Automated System for Visual Non-Destructive Testing

Galina Nikonova
Faculty of Information Technology and Computer Systems
Omsk State Technical University
Omsk, Russia
ngvlad@mail.ru

Aleksandr Nikonov
Faculty of Information Technology and Computer Systems
Omsk State Technical University
Omsk, Russia
nalvad@mail.ru

Yulia Zakirova
Faculty of Information Technology and Computer Systems
Omsk State Technical University
Omsk, Russia
zakirova94@gmail.com

Valery Makarochkin
Faculty of Transport, Oil and Gas
Omsk State Technical University
Omsk, Russia
makarochkin2004@mail.ru

***Abstract*—an intelligent defect recognition system based on artificial neural network (ANN) is proposed. A convolutional neural network (CNN) has been selected based on the analysis. To achieve this goal, the following has been carried out: creation of an image database for network training; network architecture development; implementation of a program in MATLAB. The study has been carried out for various objects of non-destructive testing. The result of the testing system work was assigning to one of the defects classes and determining whether there is a defect or not. A technique for automated visual non-destructive testing based on artificial neural network has been developed.**

Keywords—artificial intellect, convolutional neural network, defect, identification, classification

I. Introduction

Nowadays intellectualization technologies are being increasingly introduced into various areas of human life, ranging from household smart TVs and watches to unmanned vehicles and advanced Internet search. Intellectualization has also influenced the research and production area, for example, the introduction of intelligent sensors or systems, which allows, in accordance with the tasks, to process the received information [1].

One of the most acute problems is improving the quality of products. To solve such a problem various types and methods of non-destructive testing are used. Artificial intelligence, or rather one of its areas – computer vision – could be used for detecting defects. Printed circuit boards or workpiece blanks could be the objects of testing (i.e. any surface that can be photographed and then transferred to neural network).

A logical question may arise: is there any point in using such a complex algorithm for one photo? Yes, it is illogical to develop such a system for one photo [2]. However, if the batch of products is large, or it is necessary to notice a large number of minor defects, such a decision is justified.

It should be noted that, in principle, the tasks that artificial intelligence deals with are non-trivial. There is no universal algorithm for recognizing defects at particular objects, however certain approaches have been developed for such problems.

As mentioned above, machine learning algorithms are starting to play a significant role in various fields, but let's not forget that the machine operates with numbers and the result is also a number [3]. Whether it is a problem of classification, clustering or recognition, the answer is probability; therefore, the final choice (whether to trust the algorithm or not) remains with the operator, i.e. human.

II. Theory

The term non-destructive testing is understood as finding defects in a product or device without destroying or dismantling it. Nowadays, there are many different methods, and each of them is based on the interaction of a physical field with an object or some physical process. There are nine main types: radio-wave, radiation, thermal, magnetic, eddy current, electric, penetrant, acoustic and visual-optical [4].

The use of an artificial neural network (ANN) is effective when it is necessary to check a large number of identical parts. Thus, it is more profitable to automate this process than to use human labor economics-wise. Certainly, if a part or a device is of a complex shape and requires the use of several testing methods, then the knowledge and experience of a human worker is necessary, since the computing power of the neural network (NN) is not enough for such an operation.

Analyzing the articles on the use of ANNs in inspection and defects detection, one can come to a conclusion that this concept is mainly applicable to eddy current, visual, magnetic and X-ray methods. In the article [5], the author points out to the possibility of analyzing the ultrasonic signals, but there are a number of difficulties that do not allow accurate testing. The difficulty lies in a large number of parameters by which it is possible to detect a defect or non-defect with some probability. Recognition-wise, for example, the signal from a bracing and a defect are identical, and even a trained network will be wrong, because there is no clear relationship between the amplitude and the type of a defect.

As for the eddy current method, a number of articles [6], [7] confirm the use of ANNs for monitoring the surface layer of bearing parts, i.e. in a pretty narrow area. The same could be said for frequency analysis based on the Fourier transform, though it does not allow detecting local defects. The use of a neural network for predicting the time series of acoustic emission [8] is also applicable in the local area of vibration monitoring.

III. Subject Area of Research

In non-destructive testing (NDT) in general a product defect means the non-compliance of a product with the

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established requirements [9]. Defects are divided into surface and subsurface defects – those that are on the outside of the product and those that are located inside. Items made of various materials such as steel, glass, composite materials, etc. can be used as objects of testing.

