International Journal of GEOMATE, Feb., 2017, Vol. 12, Issue 30, pp. 11 - 18
Special Issue on Science, Engineering & Environment, ISSN: 2186-2990, Japan
DOI: http://dx.doi.org/10.21660/2017.30.160503

THE APPLICATION OF ARTIFICIAL INTELLIGENCE IN GRINDING OPERATION USING SENSOR FUSION

F. Junejo*, I. Amin, M. Hassan, A. Ahmed and S. Hameed

Faculty of Computing & Engineering Sciences, SZABIST, Pakistan

*Corresponding Author; Received: 3 May 2016; Revised: 12 August 2016; Accepted: 14 August 2016

ABSTRACT: The application of multi-sensor systems for the monitoring of machining processes is becoming more commonplace to improve productivity, automation and reliability. In order to enhance knowledge in this area of applications, this study proposes a novel approach for the continuous on-line condition monitoring of grinding operation using low cost infrared and visual imager alongside with more commonly used sensors i.e. AE sensor, accelerometer and dynamometer. To achieve this aim a multi-sensor system is developed and installed for the monitoring of grinding operation. The signals acquired and analyzed by the system include visual, thermal, force, vibration and AE under different grinding conditions. Image processing techniques are used to establish that an increase in sparks within grinding zone results in rise of grinding zone temperature, which in turn results in increased surface roughness. Signal processing techniques are used to establish that dressing of wheel is most influential factor for surface roughness of workpiece. Artificial intelligence is then used successfully on both infrared and visual data to establish an automated continuous on-line monitoring system for grinding operation with an accuracy of 95 percent.

Keywords: Grinding, Sensor fusion, Infrared, Condition monitoring, Artificial intelligence

1. INTRODUCTION

Grinding is a high specific energy finishing machining operation that is widely used in manufacturing of components, which requires good surface, dimensional and geometrical quality [1]. Due to this, according to [2], grinding operation is used in precision machining when surface roughness and/or geometric tolerances cannot be met by traditional cutting operations. Due to this grinding process is, usually, one of the last steps in a machining operations chain. When the workpiece reaches this point, it has high aggregated value, which makes a possible rejection very expensive. Owing to shortage of skilled operators in recent years, the need for automation of the grinding process has been rapidly increasing. Therefore, in order to establish an unmanned grinding process, it is necessary to develop a reliable monitoring system that can supervise the process and detect abnormalities [3]. In the absence of human operators, sensors must have the ability to recognize process abnormalities and initiate corrective action. There are various signals, which correlate, to the condition of the process and they are the subject of different sensing and processing techniques. Each of these signals is able to provide a feature related to the phenomenon of interest although at varying reliability.

So in order to collect maximum amount of information about the state of the process from number of different sensors i.e. sensor fusion is the best solution. To introduce such an idea into practice an intelligent sensing system embodying strategies for sensor fusion should be implemented. [4-6]. However, compared to other machining techniques, in grinding it is difficult to obtain not only the repeatability under the same machining conditions but also relationship among complex parameters [7]. Therefore nowadays a new focus of research on sensors is on Sensor Fusion i.e. using multi-sensors concurrently to monitor a machining process [8]. The aim of the study is to develop an automated on-line condition monitoring system for a grinding process. To accomplish this aim, this study uses sensor fusion of visual and infrared data alongside with other commonly used sensors such as acoustic emission, accelerometer, and dynamometer and then artificial intelligence is applied onto thermal and visual data.

2. MATERIALS AND METHOD

The experimental study involves analysis of the dynamic state of the grinding operations with varying machining parameters. During the experiment both thermal and visual images of grinding operation are captured, various other signals such as grinding force, grinding temperature, grinding zone sparks, vibration, ultrasonic emission and acoustic emission have also been used for monitoring the grinding process.

Grinding forces, which are developed between the grinding wheel and the workpiece due to grinding action [9], are one of the most important parameter in evaluating the whole process of grinding. Since, knowledge of the cutting forces is important as they have a direct influence on the generation of heat, and thus on tool wear, quality of machined surface and accuracy of the workpiece. Force dynamometers have been used widely in measuring grinding force cutting forces [10].

