Information measurement systems in the digital society

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Abstract. The transition to the next technological order requires robotics and automation in the industry. Managing such process of production is impossible without scenario modeling, forecasting and diagnostic of possible emergencies based on measurement information received from various sensors. The models used must be adequate to the real state of the object, and not to its project, on the basis of which it was designed and manufactured. Such models are called twin models of physical objects. The objective of the research is to obtain the approaches to the creation of information-measuring systems capable of processing large volumes of measurement information for implementing dynamically changing twin models of physical objects, and to carry out continuous training and adaptation to changing conditions. The proposed method allows continuous extraction of knowledge from the measurement information, accumulation knowledge about the object during its life. It was shown that hybrid models with physical and mathematical substantiation and capability of learning based on measurement data are the possible solution.

1. Introduction

Globalization processes require a transition to a new technological structure associated with the creation of advanced information and communication technologies. These technologies will become the basis of the new digital infrastructure of the research and industrial complex [1]. Digital transformation in the technical field requires the development of information measuring systems and technologies in several directions: the creation of wireless networks of sensors (with the possibility of their movement), carrying out continuous acquisition of information from physical devices and the environment. The accumulation and storage of measurement information is associated with the implementation of a platform for intelligent big data analysis, creating internal cloud infrastructure of the enterprise or application of collective cloud services.

Information-measuring systems in the industry and transport are designed for monitoring, technical diagnosis and predicting the behavior of technical objects and therefore must interact with their digital model, which allows them to be classified as a class of cyber-physical systems. When wireless data transmission pays significant part in maintenance efficiency, fault tolerance, adaptability and the possibility of self-organization of the sensor network. In our research, the IEEE 802.15.4 standard is of interest. It regulates the organization of energy-efficient sensor networks, such as ZigBee [2].

The up-to-date approach is the use of a dynamically updated object model, which, in fact, is its digital twin [3]. Dynamically updated models have the opportunity to constantly receive new measuring information from the sensors of a technical object, from the sensors of control devices and the external environment, to summarize the newly obtained and archive data to change their parameters. The digital
twin is constantly being trained on the basis of new and historical data, updates its parameters in real time, adapts to external conditions and predetermines the optimal behavior of a technical object in the current situations [4].

The necessity for continuous learning, adjusting the characteristics of the model when updating information has led to the fact that artificial intelligence, neural networks and machine learning are the methodological basis for its creation. However, the approach based on the continuous learning, adjusting the characteristics of the model when updating information led to the fact that the artificial intelligence, neural networks and machine learning are the methodological basis for digital twin creation. Though, the machine learning approach cannot be directly applied, it requires further development. The machine learning model is based only on data that forms flexible-controlled non-uniform flows coming from sensors and from other sources of information. The model improves with time as data accumulates. However, the machine learning model does not take into account knowledge of the causal relationships of a physical object; it represents an object as a blackbox; the approximations obtained by this model are not fully mathematically justified. The greatest difficulty is the prediction of the rapid deterioration of the object in the absence of such situations during training, so based only on machine learning models it is difficult to predict critical situations.

Physical and mathematical models require deep knowledge of the physics of objects, the physics of very complex processes of changing of the object properties; use a large amount of computation, making it difficult to work in real time, which makes it impossible or very difficult for the model to reflect on the changes occurring in the object.

Sophisticated technologies for digital processing of measurement information should be carried out in a common computing environment, using cloud resources with convenient network access to shared computing resources [5]. The Peter the Great St. Petersburg Polytechnic University has a supercomputer center organized, the computing environment of which supports the cloud system.

The objective of the survey is to develop modern, more complex methods of creating digital twins, which take into account both the physical and mathematical foundations of causal-investigatory relationships, and the constantly obtained measurement data specifying the model by means of machine learning. Such a model will have all the advantages of two classes of models.

