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Sensor Drift Prediction Using Neural Networks

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Abstract

The neural networks application with various properties is considered for accuracy increasing of physical quantities measurement by prediction of sensors drift. There is researched method of sensor drift prediction on early stage of sensor exploitation by simulation modeling for various kind of sensor drifts.

1. Introduction

As it is shown from [1, 2], the error of modern data acquisition systems is much less than initial sensor error in majority of cases. Besides the sensor drift is much higher than drift of the other measuring channel components. It is possible to provide accuracy increasing of physical quantities measurement by sensor calibration using special calibrator or sensor's periodic testing with reference sensor on exploitation place [3]. But operations realizing these methods are rather difficult. The low maintenance is provided by sensor drift prediction [4]. However, prediction based on average drift of similar sensors has low reliability and does not take into account an individual sensor features in conditions that are similar to exploitation conditions. The testing or calibration maintenance can be reduced by sensor drift prediction during intertesting interval. The most effective is the application of artificial intelligence methods, in particularly neural networks [5, 6, 1] for this purpose.

It is known [7, 8] the quality of neural networks training depends on the volume of training data in strong degree. It causes the main contradiction at neural networks using for sensor drift correction [2]. The high-quality neural network training allows sharply to reduce the prediction error and also to increase an intertesting interval. The obtained by calibration data volume will appear insufficient for high-quality neural network training. It is offered to use an additional neural network for increasing of data volume for predicting neural network training in [2]. A method of artificial increasing of data volume for neural network training is known also by using of historical (accumulated before) data [9]. However the historical data accumulated according to [9] do not provide sensor drift prediction. It is offered to use the real data about drift of the same types of sensors in the similar exploitation conditions as historical data [1]. The possibilities of such historical data using for high-quality individual prediction of sensor drift during intertesting interval are considered below.

2. Method of Sensor Drift Prediction

It is obviously, that the best prediction quality of sensor drift is provided by training of predicting neural network using real data about sensor drift (which can be obtained by sensor's calibration or testing at exploitation place). However, the volume of real data frequently is not enough for high-quality neural network training as was considered above. And these data are not available at the beginning of sensor exploitation. The historical data should be replaced by real data in accordance with accumulation of real data about drift of the given sensor.

The historical data should be integrated for taking into account of individual features of each sensor drift by appropriate way. It is proposed to use a set of integrating historical data neural networks (IHDNN) for such integration. Let us consider the historical data of sensor drift as curves $d1...dn$ (see Fig. 1), which are equal to dai, dbi, dci, $i = \overline{1,n}$ into calibration points a, b, c. The first calibration of the new sensor allows correcting initial sensor error at the moment 0. The second calibration of the new sensor allows receiving the first real value dak of sensor drift in calibration point a. The purpose of the historical data using is the prediction of number of points dbk, dck on the basis of dak value etc. This allows predicting sensor drift at the future calibration points.

The main purpose of the IIDNN using is the providing prediction of point dbk on the basis of dak and dai, $i = \overline{1,n}$, the next point dck on the basis of dbk and dbi, $i = \overline{1,n}$ and etc. The number of available historical curves of sensor drift determines structure of IIDNN input layer.

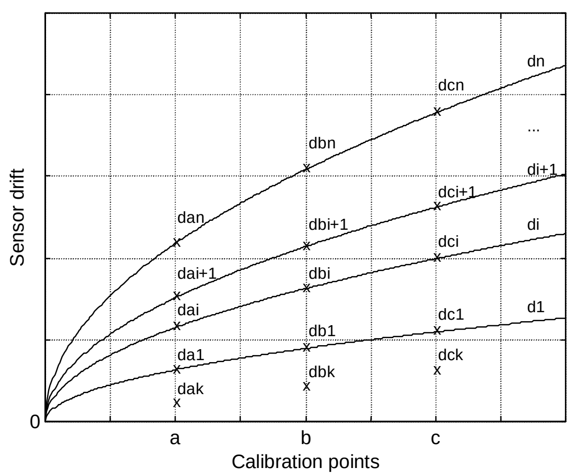

Fig. 1. Historical data about sensor drift

It is expedient to form training sample for IIDNN by special algorithm:

1. One curve of sensor drift di is considered as real and all other curves dj, $j = \overline{1, i-1}$, $j = \overline{i+1, n}$ are considered as historical data. Thus, the real data dai in point a and dbi in point b are obtained;
2. The absolute deviations $\Delta ij = |dai - daj|$ of point dai from all other points daj is defined, where $i = \overline{1,n}$, $j = \overline{1, i-1}$, $j = \overline{i+1, n}$;
3. All absolute deviations obtained on step 2 is sorted in decreasing order and maximum and minimum values are calculated;
4. Sorting of daj values according to decreasing order forms the set of training vectors.