Oscillations of cutting forces lead to the vibrations of the machine structure, these vibrations keep changing due to gradual tool wear. A complete assessment of exposure to such vibration requires the measurement of acceleration in well-defined directions, frequencies and duration of exposure; this can be achieved using piezoelectric accelerometer that actually produces an electrical signal, where the size of this signal is proportional to the acceleration applied to it [11]. It also fulfills the requirements because of the tough environmental conditions in the machine tool in terms of splash protection, moisture proofing, and resistance to aggressive media and resistance to flying chips.

In recent years, the use of acoustic emission signals for evaluating the behavior of cutting processes and the quality of machined workpieces is increasing [12]. The AE generated during a grinding process has been proven to contain information strongly related to the condition changes in the grinding zone [13]. According to [14], frequency range of AE sensor goes from 50KHz to up to 1000KHz, which is above the range of many noises coming from sources outside of the grinding process. In this study, an acoustic emission sensor from Holroyd of 92 KHz frequency is used. It is fitted at the head of the surface grinder so that it distance from cutting zone always remain constant, as according to [15] an acoustic emission transducer, which is attached close to the contact area, is ideally suitable to examine the grinding process.

This study proposes a novel approach for the continuous on-line condition monitoring of grinding operation using low cost infrared and visual imagers, as shown in Fig. 1 and to compare their performance against other traditionally used sensors mentioned above i.e. force dynamometer, accelerometer and AE sensor for condition monitoring of grinding operation. For this purpose, a low resolution and hence economical 16x16 IRISYS IRI 1002 thermal imager has been used alongside Logitech web cam, which is a standard monochrome camera. Low resolution thermal imager of 16x16 is used as it is significantly economical in comparison to that of a high-resolution 128x128 thermal imager. Whereas, web cam is used as very high resolution images are not required.

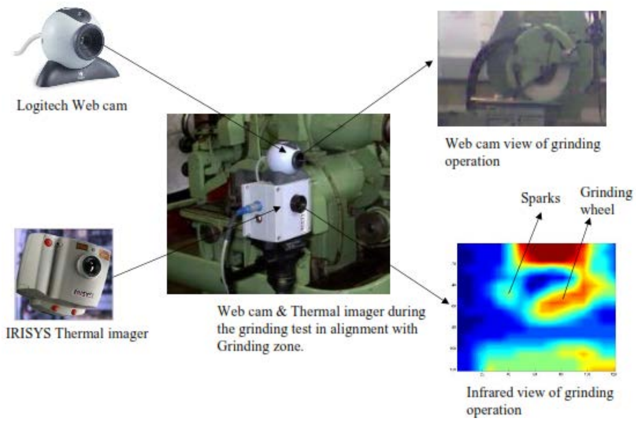


Fig.1 Thermal imager & Web cam set-up

The experiments are performed on a flat surface grinder with a grinding wheel 38 A60 KVBE having a diameter of 180mm and thickness of 13mm.

The dimensions of mild steel workpieces used are length= 250mm, width=120mm and thickness=12.7mm. Whereas, grinding wheel speed and feed rate are kept as 2880 rpm and 8 m/min respectively. Series of grinding conditions used in experiments are shown in Table 1. Variables used during series of grinding tests are as follows:

- Coolant: Water soluble oil (100%, 50%, 0% i.e. dry cutting)
- Dressing: Normal, Dull.
- Depth of cut (d.o.c): Normal =15 micron, High = 25 micron.

Table 1 Grinding tests carried out during experiment

Test Number	d.o.c (micron)	Dressing	Coolant
1	15	Normal	100%
2	15	Dull	100%
3	15	Normal	50%
4	15	Dull	50%
5	25	Normal	100%
6	25	Normal	50%
7	25	Dull	100%
8	25	Dull	50%
9	15	Normal	0%
10	15	Dull	0%
11	25	Normal	0%
12	25	Dull	0%

In order to facilitate acquisition of machining process data, a multi sensor system as shown in Fig.2 is developed and all the signals are monitored using a National Instruments NI- 6070E data acquisition card.

