Adaptive Neuro-Fuzzy Inference System for Deburring Stage Classification and Prediction for Indirect Quality Monitoring

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Abstract

Manufacturing of aerospace components consists of combination of different types of machining, finishing, and measuring processes. One of the finishing processes is deburring, i.e. a finishing process to remove burrs from work coupons after a boring hole process. Deburring is conducted to achieve required surface finish quality prior to further processes in assembly line. This paper introduces sensor data analysis as a tool to quantify and correlate the deburring stage with the features extracted from sensors data. This study covers signal processing, feature extraction and analytical method to determine its relevancy to the surface finish quality from deburring process. Wavelet decomposition and Welch spectrum estimate is used as a signal processing and feature extraction method. Consequently, the features are used as the basis for analysis by adaptive neuro-fuzzy inference system (ANFIS). The ANFIS yields the output corresponding to the predicted surface finish quality in terms of boss hole chamfer length and the stage classification of deburring process. The results show a decreasing trend in measured vibration signal, which is qualitatively well correlated the deburring stage and the development of chamfer length during deburring.

Keywords: Accelerometer; ANFIS; Deburring; Wavelet decomposition; Welch spectrum estimate.

1. Introduction

Fabrication processes, including additive manufacturing, casting, machining, and welding produce parts with surface finish imperfections (e.g. build striations, pitting, mill-lines, or weld spatter) and edge burrs/flashing. Various processes are available to remove these imperfections including sanding, grinding, bead blasting, or vibratory polishing. This paper focuses on the deburring (abrasive grinding process) which is routinely used in aerospace manufacturing industry to remove burrs on the

components. Deburring is an important finishing stage in manufacturing aerospace components to achieve the required surface finish quality within its acceptable tolerance. One example of the component is a combustor casing, the component on which fan blades will be mounted on. It is critical to have a tight surface finish tolerance for aerospace components such as combustor casing to reduce attrition on the component.

At present, the surface quality monitoring is accomplished through offline and/or direct measurement of surface roughness or thickness. In high-volume productions, manual measurement can lead to ergonomic or safety hazards. Also, inconsistency from operator to operator can lead to variations in product quality measurement. In addition, the measurement stage requires a considerable amount of time besides the production process interruption that is led by the measurement. Moreover, in some cases for measurement purpose, the component needs to be detached from the fixture. When the surface quality of the component does not meet the requirement of post processing e.g. assembly process, it then need to undergo a further re-manufacturing process. As the aerospace industry looks for process changes that would drive down the manufacturing process time, they recognize that in-process sensing solution is a potential tool to respond to the problem. To develop an in-process sensing, appropriate sensors should be taken into account. In this solution, sensors are utilized to find unique signatures that correlates the behavior of the deburring process to the surface finish quality. Accelerometer and acoustic emission (AE) are typical sensors used to characterize a certain manufacturing process based on the signal generated from the abrasive contact between tool and workpiece. According to comprehensive review by Abellan-Nebot et al. [1], accelerometer and AE sensor require least intrusive nature with reliable signal for surface prediction (accelerometer) and tool breakage detection (AE). Subsequently, a machine learning method plays an important role to build the direct monitoring system in terms of providing the decision or current condition based on sensor data analysis. A preliminary study of sensor selection has been conducted by Wijaya et al. [2].

The introduction of sensors approach in determining the state of the process and the surface finish quality in aerospace component manufacturing is to upgrade the current traditional processes towards industry 4.0. Thus, signal features extraction from sensors data is a step forward to prepare for analytical method (machine learning method) such as artificial neural network (NN) or adaptive neuro-fuzzy inference system (ANFIS). In this paper, the analytical method used is ANFIS [3]. Data based manufacturing is coherent with industry 4.0 direction towards cloud based manufacturing which is explained clearly by Tao et al. [4]. To maintain the latency of cloud based manufacturing especially in

high-volume manufacturing process, only the useful information will be sent out for further process. Therefore, the feature extraction method is also an important aspect that cannot be ignored. The feature extraction method in this paper includes the wavelet decomposition and Welch's spectrum estimate. The ANFIS in this paper serves as the black-box engine that receives input from the extracted features, and give the deduced output such as surface finish quality (e.g. chamfer length or roughness) and process state. The remaining sections of the paper is as follow: Section 2 presents the methods for signal processing, feature extraction and prediction. A brief methodology is also presented in Section 2. Section 3 includes the experimental setup, material, and data acquisition procedure. Section 4 presents the results and discussion and the conclusion is presented in Section 5.

