The use of statistical characteristics of measured signals to increasing the reliability of the rhinomanometric diagnosis

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ABSTRACT

The article concerns the assessment of possibilities to increase the reliability of the rhinomanometry diagnosis using statistical characteristics of measured signals and corresponding differential pressure of an air flow in the nasal cavity during respiration. An original method for testing the patient's nasal breathing during forced inspiration has been proposed. It shows the influence of the space dimension of informative parameters on the diagnosis error probability. It has been proving that taking into account during the measurement experiment the dynamic modes in the operation of the diagnostic object, you can obtain the information redundancy that improves the reliability of diagnosis.

Keywords: rhinomanometry, rhinomanometric test, nasal airflow, Mahalanobis distance, Fisher-Snedecor distribution

1. INTRODUCTION

At present, so-called 'gold standard' diagnostic tools are the methods of high accuracy and repeatability. The main development problem of such methods for medical diagnosis is high individual physiological variability and consequently the lack of standards for measured signals. Undefined properties of the object under study may considerably complicate the task of selection of informative parameters. It takes place especially for difficult transformations of information in the structure of diagnostic and control systems.

1.1 Actuality and state of research

Selecting the optimal informational parameters of a system (by criterion of maximum reliability) is a classical problem of statistical synthesis under a priori uncertainty. In this case, a ranking is carried out according to the levels of informativeness and depends on the index of diagnostic reliability or errors probability. Rhinomanometry methods allow us to test a nasal breathing on the base of a measured differential pressure signal and corresponding air flow rate through the nasal cavity. However, these methods have a low diagnostic reliability because of individual variability of breath indicators. Therefore, an actual task is to select the most informative parameters of measured signals that would improve a reliability of a control test of nasal breathing[1-5]. This work aims to assess the possibility of improvement of the reliability of rhinomanometry diagnosis by taking into account statistical characteristics of measured signals and a corresponding differential pressure of an air flow in a nasal cavity during respiration.

1.2 Estimation of statistical parameters of rhinomanometry signals

We analyzed the processes occurring in the system of external human breathing and many known methods for testing of nasal breathing verified by their own experimental research. On this base we proposed a method for testing of patients by active posterior rhinomanometry at forced respiration mode. In our research, we used the device for testing of a nasal breathing that was developed in KNURE and the TNDA-PRN unit for measurement of the flow characteristics. Differential pressure and air flow values within 10 cycles of the forced breath are shown in Fig. 1.

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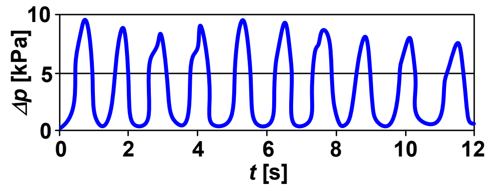
Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2016,
edited by Ryszard S. Romaniuk, Proc. of SPIE Vol. 10031, 100312M · © 2016 SPIE
CCC code: 0277-786X/16/$18 · doi: 10.1117/12.2248364

a) b)



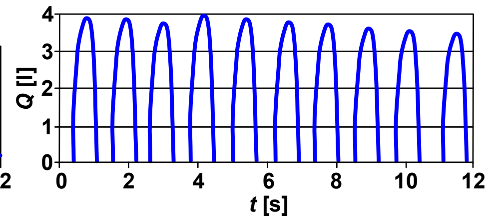


Figure 1. Differential pressure (a) and air flow (b) values within 10 cycles of a forced breath.

