Algorithmic support for the detection characteristics improving of the monitoring object

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Abstract. The paper presents: an object detection algorithm for coherent reception of signals coming from a monitoring network consisting of several sensors; an algorithm for detecting an extended object by analog signals of sensors of a monitoring network. These algorithms use statistics that take into account the most stable features of the distribution of the source data. They can be implemented in an automated decision support system. At the same time, decisions on the detection of a monitoring object made by an automated system will be more reliable

Keywords: Monitoring, Object, Sensor, Signal, Algorithm, Detection.

1 Introduction

To carry out environmental monitoring, it is necessary to conduct continuous observations over time, based on a well-thought-out distribution of measuring instruments in space, for which it is necessary to use a stationary distributed multi-sensor remote monitoring system [1]. It should work efficiently, preferably at a real time scale. Efficiency also means reducing the time frame for deciding on the classification of the observed object. Therefore, it is necessary to automate not only the data collection process, but also the classification algorithms of the monitoring object in order to attract the attention of the human operator only to objects that actually threaten the ecological state of the observed area and even at the stage of automated data processing to weed out objects that do not threaten the ecological state of the zone of responsibility. A stationary network of stations included in the monitoring system requires the availability of communication channels with a Monitoring Control Point (MCP) [2]. Laying a cable communication network is often unprofitable. Therefore, for communication purposes it is necessary to use a radio channel or satellite communication [2]. Since the sensors of the monitoring network receive energy from the batteries, in order to save energy in the monitoring network, it is often justified not to pre-process the signal on the sensor, but to send analog signals to the MCP, which is charged with processing the sensor signals and detecting the monitoring object [3]. Information exchange over the radio channel raises the problem of detecting an analog signal with an unknown law of fluctuations against the background of noise with an unknown distribution [4]. To solve this problem, in this paper, it is proposed to develop the following algorithms:

• an optimal algorithm for detecting a monitoring object during coherent reception of signals coming from a monitoring network consisting of several sensors;

• the optimal sample size for detecting the object of the analog signals of the sensors of the monitoring network.

2 Theoretical Analysis

2.1 The optimal algorithm accordingly to the signal-to-noise ratio criterion for processing spatially distributed data from a monitoring network consisting of several sensors

Let us consider the problem of coherent detection of a signal from an object distributed in N resolution elements, which are sensors of a monitoring network. It was shown in [4] that the optimal detector is that which calculates the likelihood ratio:

$$l(X) = \frac{1}{\binom{N}{k}} \left(\frac{\gamma_0}{\gamma_1}\right)^k \sum^{\binom{N}{k}} \exp\left[\left(\frac{1}{2\gamma_0} - \frac{1}{2\gamma_1}\right) \sum_{n=1}^{k} x_{n^2}\right]^2 \tag{1}$$

where x_n - detector output envelope samples , $n = 1,2,\ldots..,N$

γ_0 and γ_1 - signal variances received from $(N-k)$ sensors, that did not fix the object and k sensors, fixed object accordingly .

From equation (1) we can see, that that detector which is optimal accordingly to the signal-to-noise ratio criterion can be implemented by a rather complex circuit, and, in addition, for its implementation a priori information is required about the parameters of signal (γ_1) and noise (γ_0), which, as a rule, in real monitoring conditions are unknown. Therefore the rule (1) characterizes the potential for detecting an object and cannot be realized in many practical cases.

It is necessary to develop an optimal by signal / noise criterion algorithm for coherent detection of a signal from a monitoring object received from $(N-k)$ sensors on the background of noise interference provided that the signal and noise parameters, as well as the position of the fixed object k sensors among N sensors of the monitoring network are a priory unknown. Detection is formulated as the statistical task of testing general linear hypotheses [4-10] and the optimal rule is found in the class of so-called invariant rules [11].