2. Methods

2.1 Signal processing: wavelet decomposition – welch spectrum estimate

Wavelet decomposition

It is known that wavelet transform is among practical methods to analyse non-stationary and transient signal. The main advantage is the implementation of mother wavelet function instead of sinusoidal function as the basis function. Due to the basis function, the wavelet can represent the signal with a certain number of coefficients, where each coefficient is associated to specific energy concentration. A comprehensive review of wavelet transform is presented by Feng et al. [5].

Apart from the original intention of the wavelet transform for the analysis of non-stationary signals, wavelet transform can be used for pre-process feature extraction method [6]. The pre-processing method in this paper refers to the decomposition procedure of an input signal into a linear combination of time-scale units namely the wavelet decomposition. Consequently, an appropriate feature extraction method can be applied from the selected decomposed signal. The wavelet decomposition decomposes the original signal into several signal components according to the translation of the mother wavelet (or wavelet basis function), which changes the scale and shows the transition of each frequency component [7]. Through this decomposition, a selected coefficient can be used as the pre-processed result for present study. In wavelet decomposition, the input signal is basically decomposed into two coefficients. The input signal that passes through the low-pass filter becomes the 'approximation coefficient (cA)' and the input signal which passes through the high-pass filter becomes the 'detail coefficient (cD).' Since the low-frequency content is the most important part, the 'approximate coefficient' is passed to the next wavelet decomposition loop in multilevel wavelet

decomposition process. The illustration of wavelet decomposition is presented further in the figure part of Fig. 2.

Welch spectrum estimate

Existing feature extraction methods in time-and frequency-domain vibration signal [8] has been tested for the vibration signal of deburring process. A few common time-domain features are root mean square (RMS), kurtosis, and skewness. These features has been used for tool wear/breakage detection [9] and indirect surface integrity detection. The time-domain features are usually used to distinguish persisting pattern/trends. In frequency-domain analysis, where the captured signal is analysed in frequency domain, the features are commonly use to indicate the changes in process variables. Frequency domain analysis also helps to visualise the effect of noise filtering and various other windowing and filtering techniques. As the sampling frequency in this experiment is in the range of 40-51.2 kHz, perfoming time domain analysis proved to be challenging due to the size of captured data and hence frequency domain analysis was effective to understand process characteristics. Signal power also contains pertinent information regarding the source of signal generation. Conventially, fast Fourier transform (FFT) is in use to determine power spectrum. In stochastic processes, performing FFT will not be useful to segregate the noise embedded in the signal, as the frequency of interest might be eclipsed by the sidelobes created by higher frequency content. Hence some averaging needs to be performed to increase the S/N ratio and also to make all embedded frequencies visible. Welch's power estimate essentially does this by calculating power spectrum using FFT, coupled with averaging. Welch's method contains comparatively lesser clustered information than FFT method. Applying Welch's method thus helps to reduce spectral leakage and the effect caused by undesired frequencies.

Welch's method to compute PSD is performed by segmenting the time series data that are successive and averaging the periodograms of each segments or frames.

Consider $x_m(n)$ to be the input signal where $m = 0, 1, \dots, K-1$, K is total number of frames and $n = 0, 1, \dots, M-1$, periodogram of m^{th} frame is given by,

$$Px_{m,M}(k) = \frac{1}{M} \left[\sum_{n=0}^{M-1} x_m(n) e^{-\frac{2\pi jnk}{M}} \right]^2 \quad (1)$$

then Welch's power spectrum estimate is computed as,

$$S_x(w_k) = \frac{1}{K} \sum_{m=0}^{K-1} Px_{m,M}(k) \quad (2)$$

2.2 Stage classification on deburring process: adaptive-neuro fuzzy inference system (ANFIS)

The adaptive neuro-fuzzy inference systems (ANFIS) [3] is a specific kind of neuro-fuzzy classifier approach which integrates the artificial neural network (ANN) adaptive capability and the fuzzy logic qualitative approach. The ANFIS architecture consists of five layers as shown in Fig. 1. For the first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

Rule 1 If x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$;

Rule 2 If x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$;

where p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters and A_1, A_2, B_1 and B_2 are nonlinear parameters. The output of the i^{th} node in layer 1 is denoted as $O_{1,i}$.