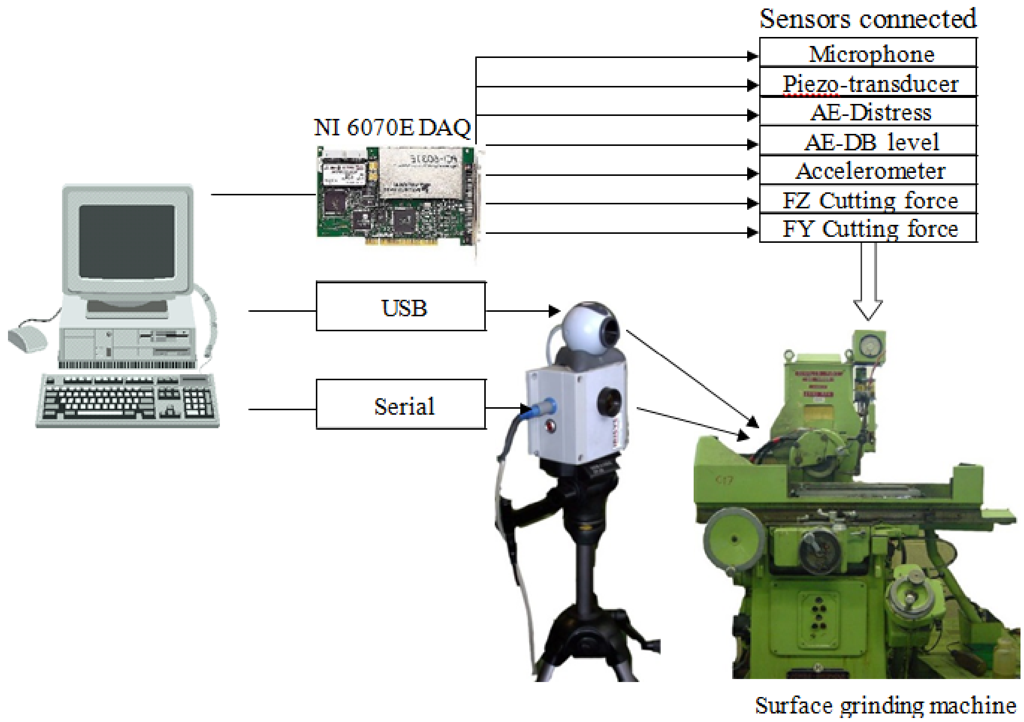


Fig.2 Schematic diagram of experimental set-up

2.1 Image Processing

The image processing methods used in this study are:

2.1.1 Binary Thresholding

In binary thresholding, pixels above background are also set to fixed pixel brightness; thus, all pixels are replaced by one of two values which can be represented by 0s and 1s (black and white respectively).

2.1.2 Image processing

Image Processing involves subtraction of datum image (in this case one with no sparks in grinding zone) from any given image for which numbers of sparks are to be determined, as shown in Fig. 3. Mathematically, it can be expressed through Eq (1).

$$g'(x,y) = f(x,y) - g(x,y) \qquad (1)$$

$g'(x,y)$= Resulting image containing sparks only
$f(x,y)$= Given image for which number of sparks to be determined
$g(x,y)$ = Datum image i.e. one with no sparks

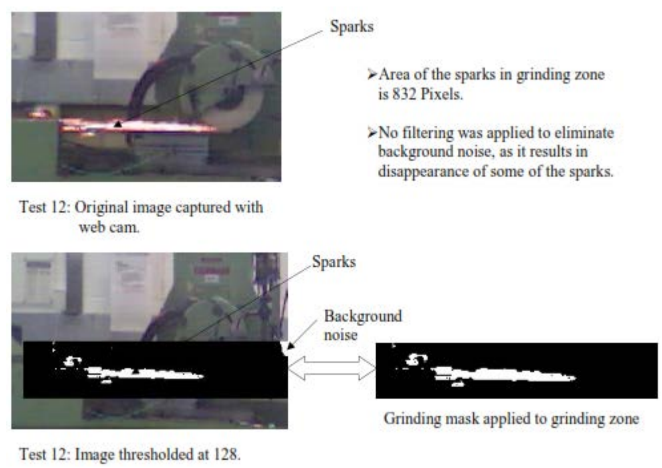


Fig.3 Thresholding analysis

2.2 Signal processing

Fast Fourier Transformation reduces the number of computations required to make transformation from time domain to frequency domain.

