International Journal of Electrical and Electronics Engineering (IJEEE)
ISSN: 2278-9944
Vol. 2, Issue 1, Feb 2013, 81-88

International Academy of Science, Engineering and Technology
Connecting Researchers; Nurturing Innovations

FEATURES OF DISPERSION ANALYSIS WHILE PROCESSING DYNAMIC RHINOMANOMETER SIGNAL

HUSHAM FAROUK ISMAIL SAIED[1] & OLEG GRIGOROVITSH AVRUNIN[2]

[1]Salman Bin Abdulaziz University, Department of AHS, Aflaj, Saudi Arabia

[2]National University of Radio Electronics, Department of BME, Kharkov Ukraine

ABSTRACT

This method can be considered as respect to the improvement information-measurement technology alternative control and technical diagnostics. This method allows planning multiple repeated measurement groups, obtained on the basis of non-stationary measurement signals with priori unknown spectral properties. By using the method of piecewise-linear regression approximation of measuring signals allowed obtaining additional information about the changes in random coefficients' partial linear regression.

It is proved that the additional information, besides partial regression coefficients, carries four members of the dispersion expansion. It has been proved by a practical rhinomanometric diagnosis that an additional increase in expected measurement information can reach 40% of the original. Proposed analysis of the partial line regression dispersion method provides the additional information by means of components of the dispersion expansion signal. also was proved that studying the dynamic properties of the breathing process may improve quality diagnostic procedures.

KEYWORDS: Input Signals, Dynamic Properties, Decision-Making, Measurement Information, Dispersion Analysis, Control Object, Regression Transformation, Regression Values, Residual Dispersion, Dispersion Analysis

INTRODUCTION

STATEMENT OF THE PROBLEM

Improvement in technical equipments for measuring control functional diagnostics and expansion of the nomenclature of primary transmitters without taking into account the dynamic properties of the input signals does not always lead to increased reliability and decision-making. This is mostly associated with the correlations and relationships between the components of the vector of input signals from information-measuring equipments for control or diagnosis. Increasing the dimensions of the vector does not give any new information; it simply leads to a similar result as obtained by technical improvement in measuring transmitters.

Increasing their accuracy does not reduce the uncertainty of the results measured under unrecoverable uncertainty of the properties of complex, diffuse objects of control, both biological and medical. In these objects, similar uncertainty is more often due to the dynamic properties.

ANALYSIS OF THE LITERATURE

Increase in the amount of expected measurement information is directly associated with a reduction in the uncertainty of measurement results [1,2]. In this case, the structural-algorithmic methods are the most effective, [3,4]. Their use together with information-measuring technologies' transformation of primary quantitative information into logical solutions [5], allows reducing every uncertainty.

PURPOSE

To demonstrate the possibility of using regression model dispersion analysis nonstationary test signals for receiving additional information about their dynamic properties, conditioned to the state changes of the control object.

MATHEMATICAL MODEL OF GROUP REGRESSION TRANSFORMATION

Let us consider the sequence of measurement results of the physical quantity X that indicate the moments of time of its measuring. That sequence represents many ordered by time, two-dimensional observations:

$$X(t) = \{(x_1, t_1), (x_2, t_2), \ldots, (x_N, t_N)\}. \quad (1)$$

Let Θ_0 and Θ_1 - indicate the functional states of the object control (in "normal" and, therefore, not in "normal"). The information about the type changing in object state controls carry informative parameters of test signal $X(t)$. The allocation of these parameters is linked with the task of synthesizing a mathematical model of the signal $X(t)$, in which the type change of object state causes a change, for example, in the average values of the informative parameters (coefficients of the model). In general, the model of test signal contains m conditional parameters $\overline{a_1}(\Theta_r), \ldots, \overline{a_m}(\Theta_r), r = \overline{0,1}$, average value of which changes while changing the state of object control:

$$a_l = \begin{cases} \overline{a_l}^{(0)}, \textit{если}\ r = 0; \\ \overline{a_l}^{(1)}, \textit{если}\ r = 1, \end{cases}$$

where $l = \overline{1,m}$.

In contrast to static signals, the measured value of dynamic signals provides further additional possibilities of receiving the redundancies' information by taking into account the correlation bonds of these signals with their observation time. The correlation may be manifested in an available trend (first-order and higher). Additional informational parameters in this case will be the coefficients included in similar trends in the mathematical model. These trends are represented as regression values X of time t. A residual variance such as a regression can be used to evaluate the received signal when controlling information (the higher informativeness - the lower residual dispersion). Let us consider the approximation of signal X(t) to the sequence К 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 $\hat{X}_{j,i} = A + B \cdot t_{j,i}$

is a common regression X on t, the coefficients of which determine the whole set (1) of two-dimensional observations.

