Analytical and Comparative Study of Using a CNC Machine Spindle Motor Power and Infrared Technology for the Design of A Cutting Tool Condition Monitoring System

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***Abstract*— This paper outlines a comparative study to compare between using the power of the spindle and the infrared images of the cutting tool to design a condition monitoring system. This paper compares the two technologies for the development of a tool condition monitoring for milling processes. Wavelet analysis is used to process the power signal. Image gradient and Wavelet analyses are used to process the infrared images. The results show that the image gradient and wavelet analysis are powerful image processing techniques in detecting tool wear. The power of the motor of the spindle has shown less sensitivity to tool conditions in this case when compared to infrared thermography.**

***Keyword*—** power sensor; infrared images; signal/image processing; tool wear; ASPS approach.

I. INTRODUCTION

Condition Monitoring Systems (CMSs) for tool wear detection and health classification of machining processes is a key factor in order to increase productivity, improve quality of the produced products and reduce their cost [1]. The progresses and cost reductions of sensors, cameras and computer technologies have encouraged researches and engineers in the development of Tool Condition Monitoring (TCM) systems for monitoring health of machining processes. TCM system could provide the necessary information in order to ensure the efficiency and reliability of the machining process, such as the detection of tool wear and tool breakage. Consequently, improving the quality of the product as well as maintaining the quality the machine tool itself. A significant damage to the work-piece caused by deterioration of tolerance or surface finish might occur when worn or broken tools are not replaced. This has a negative impact on the quality of products as well as the cost. Therefore, in order to reduce the cost of the product and to prevent damage to the machine, a TCM system is required. However, the majority of previous research found in the literature utilises in principle one-dimensional sensors (1D) such as vibrations and cutting force signals to diagnose the tool conditions. For example, a Kistler 9257B three component dynamometer implemented to measure the cutting forces has been reported in literature [1, 2]. Sensor fusion model of condition monitoring systems to detect tool wear in milling process is reported in [3]. Tool wear monitoring in face milling using acoustic emission is described in reference [4].

Different approaches have been applied in TCM include piezoelectric force sensors [5, 6], spindle motor current signals [7], vibration [7, 8], sound and acoustic emission [8, 9]. However, there are several concerns related to the above sensors as that can be summarised as follows [10]:

(1) The positioning and selection of the sensor might be a challenge.
(2) The sensors might be sensitive to other events and process's noise.
(3) There is a lack of stability during the cutting process due to changes in process characteristics.

Tool wear detection using two-dimensional sensors, such as visual and infrared cameras has been performed in research on a limited scale. For example [11] has used high speed (CCD) camera to acquire the images and canny edge detector has been applied for image processing. It has used a computer-vision approach to monitor tool wear for tools with a diameter of 7 to 9 mm drilling process. Moreover, a DEFROL metric approach has been used in order to detect tool wear in drilling processes. The pixel value of the sharp tool has been found to be lower than in the case of worn tool. The drawbacks of this approach is that the cutting tool is a rotating process, however, for high speed machining the camera will not always see the flanks directly. However, the suggested approach has not been tested for micro or small scale tools of diameter of 4mm and less. Tool tracking, recognition and identification using PCA and ANN systems is presented in Elgargni et al. [12]. It has used vision system based on visual and infrared cameras. The study has tested the detection of the existence of the tool and its health status ("Tool found", Tool not found" or "Broken tool"). However, the approach has not been tested to detect tool wear. A vision system using infrared camera and image processing has been tested in tool wear and breakage [13]. Many research work has been published in relation to monitoring electrical motors and drives, see for example [14,15]. However, limited research has been found in literature in relation to the utilisation of infrared thermography combined with image processing techniques for predicting tool health of milling processes in comparison to electric power monitoring. This research work has addressed this area and by suggesting an analytical and comparative study between 1D (power signal of the spindle motor) and 2D (infrared images) sensors with signal/image processing algorithms for the evaluation of tool wear.

II. RESEARCH METHODOLOGY

Fig. 1 presents the methodology used in this paper. Experiments are carried out on CNC milling machine. Signals of power signal (current of spindle) is recorded during end milling process. Also, images of the cutting tool are captured using an infrared camera during the process.