2. Information processing technique

The objective of measurement information processing is to create and maintain a neural network model of a physical object or process. If a physical object or process is characterized by a differential, integro-differential or differential-algebraic equation (ordinary or partial differential equation) with initial or boundary conditions of the following form:

\[ A(u) = g, \quad u = u(\bar{x}), \quad \bar{x} \in \Omega \subset \mathbb{R}^d, \quad B(u)|_{\Gamma} = h, \]  

(1)

here, \( u = u(\bar{x}) \) is the function characterizing the state of the object, \( A(u) \) is a differential, integro-differential or differential-algebraic operator, i.e. an algebraic expression containing derivatives, integrals or algebraic equations of an unknown function \( u \), \( B(u) \) is an operator defined by boundary conditions, \( \Gamma \) is a boundary of a region \( \Omega \).

We are looking for an approximate solution of problem (1) in the form of an output of an artificial neural network (ANN) of a given architecture:

\[ u(\bar{x}, \bar{w}) = \sum_{i=1}^{N} c_i \varphi(\bar{x}, \bar{a}_i), \]  

(2)

where \( \bar{w} = [w_1, w_2, ..., w_N]^T \) is the weight vector \( \bar{w}_i = (c_i, \bar{a}_i) \), which aggregates the linearly input parameters \( c_i \) and the nonlinear input parameters \( \bar{a}_i \).

Basic neuroelement is the function \( \varphi(\bar{x}, \bar{a}_i) \) defined by the choice of the type of neural network and the activation function.
Sometimes it is advisable to use ANN with different basic elements (heterogeneous ANN) [6]. Usually, such networks are used when the desired solution behaves fundamentally different in different subdomains, for example, in problems with phase perturbation, jumps, etc. In such a situation, it often makes sense to build two or more neural networks of a smaller size, each of which corresponds to its own subdomain.

The ANS weights vector \( \hat{w} \) is in the process of step-by-step network training, built in the general case by minimizing the error functional \( J(\hat{w}) \). The error functional for problem (1), is

\[
J(\hat{w}) = J_1 + \delta_2 J_2 + \delta_3 J_3
\]

where \( J_1 \) is the assessment of the error of a differential equation, \( J_2 \) is the assessment of the error depending on the initial conditions, \( J_3 \) contain terms corresponding to experimental data, and \( \delta_2, \delta_3 \) are penalty factors. The third term is introduced to ensure that the digital twin takes into account the measurement data of a physical object. The impact of measurement results on the neural network model is characterized by value \( \delta_3 \).

The calculation of integrals \( J_1 \) and \( J_2 \) in an analytical form, is possible only in exceptional cases, therefore we use a discrete form for functional when digital data preprocessing:

\[
J_1 = \sum_{j=1}^{M} \left( A(u(\xi_j)) - g(\xi_j) \right)^2; \tag{3}
\]

\[
J_2 = \sum_{k=1}^{K} \left( B(u(\xi_k^l)) - h(\xi_k^l) \right)^2; \tag{4}
\]

\[
J_3 = \sum_{i=1}^{L} \left( u(\xi_i^r) - u_i^r \right)^2; \tag{5}
\]

here \( u_i^r \) are the results of observations of the object corresponding to the points \( \xi_i^r \). Due to the fact that the initial equations (1) correspond to the simulated object inaccurately, we are not looking for the exact minimum of the functional \( J(\hat{w}) \), but a point \( \hat{w}_\eta \) in the space of weights. \( J(\hat{w}_\eta) < \eta \) which defines the so-called \( \eta \) solution \( u_\eta = u(\hat{x}, \hat{w}_\eta) \). The number \( \eta > 0 \) is chosen so as to consider the constructed model sufficiently accurate. The smaller the number \( \eta \), the more accurate the model (1).