The partial regressions of coefficient $\{A_j, B_j\}_1^k$ are determined by the results of corresponding group tests.

From [6], it is known that the sum S of squared deviations of observational results from the total average $\overline{X}$, given by

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

can be decomposed into five components:

$$S = S_0 + S_{WG} + S_G + S_W + S_R, \tag{2}$$

where $S_0 = w_0 B_0^2$,

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

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

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

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

Similarly,

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

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

$$w_0 = w_m + w_c \text{ б}$$

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

where $\bar{x}$, $\bar{t}$ - general average of sets $\{x_S\}_1^N$ и $\{t_S\}_1^N$,

$\overline{x_j}$, $\overline{t_j}$ - averages group over sets $\{x_{j,i}\}_{j=1}^k$ и $\{t_{j,i}\}_{j=1}^k$.

CHOICE OF INFORMATIVE PARAMETERS

Considering that the sum of S_R allows the estimation of the residual variance $\overline{S_R}$, the current regression model of the measuring result as

$$\overline{S_R} = \frac{S_R}{N-2k}, \tag{3}$$

we choose as informative parameters for statistical models

$$\begin{cases} F_0 = S_0 / \overline{S_R}; \\ F_{WG} = S_{WG} / \overline{S_R}; \\ F_G = S_G / [\overline{S_R} \cdot (k-2)]; \\ F_W = S_w / [\overline{S_R} \cdot (k-1)]. \end{cases} \tag{4}$$

These statistics are the ratio of average squares sums S_0 ,S_{WG} ,S_G и S_W to the average square of residual sum S_R, that represent random values with F- distribution (fisher-snedecor distribution) .

Dispersion expansion (2) allows calculating F- statistic (4) by realizations of the signal X(t). The conditions for this expansion are:

The normally distributed random residual

- $\varepsilon_{j,i} = x_{j,i} - \overline{x_j} - B_j(t_{j,i} - \overline{t_j})$, $\varepsilon_{j,i} \approx NORM(0, \sigma^2{}_\varepsilon)$;
- $M[\varepsilon_{j,i}] = 0$;
- $M[\varepsilon^2_{j,i}] = \sigma^2{}_\varepsilon$;
- uncorrelated residues

  $M[\varepsilon_{j,i} \cdot \varepsilon_{j,z}] = 0$ for all $i \neq z$.

The information content of any F-statistic (4) is determined by the amount of information, which can be obtained by the statistics that describe state types Θ_r control object. The importance of F-statistics'- is the independence from each other, in virtue of independent [6] members of dispersion expansion (2). That means, statistic (4) can be considered as a constituting vector

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

which can be considered as a multidimensional informative parameter. The complete information will be determined by the sum

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

where the terms of the right side of the equation can be calculated independently of each other [1].

The amount of information (5) characterizes the parameters, which are determined as constituting total dispersion measurement signal X(t) on observation interval $(0, t_N)$.

This dispersion is considered as a linear function of the residual dispersion.

$$\overline{S_R} = \frac{S_R}{(N-2K)}. \tag{6}$$

The measured value X is linear with regard to the time t under normal distribution law. Its transformation will be characterized by no correlation between average values and dispersion [7] (without any change in the width of observation interval). So, the information about the state changing Θ object, obtained by F-statistic dispersion expansion (2), might supplement the information obtained by measuring the average value X.

ESTIMATION OF THE AMOUNT OF ADDITIONAL INFORMATION

Let $F.^{(0)}$ and $F.^{(1)}$ be the statistic (4) dispersion expansion (2) (point that substitutes one of the indices '0', 'WG', 'G' or 'W'). The data of statistics, as random variables, generally change non-centrality F-distribution with V_1 and V_2 using power coefficient of freedom with non-centrality parameter $\lambda.^{(r)}$ (where $r = \overline{0,1}$)

$$F.^{(r)} \approx F_{V_1;V_2} \cdot \lambda.^{(r)} \quad (7)$$

the average and dispersion statistics $F.^{(r)}$ respectively are equal [8]:

$$\chi_1^{(r)} = \frac{V_2}{(V_2-2)}\left(1+\frac{\lambda.^{(r)}}{V_1}\right), \quad (8)$$

$$\chi_2^{(r)} = \frac{2V_2^2}{(V_2-2)(V_2-4)}\left(\frac{2\lambda.^{(r)}}{V_1}+\frac{(1+\lambda.(^{r}))^2}{(V_2-2)}\right), \quad (9)$$

The amount of information received by Statistics $F.^{(r)}$ is given by [1]:

$$I = \log_2 \sqrt{1+\left(\frac{\sigma_F}{\sigma_{\Delta F}}\right)^2}, \quad (10)$$

where σ_F^2 - dispersion of F-statistic before measurement (control),

$\sigma_{\Delta F}^2$ - dispersion of F-statistic after the measurement.