Figure 1. Two-input ANFIS architecture with first-order Sugeno fuzzy model and two rules.

Layer 1 All the nodes in layer 1 are adaptive nodes. The outputs of this layer are the fuzzy membership grade of the inputs, which are given by:

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i=1,2, \text{ or}$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i=3,4 \quad (3)$$

where x (or y) is the input to nodes i and A_1 (or B_{i-2}) is a linguistic label associated with the node given by (3). The membership function for A (or B) can be any appropriate parameterized membership function such as sigmoidal membership function:

$$\mu_{A_i}(x) = \frac{1}{1 + e^{-a_i(x-c_i)}} \quad (4)$$

where $\{a_i, c_i\}$ is the parameter set. Parameters in this layer are referred to as premise parameters. As the values of the parameters change, the shape of the membership function varies.

Layer 2 The nodes in layer 2 are fixed nodes labeled Π , indicating that they perform as a simple multiplier. Each node in this layer calculates the firing strengths of each rule via multiplying the incoming signals and sends the product out. The outputs of this layer can be represented as

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \text{ for } i=1,2 \quad (5)$$

Layer 3 The nodes in this layer are fixed nodes and labeled as N . The nodes indicating a normalization role to the firing strengths from the previous layer. The i^{th} node of this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_i w_i} = \frac{w_i}{w_1 + w_2} \text{ for } i=1,2 \quad (6)$$

Layer 4 The nodes in this layer are adaptive nodes. Parameters in this layer will be referred to as consequent parameters. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial. Thus, the outputs of this layer are given by:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (7)$$

where w_i is a normalized firing strength from layer 3 and (p_i, q_i, r_i) is the parameter set for the node.

Layer 5 A single node in this layer labeled as Σ . This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

2.3 Proposed method

The aim of this study is to develop an appropriate machine learning method for in-process sensing and indirect surface quality monitoring. The method is expected to be less complicated yet reliable because the method will be embedded and integrated in real time monitoring and measurement of a surface finishing process. We used wavelet decomposition and Welch spectrum estimate as a signal processing and feature extraction method, and ANFIS as a machine learning method. The combination of wavelet decomposition and Welch's method is selected to improve the accuracy in the previous study [10]. As shown in [10], it is proven that Welch's method can identify the event classification of deburring vibration data at specific frequency (i.e. 1.297 kHz). This indicates that the vibration signal characteristic on each deburring stage can be identified from a certain frequency spectrum of vibration signal.

The proposed method is presented in Figs. 2-3. Three datasets of vibration signals (x-z) were processed in wavelet decomposition and the selected decomposed signals were estimated in Welch's method to extract the important frequency content of vibration deburring data. The extracted features were then analyzed in ANFIS classifier. Once the classification model obtained, the testing datasets were classified in the model. A detail description on each process is presented in Section 4.

Figure 2. ANFIS model development for training process.

Figure 3. ANFIS model development for testing process.

3. Experimental conditions

3.1 Materials

The experiment trials were performed on a replica of the combustor casing boss hole (Fig. 4). It is designed to represent the actual Trent 700 combustor casing boss hole so that the deburring process could be simulated as in on an actual aerospace component. The diameter of the hole is 58.5mm, with the depth of 25mm. This hole is located at 50mm from the top on a 120mm x 120mm rectangular surface. Side-wise, they are identical dimension of 60mm from each side. This way, the deburring tool will be able to machine the hole easily while also minimizes the vibration caused by the machining torque as it is attached firmly to the T-slot table. In addition, there is enough space on the sides of the hole to attach the sensors easily. The work coupon is attached to the base plate using four M8 threaded screws and the base plate is firmly secured to the T-slot table below. The material used for fabrication is mild steel.

Figure 4. Work coupon (replica of boss hole) used for trials.

3.2 Experimental setup for deburring process

The machining/finishing setup as shown in Fig. 5, comprises of the ABB IRB 6660 robot with electric powered spindle (PDS Colombo RS 90). A standard mounted flap wheel (aluminium oxide) with a grit size of P80 is used as the deburring brush for removing sharp edges from the chamfer. The RPM of the spindle is controlled by a variable frequency drive set to 166.67 Hz which translates to 10000 RPM and a feed rate of 30 mm/sec.

