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Procedia CIRP 88 (2020) 335–340

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13th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '19

In-process characterization of surface finish in cylindrical grinding process using vibration and power signals

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Abstract

Grinding being a finishing process, the quality of the ground surface is one of the most important performance evaluation parameters. Grinding process being highly stochastic in nature, surface finish is affected by many factors and experimental evaluation of each factor is a tedious task. In this study, the in-process signals collected using various sensors attached to a cylindrical grinding machine such as Accelerometer and Power are processed, and their features are correlated with a surface finish parameter. This correlation is modelled using gradient boosting algorithm and surface finish obtained is predicted and validated on an industrial application.

Peer review under the responsibility of the scientific committee of the 13th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 17-19 July 2019, Gulf of Naples, Italy.

Keywords: Empirical mode decomposition; Feature extraction; Gradient boosting algorithm; *Surface finish prediction*

1. Introduction

Cylindrical grinding is an abrasive finishing process widely used across all industrial sectors for enhancing the surface finish quality of the output product. Grinding process is much more complex as compared to other machining processes like turning and milling. The variations in work piece and wheel topography largely contribute to the uncertainties in surface quality prediction. In recent times, significant efforts have been taken in developing intelligence for finishing processes like grinding [1]. The growth of data analytics, sensor capabilities, and cloud computing are revolutionizing manufacturing systems into smart environments [2]. The motivation behind the application of these artificial intelligence techniques is to capture the process intelligence and previous experience into a data driven model that can help in the future operations.

Industries vastly use cylindrical grinding process to get accurate surface finish in high precision components like bearings [3]. To ensure that those components do not fail early, strict monitoring of the surface finish (*Ra*) must be there. Surface finish (*Ra*) relies heavily on a vast number of parameters including machine tool characteristics, work piece, wheel topography and operational parameters.

Along with these, surface finish in plunge grinding, relies substantially on the process mechanics such as forces and radial (normal) direction vibrations [4]. In cylindrical grinding, the complexity of the process makes it difficult to predict surface roughness even in controlled environments. The abrasive particle distribution, change in the work piece characteristics, type of bonds and other parameters of the wheel give rise to stochastic nature in prediction of surface roughness. Hence, a data driven model is indispensable to predict surface roughness and hence, assure the integrity of the surface in plunge grinding process.

In this paper, a sensor set up using power cell and two accelerometers was used for feature extraction method. Cylindrical grinding process is predominantly a non-linear and non-stationary process. The vast number of parameters in cylindrical grinding process makes the situation even complex.

Owing to this non-stationary and non-linear behavior of the grinding process, Hilbert Huang Transform (HHT) was used as a means to extract features for surface finish prediction. Average percentage of energy of the Intrinsic Mode Function (IMF) components was used as a criterion to filter out the IMF

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Peer review under the responsibility of the scientific committee of the 13th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 17-19 July 2019, Gulf of Naples, Italy.
10.1016/j.procir.2020.05.058

components. Three IMF components were chosen by this criteria and features were extracted for surface roughness prediction. Apart from this, raw time domain parameters were also extracted from the power and acceleration signals to give as an input for surface roughness prediction by gradient boosting algorithm. To make the model robust, other algorithms like regression, artificial neural networks and support vector machines were also used. The best model was chosen based on least MSE and highest R^2 value. A comprehensive introduction to HHT is given in section 2. The experimental details and feature extraction are presented in section 3. The data driven predictive model is given in section 4. Conclusions drawn are given in section 5.

Nomenclature

ACC_N	Acceleration value in normal direction.
ACC_T	Acceleration value in tangential direction
PE	Percentage energy.
SD	Standard deviation.
SK	Skewness.
Ra	Surface finish in microns.
RF	Roughing feed in mm/min.
SFF	Semi finish feed in mm/min.
FF	Finish feed in mm/min.
WS	Wheel speed in m/s.
WoS	Work piece revolutions per minute.

2. Hilbert Huang Transform

Fourier analysis in general is used for studying the frequency distribution of the signal. However, Fourier transform is fruitful only for signals that are linear and stationary. Another tool, wavelet transform is a Fourier analysis where the window size can be adjusted. Wavelet analysis is suitable for non-stationary and linear analysis [5]. The HHT method is more suitable for analyzing non-stationary and non-linear signals like grinding signals. The analysis comprises of two steps: (1) Empirical Mode Decomposition (EMD) and (2) the Hilbert transform.

