Metrology of nerve-similar sensing systems in anthropomorphic robots and living organisms

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Abstract. The features of metrological support of nerve-similar sensor measuring systems with the use of neural networks are considered. It is established that the metrological verification of such measuring systems, by analogy with living organisms, is possible by comparing their responses, invariant to the external unstable environment. It is shown that from the standpoint of classical metrology, instrumental, methodical, static, dynamic, systematic and random errors of nerve-like sensory measurement systems with neural network results are reduced to two types – methodical and systematic errors of neural network training. It is proved that without using reference calibration tools for embedded sensors, it is possible to experimentally evaluate systematic and random errors in the presence of several similar measurement systems by multiple pairwise comparisons of their responses, and the obtained systematic error can be introduced in the form of a metrological correction in the results of responses.

1. Introduction
Humans and other animals demonstrate a remarkable ability to map sensory information from their skin onto internal notions of hardness, texture, and temperature in order to reason about their physical condition and environment. For example, human hands serve not only prehensile functions but also as powerful sensory organs. Recent advances in stretchable fiber optics and electronics, soft robotics, and non-convex optimization methods for deep neural networks (NN) now offer us building blocks on which we can start to replicate this tactile perception synthetically with different sensing mechanisms [1].

Similarly to an effective biological nervous system of living organisms, the possibility of creating small-sized distributed optic fibre sensors embedded in robot structures using additive technologies opens up the prospect of implementing a sensor network (artificial nerves) for monitoring dynamics of temperature, load and defect by continuously measuring parameters (pressure, movement, curvature, temperature, humidity and acoustic emission) during operation of people with artificial limbs and of anthropomorphic robots. Because any embedded sensors are not extracted during all term of operation of objects, it is impossible to calibrate (verify) by means of traditionally in metrological laboratories. However, due to the nonlinearity of the response characteristics of embedded sensors and their functioning in a complex internal and external environment, there is a problem of our uncertainty in the reliability of sensory information. This problem can be solved with the help of NN-approach and statistical methods of error estimation. Embedded measuring optical fiber sensor networks on the basis of small-factor sensing structures of micron and submicron scale form are a class of cyber-physical intelligent measuring systems with NN processing and fusion of sensory information [2-4].
The main metrological requirements for such distributed sensor systems are an invariance of the measurement result from the influencing quantities (factors) and a statistical correction error of the measurement result.

2. Neural network approach to metrological verification of nerve-similar sensors

Currently, there is no complete and universal system engineering and metrological description of the NN. Measurement systems based on NN are very specific and differ from classical formalized measurement systems. The choice of NN structure is carried out in accordance with the features and complexity of the task. The operation of the NN depends on the value of synaptic connections, therefore, given a certain structure of the NN, which meets any problem, the network developer needs to find the optimal values of all variables, weighting factors, that is, to make the training of the NN. The learning process requires a correct assessment of the quality, reliability of the result, evaluation of possible errors of the NN. One way to get such an estimate is to test the examples, and the learning quality indicator — determining the predictive ability of the NN— is to calculate the percentage of correctly recognized examples. Determine the confidence factor $Q$ reliable recognition of fuzzy test examples:

$$Q = \frac{M1 - M2}{R * 100\%}$$

where $M1$ is the maximum response of the NN; $M2$ is the response of the NN close to the maximum; $R$ is the level of reliability.

A neural network works with empirical examples with a fuzzy set of solutions. Therefore, the NS, in addition to the decision on the class of the input example, calculates the confidence factor $Q$ in this decision, which depends on the given level of reliability $R$, the specific value of which is selected in the range of 0.9 -0.99, for example - 0.98 and determines the degree of "training" of the NN. The formula shows that the confidence of the NN depends on the difference between the highest response and the closest to it level. If $Q$ is greater than 100 %, that takes a single value of the signal (the decision). The formula $R$ is in the denominator correctly. Indeed, with a large value of reliability $R$ and the magnitude of the difference in the numerator will also be the greatest (the response of one neuron $M1$ will be much greater than the response $M2$ of another neuron). In addition, $Q$ expresses the confidence of a particular NN trained on specific examples. That is, if the input example differs from the example in the knowledge base, a better trained NN will doubt more than a NN with less knowledge (experience).

Therefore, the arithmetic mean of the percentages of the confidence values obtained by testing each example, with a known result, gives us the necessary confidence percentage. From the point of view of classical metrology errors in one of the classifications are divided into methodological and instrumental. The division of errors into methodological and instrumental ones is related to the level and volume of a priori information used in the description of the measuring procedure and measurement results.

3. Estimation of accuracy of neural network models

Artificial NN is a very specific measurement tool. Inaccuracy of classification is determined by: incorrect choice of structure and poor-quality training of NN. Error of architecture selection and training of the NN relate to methodological errors. Learning errors are also dynamic and systematic. The application of NN models is attracted by the fact that they provide invariance of transformation in relation to noise and instability of input measuring signals.

