Usage of F-transform to Finding Informative Parameters of Rhinomanometric Signals

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Abstract–**The Active Anterior Rhinomanometry method for an objective assessment of nasal breath is carried out. The preprocessing's methods for rhinomanometric data were analyzed. It was proposed to use the method of fuzzy approximation based on F-transform for preprocessing of rhinomanometric signals.**

Keywords—**Biomedical signals, Rhinomanometry, Feature extraction, F-transform, Classification.**

I. INTRODUCTION

Patients with diseases of a nose and paranasal sinuses in most cases have nasal obstruction. Some of the common causes are acute chronic inflammatory diseases of the nose, vasomotor and allergic Rhinitis and nasal polyp Rhinitis, various nasal tumors, post-traumatic nasal septal deviation [1].

For an objective assessment of nasal breath, Rhinomanometry [2, 3] is widely used in modern medicine. The most of Rhinomanometry tests are based on the active anterior rhinomanometry (AAR), the result of which are nasal resistance coefficients [4, 5]. However, there are disadvantages that reduce the diagnostic value of this method. All diagnostic coefficients have a number of dimensions and are depended on specific anatomico-physiological features of a person's nasal cavity. Each of these facts reduces the diagnostic value of the coefficients, and doesn't allow us to systematize a biological norm indicators for a nasal cavity. The probabilistic-statistical methods for diagnosis of nasal breath are not suitable because the law of the distribution of the test data is not determined [6].

For the purposes of medical diagnosis are widely used artificial intelligence techniques based on the use of fuzzy logic, artificial neural networks and genetic algorithms [7-11].

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Applications of Pattern Recognition allow analyzing test results in decision support for any illness. The list of applications includes automated electrocardiogram (ECG) or electroencephalogram (EEG) analysis for cardiovascular or neurological disorder diagnosis, hand gesture recognition, biometrics[12-14] etc. All of these applications share a common denominator: automated classification or decision making based on observed parameters, such as a signal, image, or in general a pattern, obtained by combining several observations or measurements. The problem of measuring the parameters of biomedical signals is a common problem during the design of medical diagnostic systems. It is needed to use highly sensitive sensors to be able to register such signals. The use of such sensors is always associated with the registration of noises. Thus, it is needed to carry out preprocessing of signals to form the input set of informative features of signals. An essential, in the design of diagnostic system is preprocessing, where the goal is to condition the acquired data such that noise from various sources are removed. An important task of preprocessing is a prevention of signal distortion, which can lead to misinterpretation of the signal parameters, and as a consequence of misdiagnosis.

Preprocessing represents a filtering of noises and smoothing of signals. Various filtering techniques presented in the works [15, 16]. These approaches use Fourier analysis, moving average method, exponential smoothing method. However, they have some disadvantages [17]. In our paper we present an analysis of preprocessing's methods for rhinomanometric data. The aim of this work is to find informative parameters of rhinomanometric signals.

II. MATERIALS AND METHODS

First of all we have to consider the features of rhinomanometric data. Rhinomanometric data are the result of the measurement according to active anterior rhinomanometry (AAR) method. This method is based on simultaneous registration of two parameters: differential pressure Δp and an airflow rate Q through a nasal cavity. Rhinomanometric data were recorded by a software/hardware system for rhinomanometric measurements (see Fig.1). Functionally software/hardware system consists of the measuring module, a mask and the software. Details about the design of software/hardware system for rhinomanometric measurements can be found in [18].

Fig.1.Photograph of the software/hardware system for rhinomanometric measurements

The measurements of parameters are carried out for each side of a nose separately. The measurements result are the values of the differential pressure Δp [Pa] and the airflow rate Q [cm^3/s] on a time t [s], presented in Fig.2.