Visual non-destructive testing is aimed at identifying defects that can be detected on the surface of an object with or without auxiliary tools (visual-optical devices). Also, there is a division into direct and indirect visual testing [10]. In the first case, the path of light rays is continuous between the eyes of the operator and the object, in the second case, the use of photo or video equipment is implied, i.e. the operator perceives an image of an object from a digital pjhotograph or a video. Thus, we come to a conclusion that visual testing using video technology is most effective and acceptable in terms of automation [11].

The main advantages of using ANN in nondestructive testing could be noted: firstly, the possibility of testing automation and, accordingly, reduction of the time for an operation.

Secondly, the elimination of the so-called "human factor". Certainly, a person may miss a defect due to carelessness or negligence, or, perhaps, due to lack of experience. In this case, testing using ANN is a good auxiliary tool.

Based on the analysis of the state of the art, it can be concluded that the automation of non-destructive testing by means of ANN is carried out, but the scope is rather limited. It is not always possible to interpret the signal unambiguously, i.e. to collect the training and test sample in such a way that it recognizes and classifies even minor defects with a high probability. There are methods in which there are a lot of parameters for analyzing ANN, therefore, the process will take longer than the work of a person. Furthermore, an object of a complex or non-standard shape is analyzed by the operator much faster. Such a system fully justifies itself, during automation or as an auxiliary testing tool.

Thus, we propose to introduce a conveyor, where the parts are loaded, depending on the method, they are sprayed with a magnetic suspension, magnetized, and the resulting drawings will be classified by an ANN.

IV. Description of the Conducted Research

In this work, the well-known RGB (Red, Green, Blue) color model is proposed for an image-based representation of a defect. RGB is an additive color synthesis of the known three colors to produce a new color. One pixel according to this model is denoted as (r, g, b), and each value could be represented in decimal number from 0 to 255, and in hexadecimal from #000000 to #FFFFFF.

The defect image could be resented as a matrix of values. All elements make up a two-dimensional array, and a single value corresponds to a discrete point [12]:

$$W(t)=\begin{vmatrix} W_1(t_1) & W_1(t_2) & W_1(t_j) \\ W_2(t_1) & W_2(t_1) & W_2(t_j) \\ W_i(t_1) & W_i(t_2) & W_i(t_j) \end{vmatrix} \tag{1}$$

where $W_i(t_j)$ is the value at the coordinate point i, j (i = 1, 2 ... n, j = 1, 2 ... n).

For each object of testing, there should be created a matrix of the reference defect image, and then a library in order to iteratively compare the reference with the incoming defect. The analysis of a real sample is carried out by scanning the entire surface, where each point corresponds to an element, and the discreteness step coincides. The local area of the real sample is represented by the matrix $W_T(t)$, where T is the local area. Thus, analyzing each *T-th* matrix, a residual matrix is calculated:

$$W_{Ni}(t_j)=W_{Ti}(t_j)-W_{Ri}(t_j), \tag{2}$$

where $W_{Ri}(t_j)$ is the matrix of the reference defect image.

The algorithm used for the database should not only determine the presence of a defect, but also process images that do not correlate or poorly correlate with those in the database.

V. Experiment

A. Building a CNN model

Since MATLAB interactive programming environment has the necessary function libraries, the Deep Learning Toolbox and applications for working with images, it has been used for developing the topology of the convolutional neural network. Deep Network Designer and Deep Learning Network Analyzer have also been utilized during our work [13].

Experimentally, we select the value of the mini-batch and the number of epochs, set the learning rate, or rather the rate at which the search for the local minimum of the function will be carried out [14]. As an optimization method, we choose stochastic inertial gradient-descent (sigd) [15]. Next, we train the network on a training sample and test the result on a test sample.

B. Neural network training process

Two databases were used for training: a base of 6 groups of steel parts defects (heat scale, craze, inclusions, spots, scratches, ripples) – 300 images (200x200 pixels) [16], and an experimental base – 190 images of a reference structural element also made of steel without a crack and with a crack, detected after magnetic particle inspection (4160x3120 pixels). All images are in JPG format.

