# Nonlinear Dynamics, Artificial Neural Networks and Neuro-Fuzzy Classifier for Automatic Assessing of Tremor Severity

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*Abstract*—**Neurological diseases like Alzheimer, epilepsy, Parkinson's disease (PD), and other dementias influence the lives of patients, their families and society. In PD the brain area affected by progressive destruction of neurons is responsible for controlling movements, and patients reveal rigid and uncontrollable gestures, postural instability, small handwriting and tremor. Commercial activity-promoting gaming systems such as the Nintendo Wii and Xbox Kinect can be used as tools for tremor, gait or other biomedical signals acquisitions. This paper emphasizes the use of intelligent optical sensors or accelerometers in biomedical signal acquisition, and of the specific nonlinear dynamics parameters or fuzzy logic in Parkinson's disease tremor analysis. For classification and discrimination between healthy people and PD people we used Artificial Neural Networks (Radial Basis Function - RBF and Multilayer Perceptrons - MLP) and an Adaptive Neuro-Fuzzy Classifier (ANFC). In general, the results may be expressed as a prognostic (risk degree to contact PD).**

***Keywords—Nonlinear Dynamics; Tremor; Adaptive Neuro-Fuzzy Classifier; Artificial Neural Networks.***

## I. INTRODUCTION

It is well known that early diagnosis of many neurological diseases assures in most cases therapeutic success. The relative great occurrence of neurological diseases that imply a neuro-motor disorder, like Parkinson's disease or Parkinson-like syndromes, as well as their related risk factors, have determined us to introduce a method for objective assessment of the stage of that illness.

This paper mainly analyzes the processing of tremor biomedical signal, acquired through modern methods (using sensors Wii™ and Xbox™). The processing of tremor signal is aimed finding data and knowledge that can be used and included in new rules (fuzzy rules) for the quantity and performance of medical diagnosis. Information on tremor signal is available in the form of time series that can be analyzed with chaotic dynamics specific parameters (Lyapunov exponents, fractal dimension of attractor dynamics generated in phase space).

The data obtained from nonlinear analysis were classified by specific Data Mining algorithms, thus obtaining two separate classes: "normal" (healthy people) and "Parkinson".

Parkinson's disease is a chronic, progressive, neurodegenerative and multi-lesion disease that affects many multiple areas of the central nervous system. Some of these lesions precede many years before the first signs of Parkinsonian characteristic motor syndrome, with clinical relevance. PD occurs in approximately 100-250 cases per 100,000 people [1]. In Europe approximately 1.2 million Parkinson's patients have been reported [2].

Nowadays, there are insufficient evidences in the literature about the application of dynamical time series analysis for tremor evaluation on one hand and evaluation of the changes in brain rhythms in connection with the body movement impairment on the other hand.

Our contribution, therefore, has a major impact as currently there is no clinically approved automatic system for monitoring PD patients. In fact, there is still no reliable screening test for PD early identification, and this is a major problem and challenge for our study design.

## II. BACKGROUND ON TREMOR DATABASE

Tremor is defined as an approximately rhythmical, involuntary, irregular and continuous movement of a body part (face, jaw, palate, eyes, and extremities). Since 1993 there are two main classifications of tremor in use [3-6]: the first one identifies rest tremor – occurring when relevant muscles are not activated and action tremor – occurring when relevant muscles are activated. The last one includes postural, kinetic, intention and specific tremors.

"Parkinson's disease is a chronic progressive neurodegenerative disorder of insidious onset, characterized by the presence of predominantly motor symptomatology (bradykinesia, rest tremor, rigidity, and postural disturbances)" [5]. The three cardinal signs of Parkinson's disease are resting tremor, rigidity and bradykinesia [6]. Among them, two are essential for diagnosis: tremor and bradykinesia. Postural instability is the fourth cardinal sign, but occurs late, usually after 8 years of disease evolution [7].

In a recent research conducted by the author of this paper [8], [9], the physiological information and the time series parameters measured from gait and tremor have been combined for developing an automatic diagnosis system for PD monitoring. We have demonstrated that nonlinear dynamics parameters of PD gait or tremor signals can be used for knowledge discovery domain.

Our database contains tremor measures from 58 patients with PD (from Suceava city Hospital, Neurology Clinic) and 30 healthy subjects. Young adults (n = 35; ages: 20-35 yrs, 20 males and 15 females) and older adults (n = 53; ages: 65-82 yrs, 32 males and 21 females) participated in this study.