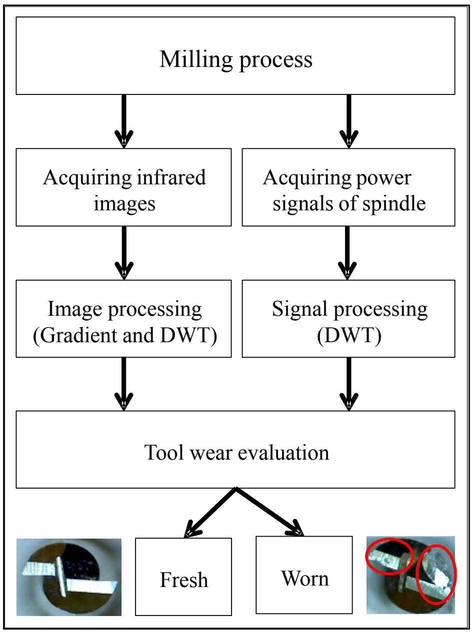

Fig. 1. The suggested research methodology.

Recorded signals and captured images are then saved on a computer for further analysis. DWT is used to process both recorded signals and captured images. Signal/image processing algorithms are used for tool wear evaluation. The methodology, as shown in Fig. 1, is to compare between one dimensional signal processing using wavelet analysis and two dimensional images processing of infrared images using image gradient and wavelets analysis.

III. EXPERIMENTAL SETUP

The condition monitoring system in this research work consists of one and two dimensional sensory data. The ultimate objective is to be integrated together in order to design sensor fusion model of CMS for milling process as shown in Fig. 2. The experimental work is performed on a milling CNC machine type (DENFORD).

Sensory signals of power sensor is used in this study. The power sensor is mounted in order to monitor the power signal of spindle motor. Monitoring the power consumption is considered one of the simplest techniques of monitoring the machining processes. Collision and faulty tools could be monitored using this technique. The sensor is easily installed without major modifications to the machine tool. The sensory signals are monitored under the machining conditions as shown in Table 1.

Table 1: Machining conditions.

Sampling rate	Material of tool	Tool diameter	Cutting speed	Cutting depth	Feed rate
50000	Solid Carbide	3mm	2490 RPM	0.22mm	250 mm/min

All the wires and cables of the sensors are connected to a National instrument connection box (SCB-100).

The signals are monitored using data acquisition card NI PCI-6071E from National Instrument using special data acquisition software written using the National Instrument CVI programming package. The two dimensional sensor is an infrared camera, which used to establish machine vision system that can track the tool and capture on line images during milling process. The infrared camera is FLIR E25 connected to an image capture card. It allows capturing images with resolution of 510 x 571 pixels in the temperature range between -20° to 250°C. Lab-view software is used to record infrared images during the milling operation. Emissivity value is assumed to be 0.9 since it can be considered constant for the same view.

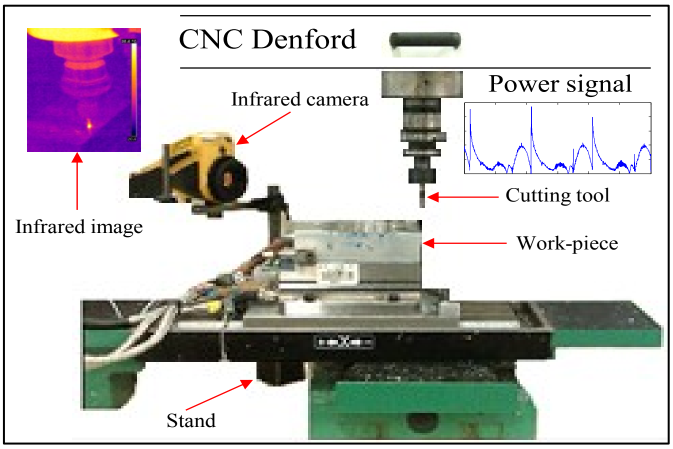

Fig. 2. The experimental setup.

