Surface Defects Classification Using Artificial Neural Networks in Vision Based Polishing Robot

Anton Satria Prabuwono[1], Adnan Rachmat Anom Besari[2],
Ruzaidi Zamri[3], Md Dan Md Palil[3], and Taufik[4]

[1] Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor D.E., Malaysia
[2] Electronic Engineering Polytechnic Institute of Surabaya, Surabaya 60111, Indonesia
[3] Universiti Teknikal Malaysia Melaka, Durian Tunggal, 76109 Melaka, Malaysia
[4] California Polytechnic State University, San Luis Obispo, CA 93407, USA
antonsatria@ftsm.ukm.my, anom@pens.its.ac.id,
{ruzaidi,drdan}@utem.edu.my, taufik@calpoly.edu

Abstract. One of the highly skilled tasks in manufacturing is the polishing process. The purpose of polishing is to get uniform surface roughness. In order to reduce the polishing time and to cope with the shortage of skilled workers, robotic polishing technology has been investigated. This paper proposes a vision system to measure surface defects that have been classified to some level of surface roughness. Artificial neural networks are used to classify surface defects and to give a decision in order to drive the actuator of the arm robot. Force and rotation time have been chosen as output parameters of artificial neural networks. The results show that although there is a considerable change in both parameter values acquired from vision data compared to real data, it is still possible to obtain surface defects classification using a vision sensor to a certain limit of accuracy. The overall results of this research would encourage further developments in this area to achieve robust computer vision based surface measurement systems for industrial robotics, especially in the polishing process.

Keywords: polishing robot, vision sensor, surface defects, and artificial neural networks.

1 Introduction

Polishing is the finishing process that is widely used in many manufacturing industries including the aerospace, automobile, dies and mould industries. It is a process that uses abrasives to smooth the part surface without affecting its geometry. In general, the purpose of polishing is to get the uniform surface roughness distributed evenly throughout the part's surface [1]. Traditionally, polishing has largely been a manual operation. It is very labor intensive, highly skill dependent, inefficient with long process time, high cost, error prone, and hazardous due to abrasive dust. Automation is a solution to overcome the above-mentioned problems of the manual operation. The importance of polishing automation has drawn many researchers to investigate

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polishing robotic technology. The major goal is to improve time efficiency together with surface quality [2].

The surface roughness measured by a computer vision system over a wide range could be obtained with a reasonable degree of accuracy compared with those measured by traditional contact methods. Researches in surface roughness inspection and defects detection are usually developed and improved with artificial intelligent (AI) techniques [3]. One of the artificial intelligent techniques that can model human reasoning in solving this polishing problem is artificial neural networks (ANN). It is used to train the system to get the best polishing pattern. The goal of this research is to build the system to act like human beings and with the ability to learn. The capability of such a skilled polishing worker is developed by using a vision based intelligent robot with two-dimensional specimens using artificial neural networks.

2 Related Works

Successful implementation of an automated polishing system requires in-depth studies of the polishing process. In the past, many researches have been carried out to investigate prospective methods for designing and implementing automated polishing systems. Researchers should decide what kinds of sensors are required to realize the ideas. The method usually used in a polishing robot sensor system can be divided into contact methods and non-contact methods [4]. Presently, contact-methods occupy a large volume in researches of practical polishing robots. Many researchers develop contact-methods like force sensors [5], ultrasonic vibration [6], and the touch trigger probe [7] due to the fact that these methods are easy to implement. In contrast this process is still inefficient, because it takes much sensing time in the polishing process.

In contradiction to contact methods, non-contact methods are rarely used for polishing robots. It is often used for surface roughness and defect inspection for evaluation in the final manufacturing process. The non-contact methods may present an alternative to allow the surface defects to be measured rapidly with an acceptable accuracy. One of the most promising non-contact methods in terms of speed and accuracy is the computer vision technique [8]. Compared to the contact method, the computer vision system is a useful method for measuring the surface defects with higher speed, lower price, and lower environmental noise in the manufacturing process [9]. Automatic surface defect detection with vision systems can bring manufacturers a number of significant benefits, especially when used on-line.

