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

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***Abstract*—Neurological diseases like Alzheimer, epilepsy, Parkinson's disease, multiple sclerosis and other dementias influence the lives of patients, their families and society. Parkinson's disease (PD) is a neurodegenerative disease that occurs due to loss of dopamine, a neurotransmitter and slow destruction of neurons. Brain area affected by progressive destruction of neurons is responsible for controlling movements, and patients with PD 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. They also can aid for rehabilitation in clinical settings. 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. Nowadays, there is no screening test for early detection of PD. So, we investigated a method to predict PD, based on the image processing of the handwriting belonging to a candidate of PD. For classification and discrimination between healthy people and PD people we used Artificial Neural Networks (Radial Basis Function - RBF and Multilayer Perceptron - MLP) and an Adaptive Neuro-Fuzzy Classifier (ANFC). In general, the results may be expressed as a prognostic (risk degree to contact PD).**

***Index Terms*—adaptive neuro-fuzzy classifier, artificial neural networks, handwriting analysis, nonlinear dynamics, tremor.**

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 the illness.

This paper mainly analyzes the processing of tremor biomedical signal, as well as of handwriting images, acquired through modern methods and using sensors like Wii™ and Xbox™ devices. The processing of tremor signal is aimed at finding data and knowledge that can be used and included in new rules (fuzzy rules) for the 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 (e.g. 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. In Europe approximately 1.2 million Parkinson's patients have been reported, of which around 16,000 in Austria [1]. In 2003 PD affected around 1 million people in North America alone, representing about 1% of the population aged over 65 years [1]. In the USA, in 2006 approximately 1 million PD cases were 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.

This vital information may be combined with a meta-knowledge system designed for archiving clinical and physiological inductions and other information about tremor and the prescribed trajectory of hand (or leg) movement to be used for Parkinson's disease screening.

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 early identification of PD, and this is a major problem and challenge for our study design.

II. Background on Tremor and Handwriting Databases

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

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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.

The second classification of tremor is based on etiology and includes:

(1) enhanced physiological tremor;
(2) tremor observed in hereditary, degenerative and idiopathic disease such as Parkinson's Disease;
(3) benign essential tremor;
(4) neuropathic tremor;
(5) cerebellar tremor;
(6) drug induced tremor;
(7) orthostatic tremor, psychogenic tremor;
(8) tremor in metabolic disease (e.g., hyperthyroidism).

"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 Parkinson's disease is a surprising neurodegenerative disorder and manifests itself very differently from one individual to another, sometimes taking several years to notice a significant deterioration of daily activities. Symptoms become increasingly visible as the disease progresses. As we have said, there is no biomarker or a screening test for early detection of PD. Developing new methods in order to extract features that can help obtaining an early diagnosis of Parkinson tremor or other neurological disease (Essential tremor, Cerebellar tremor, Psychogenic tremor, Wilson's disease) is a real challenge.

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 70% of cases, uncontrollable rhythmic gestures of the hands, head and feet are the first symptoms and occur mainly at rest and during the stress periods [8]. Tremor is diminished during movements, disappears during sleep, and is exacerbated by stress and fatigue. Tremor becomes less evident with disease progression. In the absence of other characteristic signs, tremor indicates an early stage of disease or another diagnosis (see TABLE I) [8].

TABLE I. NEUROLOGICAL DISORDERS CHARACTERISTIC SIGNS

Movement	Speed	Location	Neurological Disorders
Rest tremor	4 – 6 Hz	arms, legs	Parkinson's disease
Postural tremor	7–12 Hz	hands	Essential tremor
Intention tremor	2 -5 Hz	arms, legs	Cerebellar lesions

In a recent research conducted by the authors of this paper [9-11], 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 years, 20 males and 15 females) and older adults (n = 53; ages: 65-82 years, 32 males and 21 females) participated in this study.

Also, we used handwriting samples from 11 Parkinsonians aged 42 to 73 years, screened by neurologists and psychiatrists at the Neuro-Surgery University Hospital in Iaşi. Their handwritten samples dated 6 to 16 years before clinical diagnosis of Parkinson's disease. The 15 healthy elderly control subjects were requested to give handwriting samples when they were aged 22 to 56 years, with almost the same distribution as Parkinsonians'.

The tremor data used in this paper were recorded using a box including accelerometers (such as those in a Wii™ device), 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.