The power sensor (IP-151) is connected directly to the data acquisition system. The sensor is a hall effect-based current sensor where the magnetic flux, proportional to the primary current. The primary current is measured without electrical contact with the primary circuit providing galvanic isolation. The output signal of the Hall device is then further amplified by additional internal signal conditioning circuitry to provide an output voltage proportional to the primary current. Therefore, in this paper the voltage from the sensor output is used as an indication of the power of the spindle motor.

Magnetic stand is used to fix the camera in a suitable position. The experimental work is performed on the milling machine using an Aluminum work-piece. The acquired signals and images are saved on a computer for analysis using MTLAB software.

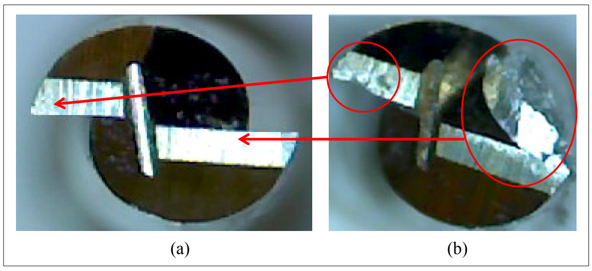

Fig. 3. Fault generation, normal (a); and completely worn (b).

The experiments have started with a fresh tool and finished with completely worn tool as shown in Fig. 3. The milling process is carried out at the following conditions: tool diameter is 3mm, cutting speed 2490 rpm, feed rate 250 mm/min and depth of cut 0.22mm.

IV. Signal And Image Processing Echniques

Because the original signals and images contain noise and other unwanted information, it is important to apply signal and image processing techniques in order to extract the information from recorded signals and captured images in the form of Sensory Characteristic Features (SCFs) [2,10, 16] and Image Characteristic Features (ICFs). Signal and image processing techniques implemented in this research work are described in the following sections.

A. Signal processing

Since the acquired signals contain noise and undesired information, it is difficult to classify the wear of the tool from the collected raw signals as shown in Fig. 4. Therefore, signal processing is required in order to simplify the collected signals for purpose of developing an effective CMS. In this case, Discrete Wavelet Transformation (DWT) is applied in order to find the frequency components of a signal buried in a noisy time domain signal as shown in Fig. 5.

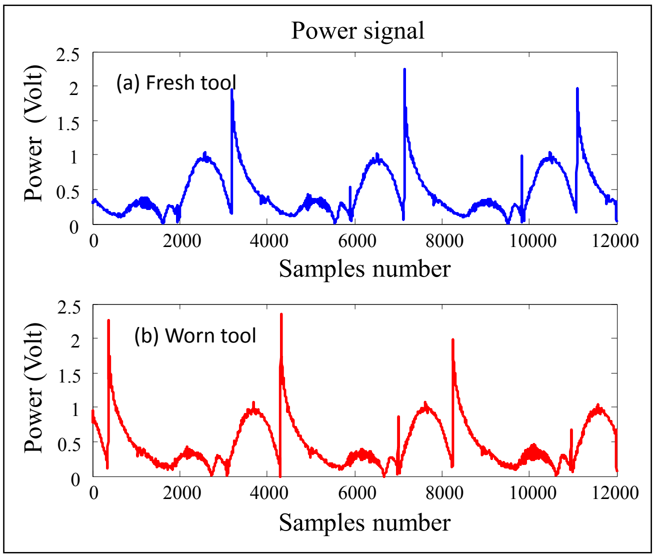

Fig. 4. Examples of the acquired volt signals from the power sensor (Hall-effect) for fresh (a) and worn (b) tools.

1) Discrete Wavelet Transformation

The frequency content of a signal is not regularly clear from the time domain. Therefore, it is essential to transform the signal into its frequency domain in order to confirm the presence of certain frequencies. The DWT algorithm is a commonly used technique in the field of signal processing. It allows transforming a digital signal from time domain (t), into a new frequency domain, whose argument is frequency with units of cycles per second (Hertz) or radians per seconds. The DWT is a very computationally intensive algorithm which contains a huge number of mathematical operations, which reduces the computation necessary to make the transformation from time to frequency domain. Example of plot of different signals after applying DWT is shown in Fig. 5.

