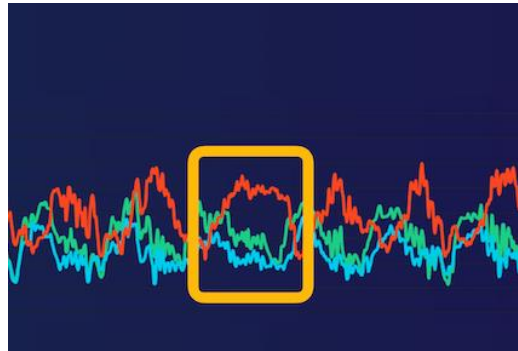


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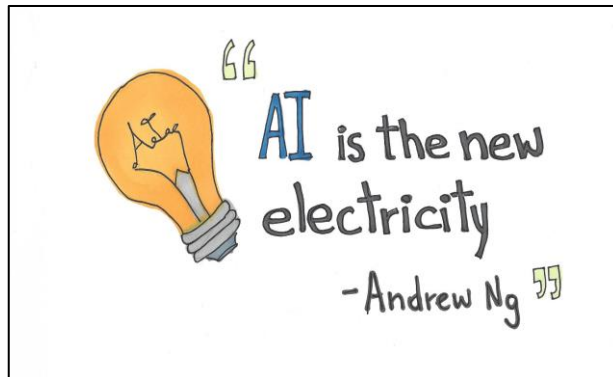
Time-frequency analysis of vibration signals for monitoring the process status in Ultra-Precision machining of complex components

Karanam Manjunath, Suman Tewary, Neha Khatri, Kai Cheng



Presented by
Karanam Manjunath
Senior Research Fellow
AcSIR-CSIO

Outline



Introduction

Ultra Precision Machining

Signal Processing in Manufacturing

Experimental Setup

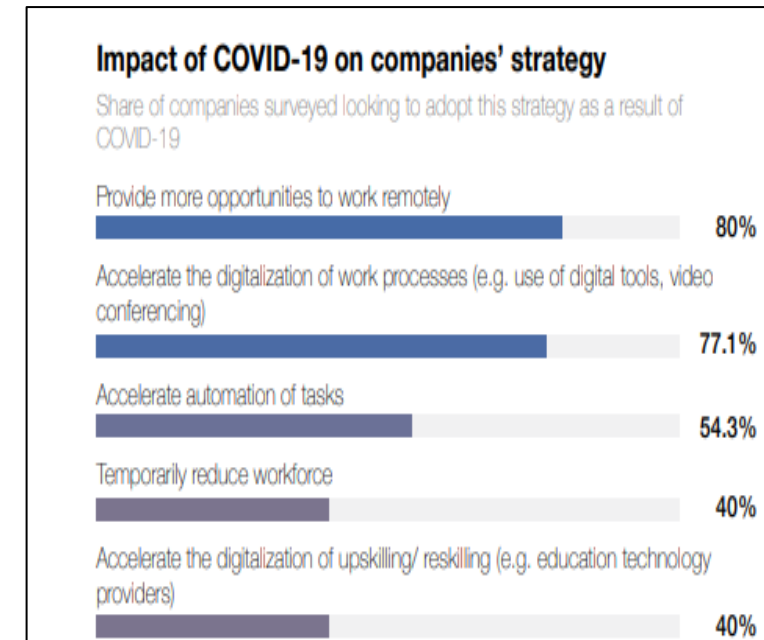
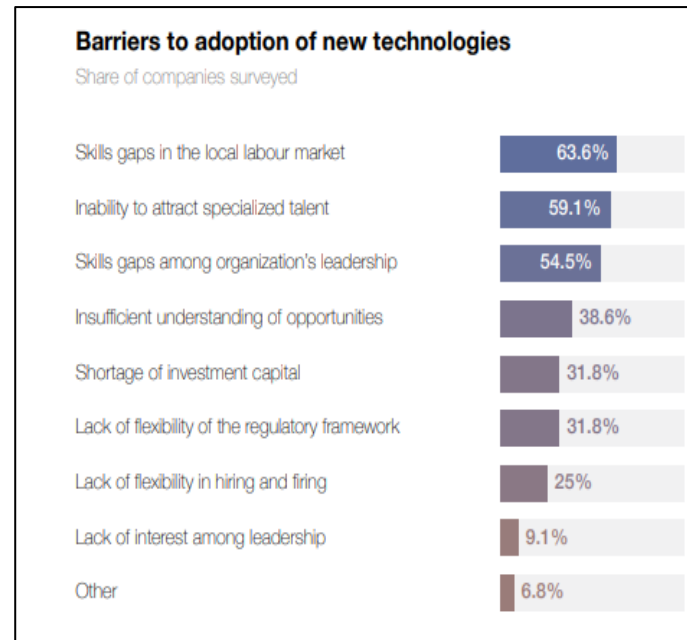
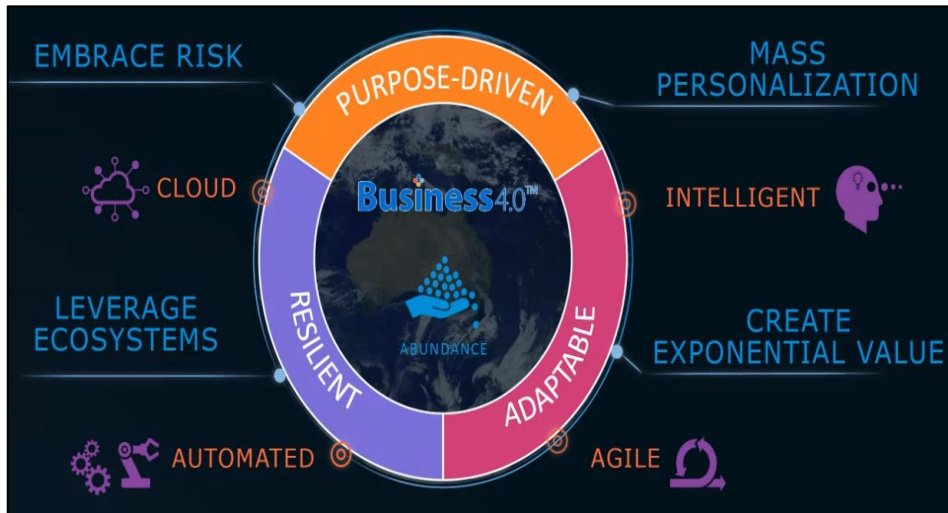
Time-frequency based anomaly detection

