Defect Detection in Drilling Pipes, using Combination of Artificial Neural Networks and Machine Vision Techniques

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Abstract

The most important parts of drilling machines are drilling pipes. The emergence of various defects in these pipes during working times due to environmental conditions, heat, ground pressures, abrasion and erosion in adjacent of very hard rocks is inevitable. Therefore defect detection and testing of these pipes before making problems in drilling oil and gas wells is an important matter. By using a combination of machine vision techniques and artificial neural networks (LVQ-NN) for defect classification, this study examines variations of drilling pipe failures and with regard to different criteria in terms of processing speed and accuracy, it has proceeded with comparison with other neural networks (FFBP-NN). Initially, images or scanned pictures are provided from the printed graph of electromagnetic testing device, and then pre-processing is carried out using noise removal, isolating the main image from the entire image, then the numerical values are obtained from the graph, and finally they are converted into the input of the neural network for classifying and diagnosis of the defect type. Neural network used for defects classification in the proposed system had and evaluated minimal error (MSE) of 0.0331 and the results were recorded for various stages.

Keywords: defect detection, drilling pipes, artificial neural networks, machine vision, classification

1. Introduction

Today, body defect diagnosis of these types of pipes is done based on non-destructive tests, the most important of which for the metals defect detection are electromagnetic testing and magnetic flux leakage and based on output diagrams of the device, the type of defect is determined by experts. The traditional superficial inspections, analysis and defect detection by humans are not approved by companies and factories because the traditional superficial inspections carried out by human operators may declare a particular diagnosis for the defect and these diagnoses are typically different from each other. During the performed studies, the general inspections carried out by humans can approximately report 60% to 75% of defects
Therefore the development of automated systems of superficial inspection is an important issue in metal defect detection. This diagnosis requires an accurate, efficient and high processing speed system. Today, we see a continuous movement from theoretical and applied research, especially in the field of information processing for problems for which exact solutions are not available or are not easy to solve. Due to this issue, an increased interest has been made toward the theoretical development of intelligent dynamic systems that are based on empirical data. Artificial neural networks are among this class of dynamical systems that using the processing of the experimental data, transfer the hidden knowledge and laws behind the data to the network structure. Hence, these systems are called intelligent systems, because they have derived the general rules and trained based on calculations on numerical data or examples. Today, the automated tools of corrosion and defect detection are used to detect damages from casting molds of pipelines in many fields for both conventional steel pipes and steel pipes used in oil and gas industry. One of the difficult aspects of using this type of technology is the method of detection and measuring the corrosion properties (Martins et al., 2010). Techniques based on machine vision and artificial neural networks which are intelligent systems, can be very important for detection and quantifying these damages.

II. Research background

A. Types of defects in drilling--pipes inspections

Defects reported due to testing the body of drilling pipes consist of holes, cracks, corrosion and abrasion of the outer wall of the pipe, internal corrosion of pipeline sand troughs. These failures are detected by devices acting based on non-destructive testing (NDT) the most important of which for metals are electromagnetic testing and magnetic flux leakage test.

Non-destructive test methods area set of techniques for evaluating and determining the properties of devices and created parts that cause no damage or change in the system.

a. Electromagnetic testing

This method uses a variable magnetic field to induce an electric eddy current in a conductive material and this electric current is measured. Discontinuities such as cracks in the material cause an interruption in the current and thus the existence of such defects can be realized (Janousek et al., 2008).

b. Magnetic flux leakage testing

Among magnetic imaging techniques, magnetic flux leakage testing method is a useful method of non-destructive testing for ferromagnetic metallic surfaces such as pipes of transporting and storage tanks of oil and gas (Zhongli and Hongda, 2007).
B. Earlier Works

In reference (Liu et al, 2010) authors have used image analysis of different defects of the steel surface for automatic inspection of the steel surface and then it detected the types of defects. Then the defect detected by an artificial neural network is classified and on this basis and the type of produced products classified depending on the defect. In this system, the image signals taken by the camera and the extracted images which include both corrupted and normal levels of images are inspected. In this system, two types of artificial neural networks have been used for classification of defects and are compared with each other. One of them is RVM and the other is BP neural network and the rates of successful classification were 90.66% and 91.21% for BP neural network and RVM neural network, respectively.

Reference (Martins et al., 2010), investigated the type of failure of the steel surface using machine vision and artificial neural networks. This system consisted of three modules of input, inspection and output. The input module is related to given images and delivering them to the inspection module which includes computer and implementation of machine vision techniques and artificial neural network and these images are detected and categorized with various corruptions and then are sent to the output module.

Features extraction is a key issue in many applications of neural networks that determines which of the available input features should be used for modeling. The goal of feature extraction is that the raw data become more usable for the subsequent statistical process. Eigenvector is prepared from a pair of thumbnail images; one without corruption and the other is corrupted. Then, the eigenvectors are normalized by the method of principal components analysis (PCA) and this stage forms the pre-processing of the input vector to the neural network. This method was used in the reference (Kang and Liu, 2005).