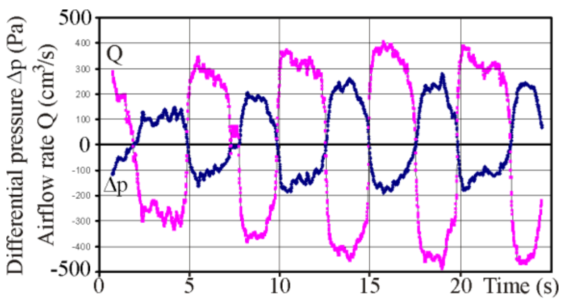

Fig.2.The dependence of pressure and airflow rate on a time

The measuring module based on two sensors: ultralow pressure sensor and low pressure drop digital flow meter. Sampling rate of measurement signals is 100 Hz. Pressure sensor uses a silicon micromachined sensing element which features a stress concentration enhanced structure to provide a highly stable linear output that is proportional to applied pressure. Sensor features calibrated offset, full scale span and thermal error calibration to ensure the highest possible accuracy for flow pressure measurement calibration to ensure the highest possible accuracy for flow pressure measurement measuring range of differential pressure. Measuring range of differential pressure is ±1200 Pa. Limit of reduced error of differential pressure measurement is $\gamma_p = \pm 0{,}25\%$. Digital flow meter designed for high-volume applications. Measuring range of airflow rate is ±1200 cm^3/s. Limit of relative error of airflow rate measurement is $\delta_p = \pm 3\%$.

Rhinomanometric signals are quasi periodic and nonstationary (Eq.1)

$$T_i = T_{i-1} + \varepsilon , \qquad (1)$$

where T_i , T_{i-1} - the duration of the current and previous repetitive signal plots respectively; ε - a random variable characterizing the difference between the duration of the current and previous periods.

III. EXPEREMENTS AND RESULTS

Let's consider existing approaches to the issues for features extraction. In work [19] it is proposed to use Fast Fourier Transform (FFT) to filter high frequency domain. Preprocessing technique used FFT for extraction of low-frequency component. Peculiarities of signals are unequal oscillation period. FFT for feature extraction low-frequency component is influenced on oscillation amplitude. Such changes will influence on the pathology identification. The source and extracted signals is shown in the Fig. 3.

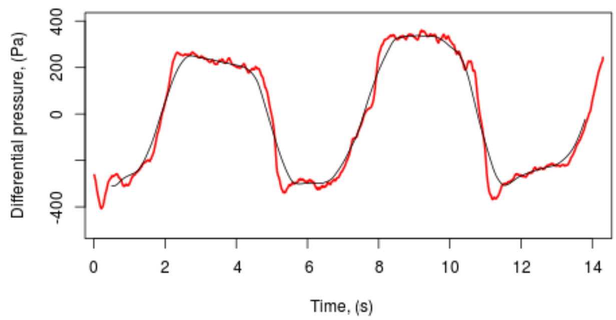

Fig. 3. The source signal and signal processed by FFT

Approach based on simple moving average (SMA) also can be used. This approach less distorts oscillation amplitude, but half-period of SMA at start and end of time series filled with NA values. This decreases size of time series, which can be used to anomaly detection (Fig. 4).

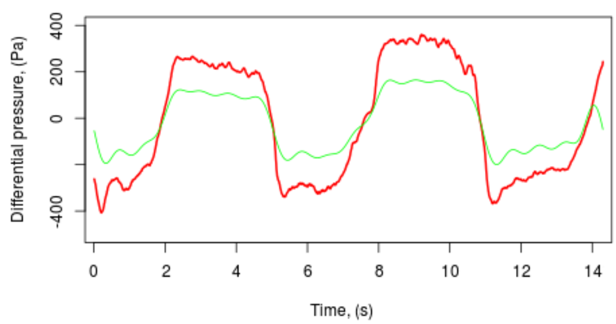

Fig. 4. The source signal and signal processed by SMA

As alternative approach exponential moving average (EMA) can be used, but the first several results also regarded as unreliable, because method should have time to converge.

After pre-processing stage filtered signal comes to the input of classification method. For example in paper [20] proposed usage of Support Vector Machine (SVM) as classifier, in [21, 22] proposed usage of HMM, Neural Networks.