Conclusion

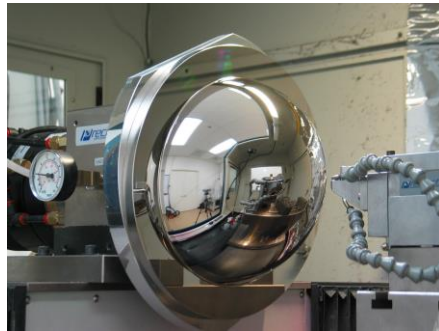
Future scope

References

- Explainable Artificial Intelligence has a very positive outlook to meet the Futuristic demand in the area of manufacturing.
- The artificial intelligence in manufacturing has encountered a turning point mainly due to advancements in machine learning, which allows machines to learn, improve, and perform a specific task.
- Due to the inherent transients & nonlinear dynamics in UPM necessitate the need for intelligent manufacturing which has emerged as wave for future.



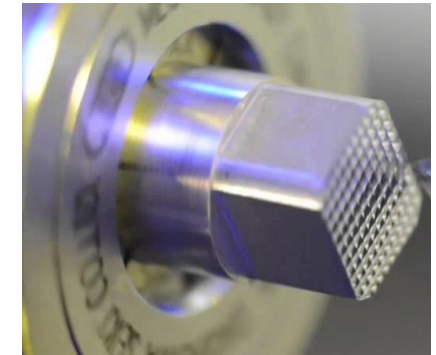
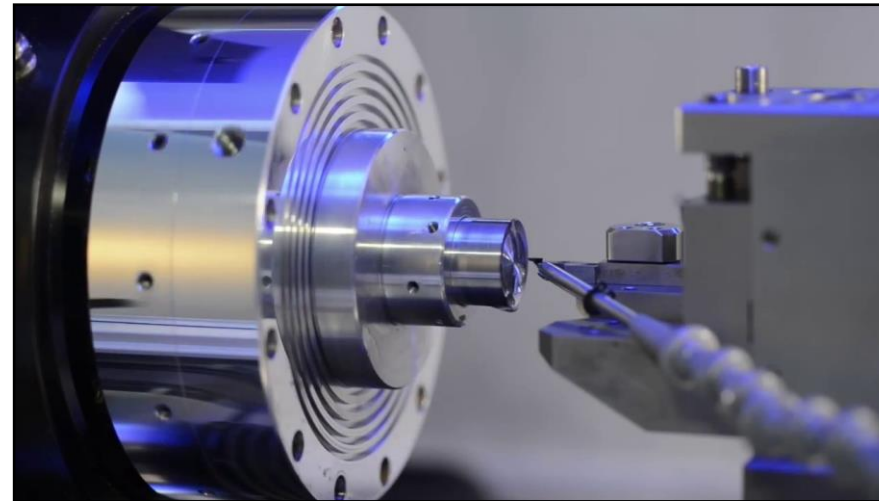
- Ultra Precision Machining (UPM) has enabled generating critical products and optical surfaces with nanometric characteristics and high levels of smoothness.
- High Precision machining need is increasing due to the requirement of miniaturized component.



