

# Event Classification from Sensor Data using Spectral Analysis in Robotic Finishing Processes

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**Abstract:** Process monitoring using indirect methods leverages on the usage of sensors. Using sensors to acquire vital process related information also presents itself with the problem of big data management and analysis. Due to uncertainty in the frequency of events occurring, a higher sampling rate is often used in real-time monitoring applications to increase the chances of capturing and understanding all possible events related to the process. Advanced signal processing methods helps to further decipher meaningful information from the acquired data. In this research work, power spectrum density (PSD) of sensor data acquired at sampling rates between 40 kHz-51.2 kHz was calculated and the co-relation between PSD and completed number of cycles/passes is presented. Here, the progress in number of cycles/passes is the event this research work intends to classify and the algorithm used to compute PSD is Welchs estimate method. A comparison between Welchs estimate method and statistical methods is also discussed. A clear co-relation was observed using Welchs estimate to classify the number of cyceles/passes.

## 1 INTRODUCTION

In machining processes, ensuring the quality of a finished product is crucial and with advances in manufacturing technology, a need exists to integrate in-process monitoring technology into the production environment, so as to avoid manufacturing induced anomalies (G. Byrne and Teti, 1999; D. Dornfeld and Vijayaraghavan, 2009). Advanced process monitoring technology coupled with an intelligent decision making support system can reduce the time taken to otherwise perform rework on finished components with defects. This will save costs and also reduce the dependency on skilled operators. A report released by the Federal Aviation Authority (FAA) in partnership with the Aerospace Industries Association (AIA) Rotor Manufacturing (RoMan) Project Team in the year 2006, stresses the importance of incorporating advance process monitoring and control technology in manufacturing processes especially for critical aerospace components (Team, 2006). Process monitoring is generally classified into direct and indirect methods. In direct method, the quantity of the output variable is measured or monitored directly whereas in indirect method, the output variable is deduced through monitoring the quantity of process variables

such as vibration, speed (P. Stavropoulos and Chrysolouris, 2013). While direct method is known for its accuracy, indirect method is widely accepted since they are more realistic to be implemented in an industrial environment as the cost incurred is comparatively less than direct method. Indirect process monitoring is performed by capturing these process variables with the means of sensor systems for e.g., accelerometer, dyanamometer, temperature sensor etc. Standard data acquisition (DAQ) systems are then used to acquire, sample and log the data. The data is further analysed to identify any significant and/or persisting trend/patterns. Subsequently, the analysed data can be used to deduce the required output variable. This analysis can also be performed real-time making indirect method more efficient than direct methods. A important step involved in the data analysis is to identify the signal signature. This paper focuses on identifying a relevant signature that gives direct information of the progress of machining process. In the sections following, an overview of sensor based monitoring and signal processing methods in machining applications is presented. Sections 3 and 4 covers the experiment setup under which this research work was performed, the results received and inferences deduced from the results.

## 2 PROCESS MONITORING IN MACHINING

Machining is the term used for manufacturing processes that involves varying range of material removal rate (MRR). Machining performed with hard tool/cutter has higher material removal rate compared with finishing processes wherein compliant abrasive tools/brushes/belts are used. In a machining process monitoring system as shown in figure 1, the cutting region comprises of several process variables, such as vibrations, cutting forces, acoustic emission, temperature, surface finish. The various factors that influence these process variables include the state of the cutter/tool, coolant flow, chip packing and other material removal process conditions.

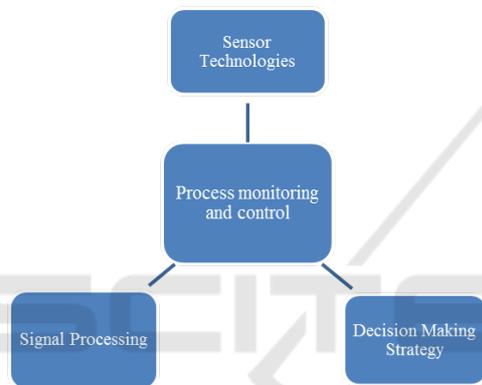


Figure 1: Building blocks of machining process monitoring (Indirect).

