SIMPLE EXPERT VISION SYSTEM FOR RECOGNITION OF BEARING'S DEFECTS

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Abstract

Defects on a bearing is usually determined by observing its vibration characteristics. This method unfortunately can not detect the visual defects on the inner and outer ring bearing surface. A pattern recognition is implemented in this paper to solve the problem. A backpropagation neural network architecture is used to recognize the visual defect pattern. This architecture is integrated in a digital image processing chain. Recognition rate of good bearing is obtained at 92.93 %, meanwhile for defected bearing is obtained at 75 % respectively. This rate shows integrated artificial neural network with digital image processing can be implemented to detect the presence of visual bearing defect.

Keywords: *backpropagation, bearing, visual defect*

Abstrak

Cacat pada *bearing* biasanya ditentukan dengan mengamati karakteristik getaran. Metode ini sayangnya tidak dapat mendeteksi kecacatan visual pada permukaan dalam dan luar cincin *bearing*. Sebuah pengenalan pola diimplementasikan dalam *paper* ini untuk memecahkan masalah tersebut. Sebuah arsitektur jaringan saraf *backpropagation* digunakan untuk mengenali pola kecacatan visual. Arsitektur yang diusulkan ini terintegrasi dalam sebuah alir pengolahan citra digital. Tingkat pengenalan *bearing* yang baik adalah 92.93%, sedangkan untuk bantalan yang cacat adalah 75%. Angka ini menunjukkan integrasi jaringan syaraf tiruan dengan pengolahan citra digital dapat diterapkan untuk mendeteksi kecacatan visual pada *bearing*.

Kata Kunci: *backpropagation, bearing, kecacatan visual*

1. Introduction

Decision to replace ball bearings is usually determined by observing the bearing noise characteristics. Bearing with defect will have different noise characteristics in comparison to the good ones [1]. This common way of determining bearing defect by observing its vibration and noise characteristics, is used widely in bearing manufacturing quality control. Unfortunately, noise characteristic test can not detect the presence of visual defect on bearing.

To solve this problem, a concept using artificial neural networks (ANN) as a simple expert vision system can be used to recognize the defects. The ANN is integrated in a digital image processing chain. One example of such detection system is for monitoring production of small pin for the electronic circuits [2]. The concept of an artificial neural network architecture with time delay also adopt similar concept. This architecture can be used in finding boundaries, direction and speed of motion of moving images [3].

In this paper, we describe efforts to implement concept of integrated digital image processing with artificial neural networks as a simple expert vision system to detect surface defects on the outer-ring of bearing. Problem to be resolved is how to recognize the surface defects presence of ball bearings outer ring. As the problem boundaries, three types of visual defects to be recognized are shoe marks, scratch and black spots, respectively. Three types of visual defects to be recognized are shoe marks, scratch and black spots, respectively. It is then necessary to design an automation system that can detect the presence of surface defects on the outer ring.

As result as production process chain, visual defects on bearing can occur on three different parts: i.e. surface of bearing, chamfer and seal/shield [4]. This surface defect can be crack, poor polishing surface and so on. This paper restrict the visual defect to three different defects:

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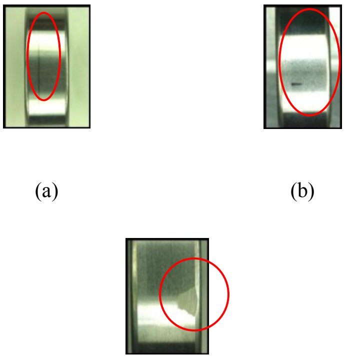
i.e. scratch, shoemark and blackspot. Scratch appears like white small mark on ball bearing, meanwhile shoemark appears like black thin line circles around bearing surface. Both don't change the roundness and roughness of bearing surface. Blackspot appears like deep grinded mark. Types of visual defect occur on outer ring can be seen in figure 1(a), figure 1(b), and figure 1(c).



(a) (b) (c)

Figure 1. (a) Shoemark, (b) Scratch, (c) Blackspot.