The tremor data used in this paper were recorded using a box including accelerometers (such as those in a Wii™), pressure sensors, and inevitably a microcontroller which runs the data acquisition, analogue to digital conversion, and transmitting the data through a Bluetooth wireless communication system. The Wii™ Remote, known as the Wiimote™, is the primary controller for Nintendo's Wii™ console [10]. A main feature of the Wii™ Remote is its motion sensing capability, which allows the user to interact with and manipulate items on screen via gesture recognition and pointing through the use of accelerometer and optical sensor technology [10]. In Fig. 1 we described the "Automatic Assessing of Tremor Severity" method.

Our Screening System consists of four components: the first component records the skeletal information, tremor information using Kinect™ and Wii™ Remote. These information are then analized using nonlinear dynamics tools (the second component), and the third and fourth steps consist in feature extraction and classification. For the last stage of our research, we used two types of Artificial Neural Networks (ANN) - a Multilayer Perceptron (MLP) and a Radial Basis Functions (RBF) Network - and an Adaptive Neuro-Fuzzy Classifier (ANFC) to identify a "normal" or a "Parkinsonian" subject.

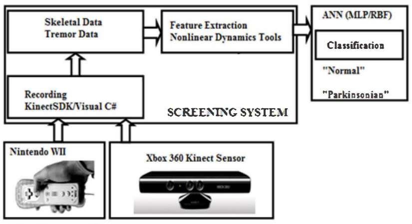


Fig. 1. Proposed automatic assessing of tremor severity method.

The accelerometer built into Wii™ Remote (Nintendo) measures gravitational and non-gravitational acceleration and the results of this paper suggest that Nintendo is useful for measurement and analysis of tremor using the methodologies described in [11], [12]. The device weights 10 grams and has flat frequency responses from steady state acceleration to 300 Hz with a sensitivity of 50 mV/g, g=9.81 m/s$^2$.

## III. Nonlinear Dynamics Tools

For the nonlinear analysis of tremor signals, we used several software packages such as CDA (Chaos Data Analyzer Programs) [13] and NLyzer (Nonlinear Analysis in Real Time) [14].

We used CDA (Chaos Data Analyzer Programs) for nonlinear signal analysis. With this software solution the phase diagram, the probability distribution, the tremor signal power spectrum, the dominant frequencies, the maximal Lyapunov exponent, the correlation dimension, the capacity dimension, the correlation function, and the Poincaré sections can be analyzed [15]. A very first stage on non-linear analysis is to draw the phase diagram. This represents the signal derivate against the signal itself . If the signal is periodic, the phase diagram is a closed curve. If the signal is chaotic, the diagram is a closed curve called "strange attractor". The positive Lyapunov exponent is the main chaotic dynamic indicator. If at least one Lyapunov exponent is smaller than 0, the system is oscillating. In case at least one Lyapunov exponent is bigger than 0, the system is chaotic. If the Lyapunov coefficient is getting to infinite, the system is called random system [15]-[17].

The main nonlinear dynamic determinant is the Lyapunov exponent that must be positive for a chaotic process. Using the CDA software solution for the gait signals of our database, we found that the Lyapunov exponent value varies between 0.05 and 0.92, depending on the analyzed signal.

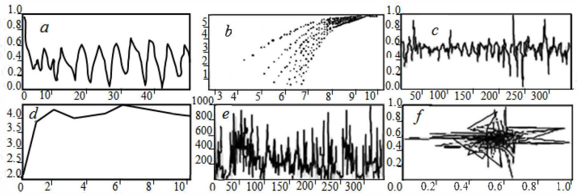


Fig. 2. The nonlinear analysis for a PD tremor time series: fast mutual information (a), the correlation dimension (b), the normalized tremor time series (c), the capacity dimension (d), the tremor time series (e) and the tremor time series "strange" attractor (f).

There were obtained various values for the fractal dimension and various shapes for the auto-correlation function or attractors (Fig. 2).

The Lyapunov exponent value varies between 0.08 and 0.7 (normal tremor) and for the Parkinson patients (Parkinsonian tremor) it varies between 0.05 and 0.92, so a clear distinction may exist between the two tremor classes. In order to reduce the representation parameter numbers and keeping the essential information, we used numerical parameters for tremor analysis.

