Analysis of Neurological Disorders Based on Digital Processing of Speech and Handwritten Text

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Abstract— **The paper deals with the methods of non-invasive analysis of neurological disorders, focusing on speech signal processing and processing of handwritten text. The paper describes the whole procedure of the automated analysis of the disorder while the greatest attention is paid to a parameterization. In the case of speech signal analysis, the state-of-the-art features evaluating a presence of hoarseness, breathiness and hypernasality are mentioned. Nonlinear dynamic parameters and parameters derived from the empirical mode decomposition (EMD) are compared. Based on the tests, from the point of description of a noise component of signal, the best results were obtained using the approximation entropy, the largest Lyapunov exponent and parameters based on Teager-Kaiser energy operator, which is calculated from the first intrinsic mode function (IMF). In the case of handwritten text analysis, the most used exercises describing a tremor and movement dynamics are mentioned. The new approaches of hand movement analysis at a time when the pen tip does not touch the paper have been also proposed. Finally the paper discusses different applications of speech signal and handwriting text parameterization.**

I. INTRODUCTION

With development of information technologies, intensity of research of digital processing of biomedical signals has also increased. Thanks to sophisticated techniques and decreasing cost of hardware, it is possible to give physicians better support in their work and provide them important information, which help them to decide on next steps of treatment, or medical intervention, respectively.

Due to the changing way of life, a greater proportion of sedentary behaviour, stress, unhealthy diet, etc. different types of neurological disorders such as Parkinson's and Alzheimer's diseases, schizophrenia, dementia, dystonia, etc. become more and more in human populations. The analysis of speech utterances and handwritten text are frequently used by physicians as non-invasive methods that help them to diagnose different stages of neurological disorders and help them recognize the success or failure of the treatment. In particular, the analysis of speech and handwritten text is often used for diagnosis and analysis of Parkinson's disease. Human speech is produced by coordinated movement of speech organs using air flow generated from lungs. Handwritten text is actually formed by coordinated movement of fingers, wrist and elbow. Based on the analysis of these signals, we can find out different information about people related to their health, emotions, mental state, etc.

Parkinson's disease can manifest in speech dysarthria of patients [1], which affects the area of phonation, articulation, prosody and fluency. The voice tremor [2], hypophonia (reduced voice intensity [3]), dysphonia (degradation of speech quality [4]), hypernasality (increased nasality [5]), dysprosody [6], hesitation (unintentional introduction of pauses [7], palilalia (rapid repetition of words or syllables [7]), bradyphemia (sudden deceleration [8]) or tachyphemia (sudden acceleration in speech [8]) may be observed in patients.

In the case of handwritten text, slower movements (bradykinesia [9]), variations in speed of writing [10], decrease of the height of letters (micrographia [11]) or uncontrollable movements (dyskinesia [12]) can be seen. Sometimes muscles of the patient may be very stiff (rigidity [12]), or motionless (akinesia [9]), which results in the patient not able to write.

All above mentioned manifestations of the neurological diseases are able to describe and quantify by using carefully chosen 1D and 2D signal analysis methods. Based on the processing of these signals, the disease can be diagnosed, monitored its progression and watched an impact on individual body parts. Moreover, thanks to the parameterization, new medicines can be developed and the impact of medication on patients can be monitored. For these reasons, the methods are also used in the pharmaceutical industry. Analysis of speech and handwritten text can also be combined with other investigative methods such as functional magnetic resonance imaging (fMRI), ultrasound investigations, etc.

The aim of this paper is to describe modern approaches to non-invasive analysis of neurological disorders with emphasis on Parkinson's disease using speech signal and handwritten text

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processing. The paper is divided as follows: a general procedure for the automated analysis of neurological disorders is given in Sec. II, a description of the parameter extraction techniques from speech signals and handwritten text follows in Sec. III, Sec. IV lists the different use of non-invasive analysis of neurological disorders and the conclusion is in Sec. V.