Computational experiments have shown that the use of a fixed set of test (trial) points \( \xi_j, j = 1, ... , M \) is impractical, since in this case small errors in these test points may be accompanied by large errors at other points in the region \( \Omega \). An increase in the number of test points in order to cover the area \( \Omega \) sufficiently dense allows us to avoid a similar situation in the case of a relatively small number of neurons (terms in expression (2)). At the same time, the computation time increases dramatically, which is significant in a situation when we want to model an object in real time. The solution to this problem was the use of periodically regenerated sets of test points \( \{ \xi_j \} \) in the region \( \Omega \) and, if necessary, regenerated sets of test points \( \{ \xi_k^l \} \) on its boundary \( \Gamma \). Re-generation of test points after a certain number of steps of the network learning process makes it more stable [7].

In this case, we organize calculations as the process of minimizing a set of functional, each of which is obtained by a specific choice of test points and is not completely minimized (between regenerations of the test set, only a few steps of the chosen minimization method are performed). Such an approach, in particular, makes it possible to circumvent the problem of falling into a local extremum, which is characteristic of most global nonlinear optimization methods. In the process of optimizing the error functional, we are obliged to include new observations as additional components in the sum \( J_3 \). If it is
necessary to take into account the obsolescence of information over time, then you should throw out obsolete observations or use a formula \( J_3 = \sum_{i=1}^{L} \delta_i (u(\xi_i^*) - u_i^*)^2 \); with variables \( \delta_i \)

In most situations, the random distribution of test points, generated over a certain number of training epochs using a uniform probability density function (PDF) or any other PDF, which ensures a more stable course of training. In some cases, it is advisable to use non-uniform PDF for test points — thickening them near features (discontinuity boundaries, angles, etc.) or in areas with large errors. It is also possible to regenerate only a subset of the set of test points. The number of test points is a compromise between the requirement of accuracy and stability of the computational process (the more points, the better these indicators) and the limited time to build and adapt the model (for a digital twin, these processes must go in real time during its operation).

3. Heating simulation
Consider the task of controlling the heating of the ship’s premises. According to the [8], the temperature field in the presence of a heating source satisfies the equation:

\[
\rho C \frac{\partial T}{\partial t} = \text{div}(k \text{grad}(T)) - h(T - T_{\infty}) + f(t, x) \tag{6}
\]

with the initial conditions \( T(x, 0) = T_0(x) \), with boundary condition \( \text{grad}(T) \mathbf{n} + h(T - T_{\infty}) |_{\Gamma} = 0 \), where \( \rho \) is the density, \( C \) is the heat capacity, \( k \) is the heat conductivity of the substance, \( h \) is the coefficient, \( T_{\infty} \) is the ambient temperature, \( f \) is the heating source, \( \text{div} \) is the divergence, \( \text{grad} \) is the gradient, \( \Gamma \) is area boundary, \( \mathbf{n} \) is outer normal line.

The problem of the analysis is to determine the influence of the current measurements results obtained by sensors under the conditions of gradual changes in the object using two approaches: traditional modeling based on the Finite Element Method (FEM) for solving equations, and the proposed neural network method.

To solve this problem was applied FEM method of the PDF solution on the grid obtained by the Delaunay triangulation with the number of nodes from 25 to 1089. The standard deviation (std) measure of inaccuracy was found in the range from 0.001 to 0.0004. These results can be made as reference measure of inaccuracy. In the neural network method, an architecture of perception with one or two hidden layers, having dimensions (2-1) and (2-2-1) were used. The hyperbolic tangent was used as the activation functions of the hidden layers, the output layer was linear. The perception was trained using 25 randomly selected data. In the table 1 the estimation results shows the errors of the neural network model testing at the nodes of the Delaunay mesh. As was expected, std-error increases as compared with the exact solution.