## IV. Results – Classification Through Artificial Neural Networks

Our study used Artificial Neural Networks (ANNs) and an Adaptive Neuro-Fuzzy Classifier with Linguistic Hedges (ANFC-LH) for medical dataset (tremor) with the goal of automatic classification of subjects in "Parkinsonian" or "non Parkinsonian" (healthy).

We used three types of ANNs: support vector machine (SVM), multilayer perceptron (MLP), and radial basis function (RBF) networks, and a backpropagation training algorithm. The MLP is a non-parametric technique for performing a wide variety of detection and estimation tasks.

A RBF ANN uses radial basis functions as activation functions. Radial basis function networks (RBF) have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. For this phase of the work we used Weka, a free collection of learning algorithms for Data Mining [18].

We used Weka tools for preprocessing, data classification, regression, association rules, and visualization. Weka is an open source under the GNU General Public License. The best results were obtained using MLP, RBF and ANFC-LH (see TABLE I-III).

Before the classification using PD database, the most salient features of database should be identified for PD assessment, by means of an ANFC-LH architecture. It was proved that fuzzy systems can be merged with neural networks, and the resulting systems are called as neuro-fuzzy systems [19].

For instance, a neuro-fuzzy classifier defines the class distributions and shows the input-output relations, whereas a rule-based fuzzy system describes systems using natural language. In neuro-fuzzy applications neural networks may be employed for training or tuning the system parameters. In general, an ANFC contains input vectors, membership function, normalization, output layers, and of course fuzzification and defuzzification processes.

The linguistic hedges (LHs) empower fuzzy sets and emphasize the importance of the fuzzy sets for fuzzy rules. They can also modify the meaning of fuzzy membership functions to another meaning. In order to improve the classification accuracy, a new layer is added into the ANFC structure. This defines the adaptive LHs. In general, the LHs are trained by using conjugate gradient training algorithm, in its scaled version (SCG). In this manner, the LH values of fuzzy sets improve the adaptability of fuzzy sets. This feature can increase the classification power, mainly in the case of (at least partially) overlapped classes.

The ANFC-LH acts based on fuzzy classification rules, that have two inputs $\{x_1, x_2\}$, one output $y$ and is defined with LHs as:

IF $x_1$ is $A_1$ with $p_1$ hedge AND $x_2$ is $A_2$ with $p_2$ hedge
THEN $y$ is $C_1$ class.

In the above expression $A_1$ and $A_2$ denote linguistic variables, defined on $X_1$ and $X_2$ feature space; $p_1$ and $p_2$ denote linguistic hedges, respectively; $C_1$ denotes the class label of the output $y$.

In TABLE II we present the classification results using different ANNs and different types of features: nonlinear (Lyapunov exponent values, correlation dimensions, capacity dimensions) from tremor signal, and parameters of gait. We used SVM (Support Vector Machine), RBF (Radial Basis Function) Neural Networks, MLP (Multilayer Perceptron) and ANFC-LH (Adaptive Neuro-Fuzzy Classifier with Linguistic Hedges).

First, a feature-level *fusion method* must be applied in order to normalize and homogenize signal-based chosen features. So, we did feature normalization on both features sets, using the sigmoid function which provides homogeneous feature values within the range [0,1]:

$$f(x) = \frac{1}{1+\exp(-A_i \times x - B_i)} \quad , \text{ i=1, 2.} \qquad (1)$$

In (1) the scaling ($A$) and offset ($B$) coefficients have the following values (for our available experimental data): for tremor features normalization: $A_1 = 2$ and $B_1 = 0.5$; for gait features normalization: $A_2 = 1.5$ and $B_2 = 1.5$.

Then, we performed local feature-level fusion in which the 2 normalized feature vectors for each signal (tremor and gait) are combined using a weighted averaging rule:

- for tremor signal the local fused vector is made by:

$$X_1(k) = \frac{w_{11}^k \times f(x_1(k)) + w_{12}^k \times f(x_2(k))}{w_{11}^k + w_{12}^k} \quad , \text{ k=\{1,2,3\}} \qquad (2)$$

- for gait the local fused vector is composed by:

$$X_2(k) = \frac{w_{21}^k \times f(x_1(k)) + w_{22}^k \times f(x_2(k))}{w_{21}^k + w_{22}^k} \quad , \text{ k=\{1,...,6\}} \qquad (3)$$

The used weights domains are: [0.3…0.4] for the tremor parameters and [0.6…0.7] for the gait statistical features.