II. Automated Analysis of Neurological Disorders

The analyzed signal of speech or handwritten text is usually acquired in a hospital or speech therapist's office. To record speech, high-quality condenser microphones are used and to register handwritten text a digital tablets are applied. Beside a current position, some tablets are also able to record pressure, azimuth and altitude. Depending on the specific disorder, it is possible to use various utterances and handwriting exercises. In the analysis of speech, the exercises of prolonged vocals, reading poems, specially adapted sentences, reading excerpts from books or exercises difficult for articulation are applied. For the analysis of handwritten text, the patients can draw ellipses, Archimedean spirals, connect points on the matrix, write selected words or phrases or draw different pictures (pointer clocks, houses, etc.). The recorded data are labelled (borders between utterances are set, written words or phrases to smaller parts are segmented, etc.) and from categorized data different databases are prepared. After the modification the data are processed automatically. Speech and handwritten text signals are further processed (re-sampling, filtering, etc.) and various parameters (features) are calculated. Based on chosen application the parameters are selected. The feature space is usually very large and it is necessary to select optimal parameters before further processing. For this reason, the mRMR (minimum Redundancy Maximum Relevance) method [13], the SFFS (Sequential Floating Forward Selection) method, the LASSO (Least Absolute Shrinkage and Selection Operator) method [14], the LLBFS (Local Learning-Based Feature Selection) method [15] or the RELIEF (Feature Weight based Algorithm Inspired by Instance-based Learning) method [16], etc. may be used. To develop a system that would identify one of the disorders, a classifier may be trained (e.g. the Gaussian Mixed Models-GMM, Support Vector Machine-SVM or Random Forests-RF). To select significant features, by which it would be possible to monitor a progression of disease or an influence of medication parametric and non-parametric statistical methods such as Student's t-test, Mann-Whitney U test, Wilcoxon paired test, etc. can be used.

III. Feature Extraction

The parameters that are extracted from speech record or handwritten text can be divided into basic, high-level and global features. The basic features are calculated directly from signal, and are expressed by scalars, vectors or are written into matrices (pitch frequency F_0, formant locations, speech intensity, etc.). If several features of one type are calculated from the same signal (pitch frequency F_0 is calculated for each speech segment with length of 20 ms), then it is suitable to select one parameter (representative) from this set to train the classifier or make statistical analysis in an easier way. From this set of features, we can calculate, for example, mean value, standard deviation, range, moments, percentiles, entropy, regression coefficients, etc. These parameters are called high-level features. Sometimes it is advantageous to calculate the global parameters, which combine individual features of different types (e.g. the first two formants calculated from different vowels). The calculation of these parameters is more difficult to automate, but the result provides a comprehensive and robust description of the disorder (e.g. possibility to describe the movement of tongue).

Based on an optimal extraction of parameters, the disorder can be appropriately quantified. It is usually the most important part of the analysis process and the improper selection of parameters can greatly distort the final result. Thanks to the optimal extraction of parameters, a physician can better quantify and objectively diagnose the disease and decide more precisely further treatment.

A. Speech Signal Analysis

In terms of analysis of patient speech records, the features which describe prosody, vocal cords function and function of speech organs (e.g. tip of the tongue) are primarily extracted. Information about vocal tract shape is not so important in this case. Disorders that are manifested in speech signal may include: Parkinson's disease, Alzheimer's disease, dementia, and schizophrenia. Speech features can be divided in terms of what they describe:

- Features describing phonation - pitch frequency F_0, jitter, glottal coefficients, etc.
- Features describing intensity of speech - shimmer, modulation energy, spectral flow, etc.
- Features describing speech fluency – index of rhythmicity, articulation rate, proportion of speech pauses, etc.
- Features describing tongue movement - location of formant frequencies and their bandwidths.
- Features describing speech quality - glottal signal to noise ratio, normalized noise energy, etc.

Segmental features such as mel frequency cepstral coefficients (MFCC) or perceptual linear prediction coefficients (PLP) are also used [17]. However, it is not clear which disorder they indicate. But, for example, regarding the MFCC coefficients Tsanas et al. [17] believe that they can indirectly describe motion of articulatory organs.

In this paper, our attention will be paid to features that are not well known in the area of speech analysis, but which can positively contribute to correct diagnosis. They are: non-linear dynamic features and parameters based on the empirical mode decomposition (EMD).