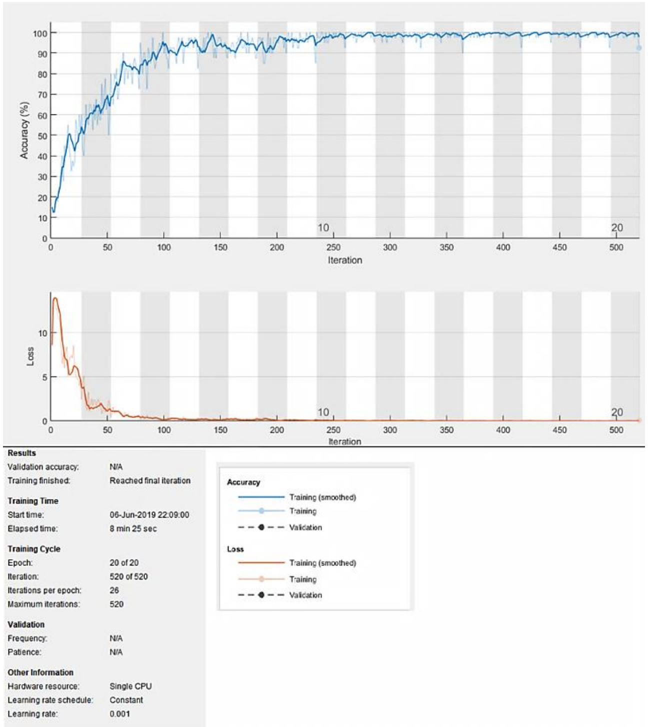

Fig. 1. Training process of the first data set

As a result of training the network for the base of the images with defects, the optimal training parameters were determined: the number of epochs – 20 and the number of batches – 40.

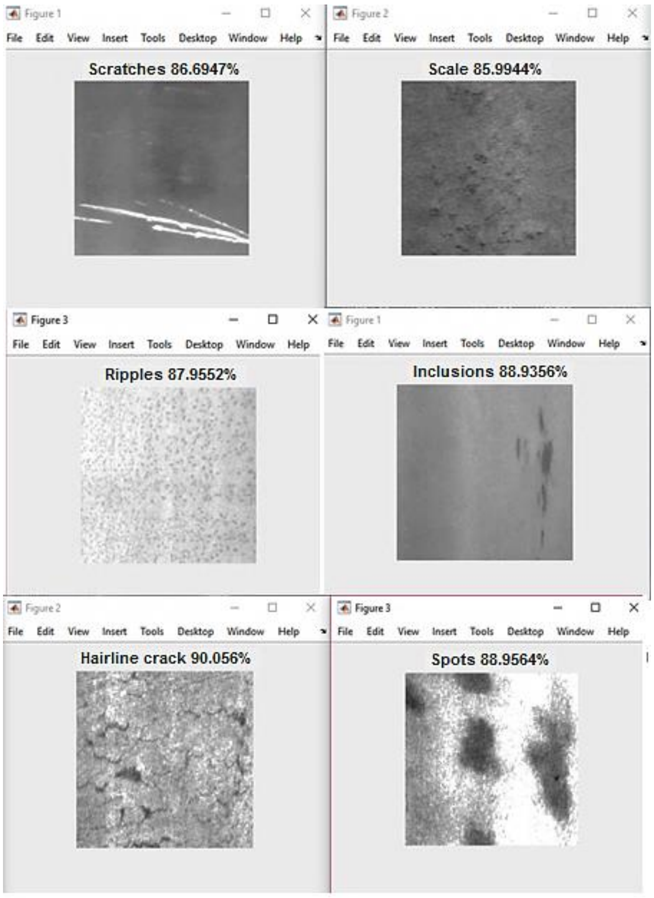

Fig. 2. Classification of the CNN defects of the steel parts

The next data set for classification was the experimental images of a steel structural element, collected after magnetic particle inspection. Optimal training parameters: number of epochs – 20, number of batches – 40. As initially the amount of data was not sufficient and the size did not correspond to the size of the input layer, all images were augmented, i.e. reduced to 227x227x3 and rotated by 180° or 90°.

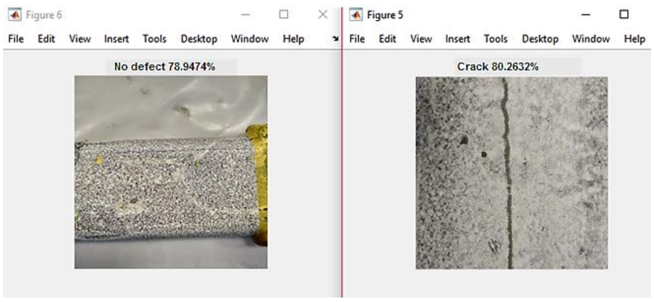

Fig. 3. Classification of a steel structural element by the CNN as defective and cracked