By using appropriate physical sensors, the variable that needs to be measured can be continually monitored and variations can be logged (R. Teti and Dornfeld, 2010). The data acquired is processed with the aim to identify patterns, trends or abnormal process conditions. Further analysis is performed on the acquired data with the help of machine learning algorithms such as neural networks and fuzzy logic. Upon detection of any process related information or process faults, the information is communicated either to the operator or fed directly to robot controller to take relevant corrective/adaptive actions (R. Teti and Dornfeld, 2010; C. Bisu and Cahuc, 2013). A majority of past research works on process monitoring is performed on processes involving hard tool, for e.g. milling, turning. In most cases the focus of the work is inclined towards tool condition monitoring (G. Byrne and Teti, 1999). Focus of this research work is to identify information that has some co-relation with the completed number of passes in a robot assisted finishing process. This was achieved by analyzing the corresponding magnitude levels of frequency domain

signal from different passes and belonging to a fixed frequency band. Further details on the experiment are mentioned in section 3.

### 2.1 Sensing System and Signal Processing

Some potential measurable process phenomena in a robotic machining environment are shown in figure 2. Power and current flow of the spindle delivers the required cutting force. Hence monitoring the power intake and current flow in motors that drive the spindle can be used to understand the MRR (G. W. Fritz Klocke, 2008; Pritschow and Kramer, 2005). However, in robot assisted finishing processes, monitoring and implementing spindle drive control is impractical due to complex architecture compared with traditional milling or turning machines or numerical control (NC) machines. As shown in figure 2, monitoring the measurable phenomena which are closer to the machining area is a better alternative to understand and analyse the nature of the process. This include acoustic emission (AE), force/torque exerted by the tool on the workpiece, vibration and spindle motion displacement.

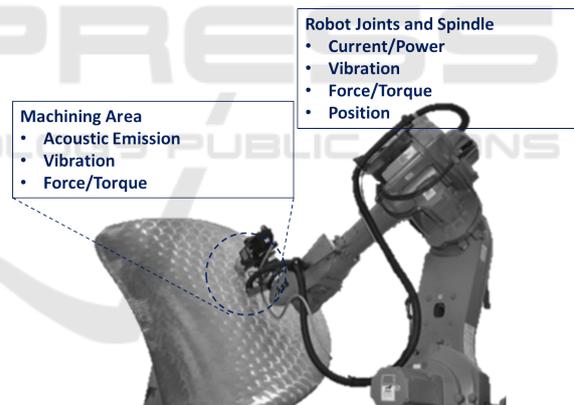


Figure 2: Measurable phenomena in machining environment.

Signal signatures often consist of embedded information which can be co-related to process variable itself. Signal processing plays a pivotal role in performing this task by extracting the relevant signatures and also to identify trends/patterns. Wide range of signal processing techniques exists and choosing an ideal technique relies heavily on the type of application. Acoustic emission (AE) sensor is known for its susceptibility towards high frequency signals (above 20 kHz) and clearly seems to be a favorite choice in most machining process monitoring applications. Using AE sensor also reduces the requirement to perform further signature extraction as AE signal has

Table 1: Process monitoring classified based on monitoring variable. (R. Teti and Dornfeld, 2010).

Monitoring Aspect	Sensor System Used	Signal Processing	Process
<b>Process :</b> Chatter, Process Faults and Conditions	AE, Vibrations, Cutting force	Frequency domain analysis, Wavelet transform, Statistical	Milling, Turning, Other
<b>Tool:</b> Wear, Breakage	AE, Vibrations, Cutting force, Camera	Frequency domain analysis, Wavelet transform, Image analysis	Milling, Band sawing, Broaching, Turning, Tapping
<b>Surface Quality:</b> Surface finish and roughness, Surface geometry	AE, Vibrations, Cutting force	Frequency domain analysis, Statistical	Milling, Turning, Hand machining
<b>Other:</b> Spindle, Surface integrity	Vibrations	Frequency domain analysis	Turning

relatively higher signal to noise (S/N) ratio and improved frequency response for high frequencies (Lee and Dornfeld, 1998). However, in applications that involve low material removal rate (MRR), magnitude of elastic waves produced by tool-workpiece interaction is much lower compared to processes like turning, milling, drilling etc. In such cases, other sensing systems must be relied upon to give meaningful information regarding the process (e.g. Vibration sensor). Table 1 gives a summary of past literature on types of sensing system and signal processing used, classified based on monitoring aspect. An exhaustive review on process monitoring including the types of sensors used and signal processing methods is given in (R. Teti and Dornfeld, 2010). In our experiments we have employed a tri-axial accelerometer to capture vibration data.