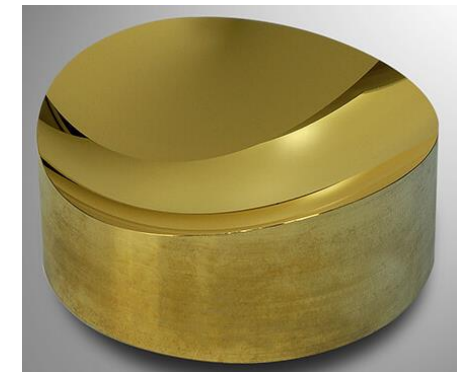
Mirrors



Aspheric lenses



Lenslet array



Freeform optics

Bio-medical

Avionics

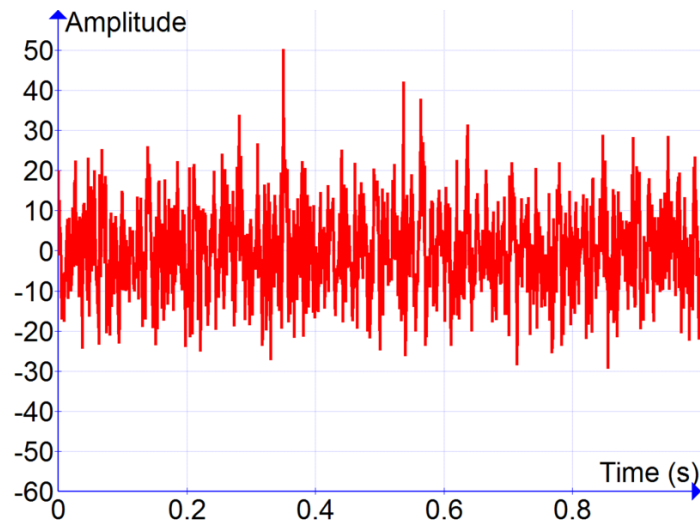
Defence

Optics

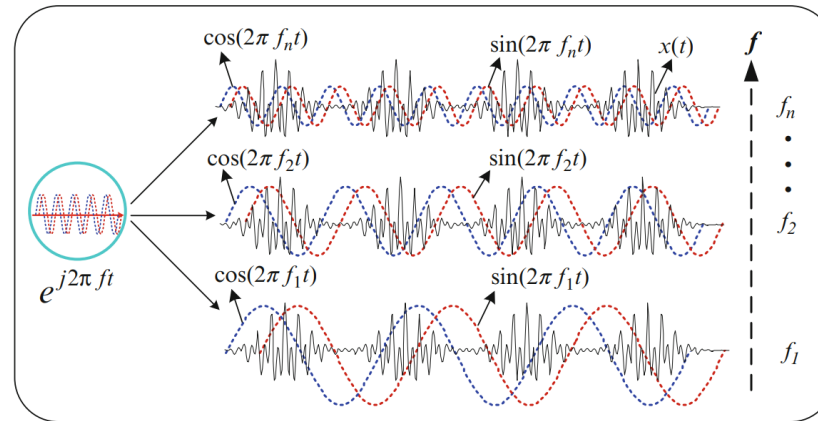
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The goal of signal processing is about the operation status of the machines and use the information for the following purposes:

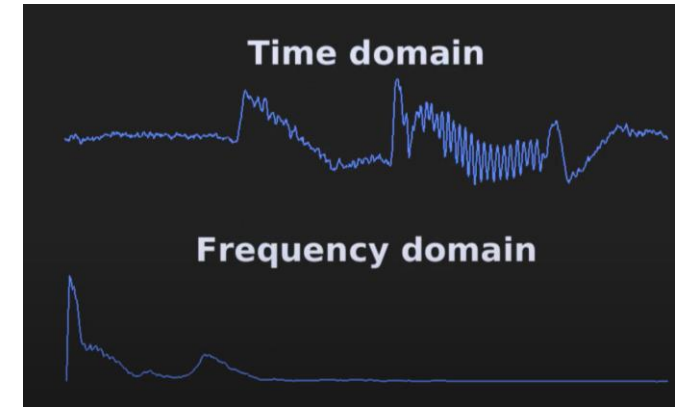
1. Identification of machine faults at the incipient stage.
2. Maintenance and production scheduling.
3. More accurate control of the quality of products being manufactured.