The results of historical data integration in calibration points are considered as basis for approximating neural network training. That actually increases data volume for predicting neural network training. The experimental researches of historical data integration of various kinds of sensor drift are considered below.

3. Experimental Researches

The error of sensor drift prediction contains three components by proposed method using: (i) an error of historical data integration, (ii) an error of approximation of drift integration results into sensor's calibration points and (iii) an error of properly prediction of approximation results for future time of sensor exploitation.

The error of historical data integration represents an error of prediction of the sensor drift dbk, dck etc. in next calibration points $b, c...n$ on the basis of second calibration results in point a (see Fig. 1). For example, the percentage error of integration in point b for sensor k is equal

$$\delta bk = (dbk_{pred} - dbk_{real}) \cdot 100\%,$$

where dbk_{pred} is the result of sensor drift prediction in calibration point b and dbk_{real} is the real value of sensor drift obtained at calibration.

The drift of certain sensors does not allow evaluating possibilities of prediction method as a whole in some specific exploitation conditions. Therefore, the experimental researches of proposed sensor drift prediction method were conducted by simulation modeling. The hypothetical data [1] about sensor drift were used as historical. They are presented as mathematical expressions simulating various kinds of possible sensor drift. The 10 curves of hypothetical data were formed per each kind of drift. During researches each from 10 curves is accepted for real sensor drift and the remaining curves are used for forming of IHDNN training sample according to Chapter 2. Thus the 10 curves of percentage errors of historical data integration are received on the basis of 10 curves of hypothetical data. It is expedient to research integration error since 3 calibration because the first and second calibrations are already executed at moment of data integration.

The first set of curves simulating drift "with saturation" is presented on Fig. 2. The drift velocity decreases during exploitation for such sensors. Such kind of drift is simple and it is possible to use a model of single-layer perceptron with linear neuron's activation function for data integration. Thus the inputs number of perceptron should correspond to number of trained data curves. For 10 researched curves the single-layer perceptron has 9 inputs.

The sum-squared error of single-layer perceptron training has made 10E-5 and the average duration of training did not exceed 3 seconds on the computer Pentium-II per each curve. The maximum and average percentage error of data integration (see Fig. 3) did not exceed 7% and 3% accordingly.

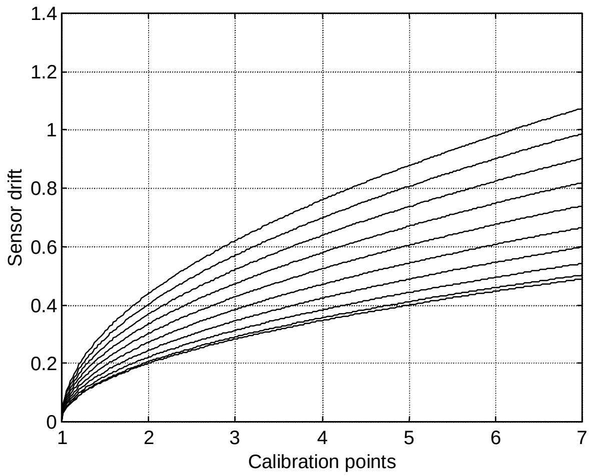

Fig. 2. First set of hypothetical data about sensor drift

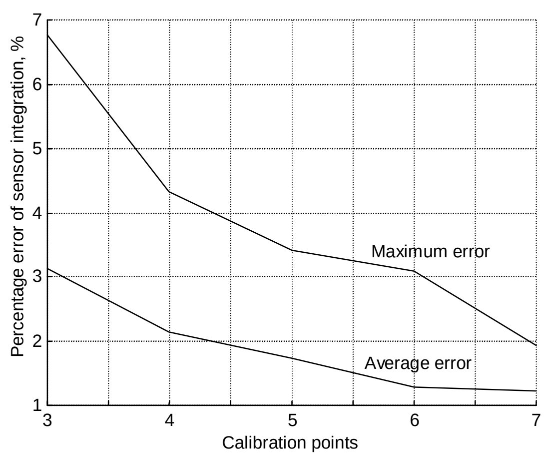

Fig. 3. Percentage integration error of first set of sensor drift

The second set of curves simulating drift "with acceleration" is presented on Fig. 4. The drift velocity increases during exploitation for such sensors. It is possible to use neural network similar previous for such drift data integration.

The sum-squared error of single-layer perceptron training has made 10E-6 and the average duration of training did not exceed 12 seconds per each curve. The maximum and average percentage error of data integration (see Fig. 5) did not exceed 25% and 8% accordingly.

