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Information Quantity Estimation of Multiplex Measurement Instrumentation

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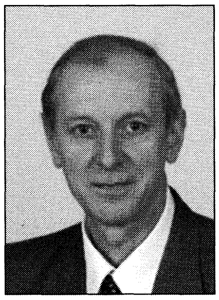

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Abstract

The measurement instrumentation information theory methodology makes it possible to take into account both the metrological requirements to the restoration of measurement signal as well as to the measurement object dynamic properties. The information quantity, received from a certain measuring channel is defined as a difference between an initial (prior to the measuring) and a conditional (following the measuring) Intropies which are based on the corresponding distributions laws. The measurement object information quantity received by the multiplex instrument with the needed accuracy is estimated.

Streszczenie

Rozwój techniki komputerowej oraz informatyki spowodowały, z jednej strony, wprowadzanie mikroprocesorów w strukturę przyrządu pomiarowego, a z drugiej strony - wykorzystywanie pojęć teorii informacji przy analizie procesów pomiarowych. Miernictwo coraz bardziej staje się dziedziną interdyscyplinarną. Z punktu widzenia informacyjnej teorii pomiaru można ocenić ilość informacji pobranej za pomocą przyrządu pomiarowego od obiektu badanego. W proponowanym artykule metodologia obliczenia ilości informacji dla przyrządu jednokanałowego została rozszerzona na wielokanałowy przyrząd czyli system pomiarowy. Przy założeniu modelu sygnału pomiarowego w postaci losowego stacjonarnego procesu z normalnym rozkładem gęstości prawdopodobieństwa i ograniczonym pasmem amplitudowym oraz z normalnym rozkładem błędu pomiarowego znaleziono zależności dla obliczenia ilości informacji. Te oceny pozwalają uwzględnić dynamiczne właściwości obiektu badanego oraz metrologiczne kryteria oceny jego stanu. Zostały sformułowane również kryteria dotyczące szybkości przetwarzania tej informacji przez przyrząd cyfrowy. Ustalono iż informacyjną efektywność można zwiększyć przez zmniejszenie wymagań co do szybkości przetwarzania informacji pomiarowej oraz mocy sygnału pomiarowego.

Keywords: entropy, multichannel system, entropy estimation parameters
Słowa kluczowe: ilość informacji, wielokanałowy system pomiarowy, szybkość opracowania informacji

1. Introduction

The investigated object or phenomena become more complex and functionally shared. Obviously, the multiplex measurement instrumentation with the application of numerous information technologies (such as the neuronal networks, expert system, fuzzy logic methodology, compression techniques etc.) is used in their serving. Nowadays we observe the combination of different techniques solving of the measuring problems, such as an information methodology combined with the traditional metrology, the so-called information measurement theory [4, 11, 12]. The measurement instrumentation information theory methodology makes it possible to take into account both the metrological requirements to the restoration of measurement signal as well as to the measurement object dynamic properties. The multiplex instrumentation information rate estimation combines such requirements, and the best decision corresponds to the object parameters entropy estimation [1]. The multiplex measurement instrumentation is created to decrease the uncertainty of the observed object. In the information theory sense, such an uncertainty is described by the entropy of the object being measured [2, 8]. Therefore, this entropy estimation mapping permits to describe the object information state as well. In practice, such a task realization corresponds to the instrumentation operating information quantity calculation due to compression algorithms and enumerative coding [6]. The information theory was successfully applied to the measurement tasks [7, 9], and its glossary was shared at the multiplex instrumentation [5].

2. Measuring signal model

The partly-stationary random process as the measuring signal adequate mathematical model can be used, and its capability to transfer a certain quantity of information depends on its entropy. On the one hand (from theoretical viewpoint), continuous random variables do not envisage the terminable absolute uncertainty measure implication, and on the other hand (from practical viewpoint), the digital continuous measurands representation is applied, which requires using the quantization and discretization operations. So, in any measuring channel, the analogue to digital conversion is carried out.

The i-th channel discreted measuring signal $X_i(t_j)$, i.e. the random process with the discrete time t_j and with the continuous informative parameter X_i as the random variable population, which are described by a m - dimensional distribution law $p_X(x_1, x_2, \dots, x_m)$, is introduced through joint distribution density of probabilities [3, 10]:

$$p_1(x_1); p_2(x_1, x_2); \dots; p_m(x_1, x_2, \dots, x_m)$$

here $x_1 = X_i(t_1), \dots, x_j = X_i(t_j), \dots, x_m = X_i(t_m)$.