Figure 5. Experimental setup.

3.3 Sensor and data acquisition

The literature review of sensors selection which is reported in [2] narrows down 7 types of sensor suitable for monitoring, namely acoustic emission (AE) sensor, accelerometer, force sensor, dynamometer, proximity sensor, thermometer, and strain gauge. The first four sensors are more common to be used than the last three. Accelerometer and AE sensor were selected based on the following graded criteria; (1) sensor placement flexibility and intrusiveness characteristic, (2) signal reliability and (3) process association. Sensors placement flexibility determines the ease of sensors placement on the existing equipment, while the intrusiveness explains how intrusive the sensor can be for integrating it to the existing setup. Signal reliability explains the amount of information the sensors signal value carries from machining process. For example, thermometer exhibits less variation in temperature in comparison to accelerometer which reveals more variations in acceleration during machining. Process association determines the relation of sensors value to the machining process. For example, strain gauge measures the strain at certain location on machining area while force sensor measures force applied by the tool throughout the process. Based on this 3 criteria, the 7 type of sensors were graded in the scale of 1-3. Grade 1 as less satisfactory, grade 2 as satisfactory while grade 3 very satisfactory. The grading is concluded based on extensive reading and comparison on various papers done in different surface finishing processes. The study for the grading can be found in the paper reported in [2]. Grading of each sensors type is stated in Fig. 6.

Figure 6. Sensors rating for real-time monitoring application.

Based on the study above, force sensor, AE sensor and accelerometer were selected as most suitable candidate for implementation. Furthermore, as force is kept constant for most of the experiments done in this research, force sensor is not considered at the moment until force variables is introduced deeper in the future studies. The accelerometer is the focus of this paper and the AE analysis will be written into another paper.

The accelerometer was attached to the work coupon that represents the combustor casing boss

hole. The accelerometer model used in this paper is Kistler 8763B IEPE with a sampling rate of 40kHz. The module to read the signal is from National Instrument, model number NI 9234 with maximum sampling rate of 51.2MS/s. The data acquisition was performed using NI-DAQ 9184 chassis, coupled with supporting modules for respective sensors.

In Fig. 7, signal flow between sensors within the physical setup, DAQ and operator PC is illustrated. The data acquisition and logging is triggered synchronously with the robot movement. Data acquisition starts when the tool comes in contact with the work coupon and automatically stops when the tool completes each cycle/pass. The data acquired by the DAQ is sent to the operator PC via Ethernet. This allows the real-time data to be visualized and for further processing.

Figure 7. Data acquisition of deburring process.

4. Results and discussion

4.1 Vibration signals

The tri-axial accelerometer was used in the experiment. In this paper, one cycle of deburring process on one-side of the work coupon (replica boss hole) is referred to as a “pass”. In one pass, there are three sets of vibration signals generated from x, y and z direction as presented in Fig. 5. The x direction is parallel to the force exerted by the tool brush to the work coupon when the tool brush position is 0 degree and 180 degree from start point. The y direction is parallel to the tool path and the

y-positive direction is in the direction of tool movement. Lastly, the z-positive direction is parallel to the force exerted to the work coupon when the tool brush position is 90 degree and 270 degree from start point. To remove the burrs and develop a chamfer, five passes data acquisition is conducted. There are three work coupons used in the experiment and there are two datasets for each work coupon, one from each side. Five passes deburring process on one-side of the work coupon result in 15 sets vibration signals which are presented in Figs. 8-10.

Prior to the deburring process, the chamfer length of work coupon is measured using gap gun. The measurement is repeated after every pass is completed. The data acquisition sampling frequency of vibration is 40kHz and the total data acquisition time is approximately 4.7sec. As can be seen from Figs. 8-10, the difference between one pass vibration signal and other passes is difficult to be identified. One thing that can be noted from the figures is that the magnitude of vibration signal from pass 1 to pass 5 is decreasing. As the chamfer length is increasing with the increase in the number of pass (as shown in Table 1), we then expect to get an appropriate features that can relate to the increasing number of pass.