The objective of EMD is to pull out each mode of oscillation from a set of time series data. Through the empirical mode decomposition of the signal, a finite number of intrinsic mode functions (IMF) can be obtained upon which Hilbert analysis is done. An IMF is defined by a function having the identical number of zero crossings and extremums, and also having symmetric envelope defined by the local extremums [6].

Since the EMD analysis method is based on the data, it is an intuitive and adaptive method [6]. Also, it is computationally less expensive since it does not involve time taking operations like convolution.

Through the application of the Hilbert transform, the IMFs are able to give instantaneous frequencies in time space which is better than the Fourier transform. The energy distribution in frequency space is not meaningful in Fourier transform for signals which are not stationary and linear. In this regard HHT give meaningful instantaneous frequency resolutions in comparison to Fourier and wavelet transforms.

In this study EMD analysis has been used upon vibration signals of grinding which are typically stochastic signals. The parent vibration signals are broken down into a finite number of IMFs in localized time space in the order of decreasing frequency and energy content in comparison to the parent signal. Consecutively, time domain features are extracted from each IMF which are discussed in details in section 3.

3. Experimental Setup and Feature Extraction

For performing the experiments, an MGTL make plunge grinding machine was used. Apart from power cell, two accelerometers of specifications as mentioned in table 1 were used which were placed on the tailstock spindle in the in-feed direction (X axis) along with the tangential direction (Y axis) as shown in Fig. 1. The setup of the power cell is shown in Fig. 2. The grinding wheel and work piece details are mentioned in table 2.

Table 1. Accelerometer and DAQ details.

Type	Make	Number	Sampling Frequency (Hz)
Accelerometer	Dytran 3055B2	2	10000
Power Cell	Load Control	1	67
DAQ	NI 9234	1	
DAQ	NI 9205	1	

Table 2. Wheel and work piece details.

Specifications			
Grinding wheel	A80L5V	Maximum cutting Speed	45mps
Work piece	EN 31	Hardness	60 HRC
Dressing cutter	Blade type diamond dresser	Width of dresser	0.9mm

3.1 Design of experiments

Typically, a grinding cycle consists of consecutives phases of roughing, semi finishing, finishing and spark out [7]. In this study, the three levels of variation of the operational parameters are given in table 3.

Table 3. Levels of operational parameters.

	WS	*RF*	*SFF*	*FF*	*WoS*
Level1	25	0.4	0.2	0.01	100
Level 2	35	0.8	0.3	0.02	200
Level 3	45	1.2	0.4	0.03	300

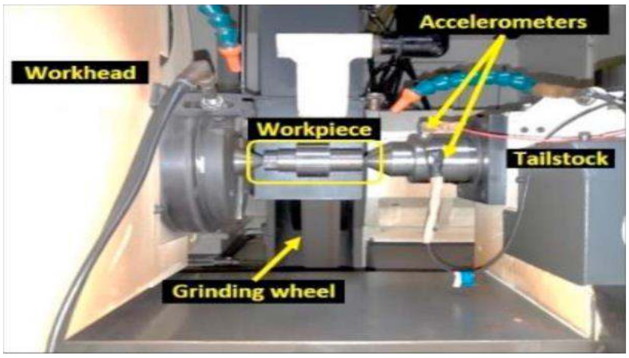

Fig. 1. Placement of accelerometers.

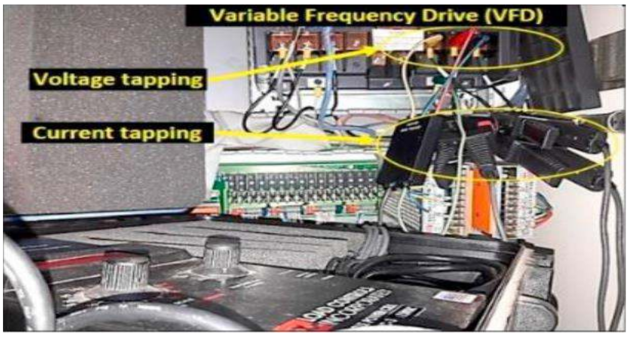

Fig. 2. Power cell.