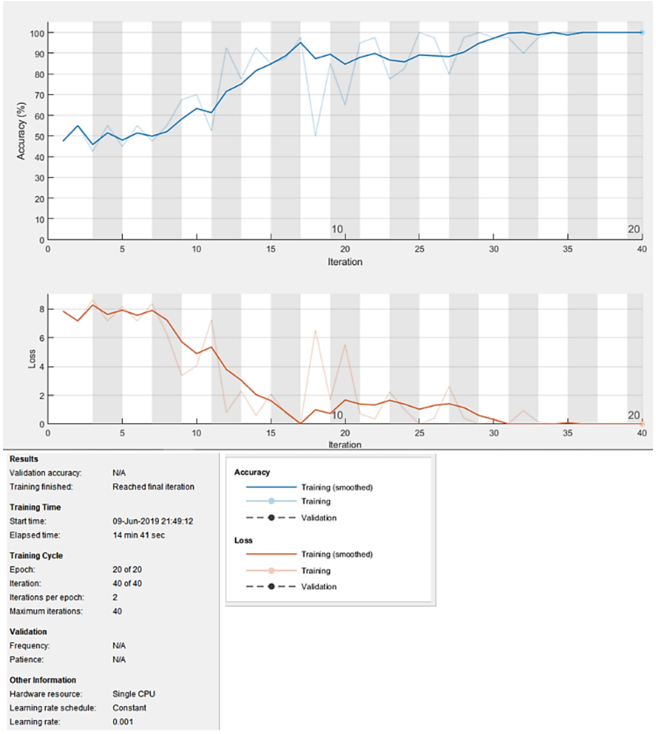

Fig. 4. Training process of the experimental data set

The probability values range from 78 % to 80 %, all images are determined correctly. As the number of images increases, the percentage should increase.

As a result, we can conclude that the developed architecture of the convolutional neural network recognizes and classifies the images [17]. Defective steel parts: from 85 % to 90 %, experimental images of the sample after magnetic particle inspection: 78 % to 80 %. As we can see, on the very first database, the probability is higher, since this base consisted of the largest number of images. Accordingly, the last sample with fewer data showed a lower percentage of probability. The developed architecture of the convolutional neural network meets the requirements of non-destructive testing and is quite capable of producing an accurate classification of various defects.

C. *Technique of the automatic CNN testing system*

The developed algorithm is proposed for visual, capillary and nondestructive magnetic particle testing. The device below allows automating this process.

It includes a conveyor, where parts are loaded and depending on the method sprayed with a magnetic suspension, magnetized and recorded by a digital camera; the resulting drawings are transmitted via a communication channel to a computer and are classified by the ANN.