$$X[k] = \sum_{n=0}^{N-1} x[n] W_n^{nk}, \qquad (2)$$
where $W_n = e^{-j2\pi/N}$ for $k = 0,1,2,3,4, \dots \dots, N-1$

3. RESULTS AND DISCUSSION

3.1 Relationship between sparks in grinding zone & grinding zone temperature

Binary thresholding is used to determine the area of sparks, whereas grinding zone temperature is determined using thermal imager, Fig. 4 shows graphical comparison between spark’ in grinding zone and grinding zone temperature.

It can be seen from Fig. 4 that there is a high degree of correlation between grinding zone temperature and spark’s area because as the number of sparks increases, grinding zone temperature also rises, therefore number of sparks or spark’s area can be considered to be a good representative of the grinding zone temperature, and hence useful for process monitoring purposes.

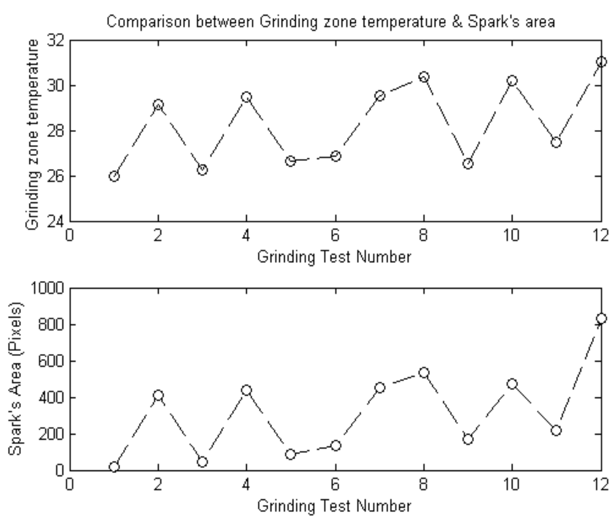
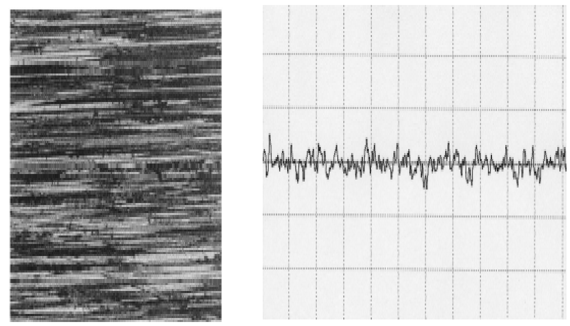


Fig. 4 Graphical comparison between spark’s area in grinding zone & grinding zone temperature

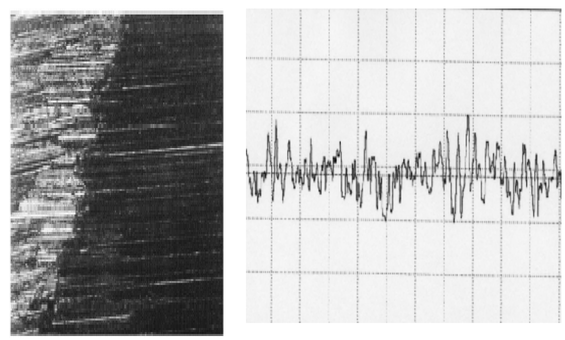
3.2 Surface roughness measurement

Surface roughness is a widely used index of product quality and in most cases a technical requirement for mechanical products. Achieving the desired surface quality is of great importance for the functional behavior of a part [16]. Surface roughness measurement is done using standard stylus method to determine relation between surface roughness & grinding troubles such as grinding burn and chatter vibration. Fig. 5 shows different states of grinding with their respective surface roughness graphs.