3.2 Signal acquisition

The independent parameters in the grinding cycle (Feed rates) were designed in such a way that the cycle time lasted 10 seconds. Power signals were acquired at sampling frequency of 67 Hz, whereas vibration signals in the normal and tangential direction were acquired at a frequency of 10 kHz. Surface roughness (*Ra*) was noted after consecutive phases of grinding cycle using roughness profilometer. The schematic diagram of signal collection system is shown in Fig. 3.

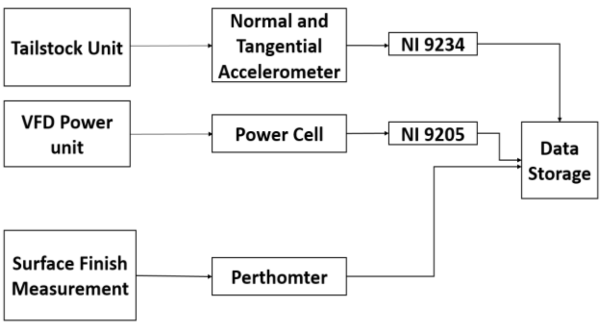

Fig. 3. Schematic setup of data acquisition.

3.3 Feature extraction

Feature extraction is an integral step through which the dimensionality of the parent signal is reduced. The whole signal is converted into features of numerical values that represents the original signal as shown in table 4. The feature extraction has been done in two stages: a) Raw time domain parameters of the parent signals, b) Time domain parameters of the IMFs of the vibration signals. It can be seen from Fig. 4 that the energy of the signal is dominantly present on IMF 1 to IMF 3. So, IMF 1 to IMF 3 were chosen for further feature extraction of their marginal spectra. The original signal and the overlap of IMF 1, IMF 2, IMF 3 and IMF 10 on parent signal are portrayed in Fig. 4.

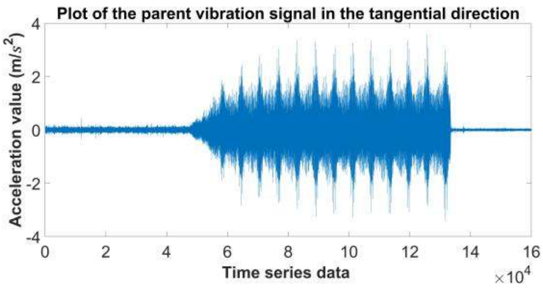

Fig. 4a. Plot of parent vibration signal in tangential direction.

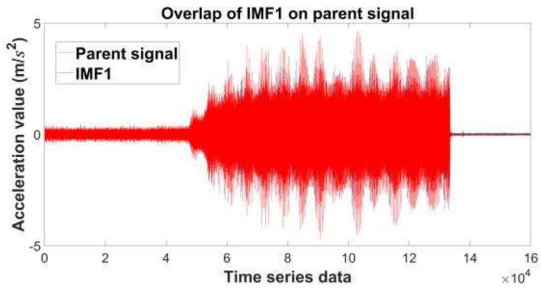

Fig. 4b. Overlap of IMF 1 and parent signal.

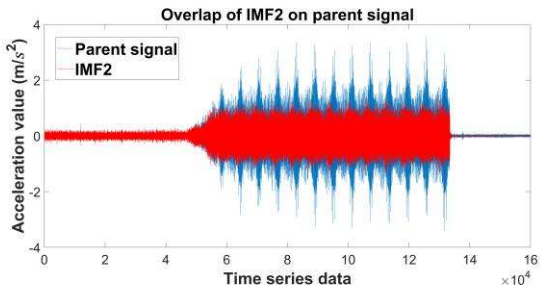

Fig. 4c. Overlap of IMF 2 and parent signal.

