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Cutting tool wear classification and detection using multi-sensor signals and Mahalanobis-Taguchi System

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ABSTRACT

The detection of cutting tool wear during a machining process is one of the most important considerations in automated manufacturing systems. This study presents a new approach for classification and detection of tool wear in milling process using multi-sensor signals and Mahalanobis-Taguchi system (MTS). The MTS is one of the decision making and pattern recognition systems frequently used to solve a multidimensional system and integrating information to construct reference scales by creating individual measurement scales for each class. These measurement scales are based upon the Mahalanobis distance (MD) for each sample. Orthogonal arrays (OA) and signal-to-noise (SN) ratio are used to identify variables of importance, and these variables are used to construct a reduced model of the measurement scale. Mahalanobis distance (MD) values were calculated based upon the feature data set extracted from the six channels of machining signals under sharp cutting tool, medium wear and critical wear conditions. Experimental data of end milling AISI P20+Ni tool steel is used to construct Mahalanobis space, to optimize and validate the system. The results show that the medium wear and critical wear stages of cutting tool conditions can be successfully detected in real-time.

1. Introduction

Tool wear is a normal phenomenon in the machining process, but is a detrimental factor that affects the quality and tolerance of machined parts. When the cutting process continues with a worn tool, it can cause a machine to breakdown; if the cutting tool suddenly fails. Therefore, tool wear should be measured periodically to avoid severe wear occurred in machining operation. Visual inspection of tool wear by using a tool maker's microscope or charged-couple-device (CCD) camera is a traditionally-based indirect method for tool wear measurement [1]. This has the advantage of capturing actual geometric changes arising from the edge of the cutting tool wear. However, direct measurement of tool wear is very difficult to obtain due to the continuous contact between the cutting tool and machined work part. It is made almost impossible by the presence of cutting fluid. In order to determine the tool wear state without disturbing the machining process, it can be performed using an indirect method of tool wear measurement by utilizing the sensor systems. In the indirect method, the tool wear is not measured directly, but detected and estimated from the measurable signal features which are obtained in real-time.

Recently, research on tool wear condition monitoring has gained increased interest and many researchers have studied tool wear monitoring during the milling process using various machining signals, such as cutting forces, vibrations, acoustic emissions, sound, torque, current, power of the spindle motor and temperature [2]. These signals correlate with the changes of tool wear, and can be used as a parameter to determine the state of the cutting tool. However, tool wear is a complex nonlinear phenomenon, and using a single sensor system for condition monitoring becomes less accurate for detecting wear changes at the edge of the tool. Tool wear changes are very small; thus making it difficult to determine whether a small change is a result of wear of the tool or a change in cutting condition parameters. Therefore, the use of a multi-sensor system is better at detecting the state of the cutting tool during the machining process [3].

A multi-sensor fusion system requires a pattern recognition algorithm to combine a variety of information from multiple sensors. Many previous researchers have used a tool monitoring system with multi-sensor fusion using Artificial Neural Network (ANN) [4], statistical methods or linear regression [5], fuzzy logic and Adaptive Network-based Fuzzy Inference System (ANFIS) [6] and other sensor fusion methods [7]. Although there are many methods proposed for tool wear detection, none of the Mahalanobis-Taguchi System (MTS) approach has been used as a

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Nomenclature

a_p	axial depth of cut, mm
a_e	radial depth of cut, mm
A_z	vibration in vertical direction, m/s^2
f_z	feed rate, mm/tooth
F_c	main cutting force, N
F_t	thrust force, N
F_{cN}	perpendicular cutting force, N
K	Kurtosis
MTS	Mahalanobis-Taguchi System
MD	Mahalanobis distance
MS	Mahalanobis space
MP	maximum peak
OA	orthogonal array
P	power spectral density peak
RMS	root mean square
$RMSP$	root mean square in power spectral density
SkP	skewness in power spectral density
Sk	skewness
STD	standard deviation
$STDP$	standard deviation in power spectral density
STP	sum of total power density
SN	signal to noise ratio
T_q	torque, Nm
T_m	tool tip temperature, °C
VB	flank wear land, mm
v_c	cutting speed, m/min
Z^∞	I-kaz coefficient

decision-making system in milling process. In the previous study, MTS was only used as a multi-sensor based decision-making prognostics tool to monitor pump failure [8], the condition monitoring of motor bearings [9], the damage detection of cooling fans [10] and the prediction of drill-bit breakage during the drilling process [11].

This study implements a Mahalanobis-Taguchi System (MTS) based approach in multi-sensor data fusion for the classification and prediction of cutting tool states in the milling process. Moreover, a wireless multi-sensor on a rotating tool is applied to collect six machining sensory data values as input variables for MTS. The signal comprises the cutting force in three directions, torque, vibration and tool tip temperature. Some of the features that can reveal the characteristics of the time and frequency domains of multi-sensor signals are extracted. By using experimental end milling data, Mahalanobis Space (MS) for normal index of cutting tool state as reference, is created using Mahalanobis distance (MD) values. The Taguchi method is employed to optimize the prediction system using Orthogonal Array (OA) and signal-to-noise ratio (SN). Then, a Mahalanobis space is reconstructed using only the useful features.