## 2.2 Frequency Domain Analysis

Signal processing techniques can be broadly classified as time domain and frequency domain. Several researches have used both techniques in applications involving tool wear/breakage detection and indirect surface integrity detection. For instance, in (T. I. El-Wardany and Elbestawi, 1996), kurtosis(time domain) and frequency domain analysis is used successfully to understand tool properties in a drilling process. In time domain analysis, statistical methods are used to distinguish persisting patterns/trends. This includes skewness, kurtosis, co-relation coefficient etc. In frequency domain analysis, captured signal is analyzed in the frequency domain and changes to individual frequency components are often indicative of the changes in process variables.

Frequency domain analysis also helps to visualize the effect of noise filtering and various other windowing and filtering techniques. As the sampling fre-

quencies in this experiment falls in the range of 40-51.2 kHz, performing time domain analysis proved to be challenging due to the size of data captured and hence frequency domain analysis was effective to understand process characteristics. Signal power also contains pertinent information regarding the source of signal generation. Conventionally, fast fourier transform (FFT) can be used to determine power spectrum. In stochastic processes, performing FFT will not be useful to reduce the noise embedded in the signal, hence some averaging needs to be performed to increase the S/N ratio. Welch's power spectrum estimate essentially calculates power spectrum using FFT coupled with averaging. This helps to minimise the signal power caused by random variations. FFT do not account in for discontinuities between successive periods as the data captured is assumed to be of a single period of a periodically repeating waveform and this phenomenon is referred to as spectral leakage. Applying Welch's estimate method also helps to reduce spectral leakage and reduces the effect caused by undesired frequencies.

Welch's method to compute PSD is performed by dividing the time series data into segments that are successive and averaging the periodograms of each segments or frames. Consider  $x_m(n)$  to be the input signal where  $m = 0, 1, \dots, K-1$ ,  $K =$  total number of frames and  $n = 0, 1, \dots, M-1$ , periodogram of  $m$  th frame is given by,

$$Px_m, M(k) = 1/M \left| \sum_{n=0}^{M-1} x_m(n) e^{-2\pi i n k / N} \right|^2 \quad (1)$$

then Welch's power spectrum estimate is computed as,

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

Upon analyzing the power readings of certain frequency components, it was noted that the changes observed was corresponding to the completed number of passes. Analysing frequency component of the vibration signal is imperative to finishing processes as the fundamental frequency and its harmonics contain coherent information which can be attributed to spindle behavior and also the finishing of the component. Shop floor operators require systems that are less sophisticated and adopting a frequency domain analysis method gives that flexibility as opposed to other machine learning algorithms or statistical methods. Welch's estimate method is preferred as an easier method to implement in such cases as it gives a more visual means of interpretation. However, machine learning algorithms provide more stability in applications involving predictive maintenance.

### 3 EXPERIMENT SETUP

The experiment setup (Fig. 3) comprises of an ABB IRB 6660 machining robot and PDS colombo spindle. The representative work coupon used for machining is a boss hole of combustor casing and the objective is to remove the burrs until a chamfer is developed. As mentioned in section 2, vibration signatures were measured using a tri-axial accelerometer, Kistler 8763B (IEPE). The RPM of spindle was kept constant at 10000 RPM and feed rate at 30mm/s. The data acquisition devices used was NI cDAQ-9184 and NI 9234 IEPE.