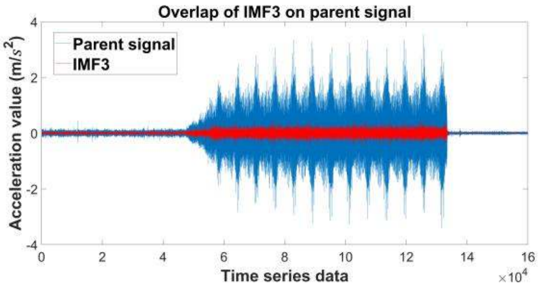

Fig. 4d. Overlap of IMF 3 and parent signal.

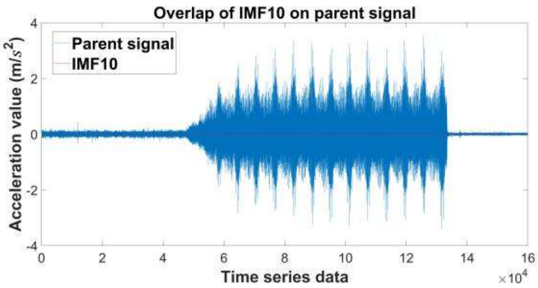

Fig. 4e. Overlap of IMF 10 and parent signal.

Fig. 4. Parent signal and overlap of IMF signals on parent signal (*RF*=1.2mm/min, *SF*=0.4mm/min, *FF*=0.03mm/min, *WS*=45m/s, *WoS*=300RPM)

Table 4. Time domain features.

Time Domain Features	Formula
Mean	$\mu = \frac{1}{N}\sum_1^N x(i)$
RMS [8]	$X_{rms} = \left[\frac{1}{N}\ \sum_{i=1}^{N} x(i)^2\right]^{0.5}$
Variance [8]	$X_{variance} = \frac{1}{N-1}\sum_1^N (x(i) - \mu)^2$
Skewness [8]	$X_{skewness} = \frac{1}{N}\sum_1^N (x(i) - \mu)^3$
Kurtosis [8]	$X_{kurtosis} = \frac{1}{N}\sum_1^N (x(i) - \mu)^4$
Energy [9]	$X_{energy} = \sum_1^N (x(i)^2)$
Percentage Energy	$X_{i\ percent\ energy} = X_{ith\ energy} / X_{energy}$

Note: $x(i)$ is the i^{th} value of the IMF of length *N*.

4. Surface Roughness (*Ra*) prediction

A data driven model is made by using data from three sensors, a power cell and accelerometers in normal and tangential directions. The feature extraction process is divided into two stages. In the 1st stage, raw time domain parameters are extracted. In the 2nd stage, time domain features of the marginal spectra of the consecutive IMFs of the vibration signals are extracted. It may be noted that the time domain parameters of the marginal spectra of the consecutive IMFs of the power signals are not extracted since the sampling rate was low (67 Hz). In addition to the features extracted from these two stages, the operational parameters of the grinding cycle: roughing feed, semi-finishing feed, finishing feed, work speed and wheel speed are included in the model for prediction of surface roughness *Ra*. In total 59 features (18 raw time domain features, 36 time domain features of the marginal spectra, 5 for operational parameters) were used to make the data driven model. To avoid the problem of over fitting, the number of features need to be reduced.

Random forest classifier has the capability to rank significance of features [10]. The importance of a particular feature is measured by a parameter called Gini index. While perturbing a feature, if the decrease in the Gini index is high, it depicts the significance of that particular feature.

Random forest classifier is applied to our data set consisting of 59 features to get the relatively important features. The results of the random forest classifier are shown in Fig. 5. In the figure, the features are arranged in the decreasing order of their relative importance. Based on relative importance, 12 features are further chosen for surface finish prediction. The list of 12 features which are further used for surface finish prediction are listed in table 5. These 12 features contain both the time domain parameters of the raw signals and the time frequency domain parameters of the marginal spectra of the IMFs of the vibration signals.