The third set of curves simulating a combination of two previous kinds of drifts is presented on Fig. 6. The drift velocity of one part of sensors is increased and the velocity of other part of sensors is reduced in this case. Such kind of drift is not characteristic for the existing sensors, however it is expedient to research the method's possibilities for such data. As have researches shown, the model of single-layer perceptron does not provide acceptable results in this case. It is necessary to use nonlinear neural networks for such drift data integration. The model of three-layer perceptron was used for experiments execution. The first layer of neural network contains 9 neurons, the second layer contains 9 neurons (with logistic activation function) and the third level contains one linear neuron.

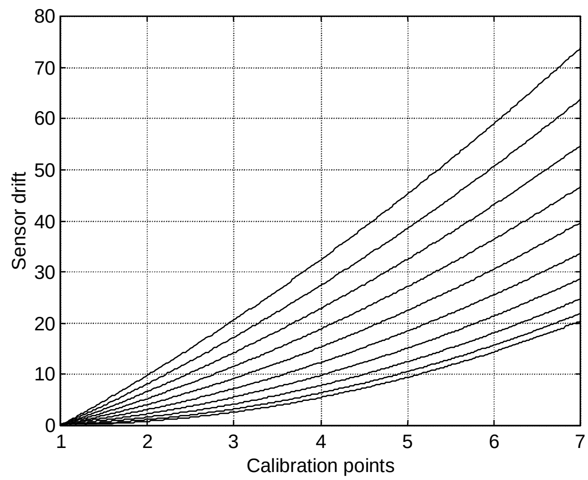

Fig. 4. Second set of hypothetical data about sensor drift

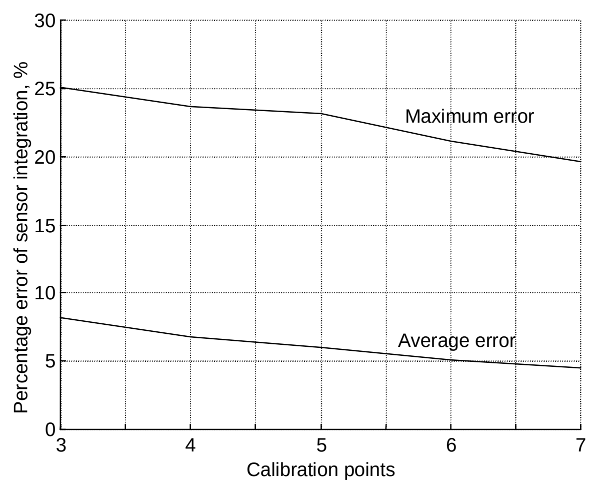

Fig. 5. Percentage integration error of second set of sensor drift

The training of multi-layer perceptron with data from Fig. 6 is instability process and has shown different prediction results in calibration points. Therefore sum-squared error 10E-4 and maximum training epoch number 30000 limited training per each neural network. It is necessary to note, that the best convergence was shown by layer-by-layer training algorithm. The average training duration did not exceed 100 seconds per each curve. The maximum and average percentage errors of data integration (see Fig. 7) did not exceed 52% and 30% accordingly.

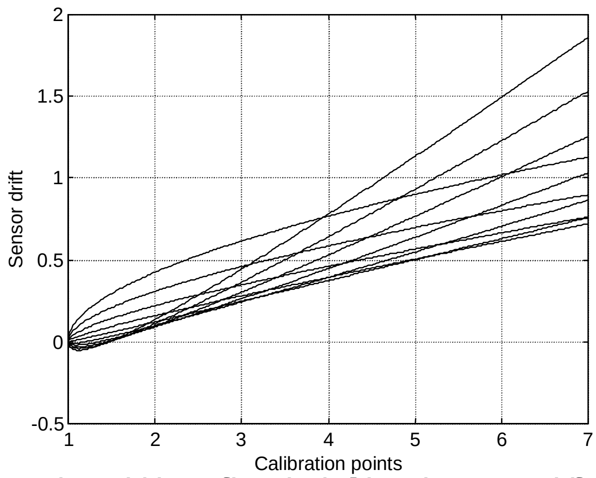

Fig. 6. Third set of hypothetical data about sensor drift

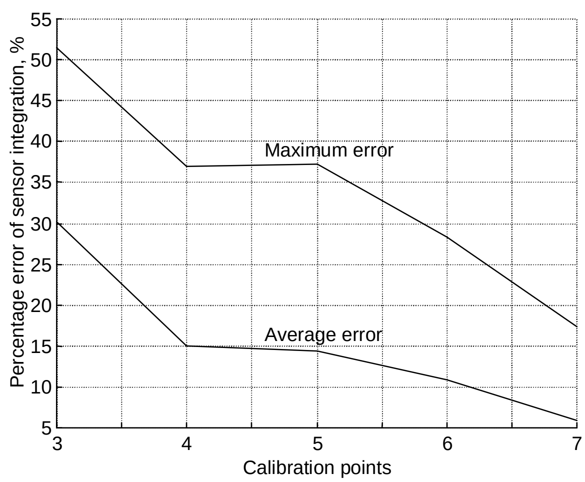

Fig. 7. Percentage integration error of third set of sensor drift

The fourth set of curves (similar Fig. 6 but with increased sensor drift velocities) is presented on Fig. 8. This kind of drift is researched for estimation of limit possibilities of proposed method. The model of three-layer perceptron considered above was used for such drift data integration.