The other methods that automatically inspect the pipe surface, CCTV cameras are used which have been employed in many applied inspections of the pipe surfaces. Here for improved lighting of CCTV systems and also enhancing the process of automated qualitative assessment, (LASER PROFILER) has been proposed (Duran et al., 2007) (Duran et al., 2004).

Also, reference (Duran et al., 2007) shows that the position as well as defect information can be extracted from the obtained laser intensity. Neural network architecture used in this system was based on MLP and BP training algorithm. In another approach, a machine vision system is presented online to detect errors during the metal forming process i.e. inspection of the production phases takes place when the plate is moving on the conveyor belt. Here an inspector robot with six degrees of freedom is used and the requested information of the metals obtained by CCTV CCD-Camera. A strong lighting source and camera have been embedded in this system to capture images. Here the goal is determining the position and orientation of the failure using the appearance-based method which includes two phases. In the first phase, a set of images were obtained. These pictures include appearance of the piece under different situations. The second phase is detection and locating the fault according to
an input image for the next step. So the process of identifying and determining the location involves finding the nearest image among a collection of images obtained during the training process (Gonzalez et al., 2006).

III. The proposed method

The proposed system is designed with six blocks (as shown in Figure 1):

1) Input block for capturing images, 2) Preprocessing the images, 3) Conversion of the graphs into numerical values, 4) The neural network, 5) Classification, 6) The output part which is defect detection. Here the steps 2 to 5 can be regarded as one block called the inspector block. The input section is associated with the images taken from the graph. Then, we have the inspector section which includes the machine vision techniques such as pre-processing operations including image compression, noise removal, separating the entire graph from the original image and then obtaining the numerical values (digitizing). Then, the designed artificial neural network is used for classifying and diagnosis of the defect type and the main and intended output is the output of the neural network.

![Figure 1. The steps of proposed system](image-url)
In the proposed inspection system, an image or scanned photo was provided from the printed graph of the Tuboscope electromagnetic testing machine and after pre-processing steps mentioned above, Engage Digitizer software is used for digitizing or obtaining numerical values of the graph. Then, a numerical matrix of peak numbers is obtained by taking a basic number into account, which are provided as input data and are fed into the input of neural network to identify the type of failure. The obtained matrix is a 40*11 matrix for 11 samples with 40 values which include a number of healthy pipes and a number of pipes with different failures. The matrix has been provided based on the monitoring of data associated with testing 160 drilling pipes among which 97 pipes were healthy and usable, 10 branches had defects due to some kind of hole, 25 branches had external corrosion and damage on the surface, 10 branches had lateral cracks, 4 branches had longitudinal cracks, 8 branches had abrasion and less thicknesses, 4 branches had troughs, and two calibrated sample branches had 8 small holes on both sides of the pipe used for testing or calibration. Neural network used in this study is LVQ-NN (Learning Vector Quantization) neural network and the results were compared with the FFBP-NN (Feed Forward Back Propagation) neural network. These results have been provided and recorded with the minimum mean square error (MSE) for both networks.

A. LVQ neural network

In Learning Vector Quantization (LVQ), due to its being supervised, each eigenvector features a label. This label represents the class that this eigenvector belongs to. Since the main neural network used in this study is LVQ network, the output class means the same as the type of drilling pipes failures. When learning LVQ networks, competitive learning is combined with monitoring learning. Like all monitored learning algorithms, LVQ network also requires a set of examples in association with network behavior:

\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_Q, t_Q\}

Where p is inputs and t is the targets. LVQ neural network is shown in Figure 2.

\[\text{Figure. 2. LVQ neural network}\]
The network error is calculated from the difference between target output $t(k)$ and the network output $a(k)$. The mean squared error (MSE) is calculated by the equation (1) X (Demuth and Beale) (Shujun, 2010).

$$MSE = \frac{1}{Q} \sum_{k=1}^{Q} \sigma(k)^2 = \frac{1}{Q} \sum_{k=1}^{Q} (t(k) - a(k))^2$$  \hspace{1cm} (1)

LVQ learning in the competitive layer is based on a set of input and target pairs. Every target vector has only a number 1. Independent of zeroes, each represents a failure class or type of network inputs. As mentioned in the study, 11 input vectors with 40 elements and a 11*11 matrix for the target have been considered.

### B. FFBP-NN network

Feed-Forward networks often have one or more hidden layers of sigmoid neurons and use a final linear layer. Several layers of neurons with a nonlinear transfer function allow the network to have the capability of learning the linear and non-linear relationship between inputs and outputs. The linear output layer lets the network to have the output value outside the range of +1 and -1. If the output is needed in the range of 1 and 0, logsig function can be used in a linear layer. The following figure (Figure 3) shows a scheme of a tansig/purelin two-layer network.