We use the following premises:

1. There are statistically independent radio pulses sent by $N(N \gg 1)$ sensors. In the absence of the object of observation, these pulses have the same average power. The law of the distribution of the noise background is considered normal.
2. In the presence of an object of observation, the resulting fluctuation in resolution is the additive sum of the signal with unknown amplitude $\xi_m (m = 1,2\ldots,k)$ and Gaussian noise with unknown variance σ^2. Coherent processing is assumed. Independent voltage samples are taken at the output of the linear path of the MCP receiver at time instants following the resolution interval. $x_n (n = 1,2,\ldots,N)$.
3. Processing is carried out during the p periods of the signal, so that each reference element n will correspond to a sample vector $(x_{n1},\ldots,x_{np})$ with multidimensional normal probability density

$$g(X_n) = \frac{\sqrt{|A|}}{(2\pi)^{p/2}} \exp\left[-\frac{1}{2}\sum_{i=1}^{p}\sum_{j=1}^{p} a_{ij}(x_{ni} - \xi_{ni})(x_{nj} - \xi_{nj})\right]. \quad (2)$$

The mean values and the covariance matrix of the vector are determined from the expressions $E(x_{ni}) = \xi_{ni}$; $E(x_{ni} - \xi_{ni})(x_{nj} - \xi_{nj}) = \sigma_{ij}$; $\sigma_{ij} = A^{-1}$, where E - is the sign of mathematical averaging, and $\xi_n = 0$, if $n \in (N - k)$, and $\xi_n > 0$ at $n \in k$. It is also believed that the matrix $A = (a_{ij})$ - is common to all vectors N, having dimension p, but unknown .

The challenge is that by sample

$$X = \begin{pmatrix} x_{11} & . & . & . & x_{1p} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ x_{N1} & . & . & . & x_{Np} \end{pmatrix}$$

determine the presence or absence of a signal about the existence of a monitoring object. Matrix X consists of p column vectors $(x_{1i},\ldots\ldots,x_{Ni})$, and each such vector has its own mean value vector $\overline{\xi_i} = (\xi_{1i},\ldots,\xi_{Ni})$.

Given the accepted assumptions, the task of detection is to test complex hypotheses H_0 and H_1 regarding parameters $\overline{\xi_i}$ and A.

$$H_0 : \overline{\xi_i} = 0 \qquad H_1 : \overline{\xi_i} > 0 \qquad i = 1,2,\ldots, p \quad \text{A is unknown} \quad (3)$$

Hypothesis testing (3) fits into the scheme of testing multidimensional linear hypotheses. As follows from the general theory [12], principles of invariance and sufficiency allows you to reduce the sample X when testing hypotheses (3) to maximally invariant statistics of the form

$$T = \sum_{i=1}^{p}\sum_{j=1}^{p} \frac{N\overline{x_i}\,\overline{x_j}}{\sum_{n=1}^{N}(x_{ni}-\overline{x_i})(x_{nj}-\overline{x_j})} \tag{4}$$

and the set of parameters $\overline{\xi_i}$ and (a_{ij}) - to maximal invariant

$$\delta^2 = N\sum_{i=1}^{p}\sum_{j=1}^{p} a_{ij}\eta_i\eta_j \tag{5}$$

In expressions (4), (5) $\overline{x}_{i(j)} = N^{-1}\sum_{n=1}^{N} x_{xi(j)}$; $\eta_{i(j)} = E(\overline{x}_{i(j)})$. Numerator of the formula (4) has off center $\chi_p{}^2$ - off-center distribution with the noncentrality parameter δ^2 and p degrees of freedom, and the denominator has central distribution $\chi^2{}_{(N-p)}$, so the statistics $(N-p)T/p$ has off-central F distribution with p and $(N-p)$ degrees of freedom and with the noncentrality parameter δ^2.