2) Wavelet analysis:

Assume the signal *f(n)* where n= 0, 1, 2, 3, ..., M-1 and $j \geq j_0$. We can approximate a discrete signal by:

$$f(n) = \frac{1}{\sqrt{M}} \sum_k W_\emptyset [j_0, k] \emptyset_{j0,k}[n] + \frac{1}{\sqrt{M}} \sum_{j=j0}^{\infty} \sum_k W_{\psi_{j,k}[n]} \quad (1)$$

Here $f(n)$, $\emptyset_{j0,k}[n]$ and $\psi_{j,k}[n]$ are discrete functions defined in [*0*, *M−1*], totally *M* points. We can simply take the inner product to obtain the wavelet coefficients as follows:

$$W_\emptyset[j_0, k] = \frac{1}{\sqrt{M}} \sum_n f[n] \emptyset_{j0,k}[n] \quad (2)$$

$$W_\psi[j, k] = \frac{1}{\sqrt{M}} \sum_n f[n] \psi_{j,k}[n] \quad j \geq j_0 \quad (3)$$

Where $W_{\emptyset}[j_0, k]$ in equation (2) are called approximation coefficients while $W_{\psi}[j, k]$ equation (3) are called detailed coefficients.

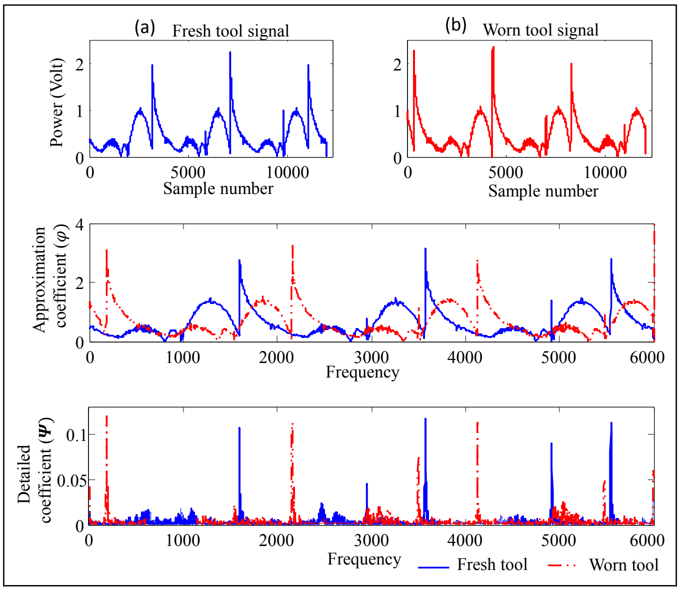

Fig. 5. Examples of the acquired signals for fresh and worn tools.

B. *Image processing*

This study utilises infrared images of healthy tools and compares them with images of worn tools. Since the captured images contain unwanted information and noise, pre-processing is required. All images are converted into grey-scale level in order to obtaining one numerical value for each pixel, instead of three RGB values. The next stage is to select the Region Of Interest (ROI), which has a significant information about the tool condition as shown in Fig. 6.

Two image processing techniques are used in this study namely, gradient algorithm and DWT. The gradient is used in order to improve visualisation of the image, also it provides a powerful function for tool wear monitoring. DWT is used in order to simplify the necessary computations and enhance the information in the data. It used to process the captured infrared image as shown in Fig. 6.

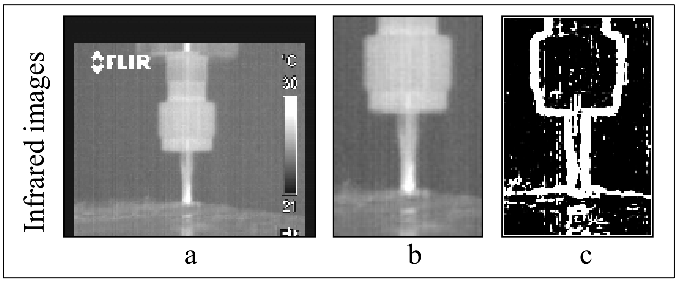

Fig. 6: The original, region of interest and gradient infrared images.

