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Procedia CIRP 46 (2016) 254 – 257

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7th HPC 2016 – CIRP Conference on High Performance Cutting

In-Process Surface Roughness Estimation Model For Compliant Abrasive Belt Machining Process

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Abstract

Surface roughness inspection in robotic abrasive belt machining process is an off-line operation which is time-consuming. An in-process multi-sensor integration technique comprising of force, accelerometer and acoustic emission sensor was developed to predict state of the surface roughness during machining. Time and frequency-domain features extracted from sensor signals were correlated with the corresponding surface roughness to train the Support vector machines (SVM's) in Matlab toolbox and a classification model was developed. Prediction accuracy of the classification model shows proposed in-process surface roughness recognition system can be integrated with abrasive belt machining process for capping lead-time and is reliable.

Peer-review under responsibility of the International Scientific Committee of 7th HPC 2016 in the person of the Conference Chair Prof. Matthias Putz

Keywords: In-process measurement; Roughness;Sensor; Predictive Model; Belt grinding

1. Introduction

Surface quality which is assessed in terms of surface roughness is an off-line process. This process is both time-consuming and laborious. It takes time when parts are relocated from the machining station to the measurement station. Much research effort previously has been devoted for studying surface roughness prediction in real time in conventional machining such as end milling & hard turning operation [1]. Intuitively, surface roughness is also correlated to the frictional property of the two sliding surfaces [2-4]. By monitoring the property, the surface roughness can also be estimated. Predictive models such as ANN, ANFIS & SVM were developed in these researches and high correlations were established between predicted surface roughness values and experimentally measured values in off-line. However In-process surface roughness prediction in compliant tools such as abrasive belt machining process still remains one of the most challenging problems in industry due to the high complexity and nonlinearity. Abrasive belt are form-adaptive due to their inherent flexibility. Khellouki et al. [5] have investigated about effective contact duration between abrasive grains and machined surface interface in abrasive belt grinding process which revealed number of active abrasive grains increase based on the interaction on the surface roughness. Xue et al. [6] established a neuro-fuzzy model and suggested that data acquired through the forces and acoustic emission sensors can be correlated with the surface roughness using signal processing algorithm there by opening opportunities for predicting the surface quality in real time for tools with multiple cutting edges. Incorporation of a sensor technology for precision manufacturing process such as abrasive machining process has been investigated by D. A. Dornfeld et al. [7], which revealed that force, accelerometer, laser and acoustic emission are most critical sensor required in precision machining for assessing surface finish. Cutting forces and machining vibrations have been reported to be much indicative than other monitoring signals in predicting surface roughness in hard tooling [8-10]. Acoustic emission sensitivity to abrasive

Peer-review under responsibility of the International Scientific Committee of 7th HPC 2016 in the person of the Conference Chair Prof. Matthias Putz
doi:10.1016/j.procir.2016.03.126

process such as grinding based on inherent frictional interactions has been applied by H.G.Cai [11]. This research tries to predict the surface roughness in coated abrasive compliant belt machining process in real time with the help of smart sensors tool by virtual verification using the machine learning based classification technique such as Support Vector Machines (SVM's). This kind of metrology adds value for the whole manufacturing process

2. Multi-sensor integration - Complementary approach

In-process sensors can be exercised strategically for machining process automation as they have the ability to predict the process state based on sensory feedback. A complementary based multi-sensor integration approach has been proposed as a strategy to estimate the values of physical variables being measured since any compliant abrasive machining process is difficult to understand and knowledge available on such processes are inadequate.