Several respiratory cycles have used for pathology detection. Differential pressure Δp and airflow rate through a nasal cavity Q represented as time series. Current dataset contains 111 measurements for 42 patients. For pathology detection it is supposed to use features of half-period of respiratory cycle, which not depends on it length.

We propose F-transform usage for filtering of rhinomanometric signal. This approach was introduced by I. Perfilieva in [23] and other papers with results extending and applications (see e.g. [24, 25, 26]).

The domain $D = [a, b]$ is then partitioned by k fuzzy partition [27] by fuzzy sets $\{f_1,..., f_k\}$.

Each fuzzy partition formed by basic function [23], $A_1...A_k$ with the following conditions for each $i = 1,...,k$

1. A_i is continuous on D,
2. A_i - strictly increase on $[t_{i-1}, t_i]$ and strictly decrease on $[t_i, t_{i+1}]$,
3. $A_i : [1..N] \to [0,1], A_i(t_i) = 1$
4. $A_i(t) = 0$, if $t \notin (t_{i-1}, t_{i+1})$, and assume that $t_0 = t_1 = 1, t_{n+1} = t_n = N$,
5. $\sum A_i(t) = 1$ for all $t \in [1..n]$.

After that time series transformed into k values $[F_1,...F_k]$ using :

$$F_j = \frac{\sum X_{t_i} A_j(t_i)}{\sum A_j(t_i)}, i = 1,...,k$$

These values form the smoothed time series (Fig 5).

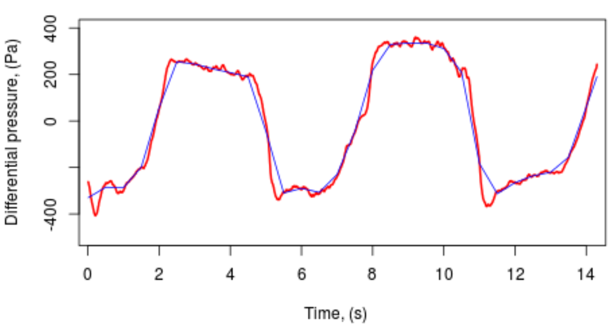

Fig. 5. The source signal and signal processed by F-transform

Result of data filtering $F_1...F_k$ used than to receive maximum value in each half wave with m elements $F_l...F_{l+m}$, where $sign(F_l) = sign(F_{l+1}) = ...sign(F_m)$, $1 \le l \le k$, $1 \le m \le k$

The maximum value $M_j = \max(|F_i|), i = l..m$, where $j = 1,2,...,S$ and S – count of half wave in measurement. After applying this procedure to both differential pressure Δp and flow rate of an air flow through a nasal cavity Q, we will receive to values X_i, Y_i for each measurement. This data used for classification.

We propose to use SVM [27, 20] with linear kernel, for binary classification of data. To compare results we have used data without any filtering, with FFT filtering (first 20 components) and proposed F-transform based method. We have summarized results of classification in Table 1. There are 111 measurements were used to classify data into two classes: “Norm” and “Pathology”.

TABLE 1

CLASSIFICATION ERRORS

Filtering method	FN	FP	Sum
F-transform based	3	5	7
FFT	7	6	13
No filtering	7	6	13

IV. CONCLUSION

The analysis of preprocessing’s methods for rhinomanometric data was conducted. Most work to date has focused on diagnosis of nasal breath pathology using diagnostic coefficients (nasal resistance coefficients). This work focused on processing of time series of rhinomanometric data. It was proposed to use the method of fuzzy approximation based on F-transform for preprocessing of rhinomanometric signals. The results show that the F-transform is a good choice for pre-process data of rhinomanometric measurements. Usage of F-transform method for filtering of rhinomanometric signal decreases error rate significantly. Future work will be related with increasing of the count of correct pathology detection and pathology differentiation. One of approaches will be related with generation of period-independent features set for quasi-periodic rhinomanometric data sets.

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