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SYNTHESIS OF AUTO CALIBRATION SYSTEM IN NON MAINTENANCE WIRELESS SENSOR NETWORK

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***Abstract.** The methods of research and development of calibration of radio sensors with use of various models of parameters drift of radio sensors is solved. The main tasks and approaches to the development and synthesis of the autocalibration system in the network of radio sensors are determined. The proposed method of error detection and correction of measurement results of radio sensors in the network is based on the assumption of spatio-temporal correlation of measurement results in neighboring sensors and the lack of mutual correlation of drift processes of technical parameters. The use of the auxiliary regression vector, according to the equation of which the forecast of future measurement results is calculated, is proposed and substantiated for the analysis of the space-time correlation. It is established that there is a certain compromise in the choice of the optimal sample length during measurements.*

***Keywords:** wireless sensor network, parameter drift, autocalibration, Kalman filter, regression analysis, spatio-temporal correlation, radio sensor*

СИНТЕЗ СИСТЕМИ АВТОКАЛІБРУВАННЯ В НЕОБСЛУГОВУВАНІЙ БЕЗПРОВОДОВІЙ СЕНСОРНІЙ МЕРЕЖІ

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***Анотація.** Безпроводова сенсорна мережа – це розподілена мережа необслуговуваних мініатюрних електронних пристроїв, які здійснюють збір даних про параметри зовнішнього середовища і передачу їх на базову станцію. З плином часу, а також через поступове зниження напруги живлення, важких умов експлуатації (великі перепади температури, вологості, тиску в навколишньому* *середовищі) має місце некерований та неконтрольований дрейф параметрів сенсорів і пристроїв знімання інформації.*

В статті вирішується задача дослідження і розробки методів калібрування радіадатчмків безпроводовоих сенсорних мереж з використанням різних моделей дрейфу параметрів радіодатчиків. Проаналізовані математичні моделі дрейфу параметрів сенсорів, які.описуються поліноміальним, експоненціальним і гармонійним трендами. Визначені основні задачі і підходи до розробки і синтезу системи автокалібрування в мережі радіосенсорів. Запропонований метод виявлення помилок і корекції результатів вимірювань радіосенсорів в мережі заснований на припущенні про просторово-часової кореляції результатів вимірювань в сусідніх сенсорах і відсутності взаємної кореляції процесів дрейфу технічних параметрів. Розглянуті особливості використання прямих і регресійних методів автокалібрування радіосенсорів.

Запропоновано і обгрунтовано для аналізу просторово-часової кореляції використання допоміжного вектора регресії, за рівнянням якої обчислюється прогноз майбутніх результатів вимірювань. Встановлено, що при збільшенні обсягу вибірки збільшується інтервал спостереження, але має місце краще згладжування помилок. Отже, існує певний компроміс у виборі оптимальної довжини вибірки при вимірюваннях.

Ключові слова: *Безпроводова сенсорна мережа, дрейф параметрів, автокалібрування, фільтр Калмана, регресійний аналіз, просторово-часова кореляція, радіосенсор*

Introduction

Wireless sensor networks (WSN) or radio sensor networks are based on low-cost, low-power multifunction devices. They are quite small and are able to transmit large amounts of telemetry and other information over relatively short distances, where there are data collection and processing centers. These centers on command from the receiving device transmit data in a short period of time for a fairly long distance. Wireless sensor network is a distributed network of maintenance-free miniature electronic devices (network nodes) that collect data on environmental parameters and transmit them to the base station by retransmission from node to node via wireless communication [1].

Radio sensors have non-renewable power supplies and they themselves are not recoverable in the event of failure. Therefore, the tasks of their design, implementation and current operation differ significantly from similar tasks for traditional computer networks, which determines the relevance of this study.

Statement of the research problem

There are a number of requirements and limitations in the development of WSN service design methods. They are due, in particular, to the following features [1, 2]:

1) Given the random nature of the distribution of elements in space, the propensity of elements to failures, and network topology – to uncontrolled changes, algorithms and exchange protocols must have the ability to decentralized self-organization of the network.