To conduct an automated analysis of the rhinomanometric data the software that uses the algorithm of automatic allocation of the maximum values of dynamic measured signals has been developed. An uncertainty of a control object must be taken into account. For example, a magnitude of a differential pressure in the nasal passages depends substantially on the anatomical structure of the soft palate and may be a constant component. The algorithm is based on averaging of the random signal, moving average for elimination of a local noise, numerical differentiation and the search for an extreme at zero value of a derivative of a measured signal[19-23]. An algorithm determines the amplitude of a signal. During this process, a pressure it must be at least 100 Pa and air flow at least 0.1 l/s. While testing of nasal breathing, there is a clear tendency to decreasing the amplitude of rhinomanometry signals in time due to the patient's fatigue that is caused by the need of overcoming the resistance of the flow meter with the hole diameter of 7÷9 mm. In contrast to the measured static values, dynamic signals give the possibility of obtaining an additional information redundancy by taking into account correlations of these signals. A correlation may occur in a presence of trends (the first and higher orders). In this case, additional informative parameters are coefficients of the mathematical trend models. A regression of the measured value X in time t and a residual dispersion of such regression can be used to evaluate of the obtained information (the smaller of a residual dispersion the larger of an information content)[6-8].

Let's consider the approximation of signal $X(t)$ to the sequence K as partial linear regression with random coefficients

$$x_{j,i} = A_j + B_j \cdot t_{j,i},\, j = \overline{1,k};\;\; i = \overline{1,n_j},$$

where k is the number of groups of measurement results for which a private regression is built and n_j is the number of measurement results in the j-th group.

The total number of measurements is equal to

$$N = \sum_{j=1}^{k} n_j .$$

Let the expression

$$\hat{X}_{j,i} = A + B \cdot t_{j,i}$$

is a common regression of X in t. Its coefficients are determined by the whole set of two-dimensional observation results. The coefficients $\left\{A_j, B_j\right\}_1^k$ of the partial regressions are determined by the results of corresponding measurement group. It is known[8] that the sum S of squared deviations of observation results from the total average $\overline{x}$, given by

$$S = \sum_{j=1}^{k}\sum_{i=1}^{n_j}(x_{i,j} - \overline{x})^2$$

can be decomposed into five components:

$$S = S_0 + S_{WG} + S_G + S_W + S_R \tag{1}$$

where

$$S_0 = w_0 B_0^2,$$

$$S_{WG} = \frac{w_c w_m}{w_0}(B_c - B_m)^2 ,$$

$$S_G = \sum_{j=1}^{k} n_j [\overline{x}_j - \overline{x} - B_m(\overline{t}_j - \overline{t})]^2 ,$$

$$S_W = \sum_{j=1}^{k} w_j (B_j - B_c)^2 ,$$

$$S_R = \sum_{j=1}^{k}\sum_{i=1}^{n_j}[x_{j,i} - \overline{x}_j - B_j(t_{j,i} - \overline{t}_j)]^2$$

On this basis, we get:

$$w_m = \sum_{j=1}^{k} n_j (\overline{t}_j - \overline{t})^2 ,$$

$$w_j = \sum_{i=1}^{n_i} (t_{j,i} - \overline{t}_j)^2 ,$$

$$w_c = \sum_{j=1}^{k} w_j ,$$

$$w_0 = w_m + w_c ,$$

where: $\bar{x}$, $\bar{t}$ – general average of sets $\{x_S\}_1^N$ and $\{t_S\}_1^N$; $\overline{x_j}$, $\overline{t_j}$ – group average of $\{x_{j,i}\}_{j=1}^k$ and $\{t_{j,i}\}_{j=1}^k$.

A guide for selection of informative parameters is that the sum S_R allows us to estimate the amount of residual variance $\overline{S_R}$ of the regression model of measurement results

$$\overline{S_R} = \frac{S_R}{N - 2k} \tag{2}$$

and choose as informative parameters of statistical models

$$\begin{cases} F_0 = S_0 / \overline{S_R}, \\ F_{WG} = S_{WG} / \overline{S_R}, \\ F_G = S_G / [\overline{S_R} \cdot (k-2)], \\ F_W = S_w / [\overline{S_R} \cdot (k-1)], \end{cases} \tag{3}$$

where $\overline{S_R}$ is the residual dispersion of the regression model, calculated using the formula (2). These statistics are the ratio of average squares sums S_0, S_{WG}, S_G and S_W to the average square of residual sum S_R, that represent random values with F-distribution (Fisher-Snedecor distribution). Dispersion expansion (1) allows the calculation of F-statistics according to (3) by realizations of the signal *X(t)*. The conditions of this expansion are:

