov exponents represent the average exponential rates of divergence of nearby orbits in phase space. Similarly, the nearby orbits correspond to nearly identical states, exponential orbital divergence means that systems whose initial differences we may not be able to resolve will soon behave quite differently and predictive ability is quickly lost. Any system containing at least one positive Lyapunov exponent is defined to be chaotic, with the magnitude of the exponent reflecting the time scale on which the system dynamics become unpredictable [18]

Thus, we can consider two points in space X_0, each generating an orbit of a given dynamic system. By choosing the first orbit, $X_0+\Delta x_0$, as a reference, it is observed that the spatial separation is changing as a function of time $\Delta x(X_0, t)$. We can study the average exponential divergence of the two orbits using the relationship

$$\lambda = \lim_{\substack{t\to 0 \\ |\Delta x_0|\to 0}} \frac{1}{t} \ln \frac{|\Delta x(X_0,t)|}{|\Delta x_0|} \tag{1}$$

where λ is the Lyapunov exponent.

TABLE I. THE LARGEST LYAPUNOV EXPONENT VALUES FOR THE EEG VS. EMG SIGNALS

The mental tasks performed	**The Largest Lyapunov Exponent values for the EEG and EMG signals**
Task 1	0.028±0.017 0.102±0.029
Task 2	0.284±0.081 0.198±0.078
Task 3	0.053±0.029 0.129±0.001
Task 4	0.095±0.025 0.049±0.015

To estimate the correlation in a time series of length N, the number, j, of pairs (x_i, x_j) which satisfy $|x_i-x_j|<\varepsilon$ are calculated. The correlation function is defined as:

$$C(\varepsilon) = \lim_{N\to\infty} \frac{1}{N^2} \mathrm{X}\,\{number\ of\ pairs\ (x_i, y_i)\ of\ points\ with\ d_s(x_i, y_i) < \varepsilon\} = \lim_{N\to\infty} \frac{1}{N^2} \sum_{i,j}^{N} H\left(\varepsilon - \|x_i - x_j\|_2\right) = P\left(\|x_i - x_j\|_2\right), \tag{2}$$

where H is the *Heaviside step function* (or a discontinuous unit step function) which has a value of either 0 or 1 and may be defined as:

$$H\left(\varepsilon - \|x_i - x_j\|_2\right) = \begin{cases} 1, & 0 \le \left(\varepsilon - \|x_i - x_j\|_2\right) \\ 0, & 0 > \left(\varepsilon - \|x_i - x_j\|_2\right) \end{cases}, \tag{3}$$

which acts as a counter for the number of pairs of points with Euclidean separation distance $<\varepsilon$ when combined with $\|x_i - x_j\|_2$ (the Euclidean separation distance between two points on the attractor, x_i and x_j).

Grassberger and Procaccia [14], [15] established that for small values of separation distance ε, a correlation function C (ε) can be found to follow a power-law. After taking logarithms of each side of the scaling relation and rearranging the terms we define the correlation dimension as:

$$D_{corr} = \lim_{\varepsilon\to\infty} \frac{\log(C(\varepsilon))}{\log(\varepsilon)}, \tag{4}$$

In practice, D_{corr} is deducted from the slope of *log(C(ε))* versus *log(ε)* which is approximately a straight line in the scaling grid. We have found that all non-linear parameters vary depending on the condition of the patient, i.e. the mental task which it executes. The nonlinear features are estimated from both EEG and EMG signals.

D. Classification

The estimated linear and nonlinear features described above are the inputs to the multilayer artificial neural network (ANN) as the classifier [19], [20]. The number of hidden layers is selected to be 1 in this trial and *sigmoid function* has been used as the neuron activation function.

The ANN is used for classification of the imbalanced and nonlinear sets of features. The performance of ANN is evaluated based on its rate of correct recognition using sensitivity, specificity, positive predictive value, and accuracy.

III. EXPERIMENTS AND RESULTS

Our designed platform in MATLAB allows to set for selection of different NNs, different number of layers and different activation functions (Fig. 1).