For any of the m distributions, the differential entropy sequence $H_1; H_2; \dots; H_j; \dots$ is obtained:

$$H_m = -\overset{(m)}{\iint \dots \int} p_m(x_1, x_2, \dots, x_m) \log\left[d^m p_m(x_1, x_2, \dots, x_m)\right] dx_1, dx_2 \dots dx_m \quad (1)$$

The differential entropy being the difference of the analyzable and of the volume ($V = d^m$) uniform distribution indeterminacy (note that the standard distribution characterizes uncorrelated values) ensures the comparison of these indeterminacies, corresponding to one sample.. That is, the measuring signal information entropy and, therefore, the measuring information quantity definition is reduced to one sample value.

The real measuring signal is featured by a restricted normal distribution law [10], as its amplitude range is limited, namely:

$$p_i(x) = \begin{cases} \dfrac{1}{c_1 \sqrt{2\pi}\sigma(X_i)} \exp\left\{-\dfrac{(x_i - m_x)^2}{2\sigma^2(X_i)}\right\} & if \quad x_{\min} \le x_i \le x_{\max} \\ 0 & if \quad x_i > x_{\max} \ or \ x_i < x_{\min} \end{cases} \quad (2)$$

here c_1 is the particular weight coefficient, which is determined by a distribution normalization requirement; $\sigma(X_i)$ and m_x are the distribution parameters; (x_{min}, x_{max}) is the measuring signal possible range of values.

Between the restricted and the unlimited normal distribution mean-square deviations there is a particular relation [10]:

$$\frac{\sigma_x}{\sigma(X_i)}=\sqrt{1-\sqrt{\frac{2}{\pi}}\left(\frac{\Delta}{\sigma}\right)\frac{e^{-\frac{1}{2}\left(\frac{\Delta}{\sigma}\right)^2}}{\Phi\left(\frac{\Delta}{\sigma}\right)}}=v \qquad (3)$$

here $\Delta=0.5(x_{max}-x_{min})$, $\Phi(\xi)=\frac{2}{\sqrt{2\pi}}\int_0^{\xi}\exp\left(-0.5\xi^2\right)d\xi$.

The entropy of the random variable subordinated to the restricted normal distribution is as follows [10].

$$H(X_i)=-M\left[\log p_i(x)\right]=\log\left[c_1\sqrt{2\pi}\frac{\sigma_x}{v}e^{0.5v^2}\right] \qquad (4)$$

3. The single channel measuring signal information quantity estimation

In practice, the measuring signal transformation is realized with some errors present, Thus, it is essential to know about the random value X_i information quantity, which is present in a random variable X_{iN}, obtained during the measuring procedure. Therefore, the information quantity, received from a certain measuring channel, is defined as a difference between an initial (prior to the measuring) and a conditional (following the measuring) entropies, i.e.

$$I(X_i)=H(X_i)-H\left(X_i/X_{iN}\right) \qquad (5)$$

On the one hand, the joint distribution law of the measuring result X_{iN}, and the particular true measurand value X_i, can be received as a composition of the distribution laws of independent random variables, i.e. the measurand X_i and the absolute error ΔX, as it holds that $X_{iN}=X_i+\Delta X$. On the other hand, the joint distribution law of these variables is as follows $p(x_i,x_{iN})=p(x_{iN})p\left(x_i/x_{iN}\right)$.

Hence, at the distribution law $p(x_{iN})$ of the measuring result value X_{iN}, its corresponding measurand conditional distribution law $p\left(x_i/x_{iN}\right)$ can be given as $p\left(x_i/x_{iN}\right)=\frac{p(x_i,x_{iN})}{p(x_{iN})}$. The conditional entropy corresponding to a defined measured value $X_i=x_i$, will be determined as:

$$H_{X_i=x_i}\left(X_i/X_{iN}\right)=-M\left[\log p\left(x_i/x_{iN}\right)\right]=-\int_{-\infty}^{\infty}\left[\log p\left(x_i/x_{iN}\right)\right]p\left(x_i/x_{iN}\right)dx_i.$$

The entropy, which has remained after the appearance of the measuring result X_{iN}, may be received by a conditional entropy average, according to the distribution law $p(x_{iN})$ of the measuring result X_{iN}:

$$H\left(X_i/X_{iN}\right)=\int_{-\infty}^{\infty}H_{X_i=x_i}\left(X_i/X_{iN}\right)p(x_{iN})dx_N=$$

$$=-\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}p(x_i,x_{iN})\log\frac{p(x_i,x_{iN})}{p(x_{iN})}dx_i dx_{iN}. \qquad (6)$$