1) Non-linear Dynamic Features

Sometimes the patients with Parkinson's disease produce breathy voice, dysphonia and hypernasality so great that any features in voiced speech segments (e.g. pitch period) cannot be found and the speech signal seems to be completely chaotic [18, 19]. Speech is in this case so degraded by noise that no conventional linear methods give useful results. The features such as F_0, jitter, shimmer, etc. or formant characteristics in

speech analysis completely fail. For this reason, chaos theory is increasingly applied. This theory helps determine how much speech is chaotic (stochastic), and thus it is possible to better assess speech properties.

One of the most useful feature is the correlation dimension (CD) [20]. This parameter describes geometry of the attractor in the phase space. The more the attractor is complicated, the more independent variables are necessary to describe it, and value of this attribute increases.

The largest Lyapunov exponent (LLE) is an often used feature that describes stability of a dynamic system as well as its sensitivity to initial conditions [19]. The more the system is stable (speech quality increases), the lower the exponent is.

To quantify complexity of the speech signal, the approximate entropy (AE) can also be used to describe a level of randomness [21]. Similar information can be extracted from the signal using the fractal dimension (FD) [22] or the Ziv-Lempel complexity (ZLC) [23]. In the case of the ZCL, it is a measure of regularity level in time series.

Other parameters are non-linear dynamic features based on the detrended fluctuation analysis (DFA) [24], features based on normalised recurrence time probability density entropy H_{norm} [18] and Hurst's exponent (HE) [25], which describes the relationship between the future and previous speech samples.

For the comparison of the nonlinear dynamic features, a simple test in which noise with the normal probability distribution is added to part of vowel [a] is performed. Such noise may represent stochastic part of speech that corresponds to hoarseness, breathiness or hypernasality. Power spectral density of noise was gradually increased, while the percentage of difference between new and original features` values was calculated. The results can be seen in Figure 1.

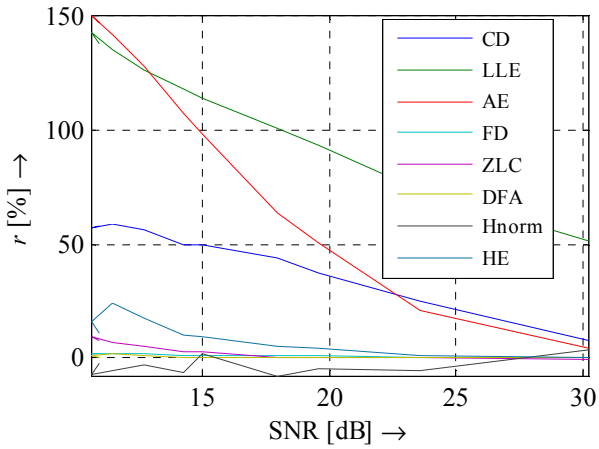

Figure 1: The comparison of sensitivity of the nonlinear dynamic features to additive noise with the normal probability distribution. Variable *r* expresses the difference between values when comparing to the situation when no noise has been added to the original signal. SNR expresses the signal-to-noise ratio.

The graph shows that the highest sensitivity to additive noise has the approximate entropy (AE) which increases exponentially with an increasing level of noise. In addition to the AE, the LLE and CD features make big differences, but their dependence is linear. The remaining features have no big changes.

2) Features Based on the Empirical Mode Decomposition

Recently, in speech processing new methods based on the EMD are used. Using the EMD it is possible to decompose the arbitrary nonlinear and time-varying signal into countable and usually a small number of the intrinsic mode functions (IMF). These functions are modulated in amplitude and frequency and their sum gives the original signal.

Tsanas et al. [17] proposed several speech parameters based on the IMF. Their idea is to represent the noise component of speech signal with the first few IMFs and stationary speech signal with the remaining IMFs. They designed a new method for SNR (signal-to-signal ratio) and NSR calculations (noise-to-signal ratio):

$$\text{SNR} = \frac{\sum_{i=4}^{K} \mu_i}{\sum_{i=1}^{3} \mu_i}, \tag{1}$$

$$\text{NSR} = \frac{\sum_{i=1}^{2} \tilde{\mu}_i}{\sum_{i=3}^{K} \tilde{\mu}_i}, \tag{2}$$

where μ_i is mean value of sequence, calculated from the original *i*-th IMF and *K* is total number of the IMF. $\tilde{\mu}_i$ is logarithmic mean value, which is calculated as mean value but for logarithm of the *i*-th IMF. In the end, it has to be defined which attributes are used for calculation of the original IMF. It can be the squared energy operator (SEO), Teager-Kaiser energy operator (TKEO), the entropy (H), or the zero crossing rate (ZCR).