An experimental robotics based on a die polishing set-up using multiple vision sensors and fuzzy ANN has been developed to recognize new surfaces and plan an appropriate strategy for the polishing process [10]. A highly complex non-linear optimal problem in path planning optimization is proposed based on an improved genetic algorithm for a polishing robot [11]. The latest vision localization method for a micro-polishing robot has been presented, which is restricted within a certain working space [12,13]. Researchers usually improve time efficiency in the polishing process by optimizing path planning. Therefore this research tries to use force adapted based on surface defects classification to reduce polishing time and cope with the shortage of skilled workers.

3 System Design

In general, the system design was built as shown in Figure 1.

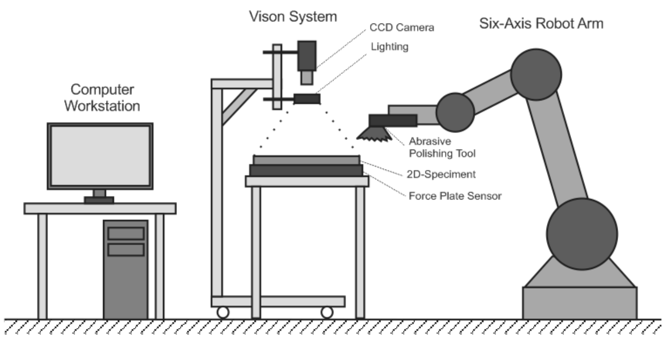


Fig. 1. The general system design

3.1 Material and Defects Classification

The material used in the experiment is aluminum steel plate. The material is mostly used in the automotive industry. A survey of surface defect classification was carried out including for scratches and corrosion. Scratches happen due to physical contact between materials and solid and rough objects.

3.2 Sensor and Actuator

OMRON F500 Vision System with 1 mega pixel resolution that enables high-precision inspections and measurements was used to grab surface image details. This camera has a standard image resolution for inspection of 512x484 (247.808 pixels). Furthermore, ring lighting was applied for illumination in surface inspection. The performance of the vision sensor depends on the combination of camera, lens, and lighting to create an appropriate combination for inspection purposes. To take force data during the polishing process, the Logic Pro LP342i force plate sensor (Texas Instrument) was used. This system was used as an actuator of a six-axis arm robot with an abrasive polishing tool as end-effectors. The model of arm robot in this research was the SMART NS 16-1.65 (COMAU Robotic Italia). The robot consists of an anthropomorphic structure with six degrees of freedom. Implementation of the polishing robot system is shown in Figure 2 and a block diagram of hardware and software is shown in Figure 3.

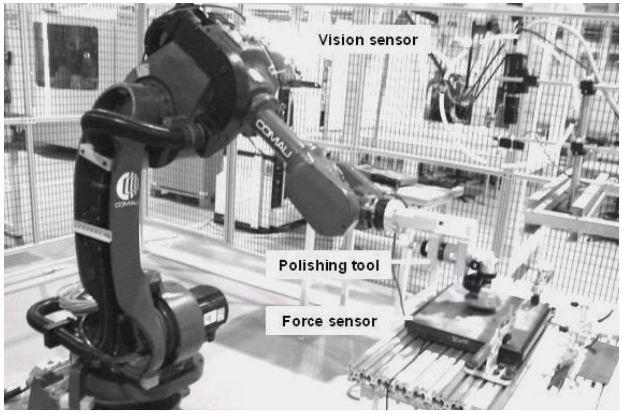


Fig. 2. Implementation of the polishing robot system

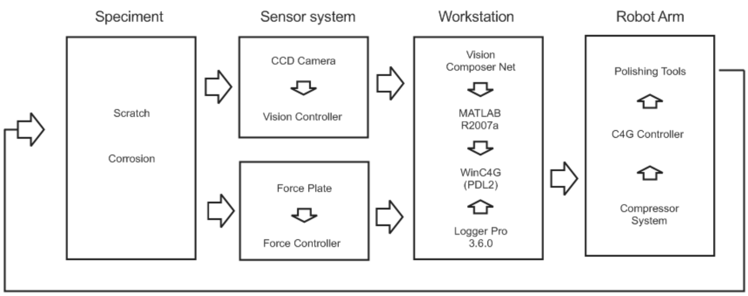


Fig. 3. Hardware and software block diagram

4 Surface Defects Classification

This section basically defines a surface defects classification using the image processing technique. The basic idea is to find an optimal gray-level threshold value for separating objects of interest in an image from the background. The method is based on gray-level distribution. There are two steps in surface defects classification. The first step is image acquisition that involves image capturing, image adjusting and noise removing by a filtering technique. The second step is multilevel threshold and image classification with contour levels to get features of the surface defects.