Visual defects can be seen by naked eyes, so we can use image processing as foundation of the solution. Image processing applications are used in various fields, ranging from medicine to engineering [5]. Various problems related to image processing can be solved with steps called image processing chain [6]. Typical chain of image processing consists step of preprocessing, data reduction, segmentation, object detection and image understanding. Converting from RGB images to grayscale image is the preprocessing steps. This step is necessary to be performed in order to simplify the defect information in acquired images. Usage of Region of Interest (ROI) is used as the step of segmentation and followed by artificial neural network (ANN) as the object recognition step. ROI usage will reduce size of the image and affect for speed of program execution. Assesment of the ANN will show the meaning of acquired image before. All image processing steps used in this paper are illustrated in figure 2. This paper will focus to discuss about usage of ANN as object recognition step in image processing chain.

The customised software mentioned above is used together with a hardware configuration as a compact automated detection system. A webcamera as frame grabber, LED and diffused light as lighting system, and shaft as bearing sample place, are set as the hardware components. Those components are placed at a solid base to support the whole system.

Future works will be devoted for gaining possibilities to increase the recognition rate of the visual defects and speed of recognition, through modification on the ANN architecture. This modification, hopefully, can be implemented for the industrial need.

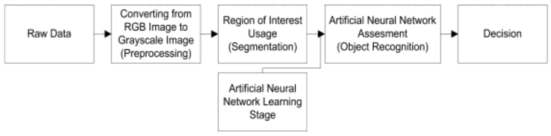


Figure 2. Image processing chain.

2. Methodology

Two different ANN architecture is used in this paper. The purpose of using two different configuration is to ensure a good recognition rate result. If one of them assess the input image as a sign of bearing with defect, then that bearing will be judged as No Good (NG) bearing. Input for ANN architecture is an image from bearing surface for each architecture. This raw image will be croped to certain size and position. The croped images have size of 247×126 pixels and 191×132 pixels. The position of croped image is related to the used area for processing, called region of interest. The second ANN architecture have 580 neurons in the input layer.

Artificial neural network architecture with backpropagation mode has several parameters and conditions for training. In this paper, we use 325 and 580 nodes in the input layer, 2 hidden layers for each architecture, 1 nodes in the output layer, maximum number of epochs at 100,000 , the average squared error (MSE) is 10^{-2}, the momentum coefficient is 0.9, and learning rate at 0.01. This learning rate is example of learning rate used in pattern recognition [7]. Training time is infinite and the learning algorithm is feedforward backpropagation (traingdx).

The data acquisition of each architecture learning will be conducted with neurons variation of each hidden layers. Activation function used in the first hidden layer and second hidden layer is sigmoid tangent function, while for the hidden layer activation function output using purelin. The training data are collected by. The design of ANN architecture is performed with increasing the amount of neurons in the first and the second hidden layer [8]. It is performed by variate the neuron in first hidden layer with 10 nodes, 30 nodes and 50 nodes. For each variation of the first hidden layer, it is also performed variations in the second hidden layer, which is 1 node to 20 nodes. Data for ANN architecture learning is image from 25 bearings. These images of bearings consists 10

OK bearings, 4 bearings with scratch defects, 6 bearings with shoemark defects, 4 bearings with blackspot defects, a bearing with chatter defect. Target value for OK bearing is 1 and target value for NG bearing is 0.

Acquisition of data in each learning will be conducted with variation of the neurons of each hidden layers. Activation function used in the first hidden layer and second hidden layer is sigmoid tangent function, while for the hidden layer activation function output using purelin. Data is collected by doing a variation on the rate of learning, the first hidden layer and the second hidden layer. Variations in the rate of learning is in the amount of 0.01 and 0.001. These rates of learning is example of learning rate used in pattern recognition [7]. The design of ANN architecture can be performed with the addition of the layers of hidden layer nodes [8]. At any learning rate, data acqusition is performed by variation of the first hidden layer of 10 nodes, 30 nodes and 50 nodes. In each variation of the first hidden layer, data acquisition is performed by variation of the second hidden layer, which is 1 node to 20 nodes. Data for learning ANN architecture is the image of the 25 bearings. The sample bearings consists of 10 OK bearings, 4 bearings with scratch defects, 6 bearings with shoemark defects, 4 bearings with blackspot defects, a bearing with chatter defect. Target value for OK bearing is 1 and target value for NG bearing is 0.