![A scheme of a tansig/purelin two-layer network](image)

**Figure. 3.** A scheme of a tansig/purelin two-layer network

A Feed-Forward Neural Network with $S^m$ neurons in m-th layer is shown with the equation (2):

$$a_2 = \text{purelin}(LW_{2,1}a_1 + b_2)$$
Input of neuron \( i \) of layer \( m \) is shown by \( n^m_i \) and output for the \( j \)-th neuron in \( m \)-th layer is shown by \( a^m_j \) and the weight of neuron \( i \) of the layer \( m-1 \) to neuron \( j \) in layer \( m \) is shown by \( w^m_{i,j} \) and \( b^m_i \) is the bias for neuron \( i \) in layer \( m \) (Kang and Liu, 2005).

Back-propagation algorithm (BP) for multi-layer networks is a generalization of the LMS algorithm and both algorithms have the same performance indicators; the "mean squared error". In order to reduce the mean square error, the algorithms should adjust the network parameters, as shown in equation (3).

\[
F(x) = E [e^2] = E [(t-a)^2] \tag{3}
\]

Where \( X \) is the vector containing the weights and biases of the network if the network has multiple outputs, the above expression can be written as follows, as shown in equation (4):

\[
F(x) = E [e^T e] = E [(t-a)^T (t-a)] \tag{4}
\]

Here again, like the LMS algorithm, the mean square error is as follows, as shown in equation (5):

\[
F^\alpha (x) = e^T (k) e(k) \tag{5}
\]

During the error back propagation learning process, the initial weights are chosen among small random numbers and are updated by calculating the derivatives of mean square error function. Using the chain rule of differentiation, errors gradient were calculated for each layer of the network and transmitted to the output layer. With the layer by layer release of the calculated error as back-propagation in the network, the weights are modified, so finally, the desired accuracy is achieved at the output of the network. There are several algorithms for back propagation or BP. In the simplest implementation of learning BP, weights and biases are updated in the direction in which the performance function decreases i.e. opposite of its slope. An iteration of this algorithm can be written as follows, as shown in equation (6):

\[
X_{k+1} = X_K - \alpha_k g_k \tag{6}
\]

Where \( X_K \) is the current vector of weights and biases and \( g_k \) is the current gradient and \( \alpha_k \) is the learning speed (Demuth and Beale) (Shujuan, 2010).
C. Comparing and analysis of the results

This research was intended to achieve the highest accuracy of the network in defect detection using two mentioned artificial neural network models and MATLAB 2013 software. We also intended to compare the two networks in terms of fault detection using several tests and different neurons in the hidden layer. The test results are shown in the tables I & II.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>THE OUTPUT RESULTS (PART ONE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIDDEN LAYER NEURON</td>
<td>LVQ-NN MSE</td>
</tr>
<tr>
<td>14</td>
<td>0.0496</td>
</tr>
<tr>
<td>18</td>
<td>0.0496</td>
</tr>
<tr>
<td>24</td>
<td>0.0496</td>
</tr>
<tr>
<td>28</td>
<td>0.0496</td>
</tr>
<tr>
<td>32</td>
<td>0.0496</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>THE OUTPUT RESULTS (PART TWO)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIDDEN LAYER NEURON</td>
<td>LVQ-NN MSE</td>
</tr>
<tr>
<td>14</td>
<td>0.0331</td>
</tr>
<tr>
<td>18</td>
<td>0.0496</td>
</tr>
<tr>
<td>24</td>
<td>0.0331</td>
</tr>
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<td>28</td>
<td>0.0496</td>
</tr>
<tr>
<td>32</td>
<td>0.0331</td>
</tr>
</tbody>
</table>

After training the neural network at any time with neurons identified in the hidden layer mentioned in the above tables, and with the matrix of input and target data mentioned in the previous section, the minimum errors observed in LVQ neural network is associated with 14,
24 and 32 neurons and with 14 neurons in the hidden layer, we will get the answer, faster. Also, in order to compare the networks used, it is necessary to explain that the LVQ network has the highest stability compared to the BP network. Because after 2 times of training the LVQ Network, we will get the minimum mean square error. But, in the BP network, even with 10 times of network training, it does not become constant and the mean square errors were recorded 10 times, as shown in table III.

TABLE III

COMPARISON OF THE PROPOSED METHOD WITH PREVIOUS METHODS BASED ON THE ACCURACY PARAMETER:

<table>
<thead>
<tr>
<th>Reference 1 Method 1</th>
<th>Reference Method 2</th>
<th>Reference 1</th>
<th>Reference 2</th>
<th>Reference 5</th>
<th>Reference 6</th>
<th>Proposed combined method</th>
</tr>
</thead>
<tbody>
<tr>
<td>90.66%</td>
<td>91.21%</td>
<td>96.58%</td>
<td>90%</td>
<td>91%</td>
<td>96.69%</td>
<td></td>
</tr>
</tbody>
</table>

IV. Conclusions and Future works:

By representing a combined method of NON Destructive testing for metals, machine vision techniques and using an artificial neural network, this article aimed at presenting a new concept for detecting the defect with the lowest error and the highest speed for checking various types of drilling pipes defects.

As we said, LVQ neural network in the combined proposed system achieved the highest level of accuracy of function. As future research, the changes in the structure of neural networks and different combinations of these types of network architectures can be reviewed so that could mean square error tends to be zero.

References