2. Experimental procedure

2.1. Milling process

In order to develop a real-time tool wear prediction system, linear end milling tests were performed on a CNC milling machine (DMC 635 V Ecoline) under dry cutting conditions. The cutting tool used was a coated carbide insert (AXMT170504PEER-G) with ACP200 grade. This grade of carbide tool is suitable for heavy duty cutting of steel and stainless steel. The machining signals, comprised of main cutting force (F_c), thrust force (F_t), perpendicular cutting force (F_{cN}), torque (T_q), vibration (A_z), and tool tip temperature (T_m), were collected by a wireless multi-sensor system. The force-torque strain gauge-based and wireless embedded sensors were developed by Rizal et al. [12,13]. The signals were recorded at a sampling rate of 5 kHz, and then analysed by a computer for the feature extraction process. A schematic of the wireless multi-sensor integrated rotating tool and experimental set-up is shown in Fig. 1.

End milling was performed on AISI P20+Ni tool steel with a hardness of 35 HRC and a composition of 0.37% C, 0.30% Si, 1.40% Mn, 0.01% S, 2.00% Cr, 0.20% Mo, and 1.00% Ni. This material is popularly used to make plastic injection moulds, extrusion dies, blow moulds, tooling designs, and other various components. The dimensions of the material were 170 mm length, 100 mm width and 80 mm height so each length of cut was 170 mm. A (2^3) full factorial design was employed for each cutting tool used as shown in Table 1. A constant axial depth of cut (a_p) of 1.0 mm was used for all combinations of experiments.

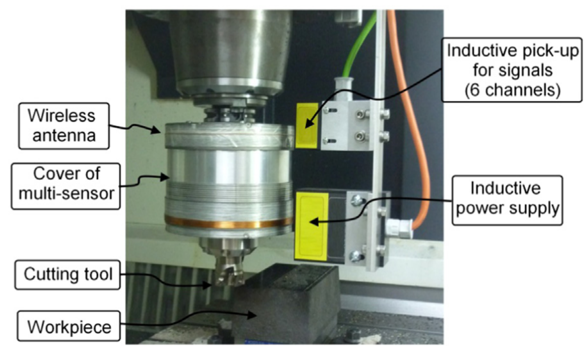

Fig. 1. Experimental and multi-sensor system set-up.

Table 1
Cutting conditions of the milling process.

Parameters	Low (1)	High (2)
Cutting speed v_c (m/min)	200	375
Feed per tooth, f_z (mm/tooth)	0.10	0.20
Radial depth of cut, a_e(mm)	0.4	0.6

During the milling process, a new tool insert was used for each set of combination parameters. For every 510 mm movement of the cutting tool in cutting the workpiece, the tool was removed periodically from the tool holder then the flank wear was measured using a Mitutoyo toolmaker's microscope equipped with a graduated scale in mm. The measured parameter to represent the progress of tool wear was flank wear width, VB. By using a standard recommended value in defining a tool life criterion based on ISO 3685:1993, the milling operation was stopped, and the cutting tool insert was discarded when VB reached 0.3 mm. The totals of the cutting tool insert used in this study were nine pieces. The ranges of flank wear values were divided into three classifications, normal wear (VB = 0 – 0.15 mm), medium wear (VB=0.15 – 0.25) and critical wear (VB=0.25 – 0.35 mm).

2.2. Feature extraction

The feature extraction aimed to reduce the dimensions of the raw machining signals, while maintaining the relevant information of the tool's condition in the extracted features. Several signal features could be extracted from any of the time domain signals, including the mean of amplitude, standard deviation, RMS, variance, skewness, kurtosis, I-kaz value, etc. [7,14,15]. They could also be transformed into a frequency or time-frequency domain (FFT, wavelet, etc.). In this study, six channels of data were transformed into features that were extracted in time and frequency domains.