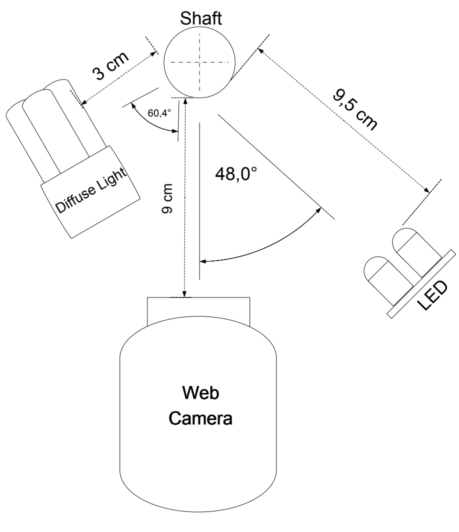


Figure 3. Lighting in detection system.

This visual defect detection system using two ANN architectures. Lighting system on this system using the lighting system in figure 3. First ANN architecture has number of nodes in the input layer of 325 neurons. Region of Interest (ROI) used in the first architecture is x = 638; y = 497; x-width = 247; y-width = 126. The second ANN architecture with number of nodes in the input layer of 580 neurons. Region of Interest (ROI) used in the second architecture is x = 484; y = 498; x-width = 191; y-width = 132. Algorithm of decision making on defect detection system software is illustrated in figure 4.

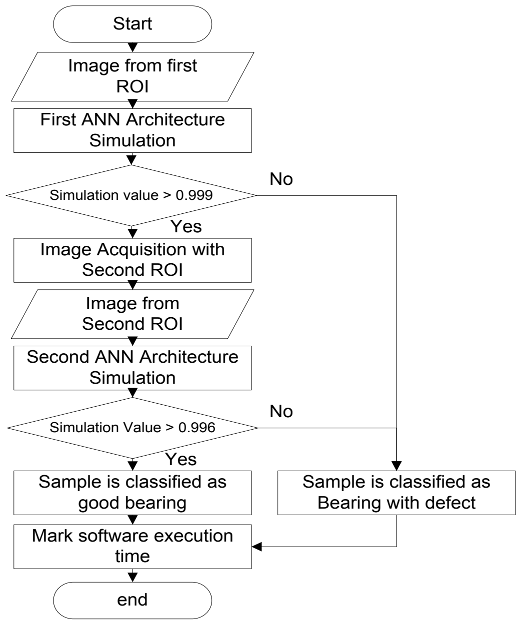


Figure 4. Decision-making algorithm for detection system software.

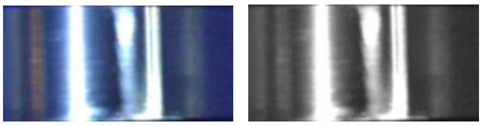
3. Results and Analysis

In this visual defect detection system, the obtained image as raw data is the bearing image of size 247×126 as many as 10 pieces in the first ROI and the size of 191×132 as many as 3 pieces in the second ROI in a single acquisition.

Figure 5(a) and 6(a) shows an example of raw data for this detection system. Then the image was processed with the grayscale process, so we get a new image of a grayscale image with the same size with the previous image. Figure 5(b) and 6(b) shows a grayscale image of the raw data. Figure 5(a) and 5(b) is an example image with scratch defects. Figure 6(a) and 6(b) is an image example with shoemark defect in the bearing. Then image resizing operation was performed with 0.25 times its original size. The image, that has been resized, will become a data matrix that will be processed in the ANN architecture. This matrix will be used as resource for defect detection.

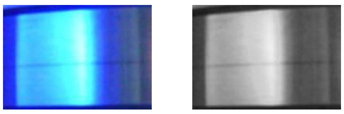
In this visual defect detection system, the obtained image as raw data is a bearing image with 247×126 pixels in the first ROI and 191×132 pixels in the second ROI. After performed learning on each ANN architecture, the best architecture can be embedded in the software. To get the appropriate neural network architecture for detecting visual defects on bearing, then tests will be conducted using new bearing image, after training processes.

Training processes for first ANN architecture are illustrated in figure 7, figure 8, and figure 9. Figure 7 illustrate the lowest MSE can be reached for first ANN architecture configuration. Lower MSE will provide less difference between target value and ANN assesment value. Best configuration for first ANN architecture is using backpropagation architecture with 10 neurons on the first hidden layer and 2 neurons on the second hidden layer. The expected MSE is 1×10^{-3} . The MSE is reached after 102 epoch training.