Regarding the parameter δ^2 of F - distribution initial hypotheses (3) can now be formulated as follows :

$$H_0 : \delta = 0; \qquad H_1 : \delta > 0 \tag{6}$$

Using the method of constructing optimal rules [13], it can be shown that the most powerful invariant criterion for testing hypotheses (6) has a critical region of the form

$$T > C. \tag{7}$$

Threshold level C determined by the given probability of false alarm α from the condition

$$\int_C^{\infty} F_{p,(N-p)}(y)dy = \alpha \tag{8}$$

where $F_{p,(N-p)}$ -is central F distribution with p and $(N-p)$ degrees of freedom.

The expressions (4), (7) determine the functional scheme of the detector with completely unknown correlation properties of vectors $(x_{n1},\ldots,x_{np})$. For practical implementation, algorithm (7), (8) can be concretized, for example, in the case of the absence of inter-period correlation. In this case, the discovery rule and parameter δ^2 take the form

$$\sum_{i=1}^{p} \frac{N \bar{x}_i^2}{\sum (x_{ni} - \bar{x}_i)^2} > C, \tag{9}$$

$$\delta^2 = \sum_{i=1}^{p} \bar{q}_i, \tag{10}$$

where $\bar{q}_i = (\sum_{n=1}^{N} \xi_n)_i^2 / N\sigma^2$ - is the average for all N signal-to-noise ratio for one observation period. The detector efficiency is determined by the power function of rule (7), (8), which shows the dependence of the probability of correct detection on the parameter δ^2. It can be calculated directly from off-center tables of F - distribution [14].

2.2 Optimal algorithm according to the signal-to-noise ratio criterion for detecting an extended object by analog signals of monitoring network sensors

To develop an algorithm for classifying an extended object (for example, classifying the observed water surface as clean or polluted by oil emissions) using a distributed multisensor geographic information system, suppose:

- The central post decides to detect / not detect an object (contamination) based on signals received from N sensors under the same observation conditions ;
- The resulting radio signal of each sensor is the additive sum of the non-fluctuating signal of unknown amplitude $\xi_i^{(j)} \geq 0$ (j =1,2- is numbers of object - e.g. clean water surface and dirty water surface, $i \in N$) and Gaussian noise with unknown dispersion σ_i^2. At the output of the receiver's linear path, the amplitude samples $x_i^{(j)}$ are taken for the signal of each sensor.
- Observation of objects is carried out for some time T , during which readings for the signal of each sensor n are taken. Thus, for each object, the sample space is represented as n sample vectors $x_\alpha^{(1)} = (x_{\alpha 1}^{(1)},\ldots,x_{\alpha n}^{(1)})$; $x_\alpha^{(2)} = (x_\alpha^{(2)},\ldots,x_{\alpha n}^{(2)})$; $\alpha = \overline{1,n}$.

Vectors $x_\alpha^{(1)}$ and $x_\alpha^{(2)}$ have a normal probability density

$$g(x_\alpha^{(j)}) = \frac{\sqrt{A}}{(2\pi)^{N/2}} \exp[-\frac{1}{2} \sum_{i=1}^{N} \sum_{k=1}^{N} \alpha_{ik} (x_{\alpha i}^{(j)} - \xi_{\alpha k}^{(j)})] \tag{11}$$

The mean values and elements of the covariance matrix are determined from the expressions
$E(x_{\alpha k}^{(j)})=\xi_{\alpha k}^{(j)}; E(x_{\alpha i}^{(j)}-\xi_{\alpha i}^{(j)})(x_{\alpha k}^{(j)}-\xi_{\alpha k}^{(j)})=\sigma_{ik}; (\sigma_{ik})=A^{-1}$, where E – is the sign of mathematical averaging. We consider that the matrix $A=(\alpha_{ik})$ is common to vectors $x_{\alpha}^{(1)}$ and $x_{\alpha}^{(2)}$, but its elements are unknown.

The classification task is by the sample $x_{\alpha}^{(1)}, x_{\alpha}^{(2)}, \alpha=\overline{1,n}$ determine whether objects belong to the same class or belong to different classes.

