Development of neural network for automatic calibration of ultrasonic thickness gauge

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Abstract. At article of the main factors rendering of influence on the reliability of material control results by ultrasonic thickness gauge are determined. The necessity of the use of automatic calibration of ultrasonic thickness gauge for reduction of measurement error is justified. The neural network for the realization of automatic device calibration is developed. The received experimental results are presented.

1. Introduction

The one of the urgent tasks of applied physics currently is the determination of defects in material, its classification and the assessment of the condition of the material itself [1-6]. To solve it, new measuring instruments being developed and improving being used, as well as being developed of new measuring method and models for information processing [5-8]. It’s related with constantly are increasing the requirements to the reliability and safety of equipment at enterprises, various trunk pipelines, for example, oil and gas sphere or heat supply [8-12]. An integral part of the technical diagnostics of the state of pipelines or welded joints is the nondestructive control. For example, the control of pipeline wall thickness, which may change due to corrosion during its long operation. For implementation of nondestructive control are not applied the destructive operations that being requiring at further of restoration work carrying out [12-16].

The ultrasonic thickness gauge is one of the most used devices for condition control of walls: pipeline, heat boiler, fuel tank, etc. The principle of measuring thickness is to measure the transit time of ultrasound in investigation medium (material). In ultrasonic thickness gauge on the accuracy of measurements can be influenced of the different factors. One of them is the heterogeneity of the material of the investigated object. The material may contain cracks, foreign matter, etc. For the obtaining of reliable results of thickness measurements, it is necessary in the calculation to use the value of the velocity of ultrasound propagation in a particular material. The velocity of ultrasound in different materials differs significantly in values [6, 7, 13, 14, 17-19]. The reliable results during measurements can be obtained if the device is pre-calibrated on the sample (reference) with known thickness. This sample should be made of the same material as the investigated object (for example, the reference material of carbon steel for the pipeline).

The process of calibration of ultrasonic thickness gauge consists in providing the measuring device with a scale or a calibration table (curve). For an ultrasonic transducer, this procedure is very laborious. The implementation of good calibration requires highly qualified specialist and at least five hours of continuous work with one sensor. In the process of calibrating the transducer sensor during long continuous operations, it is impossible to exclude the human factor, which makes mistakes.

One solution to this problem may be to use an automated system. Its use will allow of measurements without the presence of a human. For governance of the work of the calibration system
and the analysis of measurement results will be developed by us a neural network. Its use will automate the calibration process of ultrasonic thickness gauge.

2. Development of neural network for signal classification
Currently, one of the effective means for processing and classification of signals are neural networks. In the process are developing of neural networks, it is necessary to use signal preprocessing. Preprocessing is necessary to suppress noise, in order to increase the probability of correct reception. To clean the signal from noise, it is effective to apply methods based on the wavelet transform.

The input of the receiving device receives a modulated signal of 20,000 samples, the signal time is measured in microseconds, the signal amplitude in ADC units. At the first stage, it is necessary to determine the zero value in the ultrasonic signal. For this, the method of crossing through zero is used, in which the measurement of the delay time of the echo signal relative to the probe pulse is performed at the moment of transition through the zero value. The advantage of our chosen method is the independence of the delay time from the signal amplitude. The zero point is necessary for wavelet signal conversion and for data compression. In fig. 1 is a diagram of an ultrasonic sensor.

![Diagram of an ultrasonic sensor](image1.png)

**Figure 1.** The process of oscillation and patency of the signal on a timeline.

At the second stage, the areas of the useful signal are determined. For this, it is necessary to conduct binarization in order to reduce the amount of unnecessary information.

The binarization function returns an array, it is possible to select in detail the informative areas of the ultrasonic signal from the oscillations (fig. 1). In fig. 2 and 3 show the area data.

![Diagram of emitted ultrasonic signal](image2.png)

**Figure 2.** The emitted ultrasonic signal (first signal).
Figure 3. The recorded reflected ultrasonic signal (second signal).

To further refine the signal, a compression method using wavelets is used. This method is based on the breakdown of the signal into two components - low-frequency (LF), or approximating, and high-frequency (HF), or detailing. After the wavelet decomposition, the detailing coefficients are modified - rounded, subjected to threshold processing with various threshold selection rules (adaptive threshold, heuristic, minimax, etc.) or completely discarded. In fig. 4 and 5 show the detail of the signal after applying the compression method.

Figure 4. The shape of the first waveform after compression.

Figure 5. The shape of the second waveform after compression.

The obtained waveforms (Figs. 4 and 5) allow them to be classified using regression models of a deep convolutional neural network. Each layer of such a network is recursive (receives the hidden state of the previous layer as input). To process these signals, we propose to use the following neural network architecture (Fig. 6).
Figure 6. Neural network architecture for automatic calibration of a thickness gauge.

This architecture allows you to perform hierarchical processing of complex ultrasonic signals and more naturally capture the structure of time series, it’s implementation is carried out using a special PyTorch library.

There are several basic steps in developing a solution for classifying ultrasonic signals. The first is the preprocessing used to filter the signal, which may include amplitude normalization, framing, and window control. The second is feature extraction, due to the presence of noise from each ultrasonic signal, a fixed amount of data is selected, discarding the rest. The number of features representing each ultrasonic signal is increased by combining features with a certain number of adjacent (left and right) signals.

This allows you to unambiguously determine which region a signal belongs to. In our work, three classes are distinguished by the level of the ultrasonic signal: lower than permissible, permissible, higher than permissible. Based on the response of the neural network to the processed input signal, the robotic measuring system adjusts the position of the ultrasonic transducer and the removal of the calibration curve continues in the normal mode.

3. The results of the neural network during automatic calibration

In fig. 7 shows, for example, the calibration dependence obtained using the convolutional neural network that we developed. The calibration dependence is removed as follows: the transducer sensor is alternately applied to the reference standards of different denominations (thicknesses). If the level of signal is acceptable then measurements are taken.

In during of measuring on the displays of the thickness gauge is displayed the digital code taken from the ADC and proportional to the frequency. In the process of calibration each N code is a certain thickness, then this information is written to the transducer memory.

Figure 7. The calibration dependence of the thickness gauge.
An analysis of the results shows a high reliability of the automatic grading of the device.

4. Conclusion
The performed research have showed that the approach proposed by us for preliminary processing of ultrasonic signal effectively determines the area of the useful signal. The method based on wavelet transform a used in the work allows to select the signal good detailed view. In this case, the interference level is minimized by the binarization procedure.

The obtained results have shown that the applying of deep convolutional neural network developed by us allows quickly to determine the level of the ultrasonic signal and to provide automatic adjustment of the converter during calibration of the device.

The comparison of the results of instrument calibrations were performed of different ways have showed the validity of the use of the developed neural network. The applying of neural network allows to save human resources and time. As well to increase the calibration accuracy.

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