2.3. Mahalanobis-Taguchi System (MTS)

The Mahalanobis-Taguchi System (MTS) is one of many pattern recognition methods used for data classification [16]. This method combines Mahalanobis Distance (MD) and Taguchi methods. MD is a generalized distance that is useful for determining the similarities between unknown and known sample datasets. It measures the distances in multidimensional spaces; taking into account the correlations between any variables or features that may exist. Meanwhile, the Taguchi method is used to optimize the system and evaluate the contribution of each feature. If possible, dimensionality is reduced by eliminating those features that do not add value to the analysis; thus making it more robust [17]. In machining process, tool wear state can raise many symptoms such as the increase in force, torque, vibration and temperature, which also generated under standard condition of machining. Therefore, very difficult to determine whether the change of the signal due to tool wear effect or standard cutting. Mahalanobis distance can distinguish abnormalities from normal data group or data when uses sharp cutting tool by built a Mahalanobis space (MS) that sets as a reference to classify the other abnormal data for many variables. Generally, MTS consists of the following four steps:

Step I: Mahalanobis Space (MS) construction

To construct MS, feature data from the sensors (features when the cutting tool is in the normal wear stage) is collected to form a normal dataset. The data is then normalized using mean and standard deviation. Mahalanobis Distances (MD) corresponding to all data is computed using an inverse of correlation matrix method [18].

$$MD = \frac{1}{k} Z_{ij} C^{-1} Z_{ij}^{T} \tag{1}$$

where Z_i is the normalized vector obtained by normalizing the values of $X_i (i = 1, 2, 3, \ldots, k)$.

$$Z_{ij} = \frac{X_{ij} - \bar{X}_i}{S_i}, \quad i = 1, 2, \ldots, k; \quad j = 1, 2, \ldots, n \tag{2}$$

$$\bar{X}_i = \frac{\sum_{j-1}^{n} X_{ij}}{n_i} \tag{3}$$

where X_{ij} is the value of ith feature in jth sampling.

$$S_i = \sqrt{\frac{\sum_{j-1}^{n} \left(X_{ij} - \bar{X}_i^2 \right)}{n - 1}} \tag{4}$$

where S_i is the standard deviation of ith feature, k is the number of features, n is the number of samplings, Z_{ij}^{T} is the transpose of normalized vector and $\boldsymbol{C}^{-1}$ is the inverse of the correlation matrix.

Step II: Validation of MS

Observations of the medium wear stage are identified. Their feature datasets are normalized using the mean and standard deviation of the normal dataset. By using the correlation matrix of the normal wear group, the corresponding MD values are calculated. It should be ensured that the MDs of the medium wear stage have higher values than that of the normal wear stage.

Step III: Identification of useful features

In this step, the Taguchi method, through Orthogonal Arrays (OA) and signal-to-noise (SN) ratios, is used to select the important features. The suitable OA were selected depending on the number of features. Two-level factors are used: Level-1 means the feature is used, while Level-2 means the feature is not used. During this step, MDs of the medium wear stage were considered to calculate the SN ratios by using the larger-the-better signal-to-noise ratio corresponding to the ith run of the OA, which is defined as follows:

$$SN = \eta_i = -10 \log\left(\frac{1}{t} \sum_{j=1}^{t} \frac{1}{MD_j} \right) \tag{5}$$

Where t is the number of features present for a given combination of the experimental run, and MD_j is the MD of the jth sampling.

The important features are obtained by gain in SN ratio values for each feature, which is calculated as:

$$Gain = \overline{SN\text{ratio}}_{\text{Level}-1} - \overline{SN\text{ratio}}_{\text{Level}-2} \tag{6}$$

If the result of gain is positive, the feature is useful in tool wear prediction and the feature is kept; if not, it is excluded for the next MD calculation step.

Step IV: Decision making

A decision should be made in this step. If MDs are within the MS of the normal wear stage, the monitored tool wear is normal or cutting tools are still good. If MDs are out of the MS, the monitored tool exhibits abnormal wear or tool wear has occurred.

3. Results and discussion

3.1. Machining signal

For every experimental set from eight combinations of machining parameters, two types of data were obtained: flank wear width, *VB* and the raw signals in time domain. During machining operation, the typical tool wear occurred on the cutting edge are the flank wear. Fig. 2 shows flank wear progression at initial or

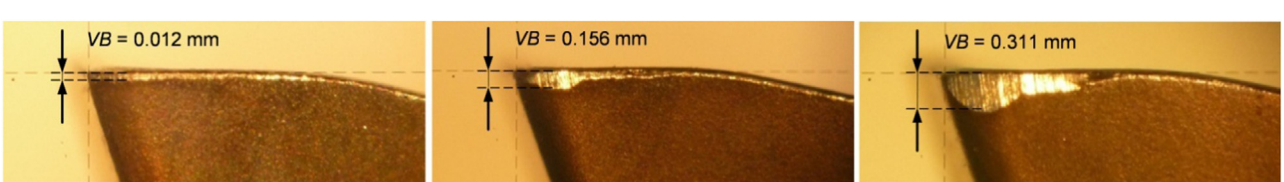

Fig. 2. Flank wear progression during milling process: (a) when flank wear *VB*=0.012 mm; (b) when flank wear *VB*=0.156 mm; (c) when flank wear *VB*=0.311 mm.