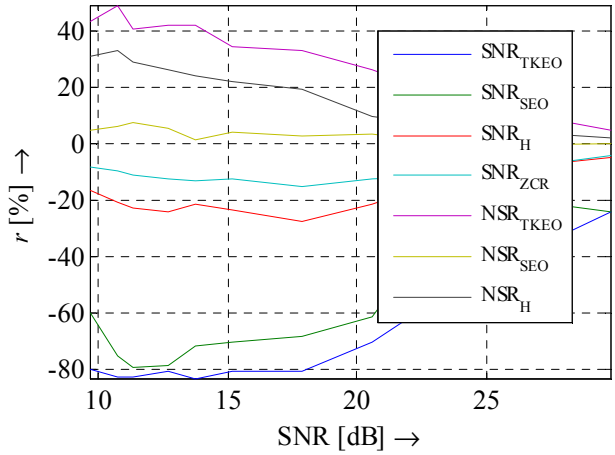

Figure 2: The comparison of the parameters' sensitivity derived from the IMF to additive noise with normal probability distribution. Variable *r* expresses the difference between values when comparing to the situation when no noise has been added to the original signal. SNR expresses the signal-to-noise ratio and NSR is noise-to-signal ratio.

To compare sensitivity of these features to additive noise, another example is prepared. The results of comparison can be shown in Figure 2. From the graph it can be seen that most of the features in dependence on noise level decrease (SNR) or increase (NSR) linearly. The best result provides SNR based on

the squared energy and Teager-Kaiser energy operators. These features show the largest deviations from the original value.

Using Figs. 1 and 2, discriminatory efficiency between the nonlinear dynamical features and the EMD parameters can be compared. If we picked up top 3 candidates for noise part description, it would be the approximate entropy (AE), largest Lyapunov exponent (LLE) and SNR based on Teager-Kaiser energy operator (TKEO).

B. Analysis of Handwritten Text

In the case of analysis of handwritten text the feature selection is highly dependent on specific written exercises. In this paper, for example, four most commonly used exercises for analysis of Parkinson's disease are chosen.

1) Archimedean Spiral

Archimedean spiral is a curve defined by equation $\theta = k + ar^n$, where θ [rad] is an angle between a point on the spiral and a point on the origin of the spiral and r is distance from the spiral point to the origin point. Variables a, k, and n are real numbers. The parameters of this exercise are: number of changes in velocity (NCV) [26], number of changes in acceleration (NCA) [11], radial oscillation speed (ROS) [27] or parameters evaluating smoothness and density of spiral coils [28]. Archimedean spiral is also a good test to describe level of present tremor. Figure 3 shows the spiral in Cartesian and polar coordinates for healthy people and patients afflicted by Parkinson's disease. As it is illustrated by the figure, due to transformation to the polar coordinates, the 2D spiral curve can be expressed by the 1D curve. Using this spiral, healthy and ill people can be easily distinguished [29, 30]. It is also possible to calculate features based on the signal-to-noise ratio, or the chaos theory.