Based on the assumptions made, this problem can be formulated as two hypotheses - 1. objects are of the same type; 2. objects are of the different type:

$$H_0: \bar{\xi}_i^{(1)}=\bar{\xi}_i^{(2)};\ H_1: \bar{\xi}_i^{(1)}\neq\bar{\xi}_i^{(2)} \text{ for all } i=\overline{1,N} \tag{12}$$

In expression (12) the parameter $\bar{\xi}_i^{(j)}$ – is matrix column having dimension $(n\times 1)$ with elements $(\xi_{1i}^{(j)},\dots,\xi_{ni}^{(j)})$.

As follows from the general theory [15], the principles of invariance and sufficiency allow us to reduce the sample space $x_{\alpha}^{(1)}, x_{\alpha}^{(2)}, \alpha=\overline{1,n}$, when testing hypotheses (12) for maximally invariant statistics (MI) of the form

$$T=\sum_{i=1}^{N}\sum_{k=1}^{N}\frac{n(\bar{x}_i^{(1)}-\bar{x}_i^{(2)})(\bar{x}_k^{(1)}-\bar{x}_k^{(2)})}{\sum_{\alpha=1}^{n}(x_{\alpha 1}^{(1)}-\bar{x}_i^{(1)})(x_{\alpha k}^{(1)}-\bar{x}_k^{(1)})+\sum_{\alpha=1}^{n}(x_{\alpha i}^{(2)}-\bar{x}_{\alpha}^{(2)})(x_{\alpha k}^{(2)}-\bar{x}_k^{(2)})} \tag{13}$$

and the parameter space is to MI

$$\psi^2=\sum\sum\frac{n}{2}\alpha_{ik}(\eta_i^{(1)}-\eta_i^{(2)})(\eta_k^{(1)}-\eta_k^{(2)}) \tag{14}$$

In expressions (13) and (14) is marked: $\bar{x}_k^{(j)}=n^{-1}\sum_{\alpha=1}^{n}x_{\alpha k}^{(j)}$; $\eta_k^{(j)}=E(\overline{x_k^{j}})$; $k=\overline{1,N}$.

It can be shown that there is uniformly the most powerful (UMP) criterion for testing hypotheses (12), (12), which rejects the hypothesis H_0 in case if

$$T>C, \tag{15}$$

where C – is the threshold constant .

The constant C should be determined from the condition that under the hypothesis H_0 $(\psi^2=0)$ the probability of the fulfillment of condition (15) was no more than a certain predetermined significance level β. Whereas statistics $\nu_1/\nu_2 T$ under the hypothesis H_0 has central F distribution with $\nu_1 = N$ and $\nu_2 = (2n - N - 1)$ degrees of freedom [16], the constant C can be found from the expression

$$\int_c^\infty F_{\nu_1 \nu_2}(\omega) d\omega = \beta \tag{16}$$

The rule (15) can be specified for the case when the matrix A is diagonal. In this case, it has the form

$$\sum_{i=1}^{N} \frac{n(\bar{x}_i^{(1)} - \bar{x}_i^{(2)})^2}{\sum_{\alpha=1}^{n} (x_{\alpha 1}^{(1)} - \bar{x}_i^{(1)})^2 + \sum_{\alpha=1}^{n} (x_{\alpha i}^{(2)} - x_i^{(2)})^2} > C_1 \tag{17}$$

where $C_1 = CN/(2n - N - 1)$.

From the expressions (13) and (17) it can be seen that $\bar{x}_i^{(j)} (j = 1,2; i = \overline{1, N})$ - are maximum likelihood estimates for parameters $\xi_i^{(j)}$, calculated for the sensor N signals for the first and second objects, and the value in the denominator is the sum of the parameter σ_i^2 estimates calculated for the signal of the first and second object of i-th sensor. Thus, to distinguish between objects, it is necessary to estimate the amplitudes of the N sensor signals, calculate the square of the distance between the parameters of the signals of the classified objects by the sensors of the same name, and sum them with weights inversely proportional to the noise variance. The amount received is compared with a threshold, in case of exceeding which a decision is made on whether the objects belong to different classes.