The information quantity (5), obtained for the i-th channel of the multiplex instrumentation due to the measuring procedure, is defined according to the expressions (3) and (6) as follows:

$$I(X_i)=H(X_i)-H\left(X_i/X_{iN}\right)=-\int_{-\infty}^{\infty}p(x_i)\log\left[p(x_i)\right]dx_i+\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}p(x_i,x_{iN})\log\frac{p(x_i,x_{iN})}{p(x_{iN})}dx_i dx_{iN}=$$

$$=-\int_{-\infty}^{\infty}\left[\int_{-\infty}^{\infty}p(x_i,x_{iN})dx_{iN}\right]\log\left[p(x_i)\right]dx_i+\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}p(x_i,x_{iN})\log\frac{p(x_i,x_{iN})}{p(x_{iN})}dx_i dx_{iN}=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}p(x_i,x_{iN})\log\frac{p(x_i,x_{iN})}{p(x_{iN})p(x_i)}dx_i dx_{iN}.$$

The joint distribution law of the variables X_i and X_{iN} can be also found as well, having taken the conditional distribution law $p\left(x_{iN}/x_i\right)$ of the measuring result X_{iN}, corresponding to a measurand defined value $X_i=x_i$, which coincides with the error ΔX distribution law, that is:

$$p\left(x_{iN}/x_i\right)=\frac{1}{\sqrt{2\pi}\sigma(\Delta X)}e^{-\frac{(\Delta x)^2}{2\sigma^2(\Delta X)}}=\frac{1}{\sqrt{2\pi}\sigma(\Delta X)}\exp\left\{-\frac{(x_{iN}-x_i)^2}{2\sigma^2(\Delta X)}\right\} \qquad (7)$$

and thus $p(x_i,x_{iN})=p(x_i)p\left(x_{iN}/x_i\right)$.

The distribution law of the measuring result X_{iN} in the i-th channel is obtained by its components X_i and ΔX distribution laws composition, as it is defined by the independent measurand true value and the error sum. Really, this is the distribution law composition of the restricted normal probability density, both the measurand X_i and the error ΔX. The measuring signal restoring error mean-square deviation is inappreciable in comparison with the measuring signal mean-square deviation itself (for example, $\delta\le 0.01$). Therefore, at the measuring signal distribution law background, an error value will be concentrated close to its mean value. Thus, the error value will be with the probability close to unity in the signal restricted value range. So, it is possible to consider the existence of an error distribution law practically in unlimited boundaries. For a measuring result X_{iN}, the distribution law can be determined by a composition of a measuring signal X_i restricted (2) and an error ΔX unlimited normal distribution laws, accordingly, namely:

$$p(x_{iN})=\int_{-\infty}^{\infty}p(x_i)p_{\Delta x}(x_{iN}-x_i)dx_i=\int_{x_{мін}}^{x_{макс}}\frac{1}{c_1\sqrt{2\pi}\sigma(X_i)}e^{-\frac{(x_i-m_x)^2}{2\sigma^2(X_i)}}\frac{1}{\sqrt{2\pi}\sigma(\Delta X)}e^{-\frac{(x_{iN}-x_i-m_\Delta)^2}{2\sigma^2(\Delta X)}}dx_i=$$

$$=\frac{1}{c_1 2\pi\sigma(X)\sigma(\Delta X)}\int_{x_{мін}}^{x_{макс}}e^{-\frac{1}{2\sigma^2(X_i)\sigma^2(\Delta X)}\left\{\sigma^2(\Delta X)\left[x_i^2-2m_x x+m_x^2\right]+\sigma^2(X_i)\left[x_i^2-x_i(x_{iN}-m_\Delta)+(x_{iN}-m_\Delta)^2\right]\right\}}dx=$$

$$=\frac{1}{c_1 2\pi\sigma(x)\sigma(\Delta x)}\int_{x_{мін}}^{x_{макс}}e^{-\frac{1}{2\sigma^2(X_i)\sigma^2(\Delta X)}\left\{\left[\sigma^2(\Delta X)+\sigma^2(X_i)\right]x_i^2-2x_i\left[m_x\sigma^2(\Delta X)+(x_{iN}-m_\Delta)\sigma^2(X)\right]+\left[m_x^2\sigma^2(\Delta X)+(x_{iN}-m_\Delta)^2\sigma^2(X)\right]\right\}}dx$$

here $\sigma(X_i)$ or $\sigma(\Delta X)$, m_x or m_Δ are the distribution law parameter "sigma" and the mean value for a measuring signal or error, accordingly (let us analyze an exponential curve index of the latter expression and introduce it as a square trinomial replaceable, having given it as a product).