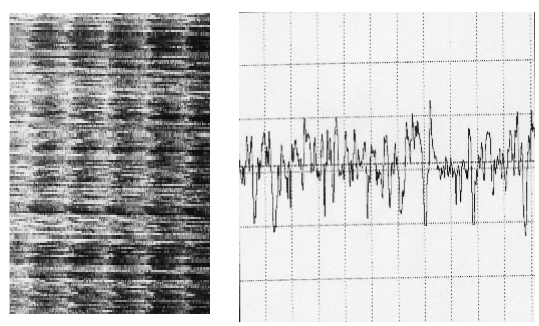
It can be seen from Fig. 5 that an increase in surface roughness results in occurrence of grinding troubles i.e. grinding burn and chatter vibration.



(a) Normal Grinding



(b) Grinding Burn State



(c) Chatter Vibration State

Fig. 5 Relation between surface roughness and grinding troubles

3.3 Relationship between grinding zone temperature and surface roughness

It can be seen from Fig. 6 that there is a high degree of correlation between grinding zone temperature and surface roughness as an increase in grinding zone temperature also causes an increase in surface roughness. Therefore, it can be said that sparks in grinding zone, grinding zone temperature and surface roughness are all directly proportional to each other.

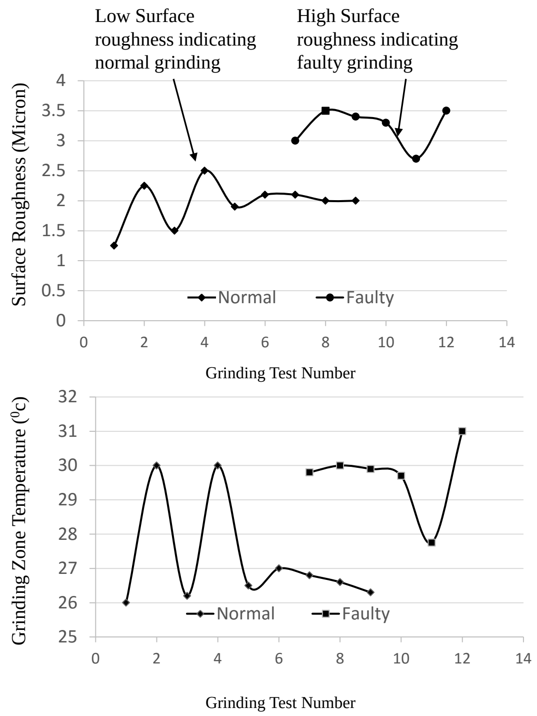


Fig. 6 Graphical comparison between Grinding zone temperature & surface roughness

3.4 FFT analysis on cutting force in z-direction

It is evident from Fig. 7 that there is a high degree of correlation between surface roughness and cutting force ‘Fz’ and both are directly proportional to each other.

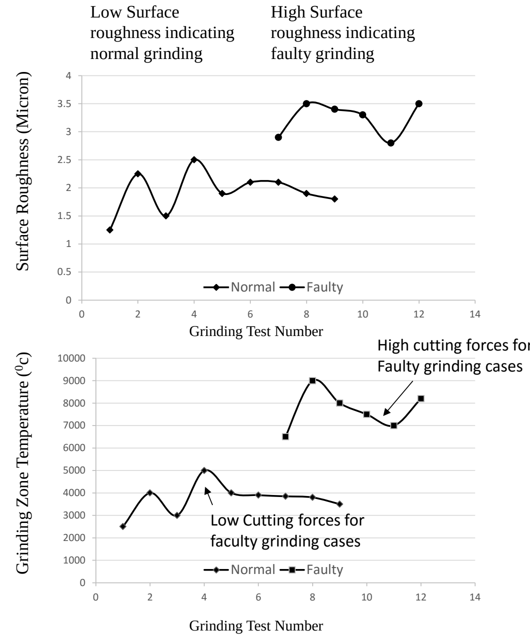


Fig. 7 Graphical comparison between cutting force 'Fz' and surface roughness

3.5 Image subtractions on infrared images

In image subtraction, a thermal image with no sparks is taken as datum image and is subtracted from a faulty grinding case image containing sparks. It can be seen from Fig. 8 that image subtraction on thermal images can be used not only to predict sparks within grinding zone but also to find out state of the workpiece and grinding wheel, which in turn influences surface roughness.