(a) (b)

Figure 5. (a) Original image for first ROI with size of 247 x 126 pixel dan (b) Grayscale image of figure 5(a).



(a) (b)

Figure 6. (a) Original image for second ROI with size of 191 x 132 pixel dan (b) Grayscale image of figure 6(a).

Same training steps are implemented for the second ANN architecture. The training processes are illustrated in figure 10, figure 11 and figure 12. Figure 11 illustrates the lowest MSE can be reached for first ANN architecture configuration. The expected MSE is 1×10^{-3} and reached at 92 epoch training, the least among another configuration on same hidden layer. The training result show the best configuration of second ANN architecture is with 30 neurons in first hidden layer and 5 neurons in second hidden layer.

After we get the best configuration for both ANN architecture, validation and test is conducted using bearing master image and a brand new bearing image. It will ensure the recognition ability of the ANN architecture. The test show a promising accuracy of the best configuration-by-MSE ANN architecture. We use 25 bearing master images for training phase and 971 new bearing images for testing phase, consist 919 new images of OK sample and 52 new images of NG sample.

It can recognize all of the bearing master images accurately. In OK bearing testing phase,the ANN architecture can recognize 854 images (92.93 %) and misrecognize 65 images (7.07 %). In NG bearing, it can recognize accurately 39 images (75 %) and misrecognize 13 images.

On the recognition of bearing with OK category, there is a mismatch pattern recognition of system with visual inspector assessment. This is because the pattern of the samples of OK bearings have similarities with the pattern of NG bearing. The bearing has a pattern resembles shoemark defects with a pattern of dark thin - bright thick - dark thin - bright thick - dark thin. The pattern of thin dark lines in the middle resembles a circular shoemark defect.

Defects pattern recognition accuracy rate have a high percentage at scratch recognition. This is because this defect can be easily detected using a direct lighting system with perpendicular direction to the bearing surface area. But there are still bearing with this kind of defect that can not be detected. This is because the camera can not capture the scratch due to the camera low framerate at 7 fps. Thus, the scratch can not be captured by the camera clearly.

The accuracy of shoemark defects pattern recognition is still quite low when compared with the pattern of blackspot or scratch defects. This is because the size of some shoemark defects are thin, thus it is not perfectly captured by the camera. The size of shoemark defects that can be detected is which has a size of more than 0.54 mm. Defect type of blackspot cannot be detected, because the camera framerate and resolution is still low. Therefore, the captured bearing defect image is not very clear.

This result show us that backpropagation algorithm can be used as object recognition tool in visual bearing defect detection system, with a promising rate. It can recognize the presence of three kinds of visual defect located in bearing surface. It will lead us that this simple algorithm will provide good defect pattern recognition rate and may be implemented for industrial need.

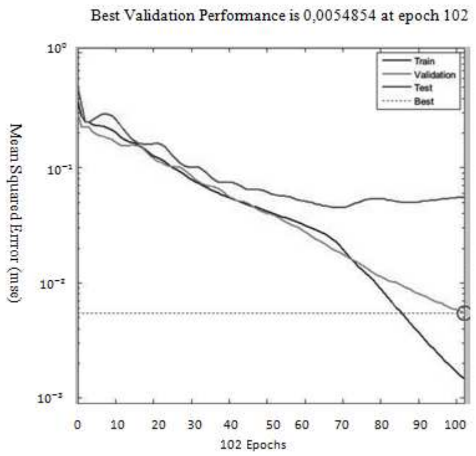


Figure 7. Training parameter for first ANN architecture with 10 neurons in first hidden layer and 2 neurons in second hidden layer.

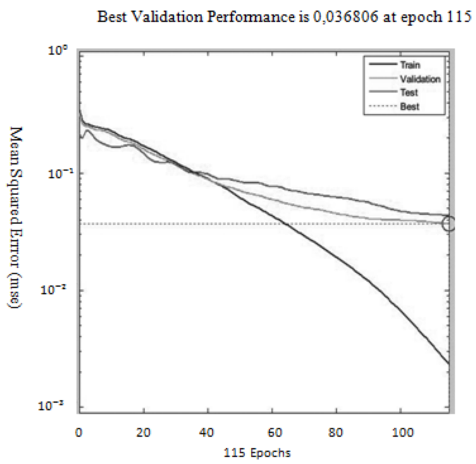


Figure 8. Training parameter for first ANN architecture with 30 neurons in first hidden layer and 2 neurons in second hidden layer.