Algorithm (15) can also be used to detect a distributed object, if we put $x_\alpha^{(2)} = 0; \alpha = \overline{1, n}$. Formula (17) in this case takes the form

$$\sum_{i=1}^{N} \frac{n\bar{x}_i^2}{\sum_{\alpha=1}^{n} (x_{\alpha i} - \bar{x}_i)^2} > C_2 \text{ , где } C_2 = CN/(n - N - 1). \tag{18}$$

Considering that under the hypotesis H_1 statistics T has off-central F distribution with off-center parameter ψ^2 and ν_1, ν_2 degrees of freedom, the probability of correctly distinguishing between objects is determined by the expression

$$P(T > C) = \int_0^\infty F_{\nu_1 \nu_2}(\omega, \psi^2) d\omega \tag{19}$$

and can be calculated according to the tables of off-central F distribution [17].

3 Results

Figure 1 shows the curves characterizing the effectiveness of the detector of oil pollution of the water surface depending on the resolving power of the network of contact sensors constructed in accordance with the algorithm described by expressions (4), (7). Characteristics calculated for false alarm probability value $\alpha = 10^{-2}$ and the number of received signal periods $p = 2$ provided that the value of the signal-to-noise ratio averaged over all N sensors for one observation period $\overline{q}_i$ is independent of resolution (uniform distribution of translational buoys (contact sensors) along the length of contamination). For comparison, the same figure shows the power function of the potential most powerful rule (MP) of coherent detection of a known signal [18] in the presence of only one sensor ($N = 1$).

It can be seen from the figure 1 that ignorance of the noise and signal levels in the decision elements leads to losses in the signal-to-noise ratio. However, with increasing resolution, the detector's efficiency increases. This is due to the fact that the increase allows a more accurate assessment of noise and signal levels. So, when $N = 8$ the loss in the signal-to-noise ratio is ~4 dB, and when $N = 22$ - less than 1 dB.

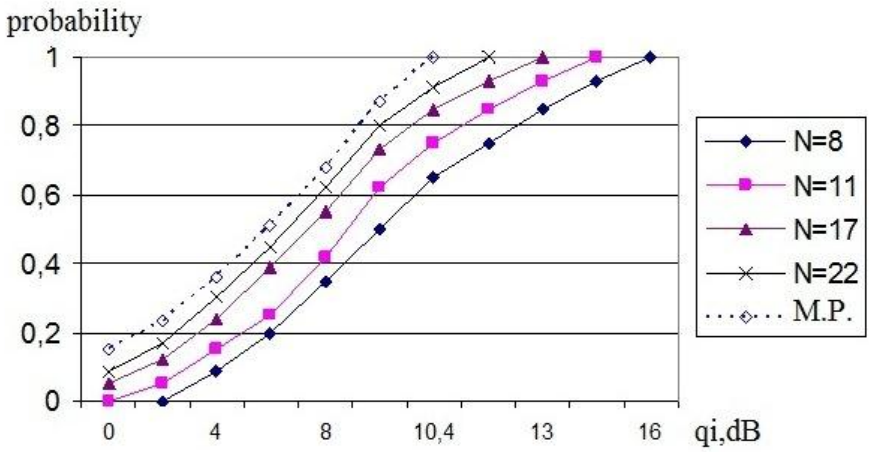

Fig. 1. The probability of detecting oil pollution of the water surface by signals received from a network of contact sensors

Figure 2 shows the dependences of the probability $P(N)$ of correct distinguishing between two objects, calculated by the formula (19), for different values of the signal sample size *n*.