The vibration signals were acquired from the following procedure: The DAQ and ABB robot controller are synced to acquire the accelerometer and AE sensor data. The ABB robot controller triggers (digital signal) the DAQ to start acquiring the accelerometer and AE sensor data when the brush first touch the boss hole surface at the start point (left side from the tool view). After the brush made a full 360 degree circle around the boss hole and about to leave the surface, the ABB robot controller sends a stop signal to the DAQ to terminate the sensor data acquisition. Thus, the data from the accelerometer and AE sensor is acquired throughout actual deburring process.

Figure 8. Vibration signal of work coupon 2 (MS2/side 1) from x-axis direction.

Figure 9. Vibration signal of work coupon 2 (MS2/side 1) from y-axis direction.

Figure 10. Vibration signal of work coupon 2 (MS2/side 1) from z-axis direction MS2 z-axis.

Table 1. Increase in chamfer length.

Pass	Average chamfer length of training data (mm)	Average chamfer length of testing data (mm)
	(Initial: 0.389 mm)	(Initial: 0.347 mm)
1	0.468	0.456
2	0.528	0.501
3	0.576	0.539
4	0.628	0.586
5	0.677	0.629

4.2 Wavelet decomposition – Welch' spectrum result

The main objective in using the combined wavelet decomposition and Welch's method is to extract more informative signature on the deburring vibration data. The paper is the extension report to our previous study that also employed the Welch's method. The Welch's method in [10] identified one particular frequency at which its magnitude is changing with respect to the change in the number of pass in deburring process. Due to the ability of wavelet decomposition in analyzing the frequency

content of nonstationary vibration signal, the present study employed the wavelet decomposition to find the corresponding signature on the sequential deburring process from pass 1 to pass 5. Three level of wavelet decomposition with Daubechies (db1) wavelet basis function is used in this study. The third detail coefficient (cD3) signal is then analyzed using Welch's method to obtain the particular interest spectrum of the signal. The power spectrum density (PSD) of cD3 signals is calculated based on Kaiser window and 1000 overlapping samples. The results of PSD for x, y, and z direction are presented in Figs. 11-13. It is depicted in the figures that the magnitude spectrum of some frequencies shows decreasing trend associated with the increasing number of pass in deburring process. Another finding that can be noted from Fig. 11 to Fig. 13 is the dominant frequency (about 2kHz) where the spectrum magnitude of five passes is not decreasing and cannot be distinguish. This has been discussed in previous study that the deburring's vibration signal basically consist of two main frequency contents. One is generated from the rotating parts of the spindle and the other is triggered from the abrasive grinding process.

According to the visual observation of all vibration datasets processed with wavelet decomposition and Welch's method, the frequency range between 600Hz to 1880Hz has more obvious content than the other frequency range. The value of feature extraction in this paper is calculated with the condition where the PSD magnitude of pass 2 is higher than the PSD magnitude of pass 1; the PSD magnitude of pass 3 is higher than the PSD magnitude of pass 2; the PSD magnitude of pass 4 is higher than the PSD magnitude of pass 3; and PSD magnitude of pass 5 is higher than PSD magnitude of pass 4. By taking only the maximum value which fulfills the above condition, the features are obtained.

The deburring experiments employed work coupons with similar material and surface roughness. The experiment is also performed under similar operating conditions, e.g. spindle speed and abrasive tool grit size. Thus, pass 1 of deburring process in the experiment is assumed in similar stage for all work coupons. Therefore, the extracted features of pass 1 are normalized into the value of "1" and the remaining features of pass 2 to pass 5 are scaled-up. The normalized features are presented in Tables 2 and 3. It can be seen from Tables 2 and 3 that the extracted features in x, y, and z direction of pass 2 to pass 5 have the decreasing trend. The decrease in signal magnitude is indicative the smoothening of edges of boss hole with increasing number of passes. In order to show more obvious visualization of decreasing trend in magnitude, the extracted features in x, y, and z direction are plotted in 3D plot and presented in Fig. 14.

Figure 11. MS2 (x-axis) (decomposition level 3 Db1).

Figure 12. MS2 (y-axis) (decomposition level 3 Db1).

Figure 13. MS2 (z-axis) (decomposition level 3 Db1).

Table 2. Wavelet decomposition – Welch estimate feature result for training data.