Sum-squared error 10E-5 and maximum training epoch number 40000 limited training per each neural network. The average training duration did not exceed 190 seconds per each curve. The maximum and average percentage errors of data integration (see Fig. 9) did not exceed 70% and 50% accordingly for the third calibration point. The percentage errors were reduced for the following calibration points. However the significant integration errors has shown some restrictions of proposed method at the beginning of sensor exploitation.

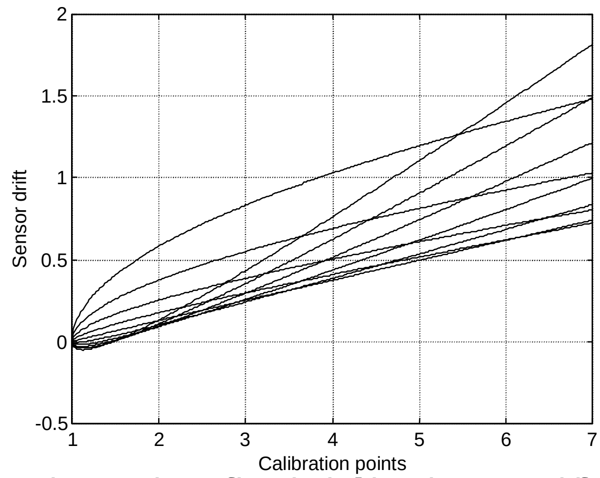

Fig. 8. Fourth set of hypothetical data about sensor drift

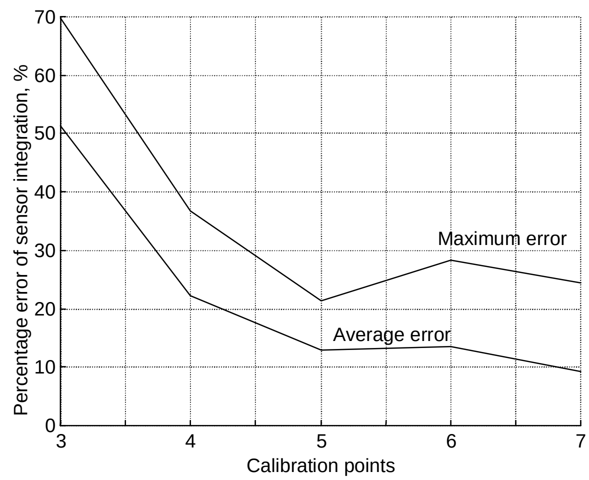

Fig. 9. Percentage integration error of fourth set of sensor drift

The results of historical data integration are approximated by special approximating neural network for correction factor prediction on sensor drift. Experimental researches (by simulation modeling) with using integration results considered above have shown that the percentage error of approximation is much lower than integration error. For example, approximating neural network (model of three-layer perceptron) consists of one input neuron, 5 hidden neurons with logistic activation function and one output neuron for data from Fig. 2. The sum-squared error 2.4E-7 of training was reached. The maximum percentage approximation error did not exceed 2% [10] in five calibration points (points 3 … 7 which corresponds to points c, d... on Fig. 1).

The approximation result contained 25 points per each curve of historical data. The predicting neural network (recurrent neural network with 10 input neurons, 10 hidden neurons with logistic activation function and one output linear neuron) was trained using these data. The maximum percentage error of properly prediction did not exceed 11% [10] for sum-squared error of training 10E-7. Thus, the proposed prediction method allows considerably to increase the intertesting interval (up to 10 times) at accuracy increasing of physical quantity measurement in 2-3 times.

4. Conclusion

The proposed method of sensors drift prediction allows providing error reduction of physical quantity measurement in intelligent systems by self-adaptation. The self-adaptation is provided by interaction of neural networks with various properties. The proposed method allows successfully to predict various kinds of sensor drift and to reduce sensor errors on early stage of their exploitation in some times. This method can successfully be used in intelligent distributed hierarchical systems [11-14] where the neural network training is performed on a higher system level (not in real time scale) and properly prediction is performed on lower levels (in real time scale).

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