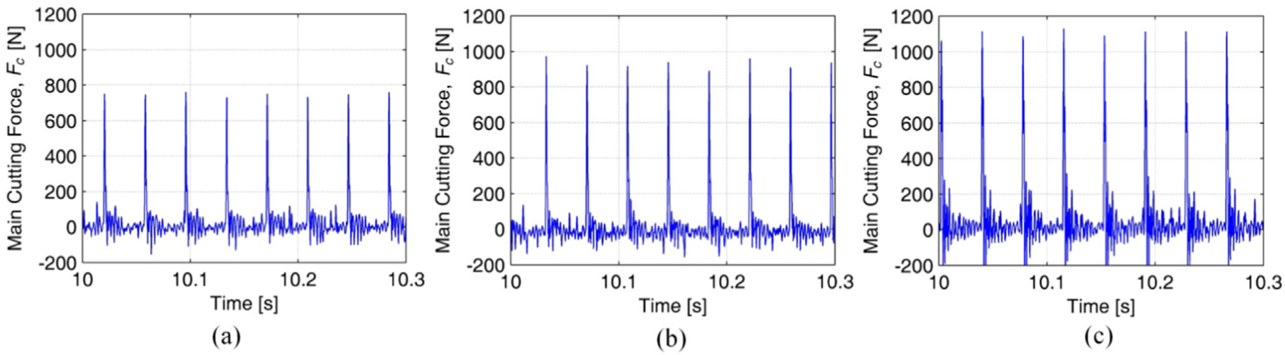

Fig. 3. Variation **s**ignal of main cutting force F_c in three conditions of flank wear: (a) when flank wear VB=0.012 mm; (b) when flank wear VB=0.156 mm; (c) when flank wear VB=0.311 mm.

normal wear, medium wear and severe wear when milling AISI P20+Ni tool steel at a cutting speed of 200 m/min, feed rate of 0.2 mm/tooth, radial depth of cut of 0.6 mm and axial depth of cut of 1.0 mm. It was found that the flank wear formed a uniform pattern along the contact zone of cutting tool and workpiece. It is obvious that the mode of wear that occurs on the flank of the tool is dominated by abrasion. However, it does not flake or failure occurs on the flank or rake face of the cutting tool, but the maximum flank wear occurred close to the nose region. It is because the small contact area which resulting high temperature at the nose of the cutting tool [19].

In addition, six channels of machining signals were collected during experimental test using milling CNC machine. These signals represents to the main cutting force, F_c, the thrust force, F_t, the perpendicular cutting, F_{cN}, torque, T_q, vibration in z-axis, A_z and tool tip temperature, T_m. A typical example of six channels machining signal are shown in Figs. 3–8. These machining signals show the pattern of raw signal when the flank wear at initial wear (a), medium wear (b) and severe wear or end of cutting (c). Fig. 3 shows the main cutting force signal when obtained at 5 kHz of sampling rate. The gap between the peaks of signal is a period in which the cutting tool is not touching or cutting of the workpiece. The characteristic of the cutting force signal pattern is almost similar for all combinations of cutting parameters, but also can change depending on tool geometry and its milling operation. It was clear that the flank wear causing main cutting force increased. At the beginning of milling operation or when the flank wear (VB) was 0.012 mm, the maximum amplitude of the force F_c was 738 N. After the flank wear reached about 0.156 mm, the reading of the main cutting force also increased until 994 N. Then the main cutting force was still continues to increase, until the flank wear was 0.311 mm, the signal amplitude reached about 1182 N. It shows that the increase in the average of the main cutting force due to flank wear was 26.8%. The results obtained in this study are in agreement with the results of the previous study which they used a commercial rotating dynamometer and found an increase in the main cutting force due to flank wear around 20–22% [20].

Fig. 4 shows the thrust force signal for three conditions of flank wear. Thrust force, F_t can be referred to as a passive force which is shown by the amplitude obtained is much smaller than the F_c force. It is caused due to the thrust force was generated by the reaction of the workpiece against the pressure of the tool in the vertical direction [21]. The amplitude of the F_t force showed a reading of only 70 N when flank wear about 0.012 mm. However, the F_t force is also very sensitive to changes in flank wear of the tool. It can be seen that the amplitude of force signal was increased significantly when the flank wear reached 0.311 mm, i.e. increased about 44.5%. It is because when the flank wear reached more than 0.15 mm; tool wear is concentrated on the nose region causing rubbing motion on the top of the workpiece.