2) A separate element has low computing and communication resources. A typical reason is the limited capacity of the energy source.

3) The elements transmit data at close frequencies, which causes mutual interference and distortion of data.

4) Often elements do not have individual identifiers. As a result, the sources of the information obtained are anonymous.

5) Over time, as well as due to the gradual decrease in supply voltage, difficult operating conditions (large differences in temperature, humidity, pressure in the environment) there is an uncontrolled and uncontrolled drift of parameters of sensors and recording devices.

When a certain level of drift is exceeded, the data received from the network becomes unreliable. To mitigate the problem of drift in each sensor of the network it is necessary to detect and correct its own drift, using feedback from data from neighboring nodes. This is due to the fact that data from nodes within a certain neighborhood (cluster) are correlated, while the correlation of errors or drift is almost absent. When detecting and timely correction of parameter drift, it is possible to increase the effective duration of the network life cycle [2, 3].

These problems have not yet been fully resolved. The most urgent tasks:

– development of effective and cost-effective methods of organizing data collection;

– routing and data delivery to the central processing point;

– elimination of drift of parameters by automatic calibration of sensors.

In this case, if to overcome the limitations of organizational and software-algorithmic nature (p.p. 1-4) are currently developed appropriate management and control methods [1, 4], the problems of eliminating the drift of parameters are still not fully resolved.

For large-scale wireless sensor networks that contain a large number of inexpensive sensors, calibration must be performed frequently. It is almost impossible to manually calibrate sensors in such a network. Therefore, it is necessary to develop methods for automatic calibration of sensors in sensor networks [3, 5].

The aim of the article is to study and develop methods for calibrating sensors using different models of drift parameters of radio sensors. To solve this problem, it is necessary to develop adequate models of drift of sensor parameters and obtain asymptotic estimates of efficiency with appropriately selected parameters of radio sensors and the network as a whole.

Mathematical models of sensor parameter drift

As shown in [5, 6], drift models are described by the following trends:

a) polynomial – $\varphi_{\mathrm{p}}(t) = \varphi_0 + at + bt^2 + \sigma\varphi(t_i)$, (1)

where $\sigma\varphi\ (t_i)$– discrete white Gaussian noise; a and b – constant coefficients, which are determined experimentally; φ_0 – the exact value of the parameter.

b) exponential – $\varphi(t)_0\{1 - exp[\varphi(t_0 - t) + \xi\varphi(t)]\}_{exp}$, (2) where k is the scale factor; t_0 – the moment of the beginning of drift of parameters.

c) harmonious – $\varphi_{tr}(t) = \varphi_0 + \sum_{l=1}^{N} k_l \, sin(l\omega_0 t) + \xi\varphi(t)$, (3)

where $k_l = k_0/l$ or $k_l = k_0 \, exp(-l^2/l_0)$; $k_0, \rightleftharpoons l_0$– scale coefficients, selected experimentally.

As shown in [3, 5, 7], the problem of empirical a priori estimation of drift coefficients in expressions (1)-(3) is quite complex and time-consuming. To solve it, you need to perform large-scale experimental studies. Therefore, when studying the methods of calibration of sensors using models of the form (1)-(3), it is easier to obtain asymptotic estimates of efficiency at the appropriately selected limit values of these coefficients. Based on these initial data, it is possible to build an algorithm for correcting the drift of the sensor parameters during its operation.

After the initial configuration of the network (detection, exchange of data on the geographical coordinates of neighbors, etc.), all nodes begin to periodically transmit data packets to the collection point. At the collection point, estimates of the correlation coefficients between packets coming from different routes are calculated, and the parameters of the correlation function and are calculated.

The method of real-time drift correction for application in BSM in accordance with the results of robots [5, 8] consists of two stages.

In the first stage, a regression training vector is used to predict the measurement results $\hat{g}_{mn}$, which contains the adjusted measurement results obtained from neighboring sensors as initial data.