4.1 Image Acquisition

The color of the specimen is silver. It causes the light to be reflected directly. This condition causes the camera to be unable to get a good surface image of the specimen.

An extra lighting system with red color is used for the gray scale camera. Figure 4 shows the vision system in defects classification with direct vertical reflected light.

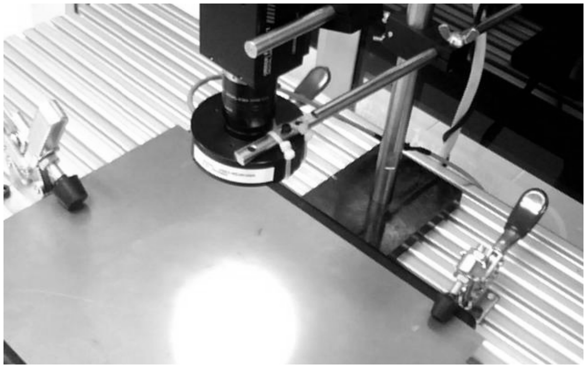


Fig. 4. Image acquisition using vision system

4.2 Image Adjusting and Filtering

There are two limitations with the grabbed image. The first is the characteristic of a material with non-uniform texture of surface. It makes features in the image to be covered by a lot of noise. The second is the use of direct lighting which generates noise in the centre of the specimen image. The noise has a circle form based on the shape of the lighting. A lot of noise in the image prevents further processes from being carried out. In the preliminary process, contrast was used to make the defects segmentation brighten up from the whole image. Then a Gaussian filter was used to remove the noise, so that noise and defects can be differentiated in order to get features of defects.

4.3 Multilevel Threshold and Contour Region

One of the segmentation techniques often used is the multilevel threshold. This technique is a process of segmenting a gray-level image into several distinct regions. The multilevel threshold technique determines more than one threshold for a given image and segments the image into certain brightness regions. It corresponds to one background and several objects. A variant of the classification algorithm by the clustering method is used to compute optimal values and to threshold the image into a number of classes [14].

After getting features of defects by performing some multilevel thresholds, simplifying the defects into some gray-level regions (image editing application known as gray-slice) has been done. The contour level is used to indicate the roughness level on surface defects. Based on the multilevel threshold image, the system can classify images in a simple manner. This method divides the surface defects features into some contour regions as shown in Figure 5.

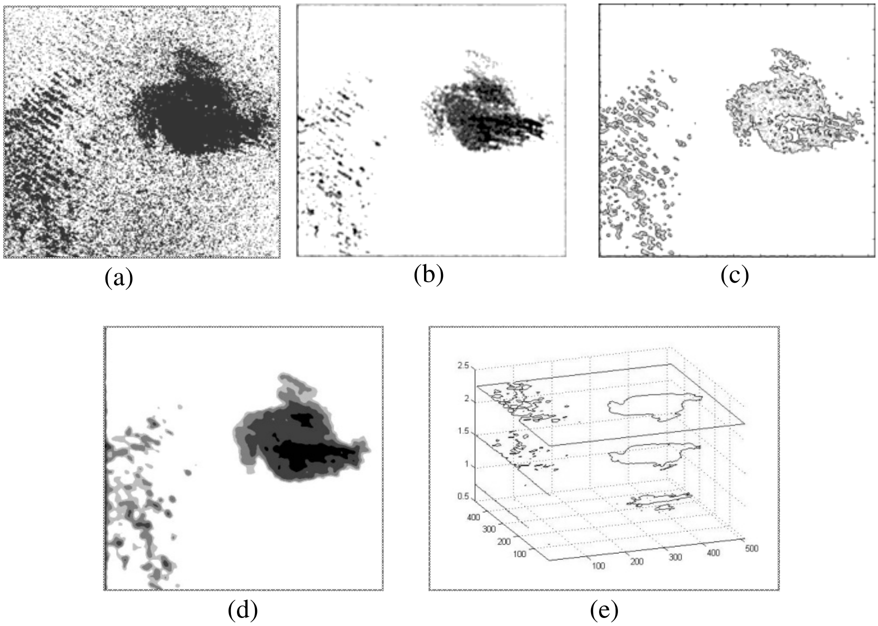


Fig. 5. Surface defects classification process (a) Defects image with non-uniform noise (b) Defects filtering from the noise (c) Defects segmentation from image (d) Multi-level threshold of defects (e) Contour region in some levels of defects.