| Number of nodes | Root-mean-square errors in the exact calculation | Root-mean-square errors of perceptron (2-1), training with 25 samples | Root-mean-square errors of perceptron (2-1) generalization | Root-mean-square errors of perceptron (2-1-1) training with 25 samples | Root-mean-square errors of perceptron (2-1-1) generalization |
|-----------------|-----------------------------------------------|------------------------------------------------------------------|--------------------------------------------------|------------------------------------------------------------------|--------------------------------------------------|
| 25              | 0.01                                          | 0.04                                                            | 0.02                                             | 0.040                                                            | 0.040                                                            |
| 81              | 0.004                                         | 0.066                                                           | 0.047                                           |                                                                  |                                                                  |
| 289             | 0.001                                         | 0.059                                                           | 0.045                                           |                                                                  |                                                                  |
| 1089            | 0.0004                                        | 0.057                                                           | 0.042                                           |                                                                  |                                                                  |

The temperature graph in a cabin with a point source of heat is shown in figure 1.
Figure 1. A temperature distribution $T/T_{\text{max}}$ in the range $\{x_1 - \bar{x}_1/x_{1\text{max}}, \ x_2 - \bar{x}_2/x_{2\text{max}}\}$ having a point source of heat.

Table 2. Errors of the traditional FEM model in the Delaunay mesh nodes during model degradation

| Number of nodes | Root-mean-square errors in the exact calculation | Root-mean-square errors in the exact calculation provided model become degraded |
|-----------------|-----------------------------------------------|--------------------------------------------------------------------------------|
| 25              | 0.01                                          | 0.22                                                                           |
| 81              | 0.004                                         | 0.33                                                                           |
| 289             | 0.001                                         | 0.40                                                                           |
| 1089            | 0.0004                                        | 0.43                                                                           |

In the case of a gradual change in parameters of physical object or in environmental, the network model, originally built on equation (6), takes into account the measurements obtained and performs continuous additional adaptation. Let the model receive additional measurements from 25 sensors placed arbitrarily. Then root-mean-square errors of the neural network generalization in different nodes of space practically do not increase. The simulation results are shown in table. 3.

Table 3. The errors of the neural network generalization provided model become degraded

| Number of nodes | Root-mean-square errors of the perceptron (2-1) training with 25 samples | Root-mean-square errors of the perceptron (2-1) generalization | Root-mean-square errors of the perceptron (2-1) training with 25 samples | Root-mean-square errors of the perceptron (2-1) generalization |
|-----------------|-------------------------------------------------------------------------|---------------------------------------------------------------|-------------------------------------------------------------------------|---------------------------------------------------------------|
| 25              | 0.04                                                                    | 0.043                                                        | 0.03                                                                    | 0.040                                                         |
| 81              | 0.063                                                                   |                                                               | 0.03                                                                    | 0.050                                                         |
| 289             | 0.055                                                                   |                                                               | 0.03                                                                    | 0.053                                                         |
| 1089            | 0.057                                                                   |                                                               | 0.03                                                                    | 0.052                                                         |

4. Problem of controlling the heating of the ship’s premises

The neural network model is used in the intelligent system for early detection of fire on the ship. Sensors located inside the ship’s premises continuously transmit fire risk measurements to the center via a wireless interface, which is based on the measurement results and the Navier-Stokes mathematical model for heating and heat transfer. Mathematical model has high computational complexity therefore is implementing at the SPbPU supercomputer center [9-10].

Additionally, the proposed approach made it possible to determine the optimal location of the sensors in the space of the room using a specially developed genetic algorithm. The fitness function of the algorithm is obtained on the basis of the recurrent neural network object model.
5. Conclusion

Information-measuring systems in a digital society are designed not only to measure a variety of parameters, but also to generalize measurements in order to gain knowledge about the physical object. Therefore, the modeling of measurement objects is an integral function of the information-measuring system.

Modern information-measuring diagnostic and forecasting systems should constantly update their models in real time. Information-measuring system designed to control the current state of a physical object, to predict its optimal behavior in the next period of time.

The proposed hybrid models take into account the causal relationships characteristic of a physical object or its block, expressed as a partial differential equation and update measurements.

In contrast to the traditional FEM method of solving PDEs, it was proposed to use solutions using neural networks, which, without complete retraining, allow the model to be adapted to newly acquired data.

The proposed method has been used in an intelligent multisensory early warning system for fire detection on a ship.

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