In the second stage, the Kalman filter [5] can be used for recursive drift correction in the read data g_{mn} using the original values $\hat{f}_{mn}$ of the regression vector to determine the adjusted measurement results $\hat{g}_{mn}$.

The forecasting procedure (at the first stage) consists of two phases–- training and working phase. In the learning phase, the measurement results collected during the initial deployment period (training data set) are used to model the function $\varphi(\cdot)$. During the working phase, the “trained” model $\varphi(\cdot)$is used to predict further measurement results $\hat{f}_{mn}$.

It is assumed that the training data (collected during the initial deployment periods) is free from any drift and can be used for training in each node. This assumption is based on the fact that sensors are usually calibrated before deployment.

The set of training data in the $m$sensor will denote as $G_{tr} = \{G_{n-1}, G_n\}$, where

$G_{n-1} = (g_{k,n-1}), k = 1,2, \dots, m-1, m+1, \dots, M$;

$G_n = (g_{mn}), m = 1,2, \dots, M$.

The model obtained on the basis of the auxiliary regression vector [9] is used during the working phase to predict further actual measurements $\hat{f}_{mn}$. To measure sensor drift, the difference between the measurement result and the model value of the regression vector component $\hat{f}_{mn}$ used as a reference is calculated. This difference is introduced in one of the modifications of the Kalman filter, which is called the Kalman filter with random search [5] together with g_{mn} to evaluate the adjusted results $\hat{g}_{mn}$ and the amount of drift d_{mn}.

Synthesis of autocalibration system in a network of radio sensors

As a result of solving the synthesis problem, the general structure of the optimal WSN should be obtained, its parameters and characteristics, possibilities of practical possibility to be realized should be estimated. As a rule, optimal (ideal) systems can not be practically implemented with absolute accuracy. Therefore, it is necessary to assess the sensitivity of the synthesized system to deviations of its parameters and characteristics from the ideal, as well as the sensitivity to deviations of a priori information from those specified in solving the synthesis problem.

In the general case, the problem of BSM synthesis with uncontrolled drift of sensor parameters aims to obtain a meter circuit that determines the current parameters and state of the object [10]. Given the systematic nature of the problem (random signals and interference), the synthesized system is usually a device for detection and measurement [11].

The structure of the control system of the parameters of the control object is shown in Fig. 1.

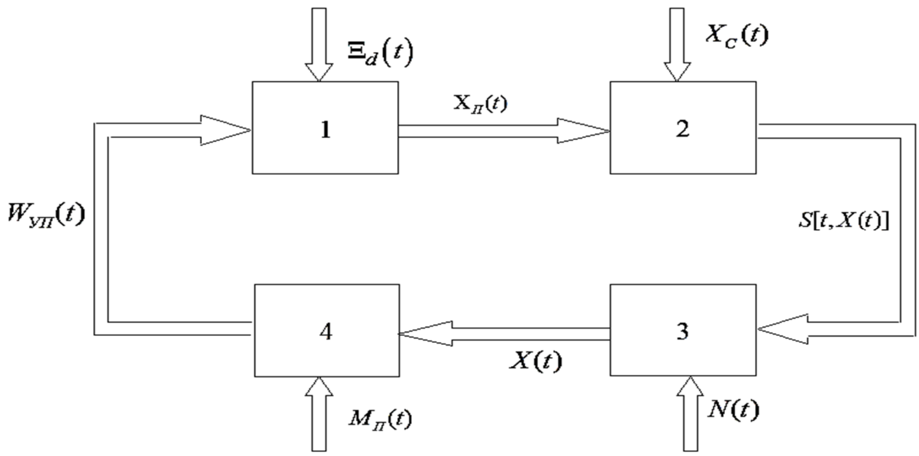

Fig. 1. The structure of the control system of the parameters of the control object