Hence, (figure 1 - for normalized values):

$$p(x_{iN})=\frac{\exp\left\{-\frac{(x_{iN}-m_N)^2}{2\sigma^2(X_{iN})}\right\}}{c_1\sqrt{2\pi}\sigma(X_{iN})}\left\{F\left[\left(\frac{x_{iN}-m_N}{\sigma(X_{iN})}\right)\frac{1}{\delta v_i}-\left(\frac{x_H-m_X}{\sigma(X_i)}\right)\sqrt{1+\frac{1}{\delta_i^2 v_i^2}}\right]-F\left[\left(\frac{x_{iN}-m_N}{\sigma(X_{iN})}\right)\frac{1}{\delta v_i}-\left(\frac{x_B-m_X}{\sigma(X_i)}\right)\sqrt{1+\frac{1}{\delta_i^2 v_i^2}}\right]\right\} \qquad (8)$$

here $\{F(z)\}$ is the probability integral; $\delta_i=\frac{\sigma_\Delta}{\sigma_{xi}}=\frac{\sigma(\Delta X)}{v_i\sigma(X_i)}$ and $v_i=\sigma_{xi}/\sigma(X_i)$ is the relative restoring signal error and the i-th measuring signal mean-square deviation to its distribution law parameter ratio (3), accordingly; $\sigma(X_{iN})=\sqrt{\sigma^2(X_i)+\sigma^2(\Delta X)}$ is the measuring result distribution law parameter.

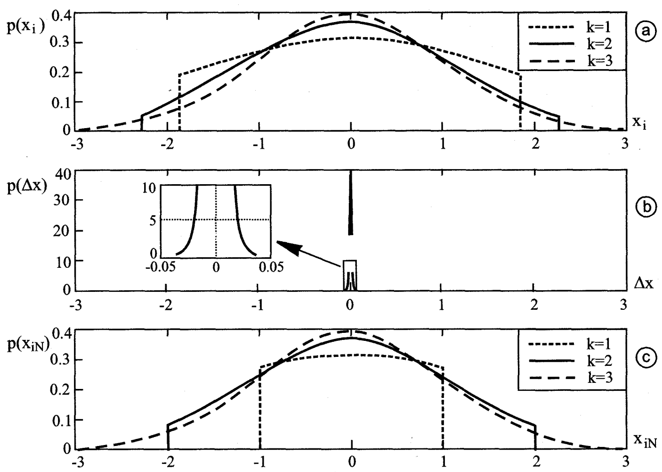

Fig. 1. The i -th channel measuring result distribution law composition for different values of parameters k(a) and d (b).

We can get the i -th measuring channel information quantity (5), using equations (4) and (6)-(8), namely:

$$I(X_I)=H(X_I)-H\left(X_I/X_{IN}\right)=log\left[\frac{c_1\sqrt{1+\delta_i^2 v_i^2}}{\delta_i v_i\{F_p(k)\}}e^{-\frac{1}{2}\left(\frac{1-v_i^2}{1+\delta_i^2 v_i^2}\right)}\right] \quad (9)$$

here $\{F_p(k)\}$ is the probability integral value for a certain parameter k; k is the measuring signal amplitude maximum value x_{max} to its distribution law parameter $\sigma(X_{iN})$ ratio.

Thus, the information quantity, obtained at the measuring procedure, will increase with a restoring measuring signal relative mean-square error diminution. If in expression (9) we accept $c_1=v_i=\{F_p(k)\}=1$, then we shall receive the relations for an information quantity estimation [8], true for the measuring signal standard (which is unlimited) normal distribution law, namely:

$$I(X_i)=\log\left[\sqrt{2\pi e}\sigma(X_i)\right]-\log\left[\sqrt{\frac{2\pi e}{1+\delta_i^2}}\sigma(\Delta X)\right]=\log\sqrt{1+\frac{1}{\delta_i^2}} \quad (10)$$

For comparison, we can find the ratio between the information quantity, obtained by the i -th channel while using two measuring signal models, through the founded on the standard (10) and on the restricted (9) normal distribution law, accordingly (fig. 2).