Pass No.	MS2			MS4			MS6		
	X	Y	Z	X	Y	Z	X	Y	Z
1	1	1	1	1	1	1	1	1	1
2	0.6067	0.8004	0.6379	0.7291	0.7683	0.7514	0.7281	0.6272	0.6830
3	0.5694	0.5892	0.6346	0.5564	0.5670	0.5689	0.5312	0.4772	0.4514
4	0.4434	0.5247	0.4979	0.4206	0.5017	0.4481	0.3561	0.2361	0.2901
5	0.3390	0.4068	0.4086	0.3168	0.4350	0.2634	0.2362	0.3570	0.2207

Table 3. Wavelet decomposition – Welch estimate feature result for testing data.

Pass No.	MS3			MS5			MS9		
	X	Y	Z	X	Y	Z	X	Y	Z
1	1	1	1	1	1	1	1	1	1
2	0.7123	0.7633	0.7753	0.6257	0.7714	0.7088	0.6613	0.6669	0.7066
3	0.6410	0.5232	0.6408	0.4676	0.5961	0.6403	0.4499	0.5474	0.6145
4	0.4590	0.4950	0.5127	0.4031	0.5211	0.5009	0.3047	0.4621	0.4379
5	0.3794	0.4416	0.4004	0.2763	0.4420	0.3422	0.2267	0.3739	0.2937

Figure 14. Feature extraction result for (a) ANFIS training process and (b) ANFIS testing process.

4.4 ANFIS

Previous study [10] presented the fuzzy inference system (FIS) in deburring vibration data. The ANFIS replaces the primary hassle in FIS's fuzzy, i.e. if-then rules manual tuning, by using the learning ability of an artificial neural network (ANN) for automated tuning of fuzzy if-then rules during the training process. The automated tuning results in a change of the membership functions of parameters, which leads to the automatic adaptation of the fuzzy system based on inputs-output space. The initial step of the ANFIS modelling system is to decide the input and output variables of the fuzzy logic controller. The ANFIS model described in this paper has three input parameters: x-axis, y-axis and z-axis vibration datasets. Meanwhile, the output is the number of pass on a deburring process. The ANFIS model described in this paper is a multiple input single output (MISO) system.

As presented in previous section, the experiment was conducted on three work coupons and each work coupon has two sides for deburring process. This results in six vibration datasets. The three datasets were used for ANFIS training stage to build the classification model and the remaining three datasets were used for testing process. The features extraction in Fig. 14 are analyzed in ANFIS and the membership function of ANFIS training is presented in Fig. 15(a). Input1, input2 and input3 indicate the features in x, y and z direction and there are five passes on each input. The parameters of MISO ANFIS classifier is presented in Table 4.

The ANFIS classifier model is then tested with the extracted features presented in Fig. 14 and the

membership function result of testing process is presented in Fig. 15. It can be seen from Fig. 15 that the shape of membership does not change significantly. This indicates that the training and testing datasets has similar pattern. The ANFIS classification result is presented in Fig. 16. Disregarding the classification of pass 1 as it has been set as a reference point, the overall accuracy achieved 83.33%. The accuracy is calculated based on the two missed classification features out of twelve features.

Table 4. ANFIS parameters.

Parameter	Value
Neuron level	3
Size of input data set	15
Training set	50%
Testing set	50%
andMethod	prod
orMethod	max
defuzzMethod	wtaver
impMethod	Prod
aggMethod	max
Number of ouput	1
Membership function	Sigmoidal membership
Learning rules	Least square estimation-gradient decent algorithm

(a)

(b)

Figure 15. Membership function of (a) training data and (b) testing data.

Figure 16. ANFIS prediction results.

5. Conclusions

An offline machine learning based on wavelet decomposition, Welch's method and ANFIS has been applied for deburring vibration data. This study was conducted primarily to understand and explore the correlation between sensor signal features and the progress of the finishing process such as deburring. Spectral analysis proved to be out performed method compared to time-domain signal analysis for high sampling data acquisition. However, the procedure of the signal processing and data analysis is more complicated. The ANFIS replaces the manual tuning of FIS for the prediction model. The results presented in this paper exhibit an accuracy below than 90%. This is due to the lack of the number of data used for training and the testing. The challenge is then how to embed and integrate the proposed method into online monitoring process of robotic finishing. This will be the future work of present research work and will be communicated in other paper.

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