Time-domain signal



Fourier Transform



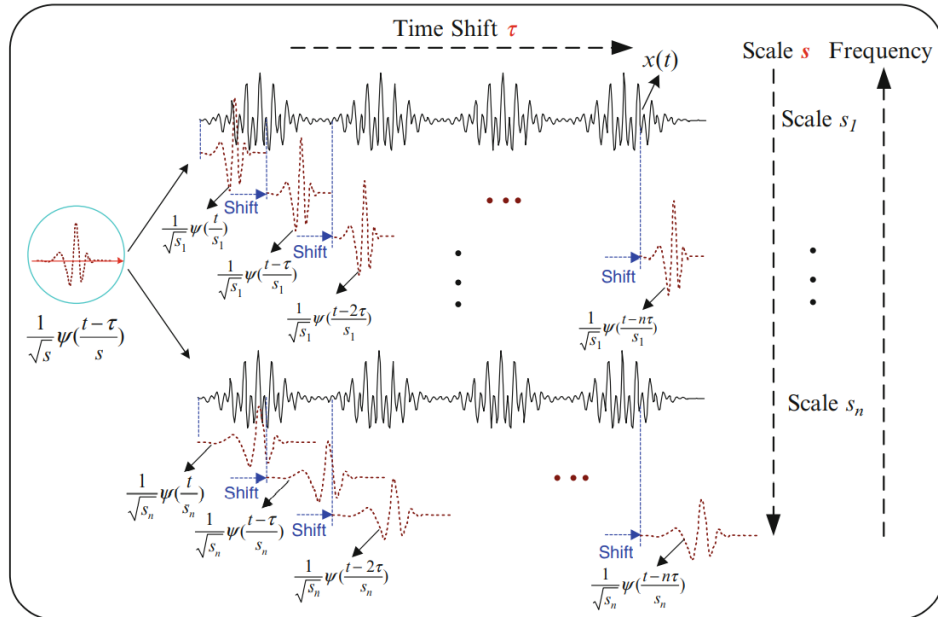
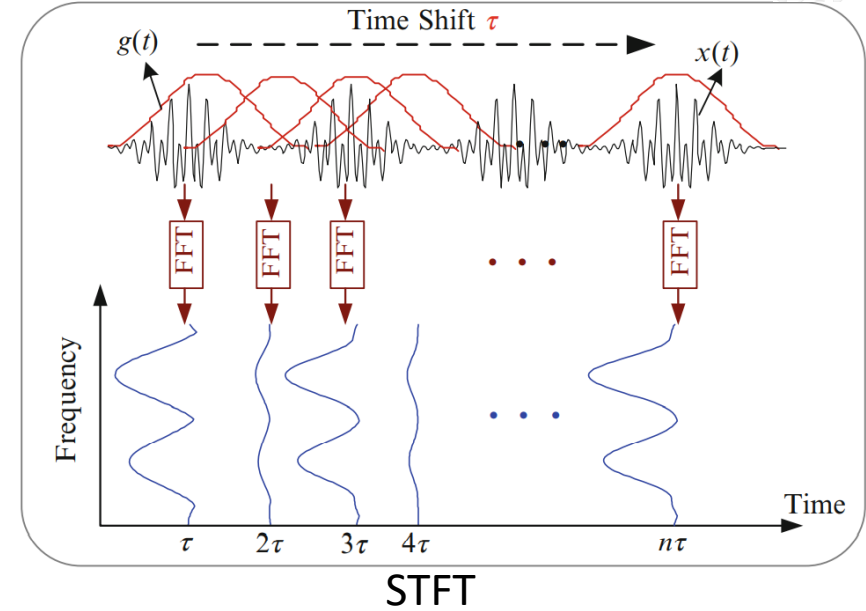
Limitations of static spectral analysis

Detection of negatively impacting signals can be challenging, as these signals are generally short in duration and weak in amplitude and often buried under heavy noise.

Short Term Fourier Transform(STFT) was developed to address the limitation of the FT. A solution to this problem is to perform a “time localized” Fourier transform within a sliding window, as in the case of STFT.

$$STFT(w f) = \int_{-\infty}^{\infty} x(t) w(t - u) e^{-j2\pi f t} dt$$

Where $x(t)$ is the time series signal, $w(t-u)$ is also window function that shifted in time and modulated in frequency.