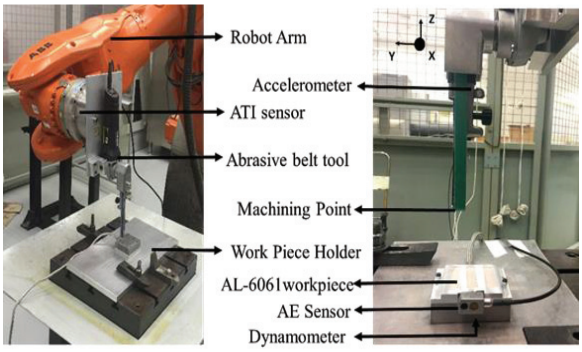

Fig. 1. Experimental setup for surface roughness prediction in abrasive belt machining

A complementary multi-sensor integration system incorporating force, accelerometer and acoustic emission is developed to give a more complete picture of the state of abrasive belt machining which is dynamic. An in-situ surface roughness prediction system based on LabVIEW platform has been developed consisting of a Kistler 9256C2 three component dynamometer, Kistler 8763A500 triaxel accelerometer and Kistler Piezotron® Acoustic Emission Sensor as shown in **Fig. 1**. Aluminium 6061 workpiece of different surface roughness (Ra) of 3 µm, 2 µm, 1.2 µm and 0.3 µm is then mounted on the dynamometer to calculate normal force and tangential force. Kistler 8763A500 triaxel accelerometer sensor is closely located near the tension arm of the electric belt grinder to obtain data on tool vibration during machining. Acoustic Emission Sensor is located in close proximity with respect to the machining zone in the workpiece with good acoustic coupling.

3. Experimentation

3.1. Methodology

Surfaces of different roughness of 3 µm, 2 µm, 1.2 µm and 0.3 µm Ra are machined with the abrasive belt with the same machining condition. The signatures during machining of different surface roughness are captured using the appropriate sensors placed at 1 kHz. The raw sensor data contain fixed-width sliding windows (100readings/window). From each window, a vector of 27 independent features are extracted from time and frequency domain such as shown in Table 1.

Table 1. List of time and frequency domain features extracted from the sensor signatures

Feature No	Feature Name
1	Mean value
2	Root mean square
3-5	Autocorrelation (Height of main peak, Height and Position of second peak)
6	Kurtosis
7	Skewness
8	Crest-factor
9	Band-power
10	Standard deviation
11-22	Spectral Peak Features (Height and position of first 6 peaks)
23-27	Spectral power (Features in 5 adjacent and pre-defined frequency bands)

Once the features are extracted, the supervised learning technique based on support vector machines such as Linear-SVM, Quadratic–SVM and Cubic–SVM are used to create a classification model with the four different surface roughness (3 µm, 2 µm, 1.2 µm and 0.3 µm) as the classifiers in Matlab Classification learner Tool. Once the model is trained, fresh set of signatures are extracted from the surface roughness (3 µm, 2 µm, 1.2 µm and 0.3 µm) with the same machining condition. These features are passed into the classification model developed and trained using SVM to check the robustness of the model. Schematic representation of the methodology is described in the Fig. 3.

3.2. Surface roughness estimation: SVM -classification modeling

Support vector machines are supervised machine learning methods for solving problems in nonlinear classification [12] using kernel trick which has been explained in this section. In a real-valued vector space (X=R^N), let's take a binary linear classification problem (i.e. $\mathcal{Y} \in \{-1, +1\}$. An n-dimensional pattern (object) x has n coordinates, ($x = x1, x2, \ldots, xn$) where each x_i is a real number ($x_i \in \mathcal{R}$ for i = 1, 2… n). Each pattern x_j fits to a class $\mathcal{Y} \in \{-1, +1\}$.

If these two classes can find a linear function $f(x) < 0$ whenever the label $\mathcal{Y} \in -1$ and $f(x) \geq 0$ whenever the label $\mathcal{Y} \in +1$ they can be linearly distinguishable of the inputs $x \in \mathcal{X}$ .This can be suitably expressed by a hyper-plane in the space $\mathcal{X}$ .For linearly separable data a hyper-plane $f(x) = 0$ can be determined as,

$$f(x) = w^T x + b = \sum_{j=1}^{n} w_j x_j + b = 0 \qquad (1)$$

Where w is an n-dimensional vector and b is a scalar which determine the optimal separating hyper-plane that leaves

