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METHODOLOGY FOR OPTIMAL PLANNING OF A MEASUREMENT PROGRAM IN A TELEMEDICINE NETWORK FOR COLLECTING DATA FROM IOMT DEVICES

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Abstract.

Planning measurements using telemedicine sensor-transducer equipment is a complex multi-criteria optimization problem, the efficiency of which directly affects the quality of medical telemonitoring. This article presents a mathematical formulation of the problem of determining the optimal telemedicine measurement program and a methodology for optimal planning of measurement operations by ranking, implemented thanks to the introduction of feedback in the medical telemonitoring system circuit based on IoMT (Internet of Matter) sensors. of Medical Things) and cloud computing.

Keywords: medical telemonitoring systems, sensor error, measurement intensity , cloud computing, Internet of Medical Things .

1. Introduction

The task of maximizing the reliability of telemedicine diagnostics is solved under conditions of conflicting requirements:

1) minimizing energy consumption, maximizing battery life of surface-mounted and implantable sensors;

2) the need to resolve conflicts in the use of network and computing resources;

Thus, if several sensors transmit data simultaneously, this can lead to collisions in a wireless channel, for example, via BLE (Bluetooth Low Energy), and ultimately lead to packet loss and retransmission, which will increase latency and energy consumption. A data stream from several sensors arriving simultaneously at the Fog node can overload the gateway, creating a processing queue. The flow can be reduced by reducing the bit depth of the data representation, i.e. by reducing the precision. Practical developments in the field of health monitoring using cloud technologies are published in the works of Rizou D., Tronchoni A., Menary W. (2012-

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2016) [1, 2], which describe the experience of designing and implementing the MediCloud platform, used, among other things, as a physician forum. The work of Australian researchers Fan Wu, Taiyang Wu and Mehmet Rasit Yuce [3, 4] is devoted to the issues of the architecture of network systems of the Internet of Things for connected applications for monitoring the condition of telemedicine service users. The issues of complex monitoring of not only physiological parameters, but also the environment, with the subsequent combination of diagnostic results based on technologies " Data Fusion " is devoted to the developments of Antolín D., Medrano N., Calvo B., Pérez F. [5, 6]. In the works of Yuce, MR, Aloi, G., Caliciuri G., Fortino G., Gravina R., Pace P., Russo W., Savaglio C. [7-9] the issues of applicability of various wireless technologies for data transmission within the framework of specialized wireless networks of medical devices located on or around the human body, based on BLE, ZigBee, ultra-wideband access and Wi-Fi technologies, and a conclusion was made on the need to use several protocols at once to increase the reliability and validity of message delivery from the patient to the medical facility. Most publications do not fully disclose the methodology for optimizing the reliability of diagnostics by varying the parameters at the transport level of the data transmission network. At the same time, access to an increasing number of IoMT devices significantly increases the load on communication networks and poses significant challenges, both in terms of the reliability of subsequent data analysis due to loss of accuracy and the leakage of confidential information during access control, sharing, and storage. A technological solution to this problem is to manage the information content of IoMT device message sources through feedback provided by the digital infrastructure of the medical telemonitoring system. This raises the scientific and technical challenge of optimally planning measurement operations in the space of measurement intensities and independent errors of IoMT devices.

2. Methodology for justifying planning

Let's assume that the patient's functional state is continuously and periodically monitored remotely. The process at the IoMT device output $Z(t)$ can be described by the functional:

$$Z(t) = F^T(t)A + E(t), \qquad (1)$$

where F(t) is the vector of basis functions of the controlled physiological/kinematic process, E(t) is a random error function, and the components of vector A are random variables and are subject to evaluation based on the measurement results. The optimal program is determined via feedback loops between the Fog node and the IoMT device by approximating the connection function. $v(w(t))$, where $w(t)$ is the control parameter (Fig. 1).