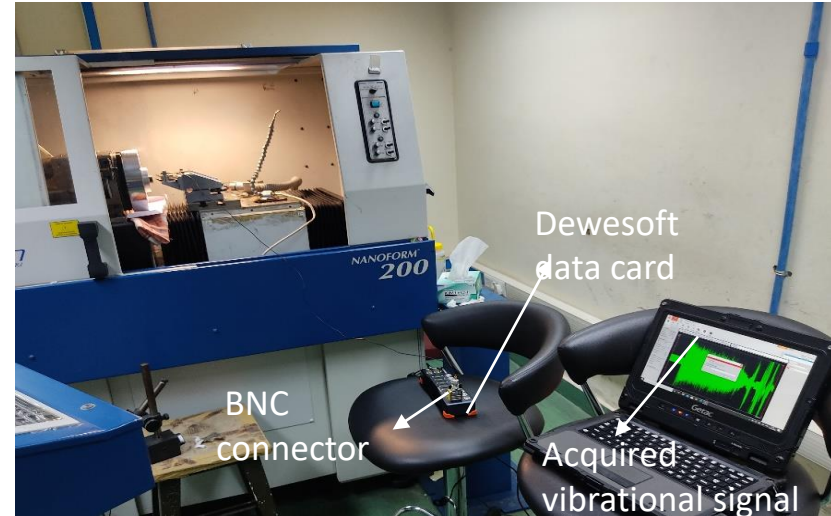
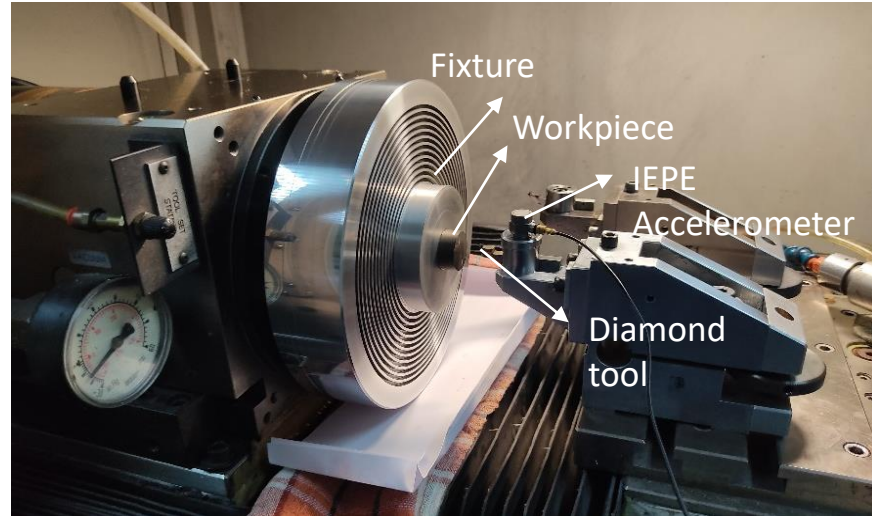


Wavelet transform

Wavelet is a rapidly decaying wave like oscillation that has zero mean. Unlike sinusoidal which extends to infinity a wavelet exists for a finite duration.

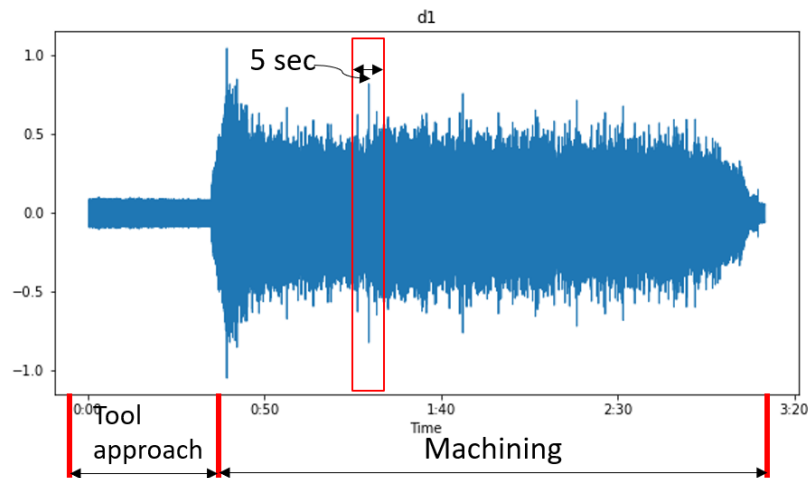
$$\psi_{u,s}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad a, b \in \mathbb{R}$$

Here a and b are called Dilation and translation parameters respectively

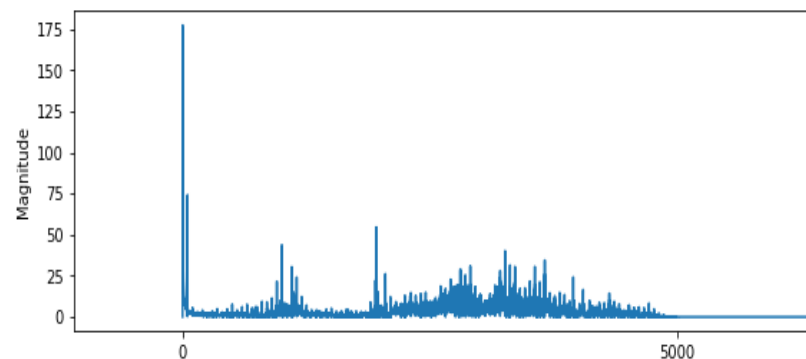


| Parameter | Value |
|----------------------|-------------------|
| Workpiece material | SLM Ti6Al4V alloy |
| Workpiece dimensions | 25mm X 10 mm |
| Tool | Diamond tool |
| Tool nose radius | 1.495 mm |
| Sensor | B&J 4533-B (IEPE) |
| Data logger | Dewesoft DAQ |

