Construction of systems for remote monitoring of measurements of medical signal parameters

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Abstract. Some non conventional methods of model identification based on data normalization are presented in the article. The method of Data Normalization can be effectively used in those fields of industry optical engineers and technology processing of optical signals, which suffer from factual difficulties while gathering experimental data. The named method helps to receive information about some tendencies and regularities in process and objects dynamics, identify similarities and differences of their structure, their quantitative estimations, to provide the statistical explanation of experimental data and real-time analysis.

1. Introduction

In medicine, monitoring is the observation of a disease, condition or one or several medical parameters over time. It can be performed by continuously measuring certain parameters by using a medical monitor (for example, by continuously measuring vital signs by a monitors device).

Monitoring of vital parameters can include several of the parameters, which allow for continuous monitoring of a patient being continuously informed of the changes in general condition of a patient.

Continuous long-term operation of remote monitoring systems is essential to avoid missing critical situations. In remote monitoring systems, the duration of continuous operation is determined by the capabilities of the wearable device. They are designed for pickup and registration of a complex of biomedical signals, preprocessing and analysis of signals and data. The purpose of this article is to develop an approach for monitoring health status based on the analysis and monitoring of biomedical signals.

Each signal has several measurements depending on the channel activation of the biomedical signal recorder. The most significant indicators for diagnostics are estimated. The active monitoring mode is set when the parameters monitored in the background go beyond the normal range.

Typically, the monitoring data is observed statistical sample parameter data.

Urgency of development of methods for analysis and processing of statistic information is explained by the fact that previously developed and successfully user methods for solving technical problems in many cases are completely unfit for use in technology processing of signals of medical systems because of much greater complexity of investigated object and boundary conditions, or they require for larger costs of computational resources, that does not correspond to received result. Thus, development of effective methods for analysis of statistic data is one of the important task while constructing models adequate to the object of the investigation.

This article discusses an approach to the analysis, identification and classification of measurement data of medical and biological signals, which allows the formation of quantitative criteria that can be used in automation systems.

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The creation of medical monitoring systems requires the solution of the following tasks:
- development of measuring instruments and organization of a system for collecting, processing and analyzing medical data from measuring devices and their integration in real time;
- integration of heterogeneous data and calculation modules into an integral distributed information processing system;
- classification of the received data and, accordingly, their sources;
- forecasting the dynamics of change and the risk of a critical situation;
- creation of a software and hardware complex for medical monitoring.

In accordance with the tasks to be solved, the software and hardware control complex includes three subsystems:
- subsystem of information collection and preliminary data processing;
- subsystem of integration and data accumulation (storage);
- subsystem for data analysis and forecasting of critical situations.

2. Materials and methods

Let us represent the measured medical signal \( f(t) \) as a function of continuous time \( t \), and its discrete sample implementation \( f(i) \), consisting of separate samples \( 1 < i < N \), where \( N \) is the sample size. From the standpoint of the theory of probability and mathematical statistics, discrete sample implementation \( f(i) \) can be considered as a distribution of instantaneous signal values and used to describe the corresponding statistical characteristics.

The initial data for this approach are digitized sequences of discrete non-stationary signals read from the measuring medical device.

We will interpret the values of medical signals obtained as a result of measurement as a time series \( x_1(t), x_2(t), \ldots, x_n(t) \).

Then the problem of signal identification can be represented as the problem of analyzing the waveform, since the form determines the information content of the signal and is not directly related to the energy of this signal.

Therefore, the tasks of signal recognition are reduced to the task of analyzing the waveforms and their characteristics. These measurements are called identification measurements [1].

The analysis of identification measurements is based on the following provisions:
- the waveform does not change when changing the shift and scale along the time axis;
- any analog signal after uniform sampling over time is partially characterized by the distribution of instantaneous values (RMZ);
- any analog signal after uniform level quantization is partially characterized by a set of distributions of time intervals (RVI);
- both distributions (RMZ and RVI) fully characterize the form of signal realization (time series of observations).

The individual features of the waveform (RMZ) are reflected in the frequency structure of functions, and the analysis task is reduced to extracting this information.

From the provisions of data analysis, subject to normalization in the interval \([0; 1]\), the form of the RMZ can be determined, for example, the moment characteristics of the RMZ signal [4].

Let distributions be given in a limited space \( [X^-, X^+] \) distributions are given:
\[ F_{x_i}(x) = \frac{(x - X^-)}{(X^+ - X^-)} = f_x, \quad (1) \]

where \( F_{x_i}(x), x \in [X^-, X^+] \) - arbitrary distribution;
\( F_{\tilde{x}_i}(x), x \in [X^-, X^+] \) - even distribution.

It was shown in [10, 11] that the average amount of information according to Kullback can be used as a measure of the difference between the compared distributions:
\[ I = \int_{x \in X} f_{x_i}(x) \cdot \ln \left( \frac{f_{\tilde{x}_i}(x)}{f_{\tilde{x}_i}(x)} \right) dx. \quad (2) \]

Using the distribution representation model [3], the formula can be transformed as follows:
\[ I = \int_{x \in X} \frac{f_{x_i}(x)}{f_{\tilde{x}_i}(x)} \cdot \ln \left( \frac{f_{x_i}(x)}{f_{\tilde{x}_i}(x)} \right) dx = \int_{0}^{1} f_{\tilde{x}_i}(r) \cdot \ln(f_{\tilde{x}_i}(r)) dr, \quad r \in [0,1], \]
\[ \text{or} \quad I = \int_{0}^{1} \frac{f_{x_i}(r)}{f_{\tilde{x}_i}(r)} \cdot \ln \left( \frac{f_{x_i}(r)}{f_{\tilde{x}_i}(r)} \right) \cdot f_{\tilde{x}_i}(r) dr, \quad r \in [0,1] \quad (3) \]

where \( f_{\tilde{x}_i}(r) = 1 \) - uniform distribution in the interval [0,1].

For \( f_{\tilde{x}_i}(r) = 1 \) complementary equality:
\[ I = \int_{0}^{1} f_{x_i}(r) \cdot \ln(f_{\tilde{x}_i}(r)) dr = -\int_{0}^{1} 1 \cdot \ln 1 dr = 0, \text{ т.е. выражение} \]
\[ I = \int_{0}^{1} f_{x_i}(r) \cdot \ln(f_{\tilde{x}_i}(r)) dr \quad (4) \]

can be defined as a measure of the quantitative measure of the difference in the sample data RVI (Id) in the interval \( r \in [0,1] \) in relation to \( f_{\tilde{x}_i}(r) = 1 \), or
\[ Id_i = \max_{y \in [0,1]} |F_{x_i}(y_i) - y_i|. \quad (5) \]

Thus, the obtained value of the measure of the difference between the measured medical signals Id can be used as a quantitative deviation of the parameter value from the stable one.

The structural and functional diagram of the identification of signal measurements can be presented as follows (Fig. 1).
Figure 1. Block diagram of identification of signal measurements.

An approach to the identification and classification of measurements of signals based on the calculation of shape indicators and its refinement using an information criterion make it possible to develop a structural diagram of the procedure for the identification and classification of measurements of medical signals for monitoring systems.

3. Results
The result of the analysis carried out in the work is to obtain quantitative measures, the possibility of algorithmization and automation, and a decrease in the computational complexity of the procedure for identification and classification of signals in remote medical monitoring systems.

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