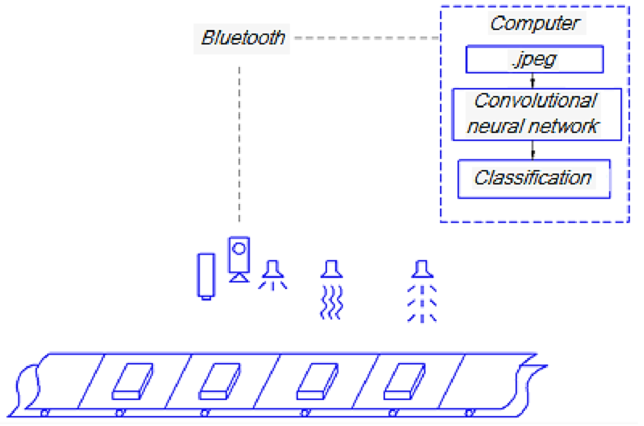

Fig. 5. Device diagram

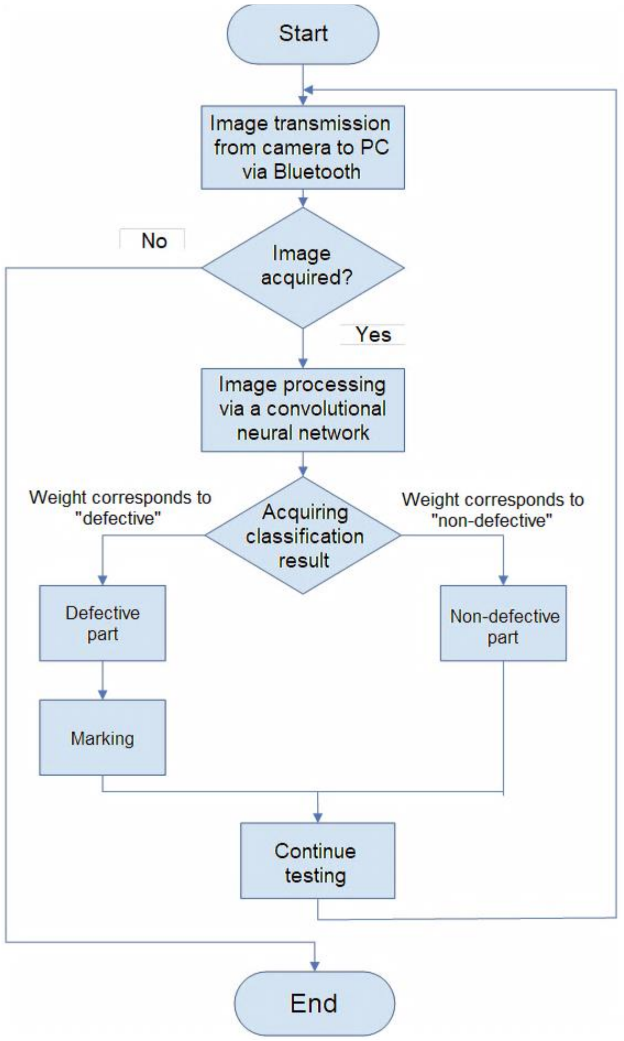

Fig. 6. Automated testing device algorithm

Visual non-destructive testing of the proposed automated testing device (Fig. 5) should be carried out according to the method proposed below, drawn up in accordance with the requirements of standards [18–21].

1. Before conducting the visual inspection, a documented procedure should be developed, including information about the object (description, volume, surface type, size), acceptance rules, personnel requirements, lighting requirements, requirements for the equipment used.

2. A laboratory performing visual non-destructive testing sould be certified in accordance with the Certification Rules and the basic requirements for non-destructive testing laboratories [22].

3. The operability of the digital camera and the data transmission interface, the serviceability of the conveyor belt and the marking device, the serviceability of the cleaning complex should be checked and the illumination measured before starting the testing.

4. For ANN testing, it is necessary to check the existence of the classification base.

5. The digital camera should provide high quality images of defects (brightness, contrast, size).

6. The digital camera should be installed perpendicular to the test object, it is also allowed to be installed perpendicular to its sides.

7. The surface of the conveyor belt should be monochrome and not contaminated.

8. To obtain a reliable result of detection or absence of defect, it is necessary to maintain the illumination of the tested surfaces at least 1000 lux.

9. The cleaning complex should properly supply the cleaning agent and/or blow compressed air.

10. The volume of products that should be tested is determined based on the requirements of the testing program (plan, instructions), which is developed by the organization performing the testing. The plan indicates objects, volumes, testing method.

11. The specialist who will oversee the automated testing should make sure that the neural network is working properly, for which the training and test process should be started to check the correctness of the determination on one image from the batch to be checked.

12. If the obtained probability value of classification satisfies the operator, testing procedure should be started. If the probability is unsatisfactory, camera and lighting settings should be checked.

13. Depending on the size, material and shape of the product, lighting method should be chose (reflected, diffused light or other schemes).

14. The distance from the testing object to the camera should be set so that the entire surface of the product is captured on the photograph.

15. The arts on the conveyor belt should be located taking into account that the distance between products should be at least 5 cm.

16. The speed of the conveyor belt for obtaining high-quality images should be set depending on the length and width of the belt. Speed range from 0.3 m/s to 1.5 m/s.

17. Defect detection is indicated by the corresponding probability and classification made by the convolutional neural network.

18. The detected defective product should be marked by a marking device.

The same principle could be applied for capillary testing (with spraying of a tracer liquid) or for magnetic particle inspection (magnetizing the part and applying dry ferromagnetic powder or suspension).

This method, firstly, facilitates faster scanning of objects, i.e. it allows continuously identifing defects, secondly, it eliminates the so-called "human factor". Mistakes due to fatigue or overwork or banal negligence could be easily made. The machine is also not perfect, but at least it is easier to observe the operation of the algorithm, rather than one person checking each product.

From an economic point of view, if it often becomes necessary to test a large volume, then the use of such device is quite justified.

VI. CONCLUSION

The article provides an algorithm for the development of an intelligent system for recognizing defects and the creation of an automated system for visual non-destructive testing based on an artificial neural network.

As a result of the analysis of the state of affairs from various sources of information, the theoretical and practical orientation of the fundamental provisions of neural networks in the field of pattern recognition for non-destructive testing was determined. A comparative analysis of pattern recognition systems and the applicability of neural networks for non-destructive testing tasks in the course of their solution has been carried out. The principles of functioning of artificial neural networks are considered, and methods of recognition of defects are analyzed. It has also been found that the convolutional neural networks do the best job of image classification.

The MATLAB interactive programming environment implements the architecture of a convolutional neural network (which has been tested on two different defective objects) and coped with the task of their classification.

The article also proposes a methodology for using the system to automate visual non-destructive testing in order to speed up the monitoring process and get rid of the "human factor".

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