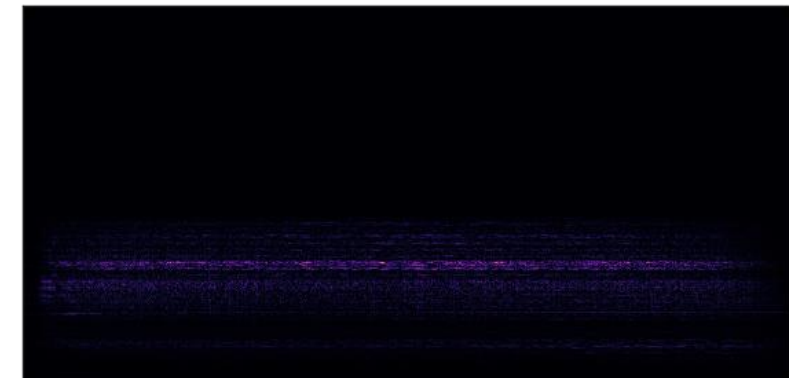
Signal Acquisition setup in UPM



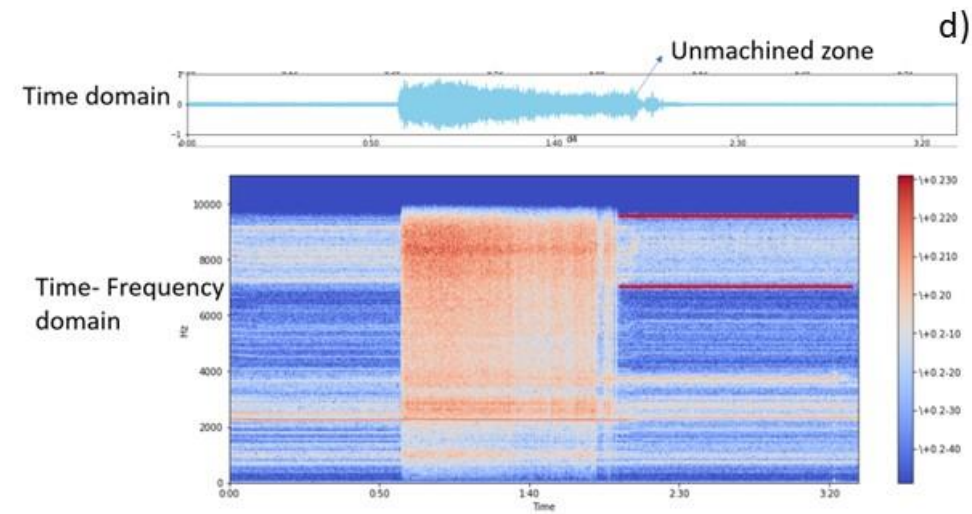
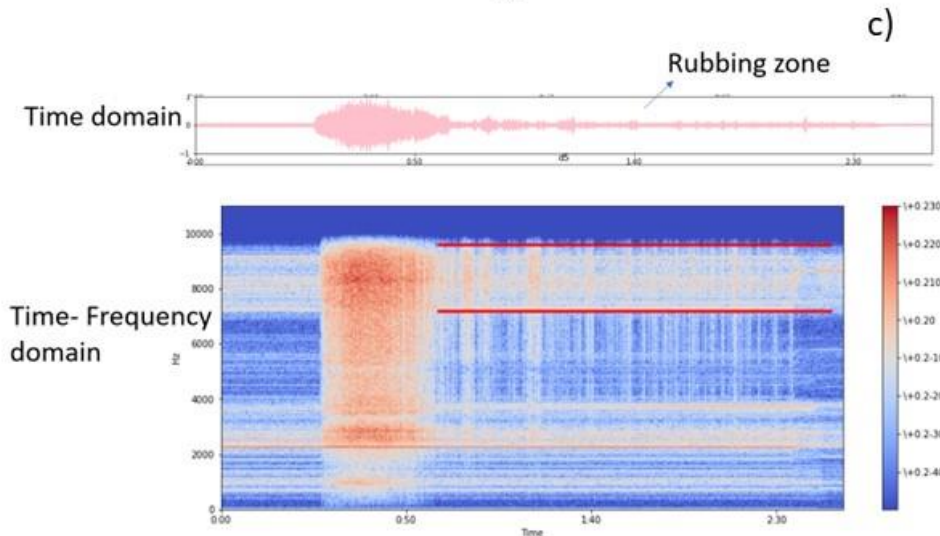
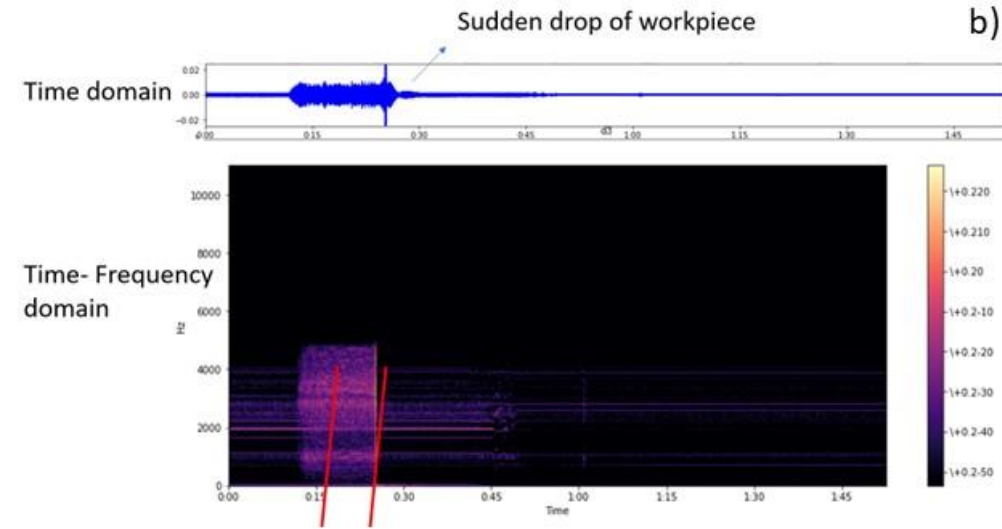
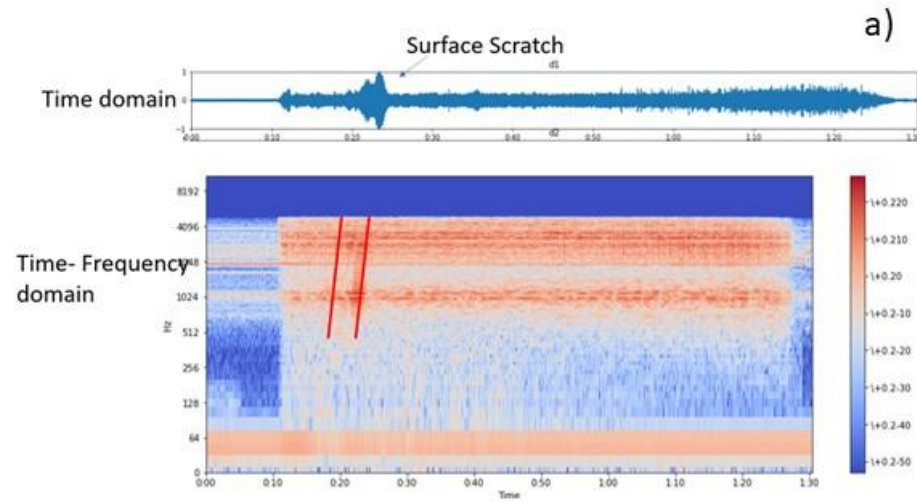
Time domain signal