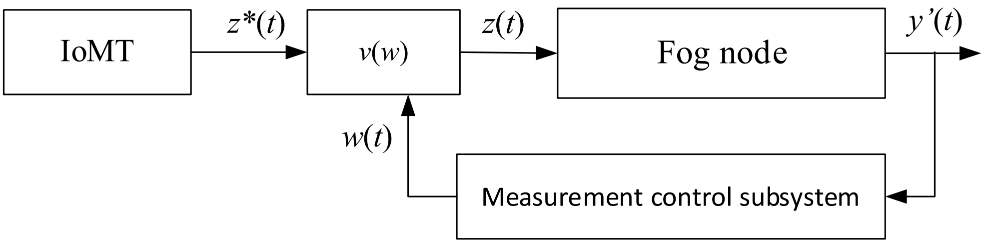

Figure 1 – Generalized IoMT sensor control scheme

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IoMT management function:

$$v\left(w(t)\right)=\Xi\left(w(t)\right), \qquad (2)$$

where $\Xi(w(t))$ is a step function: $\Xi\left(w\right)=\begin{cases}1, \text{ при } w>St;\\ 0, \text{при } \mathrm{w}\le St\end{cases}$, St is the threshold value of the patient's physiological/kinematic parameter when data transmission is critically necessary.

As a result, the monitoring function of the continuous controlled process of medical telemonitoring, corresponding to (2), can be represented as

$$Z\left(t\right)=v\left(w\left(t\right)\right)\left[F^{T}\left(t\right)A+E\left(t\right)\right]. \qquad (3)$$

Due to the fact that its physical and kinematic parameters are variable, to make a diagnosis with a given reliability it is necessary to have a high accuracy of measurements of the process $y(t)$ using w_0 IoMT devices of various purposes and accuracy classes. Organization of remote control of the implementation of the process $y(t)$ by a system consisting of w_0 IoMT devices are shown in Figure 2.

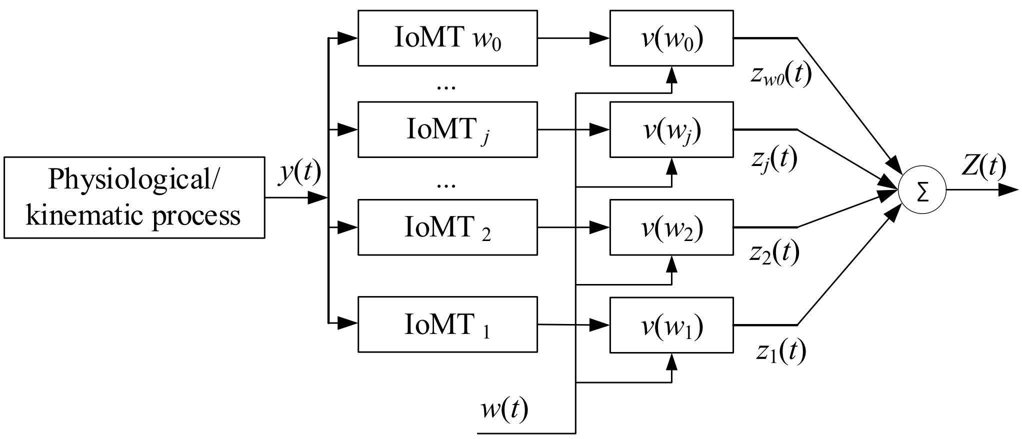

Figure 2 – Generalized control diagram of a medical telemonitoring system for one process

The use of a single Fog node implementing a sequence z_{ij} containing w_i measurements over a certain time interval τ assumes a constant value *of* $y(t)$ over the selected interval τ. This means that the actual change *in* $y(t)$ is approximated by a piecewise constant function (Fig. 3).

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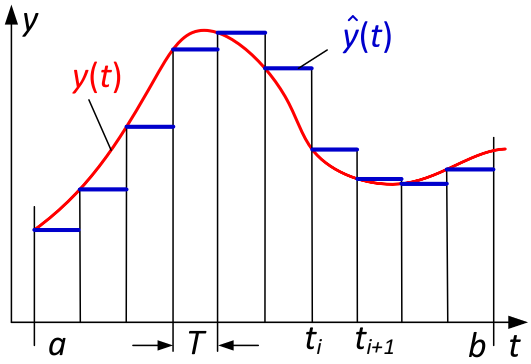

Figure 3 – Zero-order approximation

The approximation interval is adapted to the required accuracy of representation of $y(t)$.

2. Statement of the problem

The implementation of the random process $y\,(t)$ is represented by the canonical expansion

$$y(t) = F^T(t)\,A. \tag{4}$$

Then, the determination of the estimate *of* $y^*(t)$ is reduced to finding the estimate of the vector A and the subsequent calculation

$$y^*(t) = F^T(t^*)\,A^*. \tag{5}$$

Smoothing is achieved by averaging:

$$z_i = \frac{1}{w_i}\sum_{j=1}^{w_i} z_{ij}. \tag{6}$$

Mathematical model of the controlled process:

$$z_i = v(w_i)\left[F_i^T A + \frac{1}{w_i}\sum_{j=1}^{w_i} e_{ij}\right] \tag{7}$$

reflects the possibility of choosing the composition and measurement program.