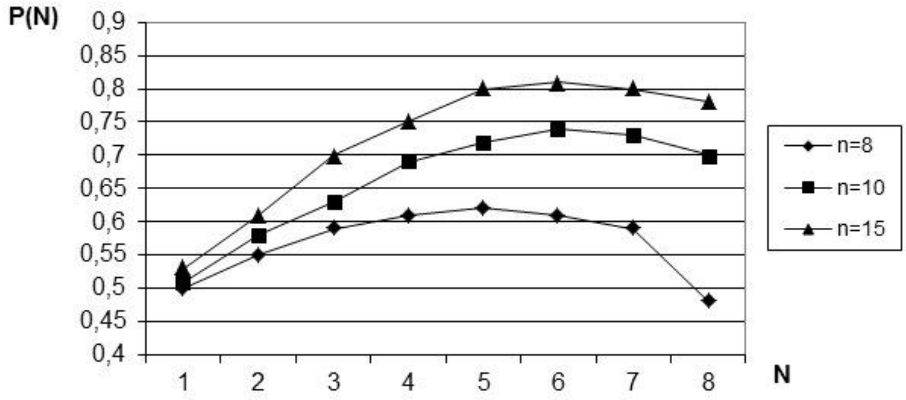

Fig. 2. The dependence of the probability of distinguishing objects P (N) for a different number of sensors in the monitoring system (N) for several values of the signal sample size (n)

In this case, the noncentrality parameter ψ^2 of F distribution was assumed constant, independent of the number N of sensors in the monitoring system . As can be seen from Figure 2, the dependences have an optimum in the probability of distinguishing between objects, and its position depends on the size of the sample n. The presence of an optimum and its position are apparently due to the following reasons. On the one hand, with an increase in the number of sensors in the monitoring system, the difference in signals increases, that is, the “distance” between objects in the parameter space increases. Let us explain what was said by the following example. Let the objects have the same area, but a different distribution of them among the sensors. The value of the parameters of the amplitudes of the signals from the first and second objects $\xi_i^{(1)}$ and $\xi_i^{(2)}$ for $N=3$ is presented in table form 1.

At N = 1, the distance in the parameter space between objects A and B is $(\sum_1^3 \xi_i^A - \sum_1^3 \xi_i^B)^2$=9-9=0 and it’s not possible to distinguish between them. At the same time, for N= 3 we get $\sum_1^3 (\xi_i^A - \xi_i^B)^2=(3-1)^2+(4-5)^2+(2-3)^2=6$, i.e. the difference in parameters is significant. On the other hand, with a decrease in the number of sensors in the monitoring network, the correlation between the signals of objects of various classes increases. Moreover, the accuracy of parameter estimates can be improved by increasing the accumulation time, i.e., increasing the size of the sample n.

Table 1. The value of the parameters of the amplitudes of the signals from the first and second objects

Object	i	1	2	3	
A	ξ_i^A	3	4	2	$\sum_1^3 \xi_i^A$ =9
B	ξ_i^B	1	5	3	$\sum_1^3 \xi_i^B$ =9

4 Conclusion

The proposed algorithm in the sense of signal-to-noise ratio for processing spatially distributed data coming from a monitoring network consisting of several sensors with the following practically important properties: a) does not depend on a priori unknown parameters σ^2 and ξ_n ($n = 1,2,\ldots,N$) and provides a constant probability of false alarm at any noise level; b) is invariant to the location of *k* sensors that recorded the object and (N-k) sensors that have not fixed the object, among *N* sensors of the monitoring network; c) has the highest probability of correct detection, depending on the average signal-to-noise ratio and for large $N > p$ close to potential.

The proposed algorithm for detecting an extended object by the analog signal of sensors of the monitoring network can be used to identify objects if, for example, as $x_i^{(2)}, i = \overline{1, N}$, a priori estimates of the parameters of the recognized object are used.

The practical significance of the results lies in the development of analog signal detection algorithms that are resistant to changes in the signal-to-noise ratio in the communication channels of the sensors of the monitoring network with a monitoring and control post. Algorithms can be implemented programmatically using various programming languages and used to automate the process of classifying monitoring objects at a monitoring and control point.

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