The global feature-level fusion for the two signals was obtained by means of simple concatenation and led to an input vector $X$ for classifiers, with 9 elements.

TABLE I. THE OBTAINED RESULTS OF DIFFERENT TECHNIQUES FOR PARKINSON DATASET CLASSIFICATION

| *Used technique* | *No. of features* | *Classification Rate Training %* | *Classification Rate Testing %* | *Proc. Time* |
|---|---|---|---|---|
| SVM | 9 | 90.20±2.1 | 91.40±2.1 | 5.4s |
| RBF | 9 | 96.12±2.1 | 95.23±2.1 | 4.8s |
| MLP | 9 | 98.32±2.1 | 96.74±2.1 | 3.9s |
| ANFC-LH | 9 | 99.18±2.1 | 98.54±2.1 | 4.1s |

TABLE II. THE RESULTS OF IDENTIFICATION AS "PARKINSONIAN" (PD) AND "NORMAL" (HEALTHY) (H) OF 88 PERSONS (58 "PARKINSONIAN" AND 30 "NORMAL")

| *Output* | *"Normal" (H)* | | | *"Parkinsonian" (PD)* | | |
|---|---|---|---|---|---|---|
| ANN type | RBF | MLP | ANFC | RBF | MLP | ANFC |
| H | 28 | 28 | 29 | 1 | 0 | 1 |
| PD | 1 | 1 | 1 | 57 | 58 | 57 |

In order to assess the discriminative power of the used ANNs we computed the overall recognition rate (accuracy), their sensitivity and specificity, as well as the standard deviation of the classification results. We used:

*Sensitivity* = (number of correctly classified "Parkinsonian") / (number of "Parkinsonian" + number of false "Normal").

*Specificity* = (number of correctly classified "Normal") / (number of "Normal" + number of false "Parkinsonian").

*Total classification accuracy* = (number of correctly classified persons) / (number of total persons).

TABLE III. STATISTICAL RESULTS

| *Statistical parameters* | *Statistics computed over all 88 patients during the leave-one-out test (%)* | | |
|---|---|---|---|
| ANN type | RBF | MLP | ANFC-LH |
| Specificity | 96.57 | 96.58 | 100 |
| Sensitivity | 92.33 | 93.24 | 92.54 |
| Total classification accuracy | 93.44 | 93.34 | 97.67 |

## V. CONCLUSIONS AND FUTURE WORK

Within this study we tested different trainable Artificial Neural Networks for classification, which were based on different approaches to classify medical data sets by the construction of Fuzzy Inference Systems or Fuzzy Expert Systems. The ANFC-LH classifier was used for the feature selection and classification, and the obtained results show that this classifier exhibits a better accuracy of the classification of Parkinson's disease database. Future work includes Certainty Factors (CF) in our rules to improve the diagnosis accuracy. Also, for the same reason, the aims of the Automatic Assessing Tremor Severity System using fuzzy tools are the optimization using heuristic evaluation, and the enlargement of the case library and of fuzzy rules [20]-[22].

Our study verifies some characteristics of persons having tremor problems, and gait disorders. We present an accurate tremor and gait analysis system (Automatic Assessing Tremor Severity Systems) that is economical and non-intrusive. Our system is based on the Kinect™ sensor and Wii™ sensors and thus can extract tremor or gait information from subjects.

During analysis of Parkinson's disease there have been advances in clinical examinations and description of the disease symptoms. To enable handling of these so called verbal information the clinical observations, impressions, and diagnosis of the disease have to be archived, analyzed, and mathematically described. Knowledge-based Systems (with Data Mining Tools) plus a fuzzy decision maker and Artificial Neural Networks Classifiers are good examples for such systems. Using a rule-based system, the verbal inductions are mapped to numerical data by exploiting a set of rules. The achieved data will then be used as constraints to our fusion learning algorithms.

A direct application of our research refers to the objective characterization of the degree of medical rehabilitation proceeded from accidents, physical traumas, rheumathological or clinical therapies. Our method allows a precise expression of locomotor handicap and will act as an important instrument of analysis in medicine of labor, in rehabilitation and occupational medicine. The research will be embedded in a software system dedicated to the medical rehabilitation.

This emphasizes the handling of decision making procedures in the PD treatment, thus encouraging future research studies, in order to perfect the proposed model (with medical expertise). Future research proposals include the testing and validation of a screening test, including handwriting analysis [23], [24], in order to detect Parkinson's disease in its early stages.

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