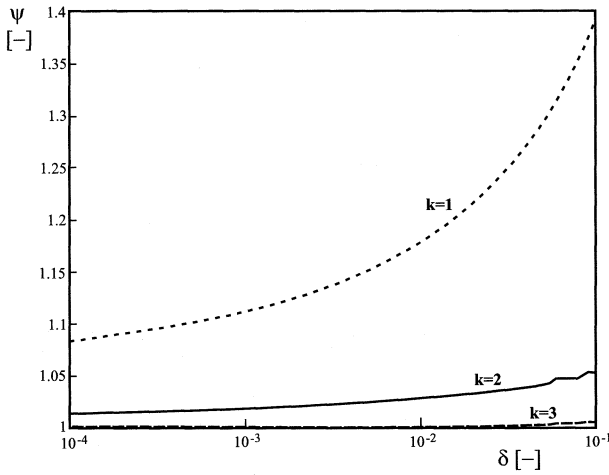

Fig. 2. The i-th channel ratio ψ of the information quantities versus the relative signal restriction error δ_i for distribution law different multiplicity values k function.

The measuring signal distribution law restriction diminishes the i -th channel information capability. If the measuring signal maximum amplitude values to a distribution law parameter "sigma" value k varies from 1 up to 3, then compared with an unlimited normal distribution law, the measuring channel information quantity diminishes from 1.19 up to 1.003 times, accordingly (at $\delta=0.01$) and from 1.087 up to 1.002 times, accordingly (at $\delta=0.0001$). That is, with a signal maximum value growing, the channel at a limitation comes closer to the channel without limitation information capability, and, in addition, with an admissible restoring error diminution, these differences become smaller. It is established that the information effectiveness of the measuring data processing at the given measuring signal restoring error, depends on a signal processing duration. Therefore, it is necessary to decrease the requirements to the measuring procedure rate and to the measuring signal power.

4. The multiplex instrumentation total information quantity estimation

The multiplex instrumentation serves the measuring object n random continuous variables $X_1,X_2,...,X_n$, which are described by the probability density $p_X(x_1,x_2,...,x_n)$. That is, it forms the vectorial value $\vec{X}_N=(X_{1N},X_{2N},...,X_{nN})$ concerning a random vector $\vec{X}=(X_1,X_2,...,X_n)$, subordinated to the joint distribution law $p(\vec{X},\vec{X}_N)=p(\vec{X}_N)p\left(\vec{X}/\vec{X}_N\right)=p(\vec{X})p\left(\vec{X}_N/\vec{X}\right)$ of these vectors, here $p\left(\vec{X}/\vec{X}_N\right)$ and $p\left(\vec{X}_N/\vec{X}\right)$ is the conditional distribution law of a vector $\vec{X}$ provided that at the measuring procedure a vector $\vec{X}_N$ is obtained, and the conditional distribution law of a vector $\vec{X}_N$ provided that by an instrumentation there is served an object parameter totality $\vec{X}$, accordingly. An entropy of two vectorial values $\vec{X}$ and $\vec{X}_N$ system is as follows:

$$H(\vec{X},\vec{X}_N)=-M\left\{log\left[p(\vec{X},\vec{X}_N)\right]\right\}=-M\left\{log\left[p(\vec{X}_N)\right]\right\}-$$
$$-M\left\{log\left[p\left(\vec{X}/\vec{X}_N\right)\right]\right\}=-M\left\{log\left[p(\vec{X})\right]\right\}-M\left\{log\left[p\left(\vec{X}_N/\vec{X}\right)\right]\right\}=$$
$$=H(\vec{X}_N)+H\left(\vec{X}/\vec{X}_N\right)=H(\vec{X})+H\left(\vec{X}_N/\vec{X}\right),$$

here $H\left(\vec{X}/\vec{X}_N\right)$ and $H\left(\vec{X}_N/\vec{X}\right)$, $H(\vec{X})$ and $H(\vec{X}_N)$ are the relevant conditional and marginal entropy pairs.

In particular, we receive:

$$H(\vec{X})=H(X_1,X_2,...,X_n)=-M\{log[p(x_1,x_2,...,x_n)]\}=$$
$$=-\int_{-\infty}^{\infty}...\int_{-\infty}^{\infty}log[p(x_1,x_2,...,x_n)]p(x_1,x_2,...,x_n)dx_1,dx_2,...dx_n$$

If random variables $X_1,X_2,...,X_n$ are independent, then $p(x_1,x_2,...,x_n)=\prod_{i=1}^{n}p(x_i)$ and $log[p(x_1,x_2,...,x_n)]=\sum_{i=1}^{n}log[p(x_i)]$.