In the scheme (fig. 1) the following designations are accepted: $\boldsymbol{X}_{\text{п}}(t)$ – vector of state variables;

$\boldsymbol{\Xi}_d(t)$ – vector of perturbations acting on objects; $\boldsymbol{N}(t)$ – vector of perturbations (interferences) that determine the program of state changes;$\boldsymbol{M}_{\text{п}}(t)$ – vector of influences that correct the program of state changes; $\boldsymbol{W}_{\text{cnt}}(t)$ – vector of control signals;$\boldsymbol{X}^T(t) = |\boldsymbol{X}_{\text{п}}(t), \boldsymbol{X}_{\text{c}}(t)|$ – state vector, which is a set of vectors of useful and related state variables;T – transposition symbol.

System of fig. 1 contains the following blocks:1 – control object; 2 – a functional transformation that reflects the formation of a signal vector; 3 – reception and optimal signal processing; 4 – formation of control signals.

In this case, control signals are usually formed on the basis of observation of data about the object of control, distorted by noise and interference. In turn, the management strategy is based on a priori information about the characteristics of the object, as well as on the previous history of variation of output and input variables.

Concomitant variables may be components that characterize the voltage instability of power supplies, drift of measurement parameters, and so on.

In the specific problem under consideration, the current state values of the object parameter drift (WSN sensor) can be considered as variables of the system state. Components of speed and acceleration of change of parameters at movement of object need to be considered at placement of the sensor on the mobile carrier (for example, on the car). When determining the location of the sensor on the ground or on the water surface, the components of velocity and acceleration can be considered as constant values or values whose changes are values of the second order of smallness, so they can be neglected in the observation interval. Accordingly, we present a generalized block diagram of a closed system for monitoring the parameters of the object (Fig. 2).

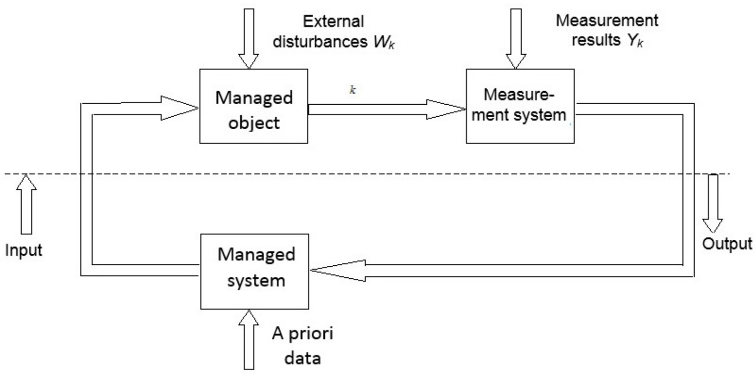

Fig. 2. Closed system for monitoring the parameters of the object

According to the theory of control and filtering in state variables [3, 5], the vector differential equation, which describes the vector of object parameters, has the form:

$$\frac{d}{dt}\overline{\boldsymbol{X}}_{\text{п}}(t) = \overline{\boldsymbol{F}}(t)\overline{\boldsymbol{X}}_{\text{п}}(t) + \overline{\boldsymbol{C}}(t)\overline{\boldsymbol{W}}(t) + \overline{\boldsymbol{G}}(t)\overline{\boldsymbol{V}}_{\text{в}}(t), \qquad \overline{\boldsymbol{X}}_{\text{п}}(t_0) = \overline{\boldsymbol{X}}_{\text{пп}} \tag{4}$$

Here $\boldsymbol{X}_{\text{пп}}$ – the value of the vector $\bar{\boldsymbol{X}}_{\text{п}}(t)$ at the initial time t_0;

$\bar{\boldsymbol{F}}(t)$ – $(n \times n)$ -dimensional matrix, which characterizes the relationships between state variables, in particular the relationship between true and measured parameters of the object;

$\overline{\boldsymbol{W}}(t)$ – p -dimensional motion control vector, according to which the object makes some movements along the route;

$\overline{\boldsymbol{C}}(t)$ – $(n \times n)$ -dimensional matrix, which characterizes the relationships between the components of the control vector of the object and the variables of the state of the object;

$\bar{\boldsymbol{V}}_{в}(t)$ – random r -dimensional vector of perturbations, which describes random changes in the state of the object;

$\bar{\boldsymbol{G}}(t)$ – perturbation matrix of $(n \times r)$ -dimension, which is characterized by the relationships between the components of the perturbation vector and state variables.