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 [12], [13]. In Fig. 1 we briefly describe the "Automatic Assessing of Tremor Severity" method.

Our Screening System consists of four components. The first block records the skeletal information, tremor information using Kinect™ and Wii™ Remote. These information are then analyzed using nonlinear dynamics tools (the second component), and the third and fourth steps consist in feature extraction and classification, respectively.

For classification 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.

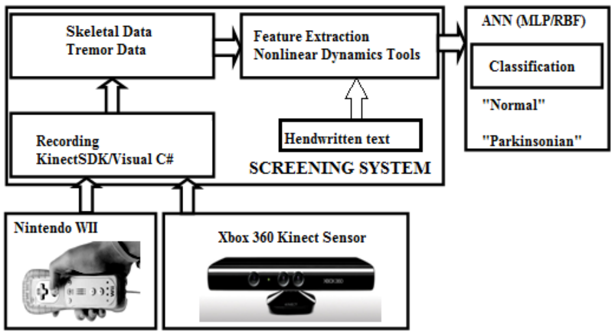

Figure 1. Proposed automatic assessing of tremor severity method

In Fig. 2 are presented the two time series for normal tremor (NT) and PD tremor, for the case x (lateral)=0, y (anteroposterior)=0, and z (vertical)=1 (equilibrium state).

The accelerometer built into Wii™ Remote (Nintendo) measures gravitational and non-gravitational acceleration and the results of this paper suggest that Nintendo device is useful for measurement and analysis of tremor using the methodologies described in [12], [13].

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. The postural tremor in each hand was recorded for two minutes.

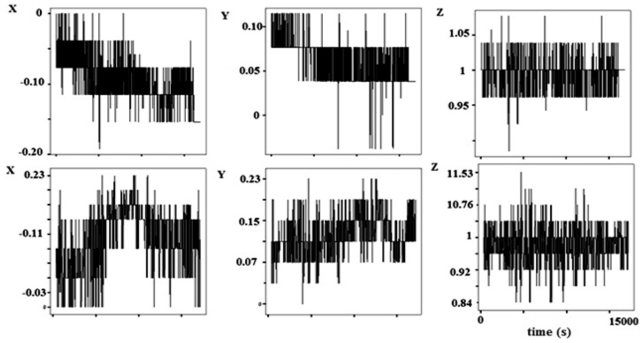

Figure 2. Time series for normal tremor (NT, first row) and PD tremor (second row) for the equilibrium state (z=1)

III. Nonlinear dynamics tools

For the nonlinear analysis of tremor signals we used several software packages such as CDA (Chaos Data Analyzer Programs) [14] and NLyzer (Nonlinear Analysis in Real Time) [15].

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 [16].

A very first stage on non-linear analysis is to draw the phase diagram. This represents the signal derivate against the signal itself [16]. 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” [9].

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 [9], [16], [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.

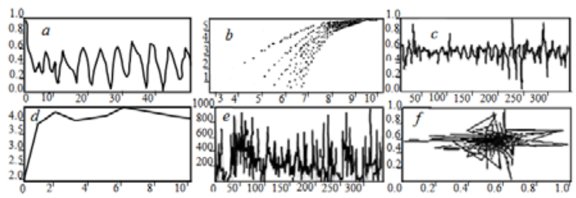

Figure 3. The nonlinear analysis for a PD tremor time series: fast mutual information (a), the correlation dimension (b), the normalized tremor time series (c), the capacity dimension (d), the tremor time series (e) and the tremor time series “strange" attractor (f)

There were obtained various values for the fractal dimension and various shapes for the auto-correlation function or attractors (Fig. 3).

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. Handwriting analysis

A complementary method to assess and predict PD is based on the automatic processing of the image of the handwritten script belonging to a candidate of PD.

In order to extract geometric features used for PD evaluation, the following steps are necessary:

(1) scanning of handwritten text;
(2) image binarization;
(3) image filtering;
(4) thinning of the handwritten text;
(5) segmentation of words for end points, fork points and loops detection;
(6) removal of entities extracted at step (5), i.e. segments achieving;
(7) feature extraction for each segment;
(8) statistical calculus for each detected feature.

The image pre-processing and first 5 steps were implemented according to a methodology developed in [18]. Scanning is performed by using an optical scanner, 256 gray levels and a resolution of 300 dpi (Fig. 4). Before further analysis, a pre-processing stage performing skew correction of line text and broken characters repair may be necessary.