In fact, artificial NN are universal approximators, which makes it possible to effectively use them as models of various nonlinear signal converters, including measuring sensors, devices and systems. Errors of NN models are caused by inaccuracy of estimates of synaptic weight coefficients of NN obtained as a result of model training, as well as inaccuracy of technical implementation of artificial NN based on digital computing devices with limited bit capacity. For the above reasons, the synaptic weights of artificial neural network $W_j$ and $V_j$ may deviate from their nominal values. In the general case, these deviations are random in nature and can be expressed in the form of a root mean square deviation (RMS) $\sigma_{W_j}$, $\sigma_{V_j}$ or in the form of limit values errors $\pm \Delta_{W_j}, \pm \Delta_{V_j}$, where $i = I, ..., m; j = J, ..., n$, so it is necessary to estimate the RMS output of the model from its nominal value $\sigma_i$ and the error limit of this signal $\Delta_i$. 

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Obtaining these estimates for the NN model of nerve-similar sensing measurement system, we use an approach that has been used in Metrology to evaluate results of indirect measurements [5].

In indirect measurements, the value of the desired value \( Y \) is found by direct measurements of other quantities \( X_1, X_2, ..., X_n \) as \( Y = F(X_1, X_2, ..., X_n) \). In our case, the output signal of the NN model depends on its parameters and the input signal \( Y = G(W_{ij}, V_j, x) \).

We assume that the values of synaptic weights of the NN model \( W_{ij}, V_j \) are statistically independent, then the estimation of the output signal dispersion is:

\[
\sigma_y^2 = \sum_{j=1}^{n} \left( \frac{\partial G}{\partial V_j} \right)^2 \sigma_{V_j}^2 + \sum_{i=1}^{m} \sum_{j=1}^{n} \left( \frac{\partial G}{\partial W_{ij}} \right)^2 \sigma_{W_{ij}}^2 
\]  

and the interval estimation of the output signal error of the network model is:

\[
\Delta_y = \pm K_p \sqrt{\sum_{j=1}^{n} \left( \frac{\partial G}{\partial V_j} \right)^2 \Delta_{V_j}^2 + \sum_{i=1}^{m} \sum_{j=1}^{n} \left( \frac{\partial G}{\partial W_{ij}} \right)^2 \Delta_{W_{ij}}^2} 
\]  

Experimental estimation of errors of nerve-similar sensing systems of the same level of accuracy without application of standard verification tools is made by multiple pairwise comparison of their responses. The number of sensor measurement systems to be compared must be at least three. As a result of statistical processing of the results of multiple \( n \) comparisons of \( X_z \) and \( X_k \) responses, the arithmetic means are obtained:

\[
\Delta_{zk} = \frac{\sum_{j=1}^{n} (X_{zj} - X_{kj})}{n} 
\]

The deviation of the arithmetic mean of its errors from the middle of dispersion of systematic errors of all measuring instruments, which is determined by the middle of the measuring instrument with a minimum deviation of the arithmetic mean, in comparison with others, is taken as a systematic error of a particular means of change. The obtained estimation of systematic error maybe introduced as an amendment to the output signal of the measuring system [6].

4. Results of modeling and applications

Simulation modeling of nonlinear neural network (three-layer perceptron, Hopfield neural network with back propagation of error, etc.) of a nerve-like sensor system allowed us to carry out a comparative analysis of NN errors (universal approximator) and polynomial approximation model of the 3rd order. During the simulation, the parameters of both models were changed by 1 % of the nominal values and the conversion functions were calculated according to the formula (1) and interval error estimates according to the formula (2)

It is obvious that in the given range of input signals the errors of the NN model do not exceed 2 %, while the errors of the polynomial model are in the range from 4 to 12 %.

Metrological characteristics of NN models of nerve-similar measuring transducers (sensors with neural network approximator) are better than those of classical transducers with polynomial approximation. Most robots today have sensors on the outside of their bodies that detect things from the surface. Optical fiber sensors are built into the body so that they can actually detect forces transmitted through the thickness of the prosthesis or robot, as we and all organisms do when we feel pain, heat, solid and liquid objects. New artificial nerves and nerves-like sensors can radically change the limb prosthetics of living organisms and improve the functionality of anthropomorphic robots. Researchers have created a new type of artificial nerve that can feel touch, process information and communicate with other nerves, as nerves do in our own body, and now managed to connect optical fiber artificial neuron to a biological counterpart [1].
The boundary values of the errors of the models neural network model, polynomial model.

5. Conclusions
Embedded nerve-similar sensor systems can be metrologically controlled by their intellectualization using fiber optics and neural networks.

Neural network models of nerve-like measuring transducer are resistant and invariant to noise and internal defects and are the most suitable candidate for use in the sensorization of cyber-physical systems - anthropomorphic robots and artificial limbs of living organisms.

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