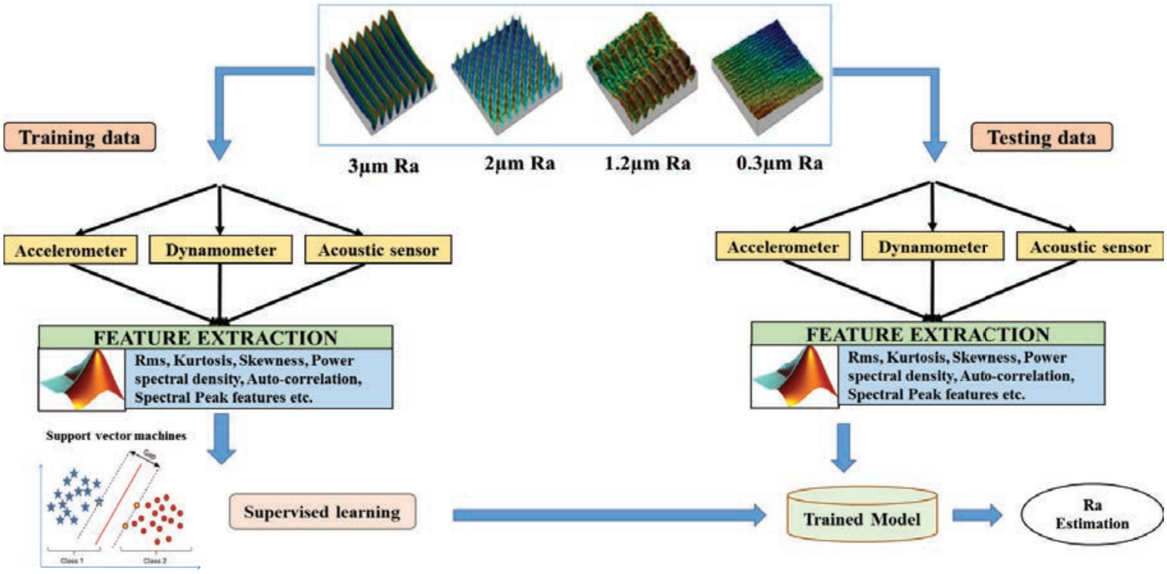

Fig. 2.Methodology to predict surface roughness using SVM classification algorithm

maximum margin from both the classes. However in-case of non-linear classification a Kernel trick is used. Kernel trick transforms the data into a higher dimensional feature space to make it possible to perform linear separation. SVM using a non-linear kernel function $\phi : \mathcal{X} \rightarrow \mathcal{F}$ transforms data from the input space $\mathcal{X}$ to a feature space $\mathcal{F}$. In the space $\mathcal{F}$ the discriminant function is:

$$f(x) = w^T \phi(x) + b \quad (2)$$

Linear classification can be derived from the non-linear SVM by implicitly mapping the input data x into the feature space and training the SVM for the mapped features $\phi(x)$. The weight vector can be expressed as a linear combination of the training examples, i.e. $w = \sum_{i=1}^{n} \alpha_i x_i$ hence the equation 2 takes the form:

$$f(x) = \sum_{i=1}^{n} \alpha_i {x_i}^T x + b \quad (3)$$

In the feature space, $\mathcal{F}$ this expression takes the form:

$$f(x) = \sum_{i=1}^{n} \alpha_i \phi(x_i)^T \phi(x_j) + b \quad (4)$$

Non-linear SVMs can then be trained by replacing the inner products in Equation 4 with the corresponding kernel $\mathrm{K}(x_i, x_j)$.

$$\mathrm{K}(x_i, x_j) = \phi(x_i)^T \phi(x_j) \quad (5)$$

The resulting classifier for the non-linear SVM is then represented In terms of the kernel function as:

$$f(x) = \sum_{i=1}^{n} \alpha_i \, \mathrm{K}(x_i, x_j) + b \quad (6)$$

In this research three kernel functions such as linear, quadratic, and cubic SVM's are used for mapping data onto a high-dimensional feature space to derive linear classification from the non-linear form using the four surface roughness values considered as classifiers.