V. IMPLEMENTATION OF ASPS-2 APPROACH

A novel Automated Sensory and Signal Processing Selection System for two types of data (ASPS-2) approach is used in this paper in order to evaluate both 1D and 2D data to detect tool wear and breakage, the approach is based on Al-Habaibeh et al [2, 10, 16]. ASPS-2 is defined as a process of selecting the most sensitive Sensory and Image Characteristic Feature (SCFs and ICFs) in order to select the most suitable 1D and 2D sensors. The absolute slope of the linear regression method is used in this paper to detect the sensitivity of the sensory and image features in order to select the most suitable 1D and 2D sensors. All SCFs and ICFs are arranged to create a matrix called the Association Matrix (ASM). The ASM can provide a simple presentation of the sensitivity values associated with each feature [2, 10, 16].

VI. RESULTS AND DISCUSSION

Twelve experiments are carried out in order to design sensor fusion model of CMS for milling process. This model of CMS based on power signals of spindle motor and infrared image using signal and image processing. The aim of this work is to compare between 1D data (sensory signals) and 2D data (infrared images) in detecting tool conditions (fresh, worn or broken tool). Results of this research work can be divided into:

A. *Evaluation tool wear based on signals (1D data) using signal processing.*

Experiments are used to evaluate the significance of the signal processing in detecting tool wear and breakage. In this work, the discrete wavelet transform has been applied to process acquired signals as described in Fig. 5.

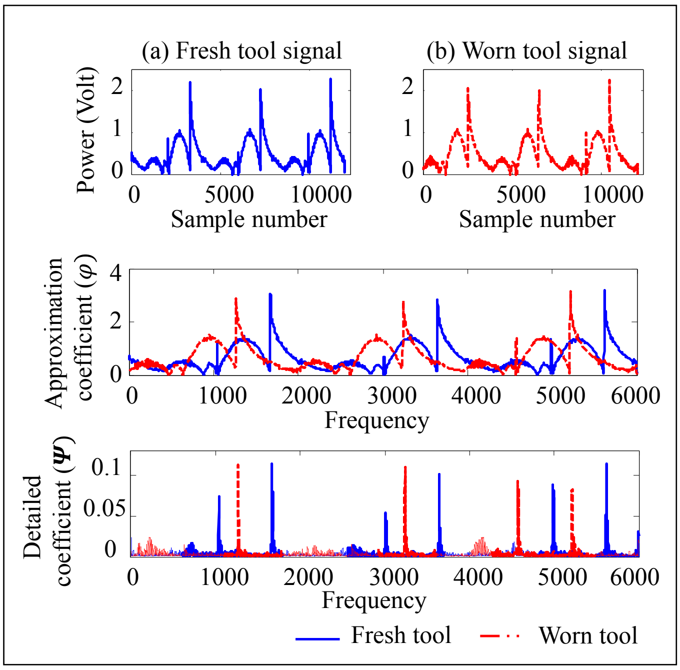

Fig. 7: Original signal of and the application of DWT.

Fig. 5 and Fig.7 show the original signals of fresh and worn tools following application of DWT (approximation and detailed coefficients). From Fig. 5 and Fig. 7 (approximation and detailed coefficients) it can be seen that there is slight difference in frequency between the two conditions (fresh and worn) tools. It also can be seen that the signals of worn tool has shifted into the left.

B. Evaluation of tool wear based on images (2D data) using infrared image processing.

Twelve tools are used to perform 12 machining runs for each tool. In total, 144 sets of data are captured. Image processing is used for tool wear evaluation as described above.

Fig. 8 presents fault generation of infrared images during the milling process. The Fig. 8 illustrates four images of: original, regions of interest and gradient images of four conditions of the tool in the end milling operation. Fig. 8 presents: (a) normal, (b) semi-worn, (c) worn and (d) totally damaged tool. From Fig. 8, it can be seen that the visualisation and the contrast of the images have been improved by using gradient technique. In addition to that, it can be seen that the gradient technique can precisely describe tool conditions. Moreover, it can be seen that gradient image can recognise the breakage point, which has been indicated on the image. This has occurred just before the breakage of the tool.