Frequency domain signal

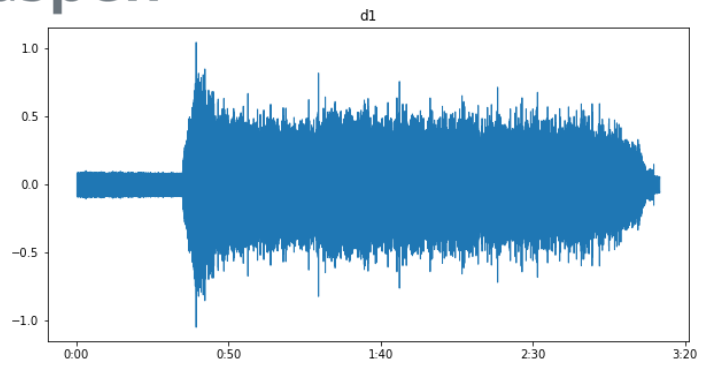


STFT

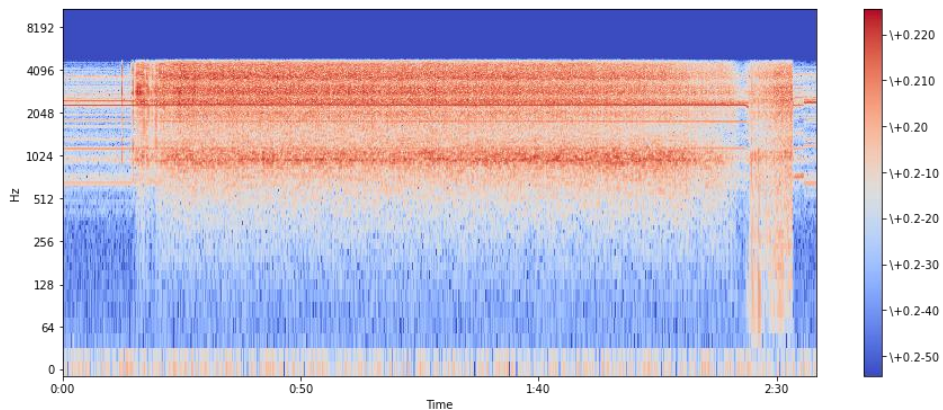


Time-frequency domain log-spectrogram analysis for monitoring various process anomalies a) surface scratch b) Work piece drop c) Rubbing or ploughing b) unmachined zones.