3.3. Experimental trials

Electrically-Powered abrasive belt tool that runs at 11,000 rpm at unloading condition and can drive belts of grit size 60 with dimensions about 8" to 3/4" wide x 18" long is moved along the linear tool path planned using ABB Robot Studio. A constant contact force of 25 N throughout the abrasive belt finishing process in normal direction (Z-axis) is achieved by using force sensor (ATI Omega 160) attached to the end effector of robotic arm of ABB 6660 robot. The signature from the dynamometer on each pass suggest that forces along X (along the direction of the pass) and Z (Normal to the workpiece surface) axis show some significance compared to force along y-axis (which is perpendicular to the pass).In case of accelerometer all the signatures from three axis showed significance. However noise component in accelerometer mounted on to the running tool are eliminated using Butterworth-bandstop filter. Once the features are extracted from the force, acceleration and acoustic signature, support vector machine (SVM) is used to create a classification model with different surface roughness's as classifier as discussed in previous sections.

4. Results and Analysis

Power spectral density comparison plot in the Fig. 3 shows variation in height and position of the first six highest peaks for different surface roughness due to different tribological conditions between surface-belt interfaces which can be used as a feature set to classify between four different surfaces in real time. All of the implementations of the three classification models were performed by using MATLAB classification learner Toolbox.

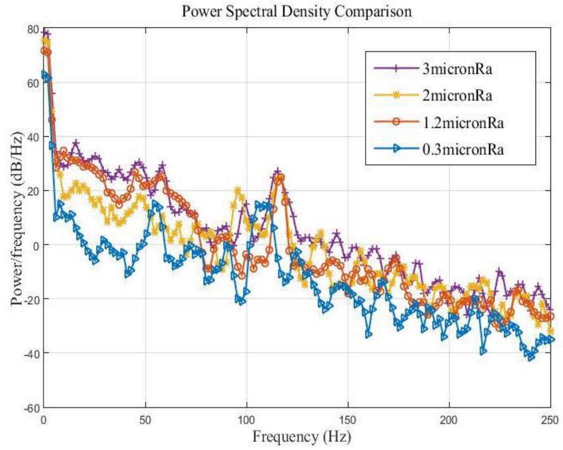

Fig. 3.Comparison between power spectral features for different roughness

Performance-testing experiment is designed to test the predictive ability of this classification models with fresh set of signatures obtained under same machining conditions. The accuracy of prediction of Linear-SVM, Quadratic-SVM and Cubic-SVM was 94.5%, 96.9% and 96.9% respectively. Fig. 4 shows confusion matrices obtained with Cubic-SVM model. As can be seen, there is a clear separation between different surface roughness classifiers and the fraction of samples misclassified of the developed model is small. Similar structure is observed for all other classifications models as well. Among three of SVM models considered Quadratic-SVM and Cubic-SVM were found to be the best in terms of predictive ability.

True class		Predicted class			
		0.3micron	1.2micron	2micron	3micron
	0.3micron	31 96.9%	1 3.1%	0 0.0%	0 0.0%
	1.2micron	1 3.1%	31 96.9%	0 0.0%	0 0.0%
	2micron	0 0.0%	1 3.1%	31 96.9%	0 0.0%
	3micron	1 3.1%	0 0.0%	0 0.0%	31 96.9%

Fig. 4.Confusion matrix of the Cubic-SVM classifier model

5. Conclusion

Sensor enabled in-situ surface roughness prediction has the potential to significantly improve productivity while reducing lead time for manufacturing components. It has been shown that it is possible and useful to use complementary multi-sensor integration technique in abrasive belt machining process to measure surface finish in real time. This technique can be further extended for surface quality prediction using other type of compliant tools. Three types of support vector classification models such as linear, quadratic and cubic has been developed, demonstrating a prediction accuracy of 94.5%, 96.9% and 96.9% respectively. Proposed in-process surface roughness identification system can predict surface finish in the micrometer range when machining surfaces with the compliant abrasive belt. Such a greater precision in this range can only be achieved using high-precision profilometers or scanners. Inclusion of higher number of features will result in higher computational time, so feature optimization technique may add a degree of robustness to the classification model developed. The technique is established on planar surfaces while machining free form surfaces are subject to further research.

Acknowledgements

The research was supported by Rolls-Royce @NTU Corp Lab.

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