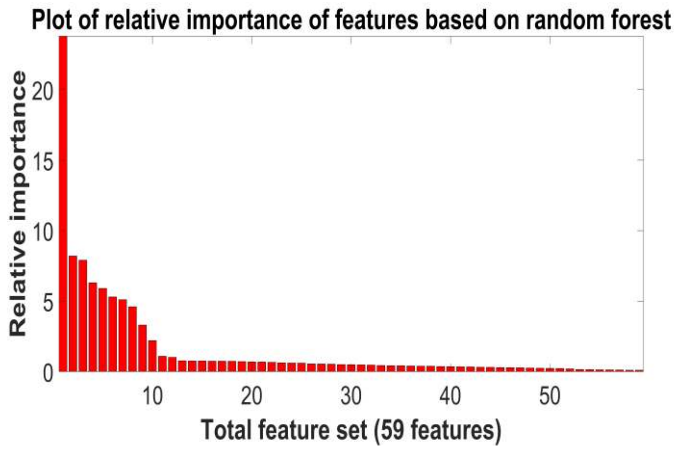

Fig. 5. Plot of the relatively importance of the feature set.

Table 5. Relatively important features along with their rank.

Time Space and Rank	Time Frequency Space and Rank
Mean of *ACC_N* (1)	*PE* of IMF3 of *ACC_T* (6)
Mean of *ACC_T* (2)	Mean of IMF2 of *ACC_N* (7)
Mean of Power (3)	Mean of IMF1 of *ACC_T* (8)
SD of *ACC_N* (4)	RMS of IMF1 of *ACC_N* (9)
SD of Power (5)	RMS of IMF3 of *ACC_N* (10)
	SK of IMF3 of *ACC_N* (11)
	SK of IMF1 of *ACC_T* (12)

Note: These are relatively important 12 features for prediction of *Ra*.

The complete flowchart for predicting surface finish in this data driven model is shown in Fig. 6.

Gradient boosting is a popular ensemble learning method for regression or classification. Gradient boosting algorithm differs from the random forests in the manner in which they are built. The gradient boosting algorithm generates one tree at a time, where each new tree generated helps to alleviate errors made by previously trained trees. The gradient boosting algorithm was applied to this data set for surface roughness prediction. If the parameters are tuned properly, the gradient boosting algorithm have proven to give less Mean Square Error (MSE) than other tree-based methods for predicting the presence of tree species [11], which is a comparison in real life application. In regard to scaling to a large number of features, gradient boosting gives much better performance than random forests [12].

The gradient boosting algorithm for surface roughness prediction was applied to two different data sets for surface finish prediction. The first data set only consisted of the time domain parameters of the raw signals among those 12 dominant features from the random forest classifier as shown in table 5. The time domain parameters of the marginal spectra of the IMFs are not considered in this case.

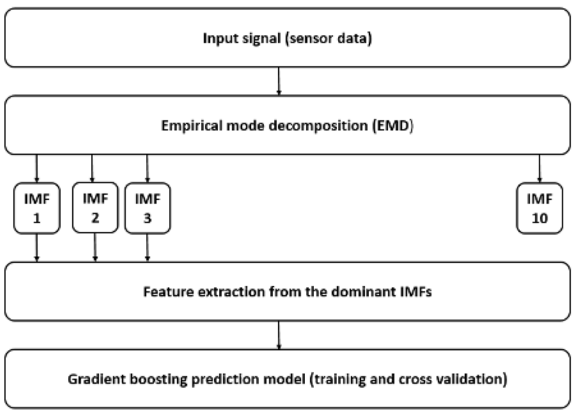

Fig. 6. Surface finish prediction methodology.

The model can predict *Ra* with R^2 values exceeding 48% with cross validation. The plot of the predicted values versus the actual values of the surface finish are shown in Fig. 7a.

In the 2nd stage, the data set for prediction consisted of both the raw time domain features of the power and vibration signals along with the time domain features of the marginal spectra of the vibration signals as shown in table 5. The feature vector contained the 12 dominant features obtained from the random forest classifier. In this case the model can predict surface finish with R^2 values exceeding 88% with cross validation. The prediction accuracy increased substantially after including the time domain features of the marginal spectra. The plot of the predicted versus actual values of the surface finish are shown in Fig. 7b.

The model with gradient boosting algorithm was not the only model used for surface finish prediction. Other algorithms such as linear regression, multiple regression, support vector machine (SVM), artificial neural networks (ANN) were used for surface finish prediction. In all the models, the dominant 12 features obtained from the random forest classifier were used for surface finish prediction. Other algorithms were applied since such approach would give us a detailed and an exhaustive approach regarding the best algorithm that can be used for prediction.