From expressions (8) and (9), σ_F^2 and $\sigma_{\Delta F}^2$ can be defined as:

$$\sigma_F^2 \geq (\chi_1^{(0)} - \chi_1^{(1)})^2 / 12,$$

$$\sigma_{\Delta F}^2 \geq 4(\max \chi_2^{(r)}).$$

Table 1 presents the results of the dispersion analysis of the measured values of signal X(t) for conditions Θ_0 and Θ_1 of the biological control object (N=9, K=3, nj =n for all $j = \overline{1,3}$).

The same table gives the values of information amount (in bits), at $\chi_1^{(0)} = F.^{(0)}$; $\chi_1^{(1)} = F.^{(1)}$. The dispersion $\chi_2^{(r)}$ is presented as a function of average $\chi_1^{(r)}$ [8] as:

$$\chi_2^{(r)} = \frac{4V_2}{(V_2-4)} \cdot \chi_1^{(r)} + \frac{2V_1^2}{(V_2-4)}\chi_1^{(r)2} - \frac{4V_2^2}{(V_2-2)(V_2-4)}.$$

Table 1: Dispersion Analysis Results

№	Mean Square Deviations	Number of Freedom Degrees	Mean Square	F-Statistics	I (bits)
1	$S_0^{(1)} = 0{,}736502$ $S_0^{(1)} = 1{,}857845$	$V_0 = 1$	$\overline{S_0}^{(0)} = S_0^{(0)}$	$F_0^{(0)} = 92{,}896$ $F_0^{(1)} = 368{,}25$	0,92
2	$S_{WG}^{(1)} = 0{,}015786$ $S_{WG}^{(1)} = 0{,}011872$	$V_{WG} = 1$		$F_{WG}^{(0)} = 1{,}991$ $F_{WG}^{(1)} = 2{,}353$	0,00078
3	$S_G^{(0)} = 0{,}0088707$ $S_G^{(1)} = 0{,}11395$	$V_G = 1$		$F_G^{(0)} = 1{,}11888$ $F_G^{(1)} = 22{,}587$	0,17
4	$S_\varepsilon^{(0)} = 0{,}039641$ $S_\varepsilon^{(1)} = 0{,}025225$	$V_\varepsilon = 1$	$\overline{S_\varepsilon}^{(0)} = 0{,}007928$ $\overline{S_\varepsilon}^{(1)} = 0{,}005045$	-	-

Note: To provide conditions $V_2 > 4$, sums S_W and S_R were combined. The number of freedom degrees ($V_2 = V_\varepsilon = 5$) were correspondingly increased.

The total information amount $I_F = 0{,}92 + 0{,}00078 + 0{,}17 = 1{,}09078$ (bit).

If we consider that value [1] is the information amount obtained by measuring the mean value of signal X(t), that is, evaluation by $\overline{X}^{(0)}$ and $\overline{X}^{(1)}$ gave a value $I_{\overline{X}} = 2{,}69$(bits), then the additional increment $I_{\overline{X}} = 1{,}09078$ (bit) is at least 40% higher, which points to the proposed effectiveness of the method of dispersion transformation measuring signal. In Fig. 1 show rows of time for measured values of the signal X(t) for $\Theta = \Theta_0$ and $\Theta = \Theta_1$ with serial regression approximation rows. From the figures, the change in angular coefficients' partial regression is clearly visible, when changing the state of control object.

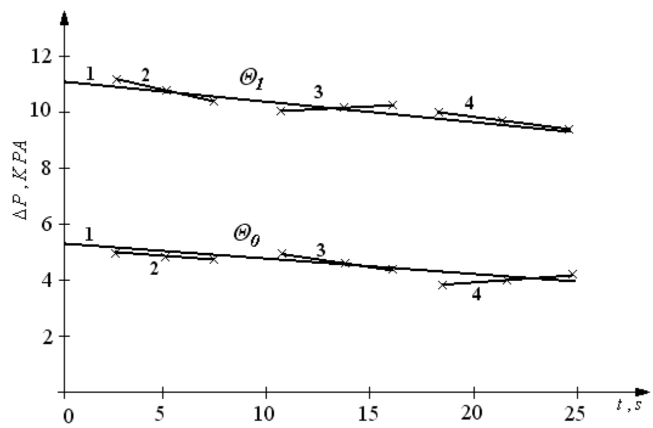

Figure 1: Time Row of Measured Signal Values for Pressure ΔP(T) with Sequential Regression Approximation Rows in Normal (Condition Θ_0) and Pathology(Condition Θ_1) . Designation: 1 - Direct Common Regressions, 2, 3, 4 - Direct Partial Regressions