At the inputs of the measuring system, which is a hardware or software-implemented measurement algorithm, there is an observation vector:

$$E(t) = E\{\bar{S}[\bar{\boldsymbol{X}}(t), t], \bar{\boldsymbol{N}}(t)\}. \quad (5)$$

As shown in [3, 9], we can assume that the sum of all interferences and noises is an additive mixture with a Gaussian distribution. This assumption is quite logical in the presence of a relatively large number of heterogeneous interferences.

Observation signals are subjected to optimal processing (detection and evaluation). In synthesis, you can go one of two ways.

The first is the solution of the problem "in the forehead": the synthesis of the device as a whole. However, as the results of the analysis show [11], such a structure is too complex for technical implementation.

It's easier to go the other way. Note that the device for detecting the input signal against the background of noise and noise with Gaussian distributions is a linear device, and divide it into two series-connected blocks: proper detection (optimal filtering against noise) of the signal and measurement taking into account the drift of the measuring device (sensor).

Direct and regression methods of autocalibration of radio sensors

In [3, 4, 6] it is shown that the data of one of the sensors can be predicted using data from other nearby sensors. These predicted data will provide an appropriate basis for the correction of anomalies in the measurement results of the sensors. Due to the early detection of anomalies in the obtained data, it is possible not only to detect drift of sensor parameters, but also to correct it.

The main idea of the solution is to evaluate not only the measurement results, but also the drift of the meter parameters (for example, the coordinates of its location). This approach is proposed to be applied to networks of radio sensors. To assess the drift of sensor parameters in real time, it is proposed to use filters and models of sensor drift. The obtained estimates are used for correction and as feedback for the next evaluation step. The presented technique provides an effective solution to the problem of auto-calibration of sensors in wireless sensor networks.

The direct solution to the offset calibration problem is to apply test signals and measure network response. The result of comparing the expected and current response can be used to find the offset and scatter for the case of linear drift. This method is called in directional calibration, because the true value of the parameter is used to calibrate the sensors. Another method of directional calibration is manual calibration of the WSN segment, after which the data of non-reference sensors are consistent with the data of the segment where the calibration was performed. The network segment with reference sensors provides reference data for calibration of other sensors [8]. However, these methods are impractical and expensive for large-scale networks.

The task of calibration of the sensor network was considered in [4] in another statement. Assume that after the production calibration of the sensors and their placement in the network, the measurement error with the sensor changes according to a linear law with a certain speed and a constant component, different for each sensor. A method for estimating the parameters of a linear function using the coordination of only the results of sensor measurements in that part of the network has been developed. In this case, to obtain comparative estimates, there is no need to measure the true initial parameters. In essence, this method is a direct calibration of sensors in the sensor network. There is no need to place high-density sensors in the area of interest to us or test signals. However, it is necessary that the data captured by the sensors within the selected location have sufficient spatial correlation.

The task of calibration in sensor networks should be considered as a task of statistical evaluation of the parameter on a network scale. Thus, instead of calibrating each sensor to optimize a single measurement result, the network sensors are calibrated to optimize the overall network response. In the general calibration method, calibrated sensors are considered in a common controlled environment. The method was tested on the Ad Hoc network and gave a reduction in range measurement error from 74.6% to 10.1% [6]. The authors argued that the combined calibration method could be modified for auto-calibration of WSN in an uncontrolled environment where the true measurement value is unknown. It is shown that the problem is reduced to the problem of quadratic programming. Direct calibration over a number of measurements to locate sensors using total signal energy and / or time delay was also considered in [6].