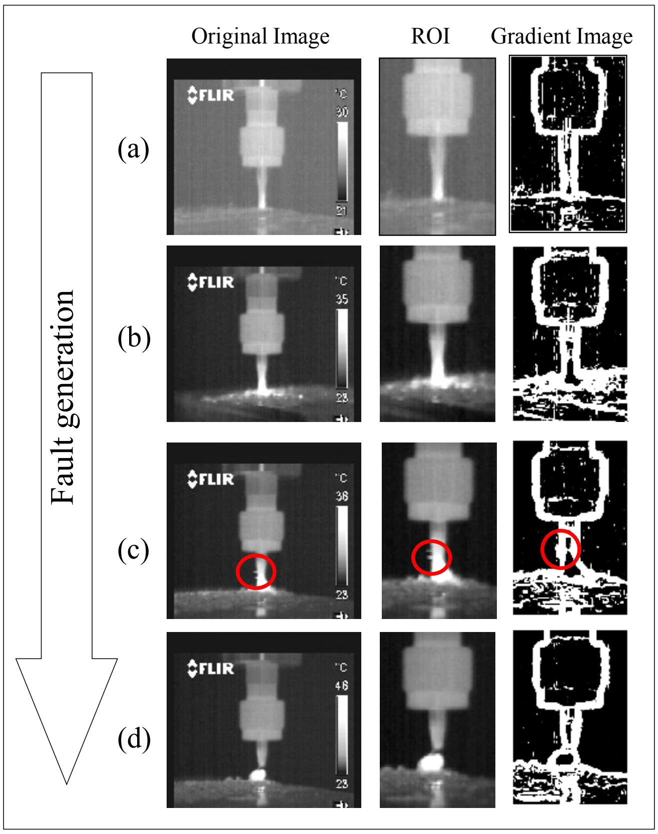

Fig. 8. Fault generation of infrared images (2D data), normal (a), semi-worn (b), worn (c) and damaged conditions (d).

Discrete Wavelet Transform (DWT) has been applied to process the acquired infrared image, which has been captured during end milling process. Fig. 9 and Fig. 10 present application of DWT (approximation and detailed coefficients). From the Fig. 9, it can be seen that approximation coefficient can distinguish between fresh and worn conditions. In contrast, detailed coefficient cannot describe tool conditions as shown in Fig. 10.

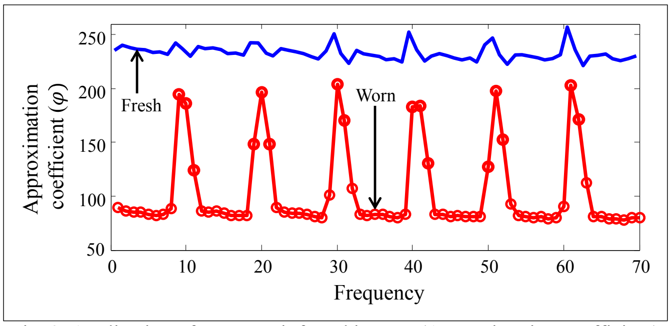

Fig. 9. Application of DWT on infrared images (Approximation coefficient).

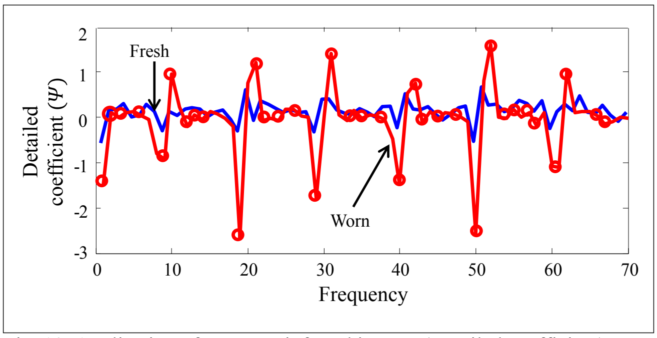

Fig. 10. Application of DWT on infrared images (Detailed coefficient).