1. Normally distributed random residue – $\varepsilon_{j,i} = x_{j,i} - \overline{x_j} - B_j(t_{j,i} - \overline{t_j})$, $\varepsilon_{j,i} \approx NORM(0, \sigma^2_{\ \varepsilon})$.
2. $M[\varepsilon_{j,i}] = 0$.
3. $M[\varepsilon^2_{j,i}] = \sigma^2_{\ \varepsilon}$.
4. Uncorrelated residues – $M[\varepsilon_{j,i} \cdot \varepsilon_{j,z}] = 0$ for all $i \neq z$.

An advantage of F-statistics is that they are independent from each other[8-10] due to the independence of members of the dispersion decomposition (1). This means that the statistics (3) can be regarded as components of the vector

$$\vec{F} = (F_0, F_{WG}, F_G, F_W). \tag{4}$$

It is a multidimensional informative parameter. Full details will be determined by the sum of

$$I = I_0 + I_{WG} + I_G + I_W, \tag{5}$$

where the terms of the right side can be calculated independently of each other[8].

Under normal distribution law, the measured value X is linear with regard to the time t. Its transformation will be characterized by no correlation between average values and dispersion[8] (without any change in the width of observation interval). Therefore, the information about the object state changing, obtained by F-statistic dispersion expansion (1), may supplement the information found by measuring the mean value of X[11-15].

2. EXPERIMENT

A linear discrimination model to estimate the error probability of the proposed diagnosis method at forced breathing and the F-statistics (3) have been used. The research material were results of patients' test in Otorhinolaryngologic Department of Kharkiv Regional Clinical Hospital. Sixty patients were divided into two groups consisting of thirty normal persons (state Θ_0) and thirty patients with difficulty in nasal breathing[4] (state Θ_1). For each patient, a medical examination was conducted by an active posterior rhinomanometry during forced breath within ten cycles of breathing. According to the above algorithm, maxima of a signal for each cycle of inhalation were automatically found and on this base the amplitudes of a differential pressure Δp and an air flow Q in the upper airways of the patient have been calculated. Next, these values were averaged over ten cycles of breathing and four F-statistics F_0, F_{WG}, F_G, F_W (3) for each measured signal (Δp and Q) were calculated. For each group of patients, mean values ($m_i^{(0)}, m_i^{(1)}$) and standard deviations ($\sigma_i^{(0)}, \sigma_i^{(1)}$) of the relevant indicators were estimated[16-18]. It made it possible to find a Mahalanobis distance

$$\delta = \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\frac{\mathrm{m_i}^{(0)} - \mathrm{m_i}^{(1)}}{\sigma_{\mathrm{i}}} \right)^2} \tag{6}$$

and associated to it the error probability

$$P_{er} \le 1 - \Phi(\delta / 2) \tag{7}$$

where $\sigma_i = \max(\sigma_i^{(0)}, \sigma_i^{(1)})$, and $\Phi(\cdot)$ is a normal distribution function.

On the basis of (6) and (7) you can see that the error probability is smaller then the largest square of a distance between the mean vectors normalized by a variance. Thus, the calculations were based on ten informative parameters ($X_i, i = \overline{1,10}$) – five for each of the measured signal. The first five parameters ($\{X_i\}_1^5$) belonged to the characteristics of differential pressure Δp and the second five parameters ($\{X_i\}_6^{10}$) belonged to the characteristics of air flow Q. The results of calculations of discriminant characteristics for differential pressure and air flow have been presented in tables 1 and 2, respectively.

Table 1. Discriminant characteristics of a differential pressure.