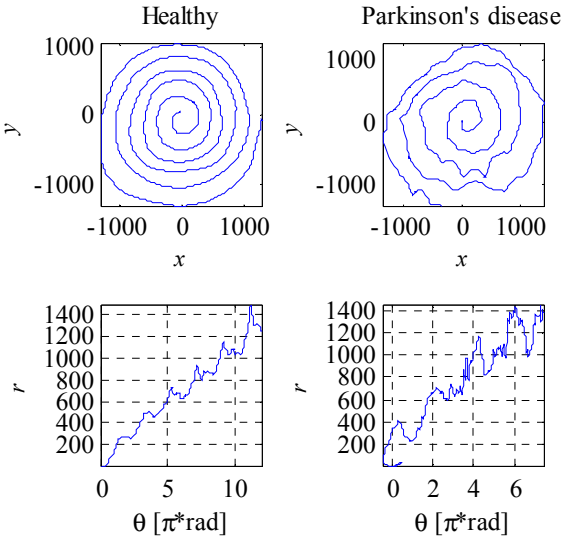

Figure 3: The comparison of Archimedean spirals, which are drawn by healthy person and patient afflicted by Parkinson's disease. In the upper part of the picture spiral in Cartesian coordinates can be seen, and on the bottom the same spiral is expressed in polar coordinates, where r denotes the distance from spiral points to centre of the spiral and θ is angle of straight line passing through this point and the origin point.

2) Ellipses

The ellipses are by patients quickly drawn over themselves, as it can be seen in Figure 5. When monitoring the vertical or horizontal movement, then dynamics of the movements can be well described. Using these curves the parameters as velocity (VE), acceleration (AC) or jerk (third derivative of length by time) can be calculated [31]. Other ways of ellipse analysis are discussed in Chap. C.

3) Connected Letters "l" Written in Italics

Using this exercise, the writing dynamics can be again seen clearly. The following parameters are usually extracted: stroke size (SS), stroke length (SL), stroke duration (SD), number of local extremes in velocity profile, the velocity (VE), acceleration (AC), and jerk (JE).

4) Syllabes, Words, Sentences

The speed of the writing and the presence of micrography can be better monitored on longer part of written text. Using these exercises we extract parameters such as: movement time (MT), writing pressure (WP), velocity (VE), acceleration (AC), jerk (JE), width and height of letters, tendency of decreasing letters over time, etc.

There are tablets which can record movements of the pen in time, when the tip does not touch the paper surface. Thanks to this information it is possible to see how patient's hand behaves at a time when the patient does not write. Figure 4 shows an example of Czech sentence "Tram will no longer go" written by a healthy person and a patient afflicted by Parkinson's disease. Blue line expresses movement of hand when the pen was touching the paper. Red line expresses movement of the pen when the tip does not touch the paper. If we focus only on pen movement on paper (blue line), we would not recognize so big differences in hand tremor between two tested participants. However, information about hand movement in air (red line) clearly indicates that one of participants has strong tremor. Using further analysis, frequency of this tremor, amplitude range, etc. can be estimated.

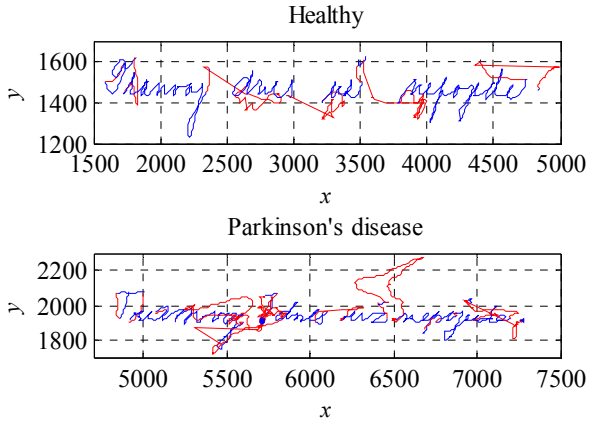

Figure 4: The comparison of Czech sentence "Tram will no longer go" written by a healthy person and a patient affected by Parkinson's disease. Blue line expresses movement of hand when the pen tip was touching the paper. Red line expresses movement of the pen when the tip doesn't touch the paper.

Authors in various publications often use lowpass filtering before processing to smooth the written text [32, 33]. However, such approach unnecessarily removes high-frequency components which are related to hand tremor. The high-frequency components should not be removed, but used for further analysis. It would be also helpful to combine parameters calculated from pressure the pen tip, azimuth and inclination.