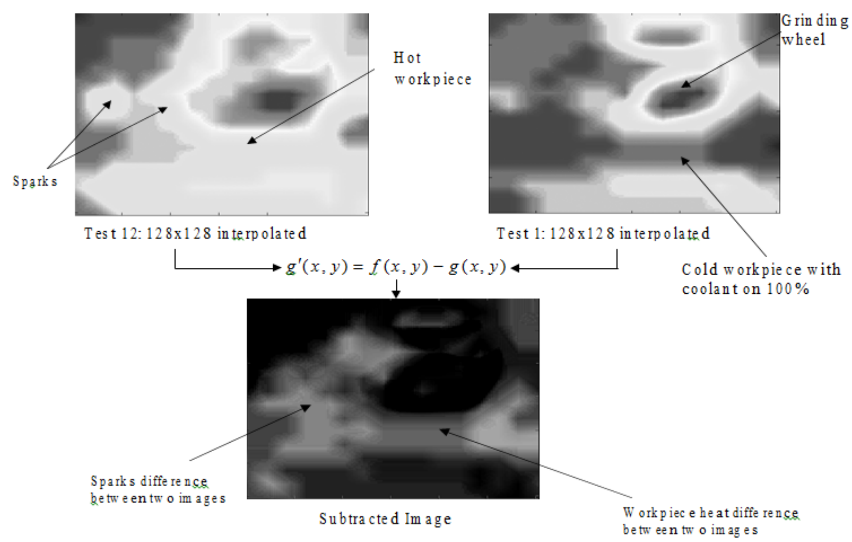


Fig. 8 Image subtraction on thermal images

Therefore, cutting force 'Fz' can be considered to be a good representative of workpiece surface roughness, and hence a useful parameter for grinding process monitoring purposes, as it can be used to distinguish between normal and faulty grinding i.e. grinding troubles such as grinding burn and chatter vibration.

3.6 Application of Artificial intelligence

In this study Back propagation and Radial basis neural networks are applied successfully on both visual and thermal images to differentiate between normal and faulty grinding conditions and therefore can be used reliably for automated condition monitoring of grinding process.

3.7 Back propagation neural network on visual images

It can be seen from Fig. 9, that back propagation neural network has been able to differentiate between normal and faulty conditions with 95% accuracy, which is very efficient and can therefore be used reliably for condition monitoring of grinding process.

3.8 Radial basis neural network on thermal images

It can be seen from Fig. 10, that radial basis neural network has performed very well as it has been able to distinguish between normal and faulty grinding conditions with almost 100% accuracy. It can also be noted that for faulty grinding conditions, the predicted values from network are between 0.1 & 0.2, which are still very good indicator of faulty conditions.

4. CONCLUSIONS

The aim of this study i.e. the development of an automated on-line condition monitoring system for a grinding process using infrared and web cam alongside with commonly used sensors is achieved, as the processing techniques used in this study can reliably distinguish between normal and faulty grinding conditions, also artificial intelligence is applied successfully on both thermal and visual images. Finally, the set of parameters that are thought to influence surface roughness and thus affect workpiece properties such as grinding burn and chatter vibration are diagrammatically displayed in Fig. 11.