Parameter		**State of the object** Θ_0	Θ_1	**Mahalanobis distance (δ)**	**Error probability (P_{er})**
X_1	$\overline{\Delta p}$, kPa	8.70	16.50	2.10	≤ 0.30
	$\sigma_{\Delta p}$, kPa	2.26	3.80		
X_2	$\overline{F_0}$	111.50	65.20	0.98	≤ 0.62
	σ_{F_0}	47.10	22.14		
X_3	$\overline{F_{WG}}$	6.41	18.70	0.87	≤ 0.68
	$\sigma_{F_{WG}}$	3.47	14.20		
X_4	$\overline{F_G}$	48.40	38.20	0.50	≤ 0.81
	σ_{F_G}	19.60	12.95		
X_5	$\overline{F_W}$	18.25	35.30	0.92	≤ 0.65
	σ_{F_W}	4.77	11.32		
$\{X_i\}_1^5$	$\delta_{\Delta p}$			2.70	≤ 0.18

Table 2. Discriminant characteristics of an air flow.

Parameter		**State of the object** Θ_0	Θ_1	**Mahalanobis distance (δ)**	**Error probability (P_{er})**
X_6	$\overline{Q}$, l/s	3.10	0.80	1.43	≤ 0.48
	σ_Q, l/s	1.60	0.43		
X_7	$\overline{F}_0$	77.95	47.62	0.74	≤ 0.72
	σ_{F_0}	40.50	12.37		
X_8	$\overline{F_{WG}}$	4.50	3.80	0.33	≤ 0.88
	$\sigma_{F_{WG}}$	2.15	1.76		
X_9	$\overline{F_G}$	6.10	7.94	0.50	≤ 0.81
	σ_{F_G}	3.12	3.63		
X_{10}	$\overline{F_W}$	9.70	13.10	0.60	≤ 0.76
	σ_{F_W}	3.77	5.65		
$\{X_i\}_6^{10}$	δ_Q			1.82	≤ 0.37

3. RESULTS AND DISCUSSION

An average signal value and F-statistics for a differential pressure has a better discriminant properties compared to the data obtained on the base of an air flow. In the analysis of average values of signals, the Mahalanobis distance increased 1.5 times after taking into account the F-statistics. This is due to the physical lungs capacity of the patient with the difficulty of nasal breathing. Momentarily, an air flow is closed to a normal form when a pressure drop in the nasal passages is increasing. Using only average signal values of a differential pressure and an air flow we get the error probability less than 0.21. Taking into account all the informative parameters of the measured signals we can obtain the Mahalanobis distance equals to $\delta_{\{X_i\}_1^{10}} = 3,25$ and reduce the error probability to a value lower than 0.1. After ranking the parameters in a decreasing order from the Mahalanobis distance point of view, we can analyze the influence of the number of parameters on the form of discriminant characteristics. In figures 2 and 3 the graphs of increasing of the cumulative Mahalanobis distance (δ) and reducing of the diagnostic error probability (P_{er}) as a function of dimension of informative parameters (j) have been shown, respectively.

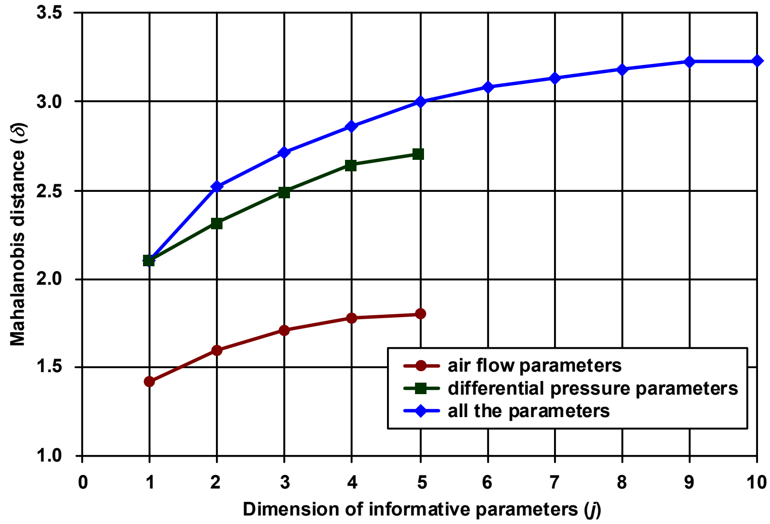


Figure 2. Increasing of a cumulative Mahalanobis distance.