The perpendicular cutting force, F_{cN} and torque, T_q also showed the significant changes due to flank wear progression as shown in Figs. 5 and 6. It can be observed that the increase of the F_{cN} force about 38.7%. This result shows that the F_{cN} force is more significant than the F_c force. It is because the direction of the F_{cN} force is perpendicular to the flank wear that cause bigger contact area between the tool and the workpiece. The T_q torque also shows the amplitude changes due to the tool wear. Fig. 7 shows the raw vibration signal in vertical direction during milling operation. The increase of vibration amplitude in the raw signal is not very significant due to a change in flank wear. However, the observed pattern of peak to peak signal shows that there is visible changed of signal pattern due to the tool wear. It can be seen the increase in number for every cycle of the wave crests; therefore indicates the frequency is increased. The sixth signal is a measurement of tool tip temperatures by wireless embedded thermocouple on the flank edge and shown in Fig. 8. The change in temperature as a result of rubbing action between flank wear land and the

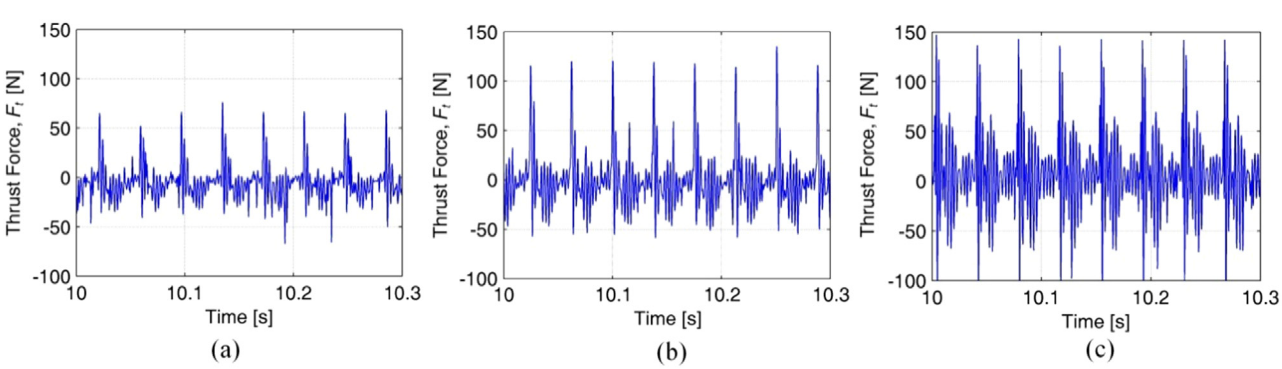

Fig. 4. Variation **s**ignal of thrust force F_t in three conditions of flank wear: (a) when flank wear VB=0.012 mm; (b) when flank wear VB=0.156 mm; (c) when flank wear VB=0.311 mm.

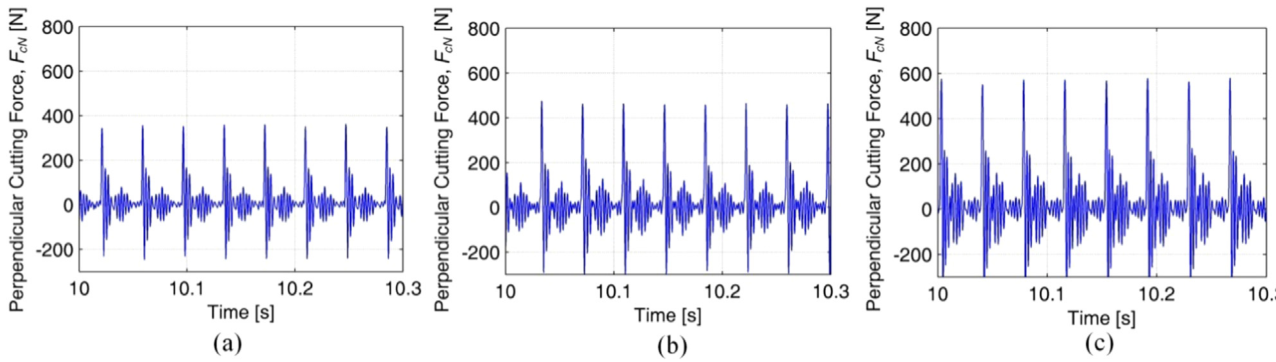

Fig. 5. Variation **s**ignal of perpendicular cutting force F_{cN} in three conditions of flank wear: (a) when flank wear VB=0.012 mm; (b) when flank wear VB=0.156 mm; (c) when flank wear VB=0.311 mm.