5 Classification Using Artificial Neural Networks (ANN)

An artificial neural network was used to model input data from a variety of surface conditions of material. The aim is to obtain a pattern by finding the relationship between input parameters and output parameters.

5.1 Parameters Selection

In the polishing process, there are several parameters which can be changed such as abrasive value (u), force (F), rotation speed (ω) and polishing time (t) as shown in Figure 6. There are several levels of abrasiveness (roughness) in polishing tools, where those with a large abrasive value will effect significant surface changes as well. Given a good surface condition, these may even cause a new surface defect.

Normally, with a good surface condition it is sufficient if it is given a little bit of force due to the fact that the value of the desired changes is not significant. On the contrary, when the surface condition is bad, desired changes must be large, so large force values are required.

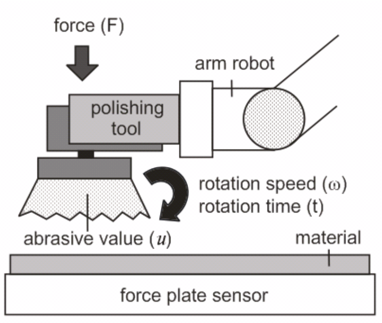
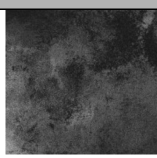
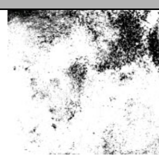
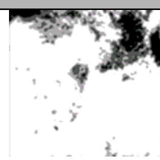
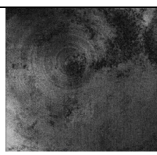
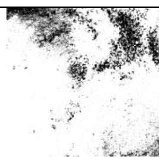
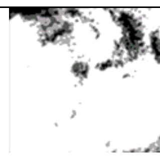
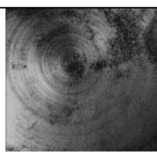
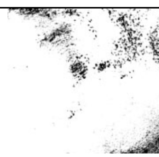
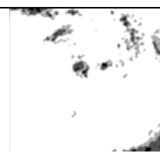
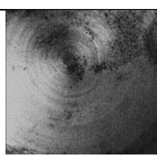
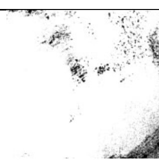
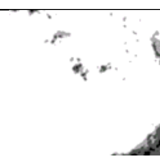


Fig. 6. System parameters

Table 1. Surface defects classification process

Experiment	Original Image	Enhanced Image	Characterized Image	Surface Defects Level
Force : 0 N Time : 0 sec				D1 : 11.11 % D2 : 7.85 %
Force : 2 N Time : 10 sec				D1 : 10.17 % D2 : 7.12 %
Force : 5N Time : 20 sec				D1 : 6.47 % D2 : 3.19 %
Force : 10 N Time : 30 sec				D1 : 3.51 % D2 : 2.61 %

Rotation speed means the rotational speed of the polishing tool, and rotation time means the time required to improve surface quality. It is not possible to provide a very high speed due to some limitations of a compressor drive system. A possible parameter for representing rotation speed (ω) is rotation time (t). For abrasive values, the parameter will be compared to the significance of surface quality change. Some levels of surface defects are easy to remove and some levels are hard to remove. From image classification, surface defects that are easy to remove are referred as D1 (Defect Lv.1) while the part that is hard to remove is called D2 (Defect Lv.2). In the next experiment, D1 will be associated with the rotation time (t) parameter, while D2 will be associated with the force (F) parameter. From this, the relationship between surface defects classification and output parameters can be determined. Table 1 illustrates some classification results with several parameter changes.

5.2 Network Architecture

Back-propagation neural network has been chosen to develop the defects classification. A supervised learning was used as a method of neural networks training. This research has considered a simple three layers of ANN with two input nodes, one hidden layer with seven nodes and one output node. Input means the data have surface defects classification with one parameter: force (F) or rotation time (*t*). Comparison of results between surface defects level (D1 and D2) and force or rotation time will be obtained from the new surface defects classification. Then a significant value of changes will be obtained. Changes in the surface defects classification before the polishing process are compared to the results. Output data is force (F) or rotation time (*t*). Each used as a target in the design of ANN. Those two parameters are divided into several discrete levels with the aim of simplifying the parameters.