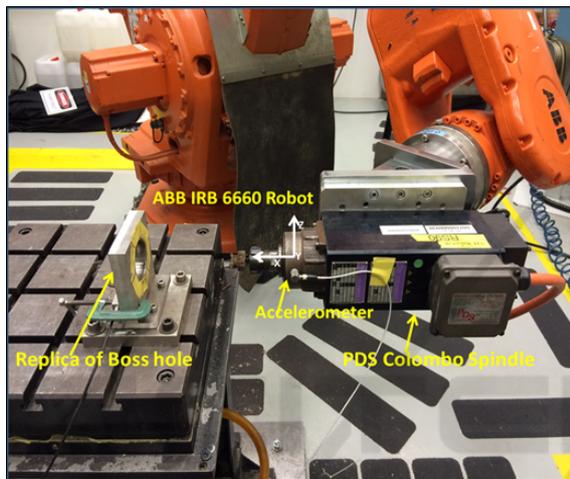


Figure 3: Trial and experiment setup.

#### 3.1 Data Analysis and Results

Data was captured at a sampling rate of 40kHz and for computational ease, pre-processed to 1000 samples per each iteration of Welch's estimate calculation. A total of 12 sets of experiment was conducted with 8 being used for offline analysis and co-relation and another 4 for validation. After each cycle of machining, the chamfer length was manually measured using laser measuring device. In offline data analysis, co-relation between the measured values and variations in estimated power spectrum is analysed. The co-relation between the power spectrum and number of cycles was subsequently validated in real-time. Figure 4 shows the process flow of how experiments were conducted.

Different data analysis techniques were used on acquired data sets. For instance, kurtosis and skewness values for respective passes were calculated but it failed to show any consistent trend or pattern with increasing number of passes. Table 2 shows calculated kurtosis and skewness values for each pass. It can be noted from the numbers that a pattern or trend

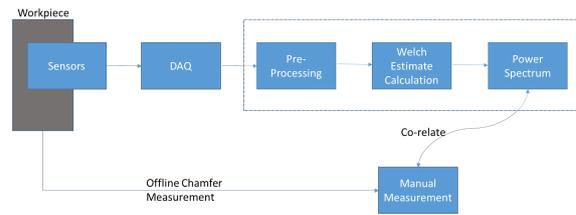


Figure 4: Process flow diagram.

Table 2: Kurtosis and Skewness Values.

Pass	Kurtosis			Skewness		
	X	Y	Z	X	Y	Z
1	11.91	11.47	8.40	-0.16	-0.06	-0.20
2	9.93	10.73	9.20	-0.18	-0.09	-0.14
3	11.21	15.43	14.38	-0.15	-0.06	-0.10
4	9.15	12.30	13.40	-0.20	-0.07	-0.13
5	7.70	8.36	6.29	-0.28	-0.10	-0.29

is not obvious. This can also be understood from the figures 6 and 7.

Results obtained after performing Welch's power spectrum estimate is shown in figure 5. Figures 8, 9 and 10 shows the Welch's power spectrum estimate at 1.297Khz. As shown in figures 8, 9 and 10, the power values of vibration signal decreases with respect to the increasing number of passes. The trend here when compared with kurtosis and skewness values is more obvious to the naked eye. The decrease in signal magnitude is indicative of the strength of the signal. It is also understood that the decrease in strength of signal is caused due to the smoothening of edges of boss hole with increasing number of passes (Table 3 shows the increase in chamfer radius with different pass).

From the vibration signatures, it can be concluded that a co-relation exists with the different number of passes and the PSD at 1.297 kHz. This signal is believed to be the 8th harmonic of the fundamental frequency generated due to the spindle RPM. The spindle RPM is controlled by a variable frequency drive (VFD) controller and the frequency is fixed at 165 Hz. This is however with the exception of Y axis measure-

Table 3: Increase in Chamfer Radius.