PRACTICAL IMPLEMENTATION

The results of the approved work on the experimental data are obtained from previous active rhinomanometer results from the database of otorhinolaryngologic department, Kharkiv Regional Hospital, by using the developed rhinomanometer TNDA-PRH [9]. The process took place while carrying out the rhinomanometric study of the dependence of air flow passing through the nasal passages, on pressure drop between the inner exit of the nasal cavity (choanae) and the atmospheric pressure. In this case, and from the graphs, the peak values of pressure drop (see Fig. 1) and from the air flow rate in nasal cavity, it is clear that studying the dynamic properties of the breathing process may improve quality diagnostic procedures.

CONCLUSIONS

Using the method of piecewise-linear regression approximation of measuring signals allowed obtaining additional information about the changes in random coefficients' partial linear regression. It is proved that the additional information, besides partial regression coefficients, carries four members of the dispersion expansion indicating the possibility of obtaining additional information.

It has been proved by a practical rhinomanometric diagnosis that an additional increase in expected measurement information can reach 40% of the original. The last one was obtained by the analysis of average value changes of measured signals.

Proposed analysis of the partial line regression dispersion method provides the additional information by means of components of the dispersion expansion signal. Such procedure is equivalent to the procedure of spectral analysis when no information about energy spectrum is available by the average measurement signal, because the studied sequence measurement results are time rows.

WORK PROSPECTS

This method can be considered as respect to the improvement information-measurement technology alternative control and technical diagnostics when there is limitations in time for observation (or by the number of measurements) at a priori uncertainty properties of control object and diagnostics. This method allows planning multiple repeated measurement groups, obtained on the basis of non-stationary measurement signals with priori unknown spectral properties.

REFERENCES

1. Ornatisky P. P,Theoretical foundations of information-measuring equipment, Kiev: Previous School, pp:455. 1983.
2. Shapov P. F,Normalization of metrological uncertain information signals for measuring control systems of dynamic objects, Mechanical object construction, № 1,pp: 280-286, 2006.
3. Volodarsky E.T, Kukharchuk V.V, PodJarenko V.O, Serdyuk G. B,Metrological support measurements and control, Vinnitsa: Velez, pp: 219, 2001.
4. Kondrashov S. I,Methods for increasing the accuracy of the systems testing electrical trials for measuring transducers in operation mode, Kharkiv: National Technical University, Kharkov Polytechnic University, pp: 224, 2004.

5. Malaychuk V. P, Mozgovoy O.V, Petrenko O. M,Information-measuring technology nondestructive control, Dnipropetrovsk National University PBB, pp: 240, 2001.
6. Johnson N., Lyon F,Statistics and experiment planning in technology and science, Methods of experimental design, translated from English under the supervision of E.K. Letsko, Moscow: world, pp: 520, 1981.
7. Juvinsky A.N, Juvinsky V.N,Engineering express-analysis random processes, Moscow: energy, pp: 112, 1979.
8. G. Boss,Dispersion analysis, translated from English, B.A. Sevastyanova and V.P. Chistyakova, Moscow: Science, pp: 512, 1980.
9. Avrunin O.G.,Methods of calculating the diameter of venture nozzle for a device by determination of fall casting-consumables characteristics of nasal passages, Industrial hydraulics and pneumatics, n:2(28), pp:62-66, 2010.

AUTHOR’S DETAILS

Husham Farouk Ismail Saied 1975, Sudan,khartum. B.Sc. physical and biomedical electronics Faculty of BME, Kharkov State technical University of Radio Electronic , Ukraine.2001-2003. M.Sc. in Physical and biomedical electronics, Faculty of BME, Kharkov State technical University of Radio Electronic ,Ukraine.2010- till this day, Ph.D student, in Biomedical Engineering, Kharkov State technical University of Radio Electronic , Ukraine.

Oleg Grigorovitsh Avrunin, Associate Professor, physical and biomedical electronics , Faculty of BME, Kharkov State technical University of Radio Electronic , Ukraine. Scientific specialty: Medical Devices and Systems. Research Interests: Design of macroscopic techniques for diagnosis and surgical interventions planning inside the human brain. Technique and methods for medical navigation systems and medical information systems. Technique and methods for diagnosis and surgical interventions planning of the upper respiratory tract. Visualization methods. Imaging techniques for automation processing of medical images and analysis.