C. Evaluation of 1D and 2D based on ASPS-2 approach

Fig. 11 presents the Association Matrix (ASM), see [2, 10, 16], which summarises the sensitivity of each Sensory Characteristic Feature (SCF) to detect the conditions under consideration. From Fig. 11 it can be seen that the 2D infrared images data is sensitive to tool wear which have the most useful features with higher relative sensitivity values in comparison to 1D data. This means that the 2D data (infrared images) is the most suitable to detect tool wear and breakage when compared to 1D data (power signals). Fig. 12 presents the relative sensitivity between the 1D (power signals) and 2D data (infrared images) using average sensitivity values. The signal and image processing techniques of Fig. 11, the vertical axis, include kurtoses (kur), skewness (skew), standard deviation (std), average (mean), variance (var), summation (sum), maximum (max), minimum (min), range, and mean absolute deviation (mad). The horizontal axis includes the original data from DWT, Gradient and power signal from the Hall-effect sensor in volts. The colours on the graph includes the relative sensitivity of the feature to tool conditions based on the presented colour-map.

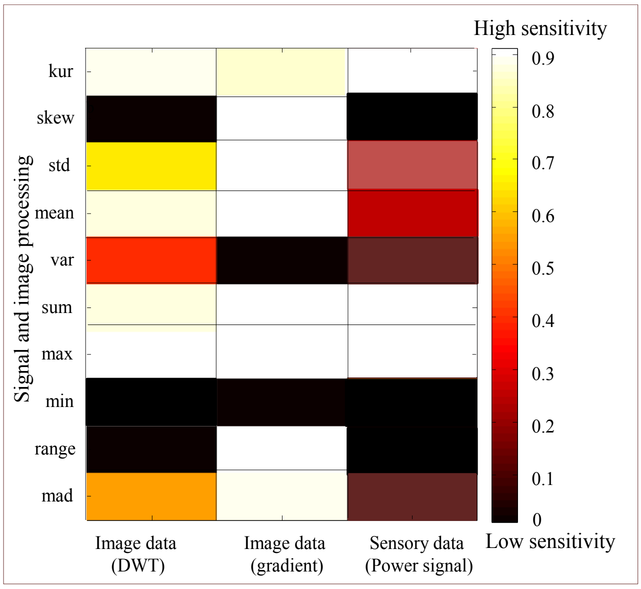

Fig. 11. The Association matrix (ASM) of this research work which represents the sensitivity of the proposed sensors and signal/image processing methods to tool conditions.

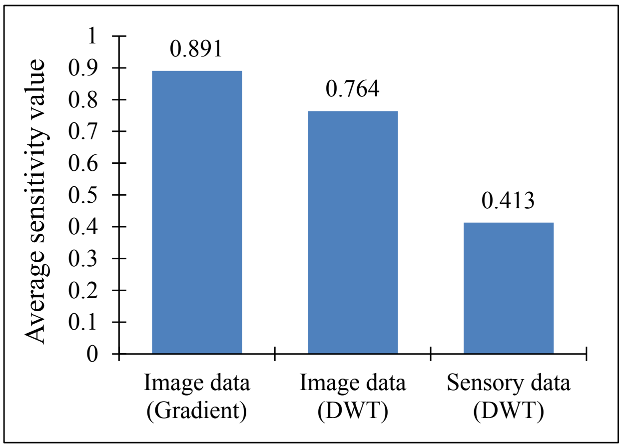

Fig. 12. The comparison between the three suggested techniques in relation to the average sensitivity of the features (SCFs).

VII. Conclusion

Analytical and comparative study between 1D data of the power of the spindle and 2D data of infrared images is presented in this paper using DWT analysis. The results show that the infrared data has been found more sensitive to detect the fault of the tool in comparison to the power of the spindle using the proposed hall-effect sensor. This could be related to the small size of the tool and the insignificance of the change in the current level relative to the condition of the tool. Future work will involve further analysis and comparison between one-dimensional and two-dimensional data using ASPS approach [2, 10, 16] and intelligent neural network for the design of tool condition monitoring system.

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