IN-PROCESS MONITORING

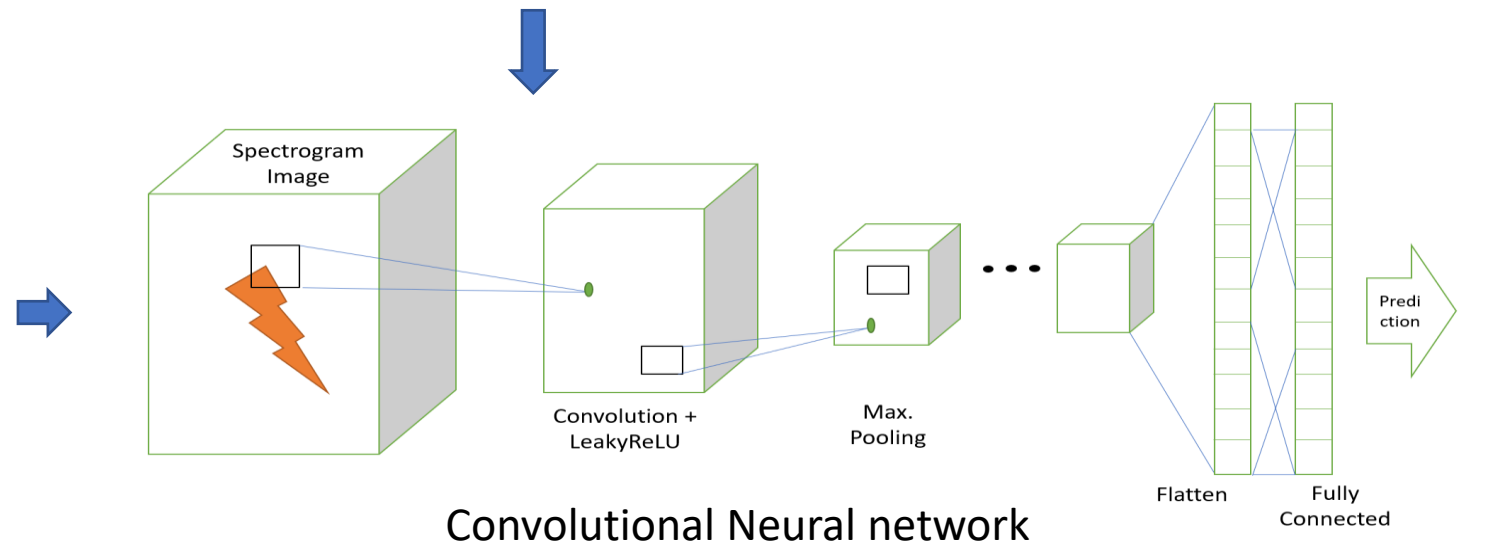
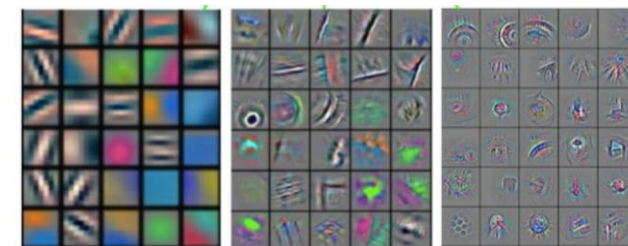


Time-domain Signal



Log-Spectrogram

colab
TensorFlow



Classification

Normal Machining
Abnormal Machining

- In this paper an attempt is made for monitoring the machining status using time-frequency analysis. By using log-spectrum analysis has shown very relevant information pertaining the machining process.
- This study is especially relevant when considering the trend towards flexible manufacturing. The main contributions of this paper are as follows:
 - In-process monitoring using a single-direction accelerometer during ultraprecision machining has been discussed. The signals analyzed using CWT reflected the changes during the cutting mechanism.
 - Time-frequency based status analysis further increases the transparency and shortened quality feedback laying the foundation for optimizing the cutting parameters.

FUTURE SCOPE

- This idea can likely be extended to other complex manufacturing process monitoring using transfer learning.
- The focus can be made on exploring transfer learning capabilities by taking advantage of the computational support from the TensorFlow hub using various networks available.

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I still have lot to
unlearn and learn

Thank you