C. *Comparison of Speech and Handwritten Text Parameters*

It is clear from previous chapter, that speech processing is very similar to processing of signals obtained from handwritten text. Fig. 5 demonstrates how the ellipse as a picture is transformed to 1D periodical signal (function of the vertical movement in time). 1D periodical signal obtained from 2D ellipse can be analysed similarly as voiced speech segments. Generally speaking, in analysis of handwritten text the features as jitter, shimmer, short-term energy, modulating energy, harmonic signal to noise ratio, the zero crossing rate, etc. can be applied. Moreover, as in an area of speech processing, even here it is possible to test nonlinear dynamic parameters and parameters based on the EMD analysis. This approach in analysis of handwritten text has not been used and it seems to bring good results.

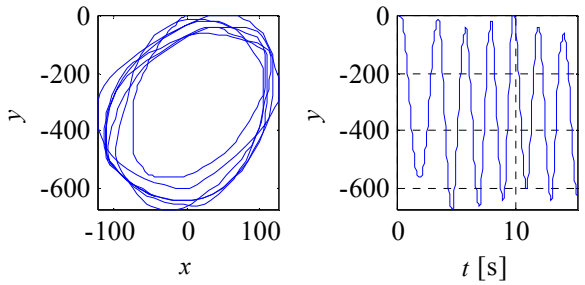

Figure 5: Monitoring the vertical movement in time when drawing the overlapping ellipses.

IV. Applications of Non-invasive Neurological Disorders Analysis

As it has been already mentioned, the most important part of the analysis of neurological disorders is quantification, i.e. feature extraction. When all patients' dysfunctions are appropriately described, it is possible to proceed to the next steps of data processing. Due to the objective description of the disorder, non-invasive analysis can be used as follows:

- Diagnosis/identification of neurological disorder - although it is possible to train a classifier which can perform the diagnosis without the presence of the doctors, this approach is not useful in practice. There is still a risk that the classifier determines inaccurately or bad diagnosis, which could have a very negative impact on the patient's health. The aim of the quantification is not to replace the doctors' work, but to make their work easier.
- To monitor disease progression - using some of the features, it is possible to follow development of the disorder over time,
- Identification of the first stages of the disorders,
- Development of new medication,
- Preparation of an individual plan of medication,
- Analysis of the effect of different stimulations in neurological disorders (e.g. the effect of repetitive transcranial magnetic stimulation rTMS on speech of patients afflicted by Parkinson's disease [34]),
- Monitoring the impact of various devices on the patient's condition (e.g. Duodopa or deep brain stimulation (DBS)).

V. Conclusion

The paper summarizes the modern methods of digital signal processing applied in the field of non-invasive analysis of neurological disorders. Emphasis is given on methods of feature extraction, which is the most important part of the whole procedure of analysis. Thanks to parameterization the disease can be adequately quantified, which can help doctors diagnose it more objectively, faster and more accurately. In increasing number of patients suffering from Alzheimer's or Parkinson's disease, an automated analysis has also positive economic impact (e.g. due to a possibility to diagnose more accurate and on time).

The paper addresses non-invasive methods of speech and handwritten text analyses. The advantage of handwritten text processing against speech processing is small influence of environment to recorded signal (low influence of noise and no influence of acoustic room properties). The main disadvantage of handwritten text processing is that some patients are not able to write anything but can speak. For this reason, it is advantageous to fuse information extracted from both signals.

Furthermore, the paper describes new methods of feature extraction which are not so much known. It is the non-linear dynamic parameters and parameters based on the empirical mode decomposition. Above introduced tests show that the attributes like the approximate entropy, the largest Lyapunov exponent or SNR derived from the squared energy operator of the IMF may well identify the hoarseness in speech, or tremor in writing.

Scientific research in this area aims to invent a system that could diagnose various neurological disorders at an early stage or to estimate their progression. Changes in speech in case of Parkinson's disease occur due to hypokinetic dysarthria in 60-90% of patients [35]. This means that error of disease identification by speech processing may be 10-40%. Moreover, each patient afflicted by Parkinson's disease may have different speech dysfunction. Therefore, first it is important to determine all patient's dysfunction (both speech and handwriting text), and then on the basis of the analysis results, the doctors could perform a reliable diagnosis. Therefore, it seems to be preferable to use artificial intelligence to recognize patient's dysfunction than to automatically determine diagnosis of the disease. Based on the knowledge of dysfunction, the doctors can diagnose the disease itself.

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