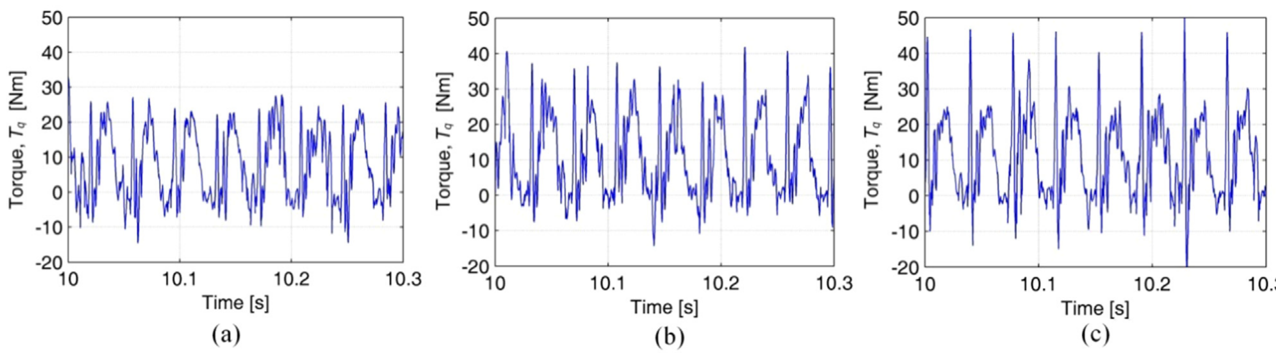

Fig. 6. Variation **s**ignal of torque T_q in three conditions of flank wear: (a) when flank wear VB=0.012 mm; (b) when flank wear VB=0.156 mm; (c) when flank wear VB=0.311 mm.

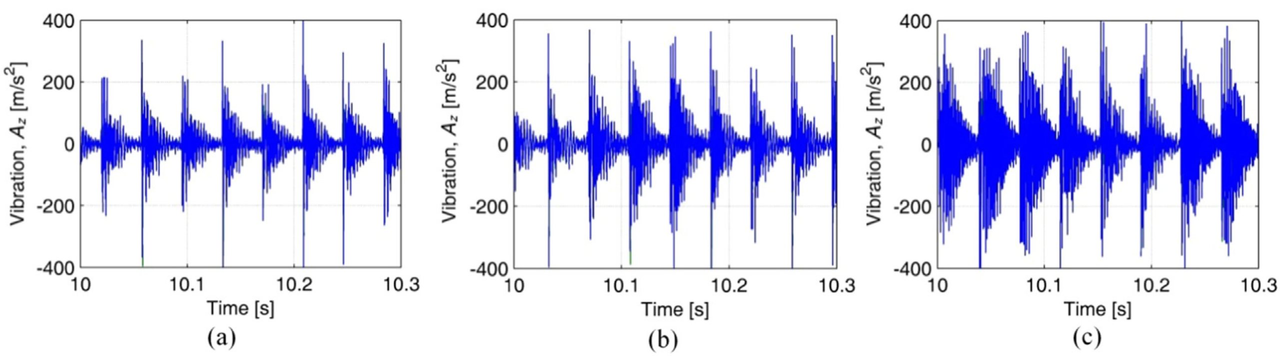

Fig. 7. Variation **s**ignal of vibration A_z in three conditions of flank wear: (a) when flank wear VB=0.012 mm; (b) when flank wear VB=0.156 mm; (c) when flank wear VB=0.311 mm.

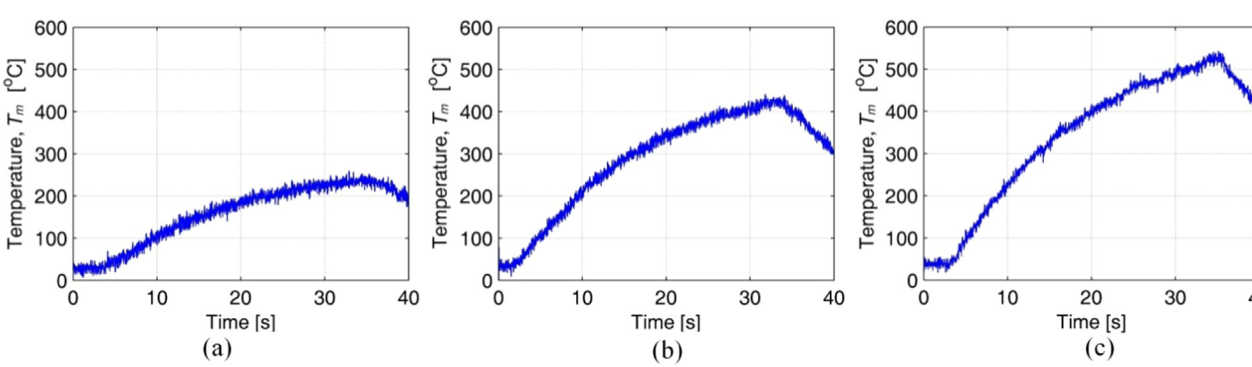

Fig. 8. Variation **s**ignal of temperature T_m in three conditions of flank wear: (a) when flank wear VB=0.012 mm; (b) when flank wear VB=0.156 mm; (c) when flank wear VB=0.311 mm.

Table 2
The signal features used in the tool wear prediction system.