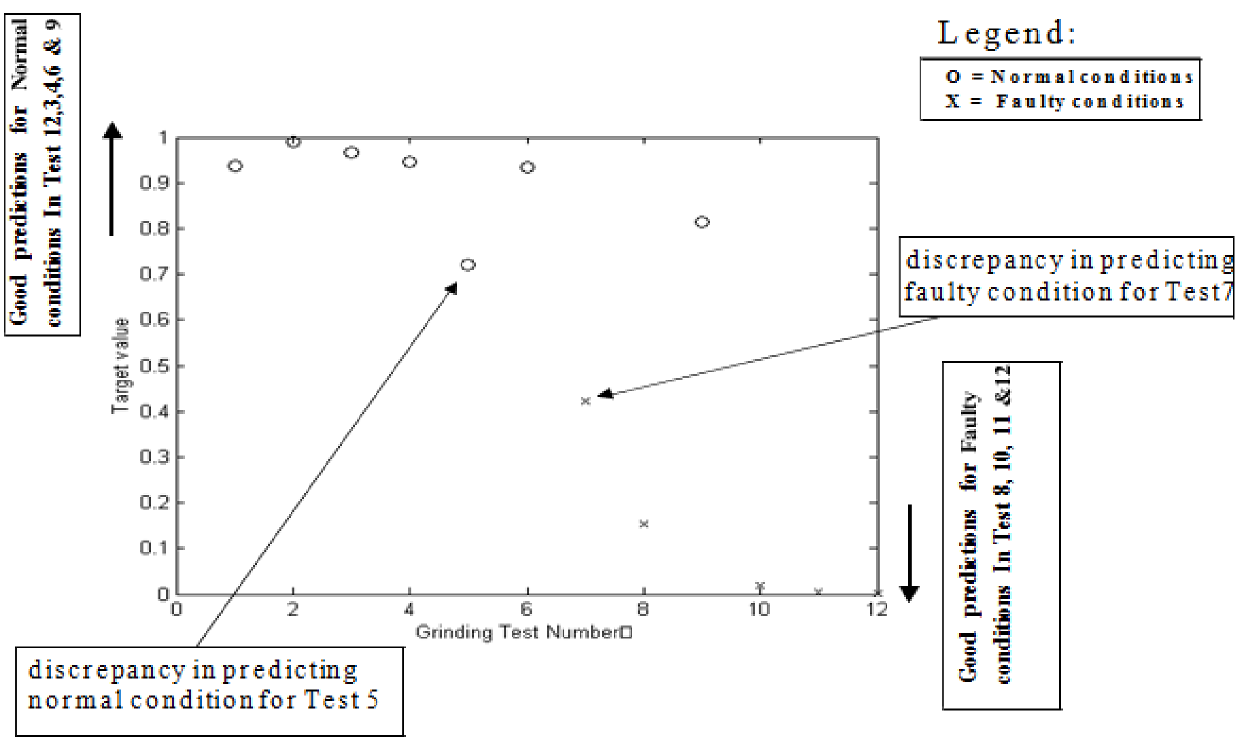


Fig. 9 Successful application of Back propagation neural network on visual images