Thus, $H(\vec{X})=-M\left\{\sum_{i=1}^{n}log[p(x_i)]\right\}=-\sum_{i=1}^{n}M\{log[p(x_i)]\}=\sum_{i=1}^{n}H(X_i)$

here $H(X_i)$ is the random variable X_i entropy.

At independent components of a vector, the relevant components of a vector are also independent, that is: $p\left(\vec{X}/\vec{X}_N\right)=\prod_{i=1}^{n}p\left(X_i/X_{iN}\right)$ and $H\left(\vec{X}/\vec{X}_N\right)=\sum_{i=1}^{n}H\left(X_i/X_{iN}\right)$.

The information quantity, which is generally possible to receive concerning the measuring object from the multiplex instrumentation:

$$I(\vec{X}) = H(\vec{X}) - H\left(\vec{X}/\vec{X}_N\right)$$

For an independent random variable set $\{X_i\}$ it holds:

$$I(\vec{X}) = \sum_{i=1}^{n} H(X_i) - \sum_{i=1}^{n} H\left(X_i/X_{iN}\right) = \sum_{i=1}^{n}\left[H(X_i) - H\left(X_i/X_{iN}\right)\right] = \sum_{i=1}^{n} I(X_i) \qquad (11)$$

that is, the instrumentation information quantity on the whole (11) consists of the total sum of information quantities from all measuring channels (9). The same concerns the multiplex instrumentation productivity, i.e. it is determined by the sum of its channel components.

5. Conclusions

The thesaurus of the information measurement theory is shared on the multiplex measurement instrumentation. The expression for the multiplex instrumentation information capacity calculation depends on the measurement signal models and on the precision value of the measuring parameter. Based on the use of the measuring signal and the error as partly-stationary random process with a restricted normal distribution law mathematical model, there were received relations for the information quantity estimation of the multiplex instrumentation, which serves a measured object. The measuring signal distribution law boundedness diminishes the channel informative capability. The information effectiveness of the measuring information with the given measuring signal restoring error processing depends on the procedure duration. Therefore, to improve the informative effectiveness of the multichannel instrumentation, it is necessary to diminish the requirements to its processing rate.

Bibliography

[1] C. Arndt: Information Measures. Springer, Heidelberg 2001.

[2] T.Cover, J.Thomas: Elements of Information Theory. John Wiley and Sons, Inc., New York/Chichester/Brisbane/Toronto/Singapore 1991.

[3] W.W.Dmitrijev: Prikladnaja teorija informaciji.Wysszaja szkola, Moskwa 1989.

[4] L. Finkelstein: Innovation through Design. Proceedings of the XVI IMEKO World Congress (September 25-28, 2000, Vienna-Wien, Austria), Vienna, 2000.

[5] O.Iwachiw: Informatywnist' bahatokanalnych zasobiw wymiriuwannia // Wymiriuwalna technika ta metrologija 2002, Wyp. 59.

[6] I.D.Kalasznikow, W.S.Stepanov, A.W.Czurkin: Adaptiwnyje sistemy sbora i peredaczi informaciji. Energija, Moskwa 1975.

[7] P.W.Novickij: Osnowy informacionnoj teorii izmerenij. Energija, Leningrad 1968.

[8] S.Obozovskyi: Informacijno - wymiriuwalna technika (metodologiczni pytannia teoriji wymiriuwan'). SDO, Kyjiw 1993.

[9] J.Piotrowski: Teoria pomiarów. Pomiary w fizyce i technice. Państwowe Wydawnictwo Naukowe, Warszawa 1986.

[10] W.N.Pugaczow,N.R.Lifszic: Werojatnostnyj analiz system awtomaticzeskogo uprawlenija. Cz.1. Werojatnostnyje i staticzeskije charaakteristiki processow. Linejnyje, stacionarnyje i nestacionarnyje systemy. Sowietskjye Radio, Moskwa 1969.

[11] L.A.Zadeh: From Computing with Numbers to Computingw ith Words-from Manipulation of Measurements to Manipulation of Perceptions. Proceedings of the XVI IMEKO World Congress (September 25-28, 2000, Vienna-Wien, Austria), Vienna, 2000.

[12] H. Zemanek: Measurement Technology- Information Technology. Proceedings of the XVI IMEKO World Congress (September 25-28, 2000, Vienna-Wien, Austria), Vienna, 2000.

Tytuł: Ocena ilości informacji w wielokanałowych systemach pomiarowych

Artykuł recenzowany