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STRATEGIES OF INFORMATION IDENTIFICATION FOR EMERGENCY SITUATIONS JUMPS IN COAL MINES

The problem of identification is defined by practical applications related to the characteristics of accidents during their investigation. Identification is aimed at solving the problem of detecting emergency situations (ES), under which accidents of various types occur, often due to the influence of so-called rarely encountered and uncontrollable factors. It is difficult to identify information about the signs of ES in mines. Really, many mine accidents are triggered by sudden changes in natural and technical factors. Due to these jumps, it is not always possible to determine the factors that are more or less manageable by the means and methods of safety assurance available to modern mines. Their characteristics are usually unknown. To accurately identify complex ES that occur abruptly, it is necessary to implement adaptive information identification, which is particularly crucial in the presence of unknown external influences. In this article, a criterion of minimum distinguishing information was used to estimate the unknown distribution function of change in the methane content in the mining faces. A modified strategy for identifying ES characterizing accidents such as flooding and mining blockages is proposed. It is based on the method of information dichotomy and diagonalization of the information matrix. Formulas have been obtained for calculating dividing information for unknown distributions, as well as for the evaluation of the identification error probability.

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Introduction

Let us make an attempt to examine processes of identification as a case-study of experimental investigation of emergency situations (ES) in the course of mining. Simulation modeling of such accidents as rock falls, collapses and flooding in mines, or shutdowns of mine hoists or main fans [1] shows that such underground accidents are fuzzy objects with a changing dynamics. On this basis, a detailed description may be nonoptimal and absolute determination of ES may be impossible. Moreover, identification can be faced with an uncertainty because of noise, unclassifiability of some ES or random scatter of values of signs of some ES. This is confirmed by the research of the ES information properties [2]. Therefore, acquisition of side information from a random vector of sign measurements {x} in apparent probabilities of hypotheses H_i and conditional probabilities of classes A_i of accidents only allows probabilistic identification of ES. Irrespective of the nature of an ES, is signs are expressed either numerically or qualitatively. This allows plotting a probability distribution and further processing of realizations. The issues of the identification accuracy evaluation were also addressed [2].

Selection of sampling volume of realizations

The volume of sampling of realizations, the information content of signs and their statistical relationships have a crucial value. The latter factor was sufficiently covered by the analysis [2]. Relative to some ES and accidents, the sampling volume can vary within wide ranges. Accurate determination of a sampling volume is only possible with the sufficient statistics collected on a certain ES, and this naturally complicates identification. In case of infrequent and uncontrollable events, such as main roof collapse in a worked-out space of a longwall face, local methane accumulation in some dead-air space and other complex techno-natural events, such statistics is almost impossible to obtain. Thus, identification of characteristics of ES is critical in this case. It is possible to use the known approaches [3] when the initial estimated values can be calculated by the statistical methods. The volumes of the consistent samplings are determined depending on a permissible error and on congruent probabilities of a certain sign frequency in the measured realization and this sign value in the general population. The identification result is evaluated according to a posterior conditional probability of a *j*-th ES in the measurements of the signs x $P(x|B_j)$, which is calculated from the known Bayes formula in terms of the probability density function $P(x)$ and the conditional probability function $P(B_j|x)$. If the signs of ES remain unaltered for the measurement period, the probability density function $P(B_j|x)$ at x = const represents a distribution of measurement errors relative to the unaltered sign value. Here, $P(x)=P(x_1, x_2,..., x_n)$ is the probability of belonging of values of the *j*-th ES signs to the certain intervals of an *i*-th class. In practice, as a rule, we have a low accuracy of measurement and the samplings are insufficiently large. Therefore, we have a high dispersion of the conditional probability function, and this leads to a substantial difference between $P(x)P(B_j|x)$ and $P(B_j|x)$. In this case, the maximum of the conditional probability shifts to the range of high values of the a priori distribution $P(x)$. If measurements are small in number, the posterior distribution becomes discrete and governed by the weighted mean of the a priori distribution. In case of a single measurement of a sign, the conditional probability density function is a delta-function and the posterior distribution turns into the posterior probability $\gamma_o P(x)$ with a normalization function γ_o. The absence of the grave proofs of the constancy of some object's signs, is assumed to be a disadvantage of this approach. In the other approach, the sufficiency of the statistics required for estimating unknown distributions, is achieved at the Kullback's principle of minimum distinguishing information [4] according to which we put the sampling under analysis in the class with minimum estimates of distinguishing information. Gas content distribution in mine air, as a random value, belongs to exponential distributions [5]. Such distributions are the Gaussian, chi-squared, Poisson, binomial, gamma, Weibull and other distributions. Such distribution follows from solving a variational problem of conditional extremum. The information measure is simply calculated in this case in terms of polynomial theory. We need only to perform summations and use tables—plog(p). The least amount of computation is achieved in presenting the function of information in terms of χ^2 –distribution though the estimation accuracy is somewhat lower in this case because of a logarithm approximation. The estimate is given by [5]:

$$2J(*:2,x)\approx\sum_{i=1}^{m}\frac{\left(x_i-Np_i\right)^2}{Np_i}=\chi^2_{1-\alpha}, \tag{1}$$

where J is the information measure; x_i is an *i*-th result in a measurement sampling with a size N; m is the number of degrees of freedom.

In this fashion, a measurement sampling can be approximately estimated using the χ^2 –distribution from tables at a degree of freedom m–1 and at a confidence level α. Puchkov and Ayurov have demonstratively proven that the change in methane content in mine air is described by the Gaussian distribution [6], and this is an exponential law. In the Gaussian distribution, interference exerts the most adverse impact on measurements [7]. We proceed from this worst condition. Let us try to approximate an unknown distribution of jumps of such ES as the change in explosive gas concentration by the Gaussian distribution using the information approach which, in the context of the identification problem, allows, as a matter of principle, determining the wanted characteristics of ES at any rate of accuracy and in real time. This is explained by that fact that we deal with representation of primary signs of ES in information space. Since the operator $J(x/A)$ is monotonous, transformation of any two signs to information functions is continuous and ensures: $(\omega_1 \geq \omega_2) => (J\omega_1 \geq J\omega_2)$, where $J\omega_1$ and $J\omega_2$ are the information provided by the signs ω_1 and ω_2, respectively.

Information identification in the Gaussian approximation of unknown distribution of methane content variation in mine air

Aiming to reduce information quantity in identification in case of an unknown and, probably, varying methane content distribution, we use the linear model of minimum discrimination min$J(x/A)$ [4]. Let explosive concentrations of methane in mine air during mining, as a state of the technosphere, be defined by the vector Y. Each component y_k of this vector apparently matches with methane content caused by an infrequent or uncontrollable event [8], for instance, main roof failure in mined-out void, change in gas leakage in the failure zone, blower etc. Random realizations $y_k \in Y_1$, because of highly intensive jumps of *ES*, comply with the probability P_k. The domain of y_k is characterized by the probability density $p(y/k)$. Expectedly, at a sufficient number $k=1, 2, \ldots, n$, the local modes of a complex unknown distribution agree with mathematical expectations of some components from y_k. In this case, the joint probability density $p(y) = \sum P_k p(y/k)$ should, in a way, resemble $p(y/k)$, at least, in terms of positions of local modes. We use a set of the Gaussian probabilities, $P^N(y)$, and write down the approximation of an unknown distribution:

$$P(y, \alpha) = \sum_{i=1}^{n} \alpha_i P_i^N(y) = \alpha^T P^N(Y), \tag{2}$$

where $\alpha = \{\alpha_i\}$ are the unknown coefficients of approximation to be estimated, $i = 1, 2, \ldots, n$; T is the sign of a transposition operation.

It can be shown [4] that the minimum information loss $\Delta J(Y)$ in approximation of an unknown distribution by the Gaussian distribution is achieved at:

$$\max \int_{y_k} \alpha_1^T p^N(y) \log \frac{\alpha_1^T p^N(y)}{\alpha_2^T p^N(y)} dy. \tag{3}$$

Then, according to the Wilks–Rao method [9], the optimum vector α^T for each interval y_k is defined by the maximization of an information function given by:

$$J(y_k) = \frac{1}{2}\left[\log \alpha^T \sum\nolimits_2 \alpha / \alpha^T \sum\nolimits_1 \alpha + \alpha^T \sum\nolimits_1 \alpha / \alpha^T \sum\nolimits_2 \alpha + \alpha^T \Delta \Delta^T \alpha / \alpha^T \sum\nolimits_2 \alpha - 1\right], \tag{4}$$

where $M_1(Y) = \alpha^T \mu_1, M_2(Y) = \alpha^T \mu_2$ are the mathematical expectations Y; $D_1(Y) = \alpha^T \sum_1 \alpha, D_2(Y) = \alpha^T \sum_2 \alpha$ are the conformable dispersions; $\Delta = \mu_1 - \mu_2$.