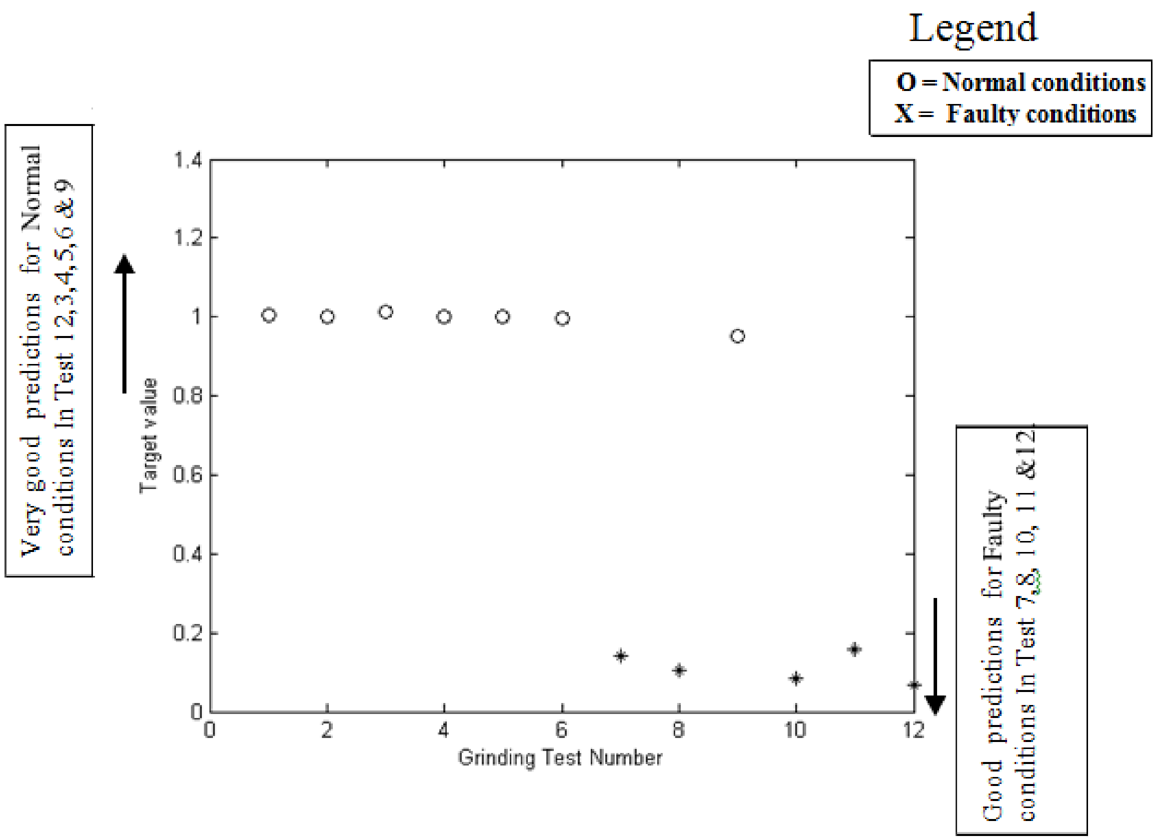


Fig. 10 Successful application of Radial basis neural network on thermal images

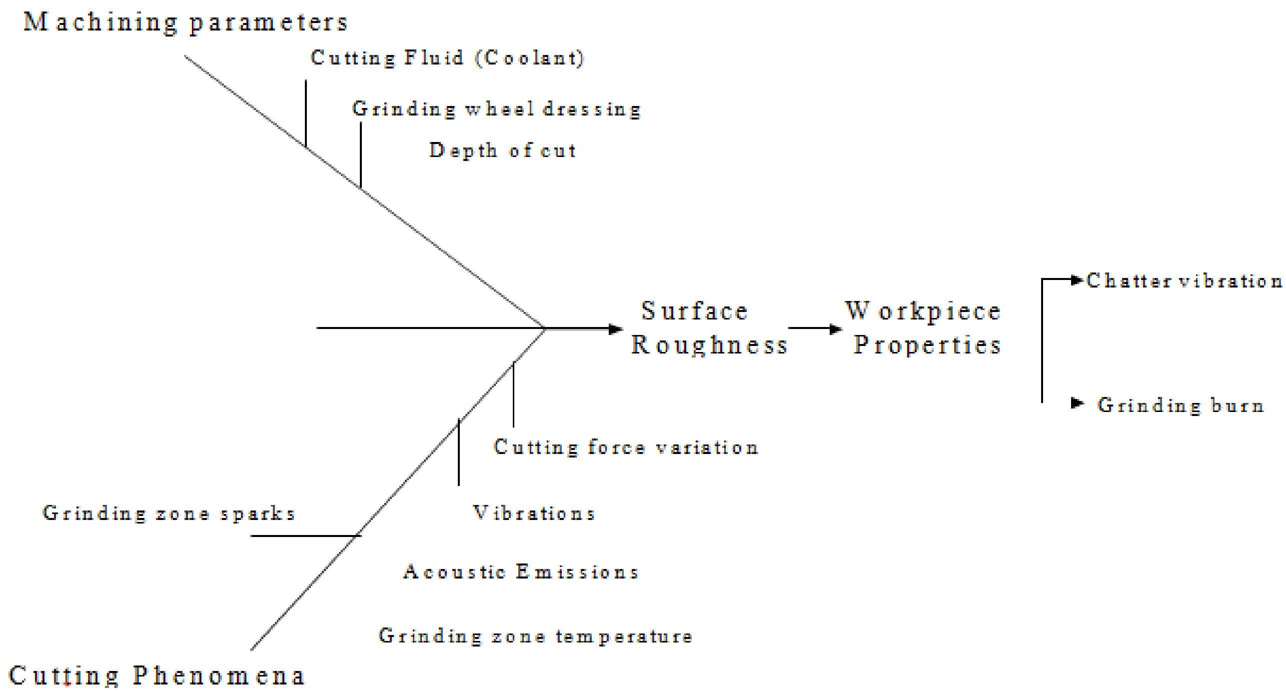


Fig. 11 Fishbone diagram with parameters that affects surface roughness

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