In [9] the problem of reducing ambiguity in the results of sensor measurements was solved. A Bayesian approach was used to clear noisy data and reduce the effect of random errors in sensor measurements in the WSN. This did not take into account systematic errors. The method was applied in a network with a centralized architecture on a model data set and showed good results.

When implementing the method of direct calibration of sensors in the sensor network [6], the use of Kalman filter sets makes it possible to specify the values measured by the sensors. The state vector was varied according to the calibration parameters, and then the displacement and the slope were estimated to restore the correctness of the measurement results.

Another method of detecting errors and malfunctions of the sensor, which is part of an automatic system (such as a sensor network), is described in [5, 8]. Based on the results of incoming measurements, a model of sensor behavior was created. It was then optimized based on a maximum likelihood algorithm. The measurement results were compared with the model. If the deviation of the measurement result of the sensor from the simulated value exceeded a certain threshold, the system recorded this result as erroneous. On the other hand, with small deviations not exceeding the threshold, the system was automatically adjusted. This made the system able to adapt to slow drift.

In [5], the method of linear regression in the state space was used to detect anomalies and erroneous data of the sensor network. The data measured by the sensors were displayed from the input signal space (the space where the features are observed) to the feature space (larger dimension space) using the equation core. The projected data were classified into clusters. Data on points that did not fit into the rules were considered erroneous. The sensor, which always gave erroneous data, was considered to have failed.

In [12] the method of data modeling in WSN is described. Linear regression was used to fit the approximating functions to the data measured by the sensors in the observation interval. The sensors were adjusted to the basic (weight) functions used. Thus, if the sensor knew the weight functions of its neighbor, it could respond to a request for a neighbor during the observation interval. Therefore, when sending weight functions instead of sending measurement data of the entire observation interval from one sensor to another, the amount of data exchange at the upper levels of the network hierarchy is significantly reduced. This was one of the goals of the method. Another goal is to enable a sensor in the network to estimate the measured variable at points within the network where there were no sensors, using the spatial correlation between the sensors.

An appendix of the introduced method is the calculation of contour levels of measured values [12]. Even with unreliable communication between sensors and the presence of noise in the read data, this does not lead to systematic errors (drift and bias). The presence of such errors would necessitate constant correction of model functions to obtain estimates that deviate from the true initial values.

Thus, given the good ability to scalability, high-precision estimates and adaptation, vector support mechanisms should be used in other applications to predict and evaluate the physical parameters of the analyzed phenomena and processes. To predict the measurement result, in addition to the state space method, at certain points in time (each time measurements were made), the use of a Kalman filter has a good effect. This allows you to maintain the accuracy of the predicted values close to the measurements taken at the point of data acquisition, and reduce prediction errors.

Conclusions

Dedicated wireless sensor networks (WSN) or radio sensor networks contain a large number of signal processing facilities (elements), which are often placed in the surveillance area at random. In addition, access to BSM elements may be difficult or impossible (for example, for military or critical application networks).

The problem of research and development of methods of calibration of radio sensors of wireless sensor networks with use of various models of drift of parameters of radio sensors is solved. Mathematical models of sensor drift parameters, which are described by polynomial, exponential and harmonic trends, are analyzed.

The main tasks and approaches to the development and synthesis of the autocalibration system in the network of radio sensors are determined. The proposed method of error detection and correction of sensor measurement results in WSN is based on the assumption of spatio-temporal correlation of measurement results in neighboring sensors and the lack of mutual correlation of the processes of drift of technical parameters. Peculiarities of using direct and regression methods of autocalibration of radio sensors are considered.

The use of the auxiliary regression vector, according to the equation of which the forecast of future measurement results is calculated, is proposed and substantiated for the analysis of the space-time correlation.

Note that as the sample size increases, the observation interval increases, but there is better error smoothing. Therefore, there is a trade-off in choosing the optimal sample length for measurements.

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