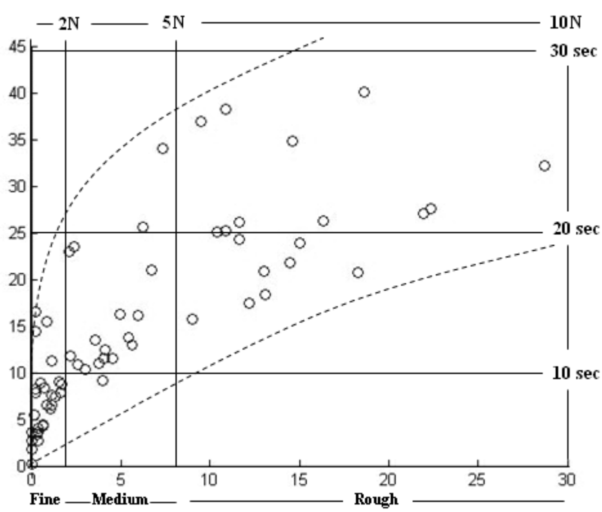


Fig. 7. Distribution of surface defects data (D1 and D2) compared to output parameter: force (N) and rotation time (sec)

The section focused on combining two main parameters of force (F) and rotation time (*t*). Many samples of data representing surface conditions are used to model the relationship between surface defects level with force and rotation time. D1 and D2 are described in Cartesian coordinates, and then made to determine boundaries of force and rotation time. The relationship between D1 and t is described in x coordinates, while D2 and F are described in y coordinates. Data can be classified into nine clusters. In data distribution, there are three clusters which are fully filled with data, four clusters are half-filled with data, and two clusters are not filled by the data (empty cluster). From this condition, seven clusters (three fully-filled clusters and four half-filled clusters) will be used for grouping the data. Artificial neural networks will be modeled to get the classification from the data as shown in Figure 7.

6 Result and Discussion

Some experiments have been done in the Robotic Laboratory of UTeM. However the maximum value of force is 10N. It means when the force value reaches 10N the polishing tool will be stopped immediately. Besides the maximum value of rotation time parameter is 30sec. This happened due to the fact that changes of surface defects values are not significant when rotation time increased to more than 30sec. Experiments have been conducted 66 times, in detail 30 times with force parameters of 2N, 4N, 6N, 8N and 10N respectively. Each condition is done with five different surface defects. Furthermore the 36 experiments have been done with rotation time parameters of 5sec, 10sec, 15sec, 20sec, 25sec and 30sec respectively. Each made five different surface defect conditions.

Supervised learning was used for data classification. For each class, the values of classification have been given. Values for the fine class are 1 & 1.3, for the medium class are 1.7, 2 & 2.3, while for the rough class they are 2.7 & 3. The purpose of this experiment is to classify the data into several groups by using a simple three layers of ANN. To achieve an error value = 0.05, ANN training has been done with 534 epochs. This training is experienced enough to teach the network forming groups of data. Learning error from this network is about 0.18; this value is assessed according to stages of the supervised learning method. The surface defect can be classified in order to get features and details of defects especially for scratches and corrosion.

7 Conclusion

This paper presents preliminary research in vision based polishing robots. The system is based on images taken by a CCD camera. Lighting and image pre-processing have been developed to divide surface defects into two levels. Polishing tasks require force control adapting to current levels of surface defects. The greater magnitude of unidirectional force normal to the surface polishing force must be adjusted for a rougher surface, while a lighter magnitude must be regulated for a smoother surface.

Artificial neural networks were used to train the robotic system to emulate a human's example in the polishing process. However defining the rules for the polishing process from image data which has natural variations would be a very difficult task. By using neural networks, any explicit classification rules do not need to be understood. Another advantage is, if the errors happened it can be retrained by using a larger training set. Besides, the system can be easily modified to inspect the different surface defect types. In future, several intelligent methods called hybrid technology will be combined to minimize the learning time of neural networks. It can increase the system's ability to be adaptive in dealing with various defects in a variety of surface conditions.

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