Codes of signal features (No. Feature) from six channels of wireless sensor integrated on rotating tool					
Main cutting force, F_c	Thrust force, F_t	Perpendicular cutting force, F_{cN}	Torque, T_q	Vibration, A_z	Temperature, T_m
F_c_MP(X1)	F_t_MP(X7)	F_{cN}_MP(X13)	T_q_MP(X19)	A_z_STP(X25)	T_m_MP(X31)
F_c_STD(X2)	F_t_STD(X8)	F_{cN}_STD(X14)	T_q_Sk(X20)	A_z_K(X26)	–
F_c_RMS(X3)	F_t_RMS(X9)	F_{cN}_RMS(X15)	T_q_RMS(X21)	A_z_Sk(X27)	–
$F_c\_Z^\infty$ (X4)	$F_t\_Z^\infty$ (X10)	$F_{cN}\_Z^\infty$ (X16)	T_q_P(X22)	A_z_RMS(X28)	–
F_c_P(X5)	F_t_P(X11)	F_{cN}_P(X17)	T_q_SkP(X23)	$A_z\_Z^\infty$ (X29)	–
F_c_STDP(X6)	F_t_STDP(X12)	F_{cN}_STDP(X18)	T_q_RMSP(X24)	A_z_P(X30)	–

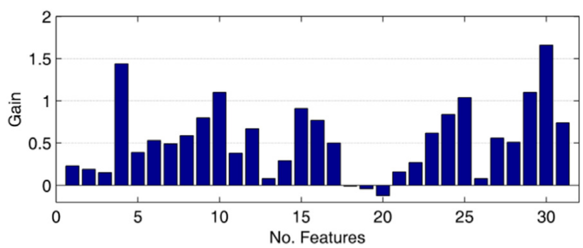

Fig. 9. Gain for each feature.

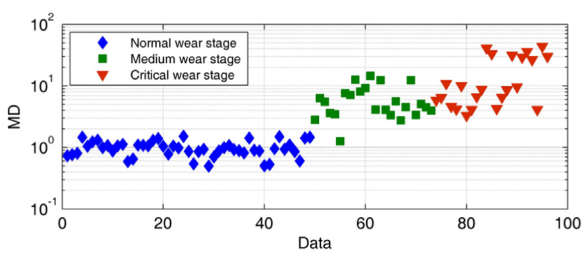

Fig. 10. MD values distribution of multi-sensor using all features.

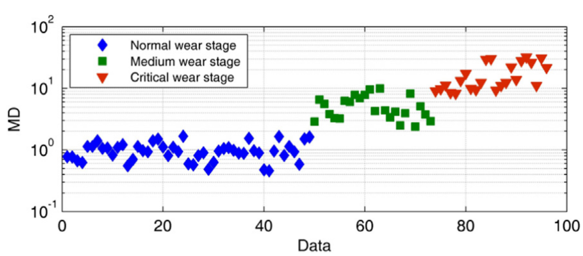

Fig. 11. MD values distribution of multi-sensor using MTS.

Table 3
Results of the experiment: detection tool wear stages under set a.

Wear stages	MD database Avg. [range]	MD Test 1	MD Test 2	MD Test 3	False detection
Normal	0.98 [0.45, 2.45]	0.84	0.96	1.03	0%
Medium	5.19 [2.38, 9.93]	4.65	3.69	5.57	0%
Critical	16.83 [8.21, 32.21]	9.95	11.81	6.18	33%

Table 4
Results of the experiment: detection tool wear stages under set b.

Wear stages	MD database Avg. [range]	MD Test 1	MD Test 2	MD Test 3	False detection
Normal	0.98 [0.45, 2.45]	1.63	0.71	1.22	0%
Medium	5.19 [2.38, 9.93]	2.61	2.89	2.34	33%
Critical	16.83 [8.21, 32.21]	27.25	22.17	21.39	0%

workpiece surface are very significant. Therefore, the temperature signal data can also be used to detect the tool wear in tool condition monitoring system although many previous researchers rarely use the temperature sensor.

In addition to the signal feature that can be observed such as amplitude in the time domain, each signals is still contains a lot of significant information related to the tool wear. The details of the signal features from the six sensor channels which were extracted in time and frequency domains are described in Table 2.

3.2. Tool wear classification and detection using mts

Mahalanobis–Taguchi system (MTS) is a method of pattern recognition, to make quantitative decisions by constructing a multivariate measurement scale [22]. Basically, this method is used to classify data into two categories, namely normal and abnormal. In this study, MTS is used to classify and detect the state of the tool in real time. Therefore, the condition of flank wear (VB) for the range of 0 – 0.35 mm is divided into 3 groups. It consists of wear in stage-1, VB = 0–0.15 mm classified as normal stage. Wear in stage-2, VB = 0.15– 0.25 mm classified as abnormal medium stage. Wear in stage-3, VB = 0.25–0.35 mm classified as abnormal critical stage.

In the first step of MTS, Mahalanobis Distance (MD) of normal wear were constructed using 31 signal features as shown in Table 2. These features contain 49 datasets from all combination machining experiment in the range of normal wear condition. After MS for the normal group was constructed, MD values were found in the range 0.49 to 1.51 with an average MD of 0.98. This unit space was referred to as reference space.