Pass	Chamfer Size (Initial : 0.84 mm)
1	0.956
2	1.028
3	1.083
4	1.098
5	1.118

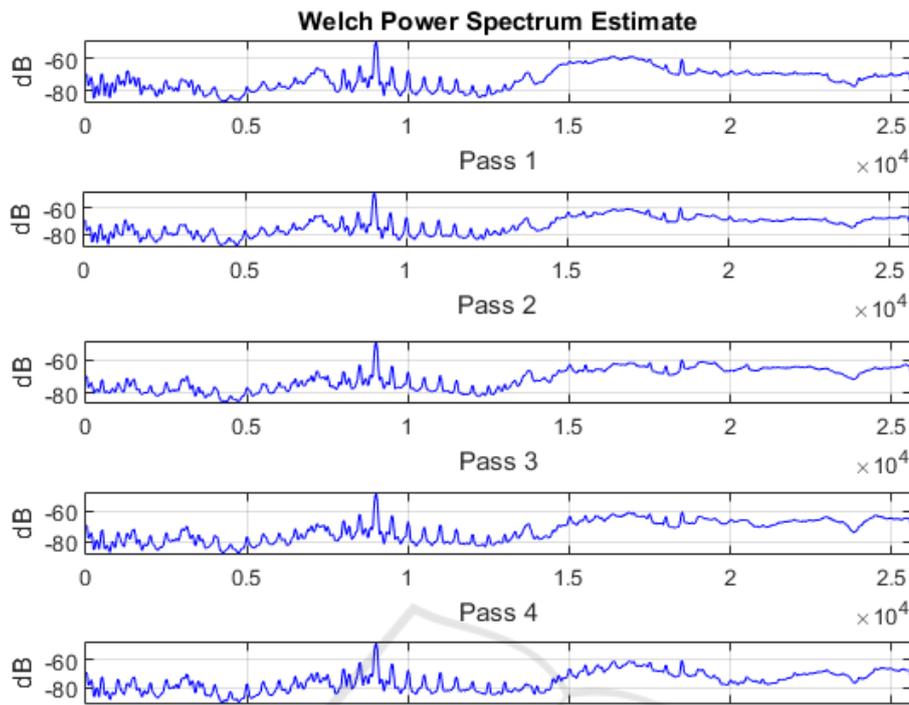


Figure 5: Welch's Power Spectrum Estimate for each Pass/Cycles.

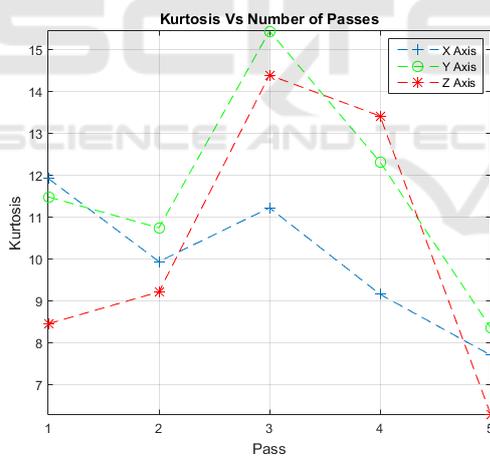


Figure 6: Kurtosis Vs Number of Passes.

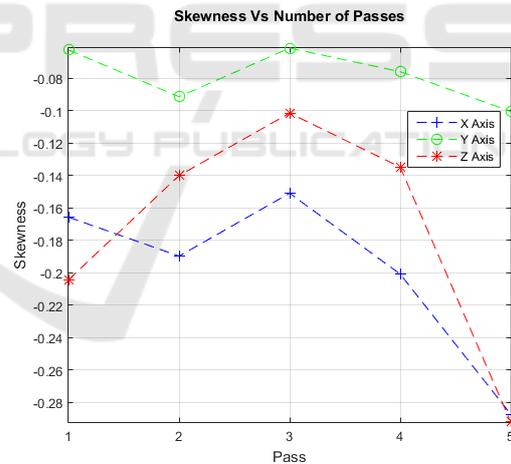


Figure 7: Skewness Vs Number of Passes.

ment and is caused due to the orientation and placement of the sensor. Figure 11 shows the correlation between magnitudes of the captured signal with increasing number of passes. From the figure it can be seen that, magnitude of vibration signal in Y axis is relatively low as compared to X and Z axis measurement which further confirms the assumption on sensor location aspect.

#### 4 CONCLUSION

The focus of this experiment was to explore the relationship between captured vibration signal and the progress of the actual finishing process. The experiment result establishes a linear co-relation between vibration signals with completed number of passes. One major limitation which the authors noted during this research work is that, the results obtained were dependent on the training experiments and hence ap-

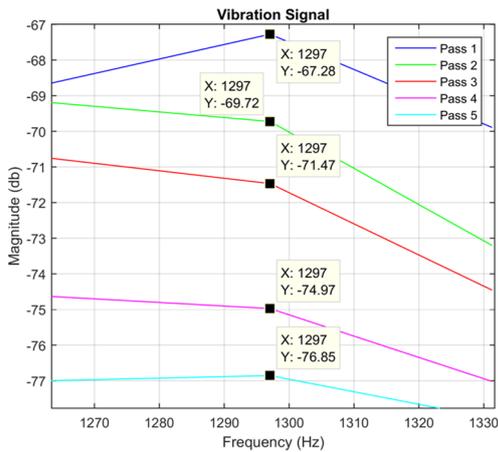


Figure 8: Vibration signature in X direction.