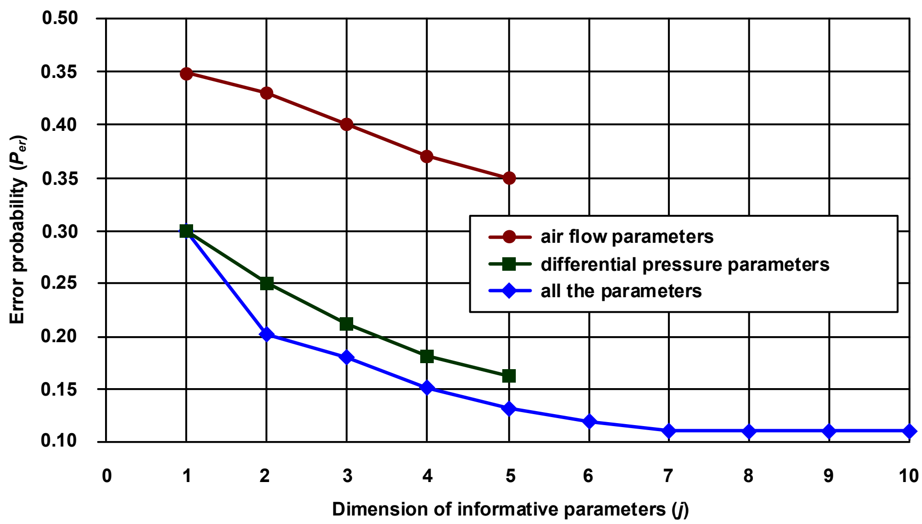


Figure 3. Reducing of a diagnostic error probability.

It is obvious that the three least significant parameters practically don't affect the probability of a diagnostic decisions making and may be excluded from the calculations. An analyze of rhinomanometry methods and their theoretical fundamentals made it possible to develop the method and apparatus that can by used for testing of a nasal breathing in a computer rhinomanometry TNDA-PRN. We suggested an original method for testing of a patient's nasal breathing during a forced breath. This method revealed the following pattern: the parameters of a differential pressure signal have the largest discriminant properties – the patient with difficulty in nasal breathing can momentarily provide an air flow through the nasal passages that is close to a normal form by increasing a pressure drop in the nasal passages.

Using for the analysis of a breath only an average value of the signal maxima both for a differential pressure and an air flow, you can get the probability of a diagnostic error that is less than 0.21. Taking into account all the parameters of diagnostic signals can reduce the error probability of diagnosis in a hindered nasal breathing to less than 0.1. Such a significant reduction in the probability of the error diagnostic decision (from 0.21 to 0.1) was possible by taking into account F-statistics of measured signals.

4. CONCLUSIONS

In this paper, the possibility of using of accumulated sums statistics as informative parameters of transient measurement signals to improve the reliability of diagnostics systems of biological objects was demonstrated. The use of a regression of non-stationary signals and a residual dispersion of this regression improves the effectiveness of information-measurement technologies. Such an approach provides an additional information about a biological object during its functional diagnosis. An influence of dimension of informative parameters on the probability of diagnostic error has been shown. It has been proving that an introduction of dynamic operation modes of a diagnostic object to the measurement experiment allows to obtain an information redundancy which improves a diagnosis accuracy (eg. an introduction of a forced breathing when rhinomanometry test). An example of diagnosis in rhinomanometry showed that if we use in analysis of a breath only average values of signal maxima both for a pressure drop and an air flow then we can obtain the probability of a diagnostic error that is less than 0.21. Adding the F-statistics to the measurement methodology provides significant reduce (from 0.21 to 0.1) the error probability of a diagnostic decision in testing of a nasal breathing. A prospect of this work is to study the influence of individual characteristics on the patient's breathing results in rhinomanometry diagnosis and improvement of methods for automated results analysis during testing of a nasal breathing.

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