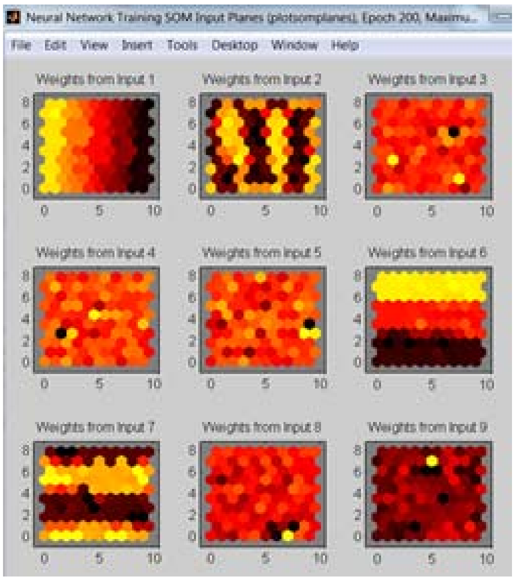

Figure 1 Neural network training input planes.

After the statistical analysis, all selected non-linear features were fed to few classifiers to select the best classifier. It also allows for different training algorithms such as backpropagation algorithm.

The training process is controlled by cross-validation which includes a random selection of training sets. A multi-fold cross-validation is often necessary to ensure the efficient design of the classifier (Fig. 2). In this paper, we used a ten-fold cross-validation to ensure the classifier hyperplane (threshold) is set optimally.

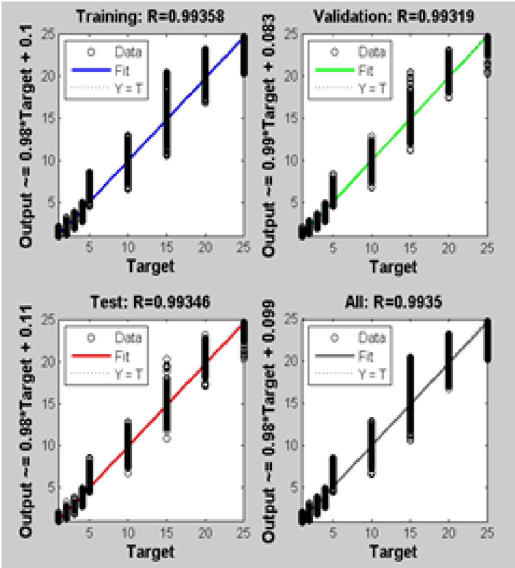

Figure 2 Neural network training input planes.

After the ANN classifier was optimized by cross-validation, the following parameters were used for the assessment and evaluation of the classification process:

1. Number of data classified correctly as belonging to the class of interest: True positive cases (TP);
2. Number of data classified correctly that define the class of interest: True negative cases (TN);
3. Number of data incorrectly classified as belonging to the class of interest: False positive cases (FP);
4. Number of data incorrectly classified as non-class of interest: False negative cases (FN).

The percentage of correct classification may be calculated as:

$$Correct\ \ percentage\ = 100 \times \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

In Figs. 3 and 4 it can be observed that the Multilayer Perceptron (as a feedforward ANN classifier [19]) performs very well. In Fig. 4 a confusion matrix for both counts and percentage has been illustrated.