Let us represent the possible values of measurements z_i on the observation interval $(t_0, t_f]$ in the form of a vector. $Z = [z_1, z_2, \ldots, z_i, \ldots, z_l]^T$. Estimate A^* is found from the condition

$$w\{Z/A\} \to \max_A, \tag{8}$$

in which the function $w\,\{Z/A\}$ according to (7) depends on the density of the joint distribution $w\{E_1, E_2, \ldots, E_l\}$:

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$$A^* = \left[\sum_{i=1}^{l} v(w_i)\frac{w_i}{D_{ei}} F_i F_i^T\right]^{-1} \sum_{i=1}^{l} v(w_i)\frac{w_i}{D_{ei}} F_i z_i. \quad (9)$$

Let us introduce the notation

$$S_i = \left[\sum_{i=1}^{l} v(w_i)\frac{w_i}{D_{ei}} F_i F_i^T\right]^{-1} F_i, \quad (10)$$

taking into account which algorithm (9) will take the form

$$A^* = \sum_{i=1}^{l} v(w_i)\frac{w_i}{D_{ei}} F_i z_i. \quad (11)$$

The estimation error $E_Q = |A^*\text{-}A|$ when using algorithm (11) and mathematical model (7) is determined by the expression

$$E_Q = \sum_{i=1}^{l} v(w_i) w_i S_i E_i D_{Ei}^{-1}, \quad (12)$$

from which it follows that the mathematical expectation of the estimation errors M $\{E_Q\} = 0$, and the correlation matrix of errors

$$K_Q = M\left\{E_Q E_Q^T\right\} = \sum_{i=1}^{l} v(w_i) w_i D_{Ei}^{-1} S_i S_i^T. \quad (13)$$

variances of the estimation errors $y^*(t^*)$:

$$\sigma_y^2(t^*) = \sum_{i=1}^{l} v(w_i)\frac{\lambda^2(t^*, t_i)}{D_{Ei}} w_i, \quad (14)$$

where $\lambda(t^*, t_i) = F^T(t^*) S(t_i)$ is the weighting coefficient that determines the influence of the measurement values z_i to estimate $y(t^*)$.

It is necessary to determine a program (values w_i, $i = 1, \ldots, l$) that ensures, with a minimum number of measurements, the required accuracy (reliability) of assessing the state of the patient's physiological process from the condition

$$\sum_{i=1}^{l} w_i \to \min, \quad (15)$$

under restrictions

$$\sum_{i=1}^{l} \frac{\lambda^2(t^*, t_i)}{D_{Ei}} w_i \geq \sigma_{ST}^2, \quad (16)$$

where σ^2_{ST} is the given acceptable value of the dispersion of estimation errors.

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4. Methodology for synthesizing a measurement program

The methodology includes five stages:

Step 1. We will carry out l discrete measurements at time t_i over the observation interval $\left(t_0, t_f\right]$. We will assume that $w_i \in \{0,1\}$. In this case, with l measurements, the accuracy of the estimate $y(t^*)$ is achieved:

$$\sigma_y^2\left(t^*\right)=F^{\mathrm{T}}\left(t^*\right)\left[\sum_{i=1}^{l}\frac{1}{D_{Ei}}F_iF_i^{\mathrm{T}}\right]^{-1}F^{\mathrm{T}}\left(t^*\right) \tag{17}$$

and the correlation matrix of the errors of the vector A estimate

$$K_A=\left[\sum_{i=1}^{l}\frac{1}{D_{Ei}}F_iF_i^{\mathrm{T}}\right]^{-1}. \tag{18}$$

Step 2. Let us identify the influence of any j -th measurement on the resulting value of the K_A matrix

$$K_A=\left[\sum_{\substack{i=1\\ i\neq j}}^{l}\frac{1}{D_{Ei}}F_iF_i^{\mathrm{T}}+\frac{1}{D_{Ej}}F_iF_i^{\mathrm{T}}\right]^{-1}. \tag{19}$$