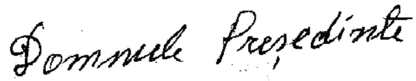

Figure 4. A scanned Parkinsonian handwritten text

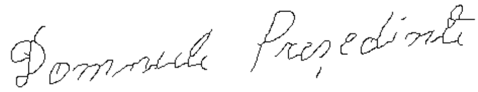

Figure 5. The same image after binarization, noise removal and skeletonization

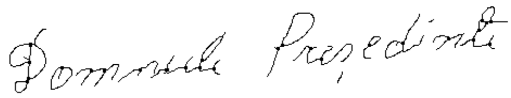

Figure 6. The detection of end and fork (intersection) points

Figure 7. Loops identification

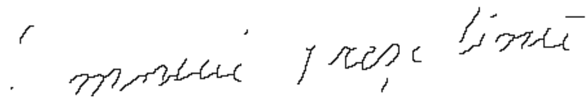

Figure 8 The text after loops, end and fork points removal. Segments detection

The binarization (step 2), i.e. the obtaining of only black and white levels, is then achieved by using an automatic procedure for threshold computation that uses the image histogram [19-21].

The result is a noisy image that must be filtered using, e.g., a (3x3) window median filter exploring the whole image (step 3). Then, a line thinning algorithm has to be performed in order to obtain the so-called "skeleton" of the object image (Fig. 5), which is a one-pixel width handwritten text and concentrates the essential topological information of the analyzed pattern (step 4).

There are many thinning algorithms, sequential or parallel, based on different approaches [22-24]. In our study, a thinning algorithm based on fuzzy logic, and performing directly on grey images, was used with good results [22], [23].

The *segmentation* step (5) divides the thinned text into strings of connected pixels, which are delimited by special points: *end pixels* and *intersection* (*fork*) *pixels* (Fig. 6). An end pixel is a dark pixel having only one other dark pixel, while a fork point is a dark pixel connected to at least three dark pixels. Thus, one may define and compute *non-crossing strokes* and *loops* (closed traces) of the handwriting (Fig. 6). If segments smaller than 6 pixels in length (0.5 mm) are provided by the program, they are removed as they are irrelevant for the further analysis. Then, in step 6, the end pixels, fork pixels and loops are removed in order *to extract the segments* of handwriting (Fig. 8).

Features extraction stage has to detect and compute handwriting-specific characteristics, which have strong structural information and differ essentially from the general features extraction and selection methods.

For each segment the following features were computed:

(1) Segment length, i.e. its number of pixels;
(2) Segment width - the average width of the trace before thinning;
(3) Normalized horizontal / vertical size, computed from the minimum and maximum horizontal / vertical pixels position.
(4) Normalization is obtained dividing by the segment length;
(5) Slant of the regression line through segments, i.e. the slant of the line having the minimum sum of the squared distances to all segment pixels;
(6) Normalized loop area, i.e. the square root of the area divided by the segment length;
(7) Normalized archedness that is the ratio between the squared root of the area enclosed by a segment and the line connecting its start and end pixel, and the segment length. Positive archedness defines an arcade, and negative archedness means a garland.

A segment normalization stage is needed and yields, as in many applications, features independent of the segment size. Finally, statistical measurements of extracted features were performed (step 7) [23].

In this way, a fragment of handwriting may be globally characterized by the mean features computed by using all its segments. Another statistical measure, per feature, is the relative standard deviation across all segments (standard deviation divided by the mean), which also provides a scale-free measure of the handwriting modulation.

The frequencies of occurrence of loops, arcades and garlands, i.e. their number divided by the total number of segments, are other useful statistical features for our study.

Two lines of handscript per subject were used, that means an average of 76 letters. Also, a special form containing lower and upper case letters and numerals was filled in by all subjects.

There is some general impairment found in well-established Parkinsonians' handwriting [24]: variable baseline, small strokes with variable shape (sharp, less round, often down and overlapping strokes, and discontinuous, backward slanted and steep strokes), ornaments and infrequent archedness.