The model with the best R^2 value (statistical coefficient) and the least mean square error (MSE) was chosen as the best model for prediction. The gradient boosting algorithm proved to be the best model with R^2 values exceeding 88% with cross validation. The methodology to obtain the best algorithm model is shown in Fig. 8. And the comparison bar graph for the various algorithms are shown in Fig. 9.

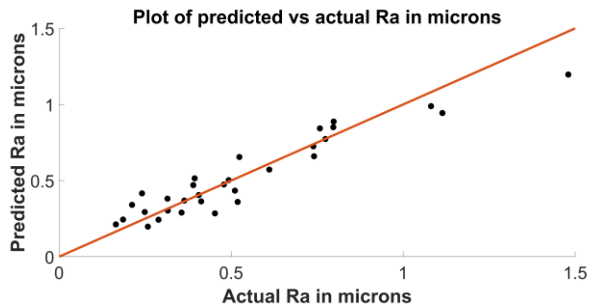

Fig. 7a. Plot of predicted vs actual Ra in microns.

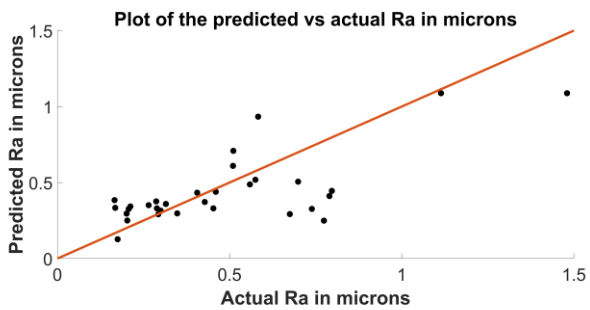

Fig. 7b. Plot of predicted vs actual Ra in microns.

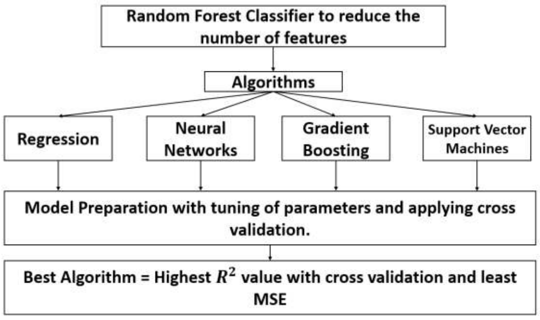

Fig. 8. Flowchart to choose best algorithm.

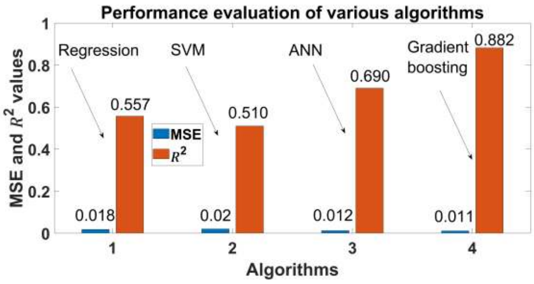

Fig. 9. Performance evaluation of various algorithms.

5. Conclusions

In this study, Empirical Mode Decomposition (EMD) was used for feature extraction in order to predict surface finish. The raw time domain features were also extracted additionally from the power and vibration signals. It was found that only the first three Intrinsic Mode Functions (IMF) contained the maximum energy. So, they were picked out and their marginal spectra were calculated. Subsequently their time domain features were found out.

Using EMD and gradient boosting algorithm, this model can predict surface finish with accuracies exceeding 88%. Using only the time domain features of the raw signals, only a prediction accuracy of 48% could be achieved. After the inclusion of features of the marginal spectra in the domain of time and frequency, the prediction accuracies exceeded 88%. It can be concluded that the application of EMD is fruitful for prediction of surface finish in outer diameter cylindrical grinding which is typically a non-linear and non-stationary process.

Acknowledgements: We would like to extend our gratitude to the project group from Indian Institute of Technology Madras, Machine tools lab for carrying out the experiments under Global Initiative of Academic Networks (GIAN) course. We would also like to thank the staff members of Advanced Manufacturing Technology Development Centre, IIT Madras for rendering their support in the completion of this study.

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