Let us denote by

$$K_A^{(-j)}=\left[\sum_{\substack{i=1\\ i\neq j}}^{l}\frac{1}{D_{Ei}}F_iF_i^{\mathrm{T}}\right]^{-1}. \tag{20}$$

the correlation matrix of the estimation errors of the vector A over j -1 measurements (without the j -th measurement). Then we can write:

$$K_A=\left[K_A^{-1(-j)}+\frac{1}{D_{Ei}}F_iF_i^{\mathrm{T}}\right]^{-1}. \tag{21}$$

To explicitly represent the influence of the j -th measurement on the resulting accuracy (matrix K_A), we give the following form of expression (21):

$$\left(A+BCB^{\mathrm{T}}\right)^{-1}=A^{-1}-A^{-1}B\left(B^{\mathrm{T}}A^{-1}B+C^{-1}\right)^{-1}B^{\mathrm{T}}A^{-1}, \tag{22}$$

where A and C are non-singular square matrices of order m and r ; B is an arbitrary $m \times r$ matrix [10-12]. Taking this into account

$$K_A=K_A^{(-j)}-K_A^{(-j)}F_j\left[F_j^{\mathrm{T}}K_A^{(-j)}F_j+D_{Ei}\right]^{-1}F_j^{\mathrm{T}}K_A^{(-j)}. \tag{23}$$

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Step 3. Let us represent the accuracy of the estimate $y(t^*)$, highlighting the influence *of* the j - th measurement based on (23) :

$$\sigma_y^2\left(t^*\right)=F^{\mathrm{T}}\left(t^*\right)K_A^{(-j)}F\left(t^*\right)-F^{\mathrm{T}}\left(t^*\right)K_A^{(-j)}F_jF_j^{\mathrm{T}}K_A^{(-j)}F\left(t^*\right)\frac{1}{D_{Ei}+F_j^{\mathrm{T}}K_A^{(-j)}F_j}.$$

(24)

In expression (24), the minuend $F^{\mathrm{T}}\left(t^*\right)K_A^{(-j)}F\left(t^*\right)$ is the variance of the estimation errors $y(t^*)$ over l - 1 measurements (excluding *the j* -th), and the subtrahend is the change in variance $\sigma_y^2\left(t^*\right)$ due to *the j -th* measurement. Therefore

$$p_j=F^{\mathrm{T}}\left(t^*\right)K_A^{(-j)}F_jF_j^{\mathrm{T}}F\left(t^*\right)\frac{1}{D_{Ei}+F_j^{\mathrm{T}}K_A^{(-j)}F_j} \qquad (25)$$

represents the "contribution" (weight) of *the j* -th measurement to the resulting accuracy of the IoMT device.

Step 4. Let's create a set ordered in descending order.

$$P=\left\{p_1,p_2,\ldots,p_k,\ldots p_l\right\}, \qquad (26)$$

p_j calculated according to formula (25) are assigned new order numbers.

Stage 5. The next task of synthesizing the optimal measurement program consists of selecting the first elements p_k from the set *P*.

$y(t^*)$ are satisfied in accordance with the expression

$$F^{\mathrm{T}}\left(t^*\right)\left[\sum_{k=1}^{l_k}\frac{1}{D_{Ei}}F_kF_k^{\mathrm{T}}\right]^{-1}F\left(t^*\right)\le\sigma_{st}^2, \qquad (27)$$

where l_k is the number of the last measurement corresponding to the ordinal number from the set P that is included in the program.

Thus, to adjust the measurement program by adapting IoMT output signals to both the diagnostic object and the Fog node workload during patient service planning, the following is required:

1) constructing a coordination task and developing a methodology for solving it;

2) developing mechanisms for influencing IoMT devices and modifying their specific planning tasks;

3) developing rational procedures for exchanging data between IoMT devices, Fog nodes, and control subsystems.

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5. Conclusions

The developed methodology essentially implements a sequence of steps for solving an integer programming (optimization) problem, resulting in the synthesis of a program with w_i measurements of IoMT devices at a single point in time t_i. This effectively becomes the point on the interval $\left(t_0, t_f\right]$, where measurements yield the greatest effect in terms of the accuracy of the $y(t^*)$ estimate, and, accordingly, the maximum reliability of telemedicine diagnostics.

At the hardware level, the methodology allows us to formulate requirements for the maximum bit depth of encoding deviations of physiological or kinematic parameters of IoMT devices by patient devices, as well as to evaluate the effectiveness of both newly created and existing remote operational medical monitoring systems that include intermediate Fog nodes for preliminary data processing.

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