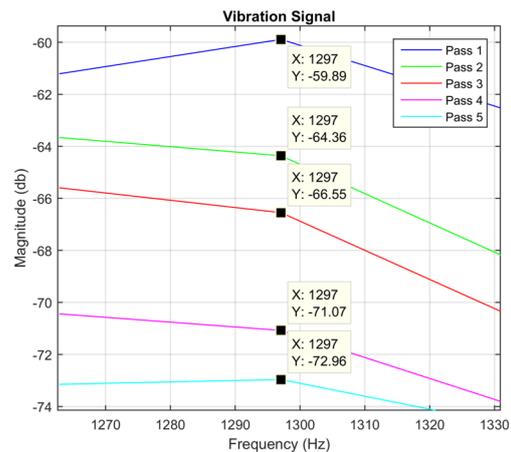


Figure 10: Vibration signature in Z direction.

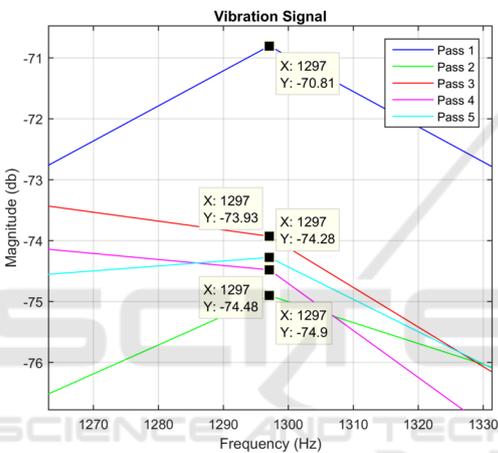


Figure 9: Vibration signature in Y direction.

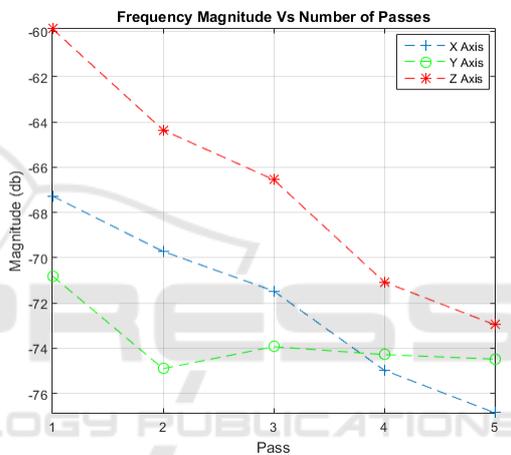


Figure 11: Signal Magnitude Vs Number of Passes.

plying the classification technique to other finishing processes may not yield the same expected outcome. This will be the focus of future research directions of this work; to validate and set up a similar classification technique across other finishing processes like polishing. Spectral analysis proved to be a viable solution for performing this task and is seen as a promising technique to be implemented in real-time applications involving high sampling frequencies. The advantage seen here is that, analyzing a particular frequency component relieves the need of bulk data processing as opposed to statistical methods wherein packets of data needs to be computed to understand the co-relation between different statistical attributes with the number of passes completed. Besides, the welch spectrum estimate showed significant co-relation with the completed number of passes as opposed to time-domain features like kurtosis and skewness.

This research work was conducted primarily to understand possible co-relation between sensor signal

features and the progress of the finishing process. The co-relation observed will be integrated to the robotic finishing software environment used for tool path programming and will serve as a visual aid to shop floor operators enabling them to monitor the progress of the finishing process. In the next phase of the project, the signature identified as a classifier will subsequently be used as an input parameter for machine learning algorithms. Additionally, a control strategy could be deployed with a feedback loop in the robot control system to dynamically adjust the process variables to compensate for any unexpected behavior.

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