Here,

$$\mu_i = \frac{1}{n_i} \sum_{i=1}^{n_i} y_{ij}; \sum_i = (y_i - \mu_i)^T (y_i - \mu_i), \; i = 1, 2;$$

where μ_i is the vector of average values; n_i is the number of the realizations y_k in the interval k; Σ_1, Σ_2 are the large-dimension matrices of covariation [4].

We omit the index k in (4) for the simplicity. Maximization of (4) using the known methods of differential calculus finds that the optimal value of α is obtained from the equation

$$\sum\nolimits_1 \alpha - \lambda \sum\nolimits_2 \alpha = \beta \Delta, \tag{5}$$

where

$$\lambda = \frac{\alpha^T \sum_1 \alpha}{\alpha^T \sum_2 \alpha} \left(1 - \frac{(\alpha^T \Delta)^2}{\alpha^T \sum_2 \alpha - \alpha^T \sum_1 \alpha}\right), \tag{6}$$

$$\beta = (\alpha^T \Delta)\left(\alpha^T \sum\nolimits_1 \alpha\right) / \left(\alpha^T \sum\nolimits_2 \alpha - \alpha^T \sum\nolimits_1 \alpha\right), \tag{7}$$

being dependent on α, are found through iteration, and λ and β are the Lagrange multipliers. Making β in (5) equal to one allows assuming the initial value as:

$$\alpha_0 = \sum\nolimits_1^{-1} \Delta, \tag{8}$$

where $\sum_1^{-1}$, is the inverse covariance.

Then, we find $\alpha_0^T \Delta, \alpha_0^T \sum_1 \alpha_0, \alpha_0^T \sum_2 \alpha_0$ using (8) and determine λ_0 from (6). After that, using the expression:

$$\alpha_1 = \left(\sum\nolimits_1 - \lambda_0 \sum\nolimits_2\right)^{-1} \Delta,$$

we determine $\alpha_1^T \Delta, \alpha_1^T \sum_1 \alpha_1, \alpha_1^T \sum_2 a_1$ and, then, λ_1. Iteration process continues until satisfaction of the conditions:

$$\alpha_i / \alpha_{i-1} \leq \varepsilon_0,$$

where ε_0 is the preset small.

The upper bound of the distinguishing information can be the distribution χ^2 at 100% confidence. Modeling used the methane sensor data during mining for two intervals: the first included 10 points and the second included 8 points. We found: $\mu_1 = 6.0$; $\mu_2 = 4.0$; $\Sigma_1 = 0.6$; $\Sigma_2 = 1.0$; $\Delta = 2.0$. The initial value $\alpha_0 = 1.2$ when $\sum_1^{-1} = 1.67$ since $\sum_1 \sum_1^{-1} = 1$. Convergence of iteration proceeds monotonously and stops at the third iteration when $\varepsilon_0 = 0.05$. According to (1), at the confidence of 95%, the upper bounds of the distinguishing information were 1.66 bit and 1.08 bit for two realizations. The calculated values of α_i were inside a range of 0.5–1.4, and the average approximation error in percentage terms over all measurements according to [4, 5] was 5.4, which was admissible for practical purposes. Naturally, any optimization, including identification processes, involves a certain error. Approximately, we can take the distribution $p(y/k)$ as the Gaussian distribution with an average value of 5.0 and at dispersion of 0.8 on the basis of the presented initial data. Sufficient simplicity of the described method makes it applicable for determining characteristics of mining objects in problems of forecasting [10, 11].

Modified strategy of dichotomic information identification

Based on the comparative analysis of the known identification strategies, in particular, [12–14], it is inferred that it is necessary to develop and practice adaptable information method with calculation using the most informative signs of *ES* [2]. A disadvantage of the strategy from [2] using the Shannon–Fano coding algorithm is connected with a large error of a minimum sign coding length at high initial probabilities and small number of classes.