Performance Metrics

	Training			Cross Validation			Testing		
Model Name	**RMSE**	**r**	**Correct**	**RMSE**	**r**	**Correct**	**RMSE**	**r**	**Correct**
MLPR-1-O-M (Regression MLP)	0.47151	1.538889	100.00%	0.281644	0.826787	100.00%	0.321151	0.84907	100.00%
MLPC-1-O-M (Classification MLP)	0.346278	1.199159	100.00%	0.294842	0.853303	100.00%	0.353458	0.890708	100.00%
LinR-0-B-R (Linear Regression)	0.392248	1.164334	98.98%	0.44099	1.229165	100.00%	0.579106	1.492461	100.00%
LinR-0-B-L (Linear Regression)	0.392147	1.157604	99.04%	0.440191	1.218529	100.00%	0.578988	1.482045	100.00%
LogR-0-B-R (Logistic Regression)	0.394967	1.364981	100.00%	0.41173	1.355324	100.00%	0.516026	1.617221	100.00%
LogR-0-B-L (Logistic Regression)	0.391549	1.240205	100.00%	0.415985	1.313406	100.00%	0.532054	1.598978	100.00%
MLPR-1-B-L (Regression MLP)	0.321258	1.217238	99.02%	0.327827	1.281418	100.00%	0.44846	1.42548	100.00%
MLPC-1-B-L (Classification MLP)	14180.43	14356.92	100.00%	14175.51	14356.92	100.00%	14177.91	14355.92	100.00%
PNN-0-N-N (Probabilistic Neural Network)	0.08614	0.457245	100.00%	0.258252	1.451033	100.00%	0.292751	1.954839	100.00%
GFFR-1-B-L (Reg Gen Feedforward)	0.311807	0.943553	99.67%	0.333379	1.30444	100.00%	0.522802	1.844503	100.00%
GFFC-1-B-L (Class Gen Feedforward)	5.558881	18.76222	63.15%	9.260921	22.77261	62.14%	10.34454	24.09229	66.88%
MLPR-2-B-L (Regression MLP)	0.338536	1.256191	100.00%	0.336769	1.232432	100.00%	0.428431	1.472461	100.00%
MLPC-2-B-L (Classification MLP)	0.359505	1.096917	100.00%	0.321792	1.115135	100.00%	0.40017	1.321741	100.00%
MLPR-1-B-R (Regression MLP)	0.286327	1.13758	99.42%	0.272735	1.106161	100.00%	0.360102	1.363139	100.00%
MLPC-1-B-R (Classification MLP)	0.29243	0.89621	100.00%	0.265848	0.878148	100.00%	0.332435	1.184906	100.00%
MLPR-2-O-M (Regression MLP)	0.190693	1.020292	100.00%	0.081148	0.645016	100.00%	0.254051	1.011834	100.00%
MLPC-2-O-M (Classification MLP)	0.334052	1.314358	100.00%	0.296249	0.967245	100.00%	0.362797	0.925399	100.00%
MLPR-2-B-R (Regression MLP)	0.282904	0.928129	99.25%	0.269217	0.851154	100.00%	0.311995	0.940949	100.00%
MLPC-2-B-R (Classification MLP)	0.386127	1.452334	100.00%	0.385583	1.258492	100.00%	0.461431	1.544325	100.00%
GFFR-1-O-M (Reg Gen Feedforward)	0.398375	1.543431	96.49%	0.320286	1.307416	99.95%	0.348661	1.203597	100.00%
GFFC-1-O-M (Class Gen Feedforward)	0.311027	1.133566	100.00%	0.277067	0.893119	100.00%	0.331471	0.920421	100.00%
GFFR-1-B-R (Reg Gen Feedforward)	0.3446	1.089985	98.81%	0.412404	1.165917	100.00%	0.55056	1.441866	100.00%
GFFC-1-B-R (Class Gen Feedforward)	0.37714	1.291747	100.00%	0.412486	1.350653	100.00%	0.53747	1.644042	100.00%

Figure 3. Neural Networks Performance Metrics.

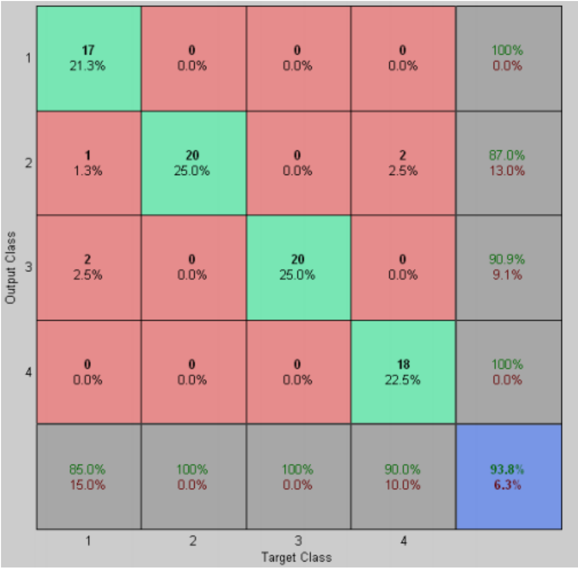

Figure 4 The confusion matrix which shows the class association.

IV. CONCLUSIONS

The proposed process for identification of the mental task classes has a good specificity and accuracy. The size of the correlation and the values of Lyapunov exponents may vary according to the status of the patient. Chaotic dynamics is characterized by a broadband spectrum. In contrast, periodic phenomena are characterized by a limited number of frequency components. The chaotic dynamics represent the high resonance capacity of the brain. Thus, there is an internal instability originated by the existence of positive Lyapunov exponents, although globally a chaotic attractor reveals an asymptotic stability. From these definitions, this means a great sensitivity to the initial conditions and, in this way, an extremely rich response to an external input. For example, depending on how stressed or relaxed the patient is, and how the mental tasks are responded. Both, the size of the correlation and the Lyapunov exponents are useful features. Better identification and recognition of the mental tasks carried out by the patient would lead to a better diagnosis of the disabilities. The classifier outputs can also be applied to some assistive technology hardware to mobilize the paralyzed body parts, particularly those suffering from neurodegenerative diseases. Also, MS, PD, stroke, obesity, and alcoholism (when suffering from tremor and disability) can be analyzed and characterized by our proposed method.

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