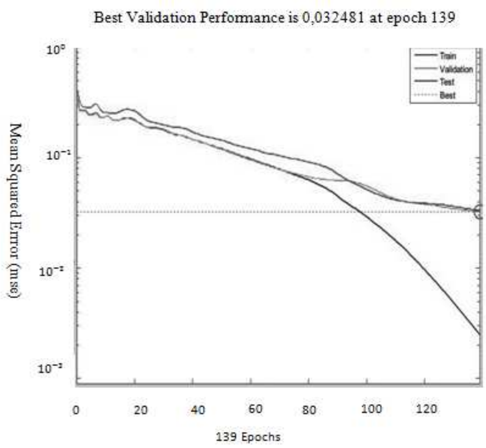


Figure 9. Training parameter for first ANN architecture with 50 neurons in first hidden layer and 2 neurons in second hidden layer.

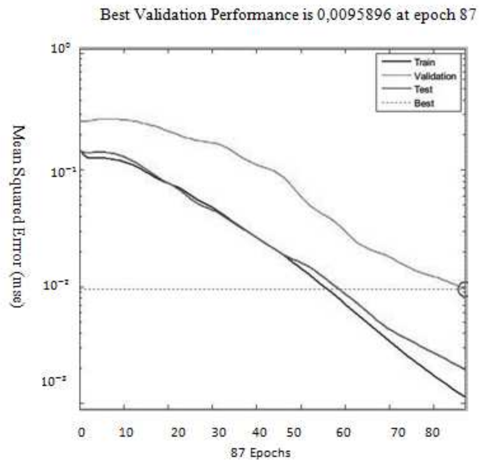


Figure 10. Training parameter for second ANN architecture with 10 neurons in first hidden layer and 5 neurons in second hidden layer.

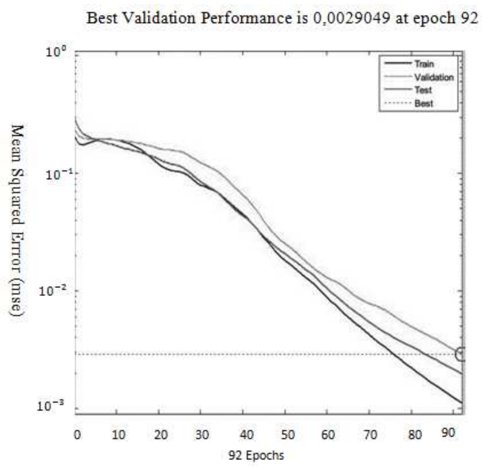


Figure 11. Training parameter for second ANN architecture with 30 neurons in first hidden layer and 5 neurons in second hidden layer.

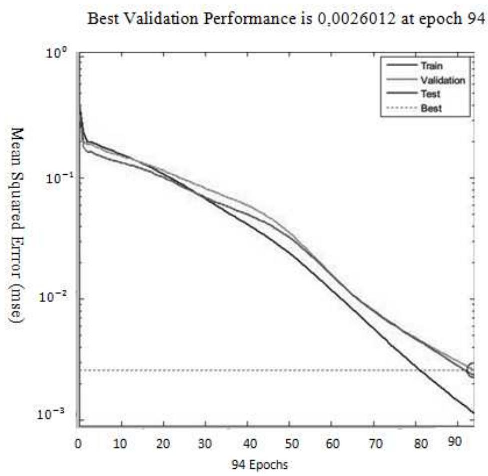


Figure 12. Training parameter for second ANN architecture with 50 neurons in first hidden layer and 5 neurons in second hidden layer.

4. Conclusion

The conclusion can be drawn about the determination of the presence of surface defects on ball bearings using digital image processing is as follows. Pattern recognition of visual defects on the bearing surface can be performed using integrated artificial neural network with digital image processing as foundation of a simple expert vision system to detect the presence of visual bearing defect. All of artificial neural network architectures used in this paper are backpropagation.

Future works can be devoted with designing prototypes by using development of object recognition tool. It can be done by using other artificial intelegence algorithm, like ANFIS, Neuro-Fuzzy, Genetic-Algorithm, etc.

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