There is a known strategy based on successive splitting of a space of classes into two approximately equiprobable groups, which is equivalent to information dichotomy [2]. When comparing ES, the initial class is assumed to be class of the maximum *J(A/x)*. The group, which is picked relative to the average value of information, involves classes fit with the higher information values. After overdetermination of average values and maximum *J(A/x)*, the same principle-based grouping is carried out. The process of identification is continued down to the comparison of *ES* with the last class. Such statistical processing of samplings of signs estimates simultaneously the vector of the highest informative signs of *ES*. Their subsequent comparison by the criterion of the minimum distinguishing information finalizes the classification—determination of belonging of *ES* to a certain class, and, eventually, the whole process of identification. Such information may be approximately calculated using plog(p). When finding maximum value of average information, i.e. maximum matrix element *J(A/x)*, it is possible to take advantage of the known properties of matrices. A nonnegative matrix has a highest absolute value component that satisfies the relation:

$$\min\sum_{j}^{n}J_{ij} < J_{\max} < \max\sum_{j}^{n}J_{ij}, \tag{9}$$

where $J_{\max}$ is the maximum value of average information; J_{ij} is the matrix information at the intersection of an i-th line and a j-th column.

However, this needs searching of n columns in the matrix J. The signs x_i are matched with their probability matrices calculated as the ratios of frequency of the sings to their total number N. This way of determining maximum information from relations (9) involves much less amount of calculations as compared with exhaustive search.

The most economic method to find $J_{\max}$ is the modified dichotomy method including matrix diagonalization. As the method is linear, no information is lost during diagonalization. The amount of calculations drops. If the probability distribution is unknown, a polynomial distribution may be adopted as an asymptotic distribution. In this case, with the matrix rank $R(J) = r$, for calculating components of a minimum distinguishing information, we have:

$$N_i = N - \sum_{i=1}^{r-1}x_i,\ i = 1,\ldots,r-1. \tag{10}$$

The use of the dichotomy method in comparison of each element of the matrix J with the other elements in a given column, with regard to the results [4], produces the expressions below to find $J_{\max}$(*:H_2):

$$\frac{J_{j1}}{\sum_{j=2}^{r-1}J_j} = \frac{x_1\log\dfrac{x_1}{Np_1}}{(N-x_1)\log\dfrac{N-x_1}{N(1-p_1)}}\ , \tag{11}$$

$$\frac{J_{j2}}{\sum_{j=3}^{r-2}J_j} = \frac{x_2\log\dfrac{x_2}{Np_2}}{(N-x_2)\log\dfrac{N-x_2}{N(1-p_2)}}\quad \text{etc.,} \tag{12}$$

where p_1 and p_2 are the probabilities of the signs x_1 and x_2, respectively. Hereinafter, we assume that the logarithm base in (11) is 2. The process of identification ends as one of series relations (11) and (12) reaches a value smaller or equal to some small positive number ε. The identification error probability never exceeds:

$$P(\varepsilon) \le \exp\left[-\Delta J_{ik}\right], \tag{13}$$

where $\Delta J_{ik} = \sum_{j=k}^{r-k+1}J_{ij} - J_{ik}$.

When the law of a distribution raises no doubts and only its parameters are unknown, the parametric identification methods are applicable. In this case, the asymptotic distribution of the distinguishing information estimate is a chi-squared distribution with the number of degrees of freedom, equal to $k(k+1)/2$, where k is the number of independent r-dimensional samplings.

From testing the dichotomy method, the most informative factors that influence flooding events in mines are: failures of water pumping units (0.5 bit); absence of impermeable seals under flooded openings (0.375 bit); non-drilling of advance holes as per geological surveying chart and unplugged holes being undermined (0.25 bit each). The information contents of factors that influence rock falls are: roof rock wear, alteration of rock pressure and faulting (0.25 bit each); deficient density of mine support, lag between heading front and support installation, and knockouts of mine support by mining machines (0.16 bit each); defective support system and violations of support system patterns and designs (0.095 bit each). The identification error in cases of these accidents was not higher than 0.3.

The data on information contents of factors that characterize the listed accidences agree with predictability of these factors using searching techniques in terms of the prediction errors [1].

According to (13), informativeness of the factors–influences is connected with the error probability as a negative exponential curve. This points at the need to take into account both controllable and uncontrollable factors of accident risk.

Conclusions

This article presents some results related to the development of information analysis strategies for complex, potentially pre-emergency situations, to enable the identification of these situations with an unknown probability distribution of *ES* features. The described identification method with a Gaussian approximation of the unknown distribution and the modified dichotomous assessment method provides a tool for solving a wide range of identification problems using linear models to determine the feature characteristic of the phenomena under consideration. The simplicity of computer implementation of these methods allows extending them to other types of underground accidents, such as gas contamination of dead-end mine workings, shutdown of mine hoists and main ventilation fan failures.

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