All these characteristics act as subjective features, which must be quantified, computed and verified by an automatic analysis. Referring to our study, one may formulate the following hypotheses dealing with geometrical and statistical features of pre-clinical Parkinsonian handwriting:

(1) smaller normalized horizontal and vertical size;
(2) smaller component (segment) length;
(3) larger slant size;
(4) smaller normalized archedness;
(5) smaller garland and arcade occurrences;
(6) smaller standard deviation of component length;
(7) greater standard deviation of normalized area of arcades and garlands.

The statistical analysis showed significant differences between Parkinsonians and normal subjects [22]. Thus, horizontal and vertical sizes, as well as mean segment length, were smaller for Parkinsonians than for controls (2.6 mm vs. 3.1 mm for segment length).

The same relation was observed for the standard deviation of segment length (56% vs. 68%), this demonstrating that pre-clinical Parkinsonians write more discontinuously than healthy subjects, with less modulation between different strokes.

This interpretation of discontinuity comes from the relative constant size of vertical segments belonging to the two groups. As to loops, arcades and garlands, the lower frequency of their occurrence argued hypothesis (9%, 18%, 14% respectively, from the number of segments).

The loops area (1.6 mm^2) had a mean value of pixels sensible lower than for controls (2.2 mm^2), this confirming the general remark of micrographical character of Parkinsonians' handwriting.

We used for experiments an usual desktop PC and an image processing software, IMAG, developed with special routines for this application, written in Visual C# programming language.

V. 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 datasets (tremor, handwritten text images) 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 [25]. We used Weka tools for pre-processing, data classification, regression, association rules, and visualization. Weka is an open source library under the GNU General Public License.

The best results were obtained using MLP, RBF and ANFC-LH (see TABLE II-IV). 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. 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 was 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 {*x1, x2*}, one output *y* and is defined with LHs as:

IF *x1* is *A1* with *p1* hedge **AND** *x2* is *A2* with *p2* hedge **THEN** *y* is *C1* class.

In the above expression *A1* and *A2* denote linguistic variables, defined on *X1* and *X2* feature space; *p1* and *p2* denote linguistic hedges, respectively; *C1* 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 handwriting images such as VS - Vertical Size (pixels), NHS - Normalized Horizontal Size, NVS - Normalized Vertical Size, MSL – Mean segment length, RSTDEV_SL - Relative standard deviation of segment length, NLA - Normalized loop area. 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 and image-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]:

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

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 handwriting 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 handwriting) are combined using a weighted averaging rule:

- for tremor signal the local fused vector is made by

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

- for handwriting the local fused vector is composed by

$$X_2(k) = \frac{w_{21}^k * f(x_1(k)) + w_{22}^k * f(x_2(k))}{w_{21}^k + w_{22}^k},\ k = \overline{1,6} \quad (3)$$

The used weights domains are: [0.3…0.4] for the tremor parameters and [0.6…0.7] for the handwriting 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 II. 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	91.22±2.1	92.43±2.1	5.2 s
RBF	9	95.42±2.1	94.13±2.1	4.7 s
MLP	9	97.52±2.1	95.44±2.1	3.8 s
ANFC-LH	9	99.68±2.1	98.94±2.1	4.3 s

TABLE III. 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 IV. STATISTICAL RESULTS

Statistical parameters	Statistics computed over all 88 patients during the leave-one-out test (%)		
ANN type	**RBF**	**MLP**	**ANFC-LH**
Specificity	95.57	95.58	100
Sensitivity	91.33	92.24	95.54
Total classification accuracy	92.44	92.34	98.67

It can be seen that using an ANFC-LH we have obtained the best classification rate of the two classes analyzed: "Parkinsonian" and "Normal".

VI. Conclusions and Future Work

Within this study we tested different trainable Artificial Neural Networks for PD 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. Our study verifies some characteristics of persons having tremor problems, and expressed in a linguistic manner by neurologists, psychiatrists and graphologists: variable baseline, micrographic, smaller strokes with variable shape (sharp, less round, often down and overlapping strokes; backward slanted, discontinuous, and steep strokes), ornaments and infrequent archedness, reduced modulation (differences) of stroke size. These characteristics are robust, that means they are independent of writer's style or the meaning of the text.

We present an accurate tremor and handwriting 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 of 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, hematological or clinical therapies. Our method allows a precise expression of motion handicap and may 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 (e.g., with medical expertise). Future research proposals include the testing and validation of a screening test, in order to detect Parkinson's disease in its early stages.

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