During the second step, the MS, as the measurement scale, was validated. Datasets in this range of flank wear of medium and critical wear stages were used to obtain MDs. It was found that the average value of MD for medium wear was 6.17 (in the range 1.26 – 14.48). Meanwhile, the average value of MD for critical wear was 16.01 (in the range 3.30 – 43.82). Therefore, it is clear that MDs in the medium and critical wear stages can be distinguished.

During the third step, the impact of each feature was investigated using OA and SN ratios. Then, the gain was calculated for each feature for medium and critical wear stages. Since the initial number of signal features was 31, a L_{32} (2^{31}) orthogonal array was used. As shown in Fig. 9, feature X18, X19 and X20 did not have a significant impact on MD. Therefore, the number of features was reduced from 31 to 28, including X30 (peak of frequency of vibration) with the highest impact and X13 (maximum amplitude of perpendicular cutting force) with the lowest impact.

After all the insignificant features were removed, the MS and MD were recalculated using only 28 useful features from six channels sensor. In order to evaluate Taguchi optimization, Fig. 10 and Fig. 11 show the distribution of MDs in the three stages of flank wear. In Fig. 10, MDs are obtained from 31 features showing the grouping of MDs between each wear stage, however there is an overlapping of MDs range between medium and critical wear stages. However, it is clearly observed in Fig. 11, only 28 features are used after optimizing using OA and SN analysis, resulted in improvement of the distribution of MDs. It was found that the new average MDs and ranges of medium and critical wear are 5.19 [2.38, 9.93] and 16.83 [8.21, 32.21].

The fourth step determined the state of flank wear, based on the threshold of MDs, which were analysed and developed by MTS. If the MD was in the range 0.4 to 2.4, the flank wear was detected in the normal stage or the cutting tool was still in a good condition. If the MD was in the range 2.5 to 9.4, the flank wear was detected in the medium stage. This meant the cutting tool can be used continuously, but careful should be taken; because it may enter the critical wear stage quickly. If the MD was in the range 9.5 to 35.5, the flank wear was detected in the critical stage. This meant the flank wear condition was approaching 0.3 mm; therefore, machining needed to stop immediately.

Validation tests were conducted to evaluate the performance of classification or prediction tool wear through MTS using datasets that were different from the data used in the last analysis. Two sets of combination parameters were used, set v_c= 200 m/min, f_z= 0.1 mm/tooth, a_e = 0.4 mm and a_p = 1.0 mm (set a) and set v_c= 375 m/min, f_z= 0.2 mm/tooth, a_e = 0.6 mm and a_p = 1.0 mm (set b). Each parameter set of experimental data was taken from nine datasets comprised of 3 data taken for each tool wear stage. The signals from experimental machining tests were directly observed by the developed software to automatically obtain MD.

Tables 3 and 4 show the results of tool wear stage detection. In Table 3, all MD values obtained were still in the range of MDs in the database. The number of data test used in MTS is 18 data with the different flank wear state. The results shows there are two sets of data with MD value is outside the range of MD database. In the test 3 (set a) i.e. at the critical stage, one predicted MD was detected out of the MD range; therefore, it became overlapped and made a false detection of about 33% or accuracy about 67%. As well as in the test 3 (set b), MD value of medium stage was found out of the MD range. When seen in the normal stage of two combination parameters show the false detection errors are 0%. Its means that the accuracy of tool wear classification between flank wear 0 – 0.15 mm reached 100%. However, when detecting wear in medium and critical stages, it was found an error just for 2 trials from 18 trials. The root cause of this error is the Mahalanobis space was developed using only normal data. Any data outside the normal space would be detected as abnormal data. This approach is a common result of MTS that was reported in the previous studies [8,16]. However, the abnormal space range in this work is divided into two stages or ranges; medium wear and critical wear stages. So, it is a new approach of MTS method for classification of tool wear stage in real time during milling process. The result shows that the average accuracy of all trials of the MTS in tool wear classification is 88.89% or in false detection about 11.11%. Therefore, the results have been verified and the proposed approach can be use as classification and prediction systems to detect wear occurred during milling process without stop the process.

4. Conclusions

An integration wireless multi-sensor and Mahalanobis-Taguchi System (MTS) was developed and applied to classify and detect the flank wear stage under milling process. Six machining signals from the wireless multi-sensor system that were obtained became a group data as input parameters into MTS. A number of useful features from six sensor channels were selected through OA and SN analysis, and became input parameters to obtain MD values as a wear index to decide the tool wear state. This approach has the ability to classify different tool wear state within the abnormal group. The experimental results show that the proposed prediction system was successful with the average accuracy of 18 trials is 88.89% or false detection error of 11.11%. The work is currently can be extended by development a representative software which consists of MTS to enhance real-time tool wear monitoring system. So, it is able to give an early warning system to replace the tool during milling operation before severe wear occurred.

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