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Research Article

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Real Time Remote Monitoring and Anomaly Detection in Industrial Robots Based on Vibration Signals, Enabling Large Scale Deployment of Condition based Maintenance

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Abstract
Loss of wafers and expensive repairs of process equipment are often caused by uncontrolled and unmonitored failures of critical components during semiconductor process. High volume manufacturing (HVM) of semiconductor chips employ large number of robots. Malfunctioning of these robots causes particle contamination, wafer slip and wafer breaks, resulting in production yield loss, equipment down time and factory throughput. Presently, wafer handling monitoring instruments diagnose vibrations of a robot at the end-effector. Detection of anomaly in these vibrations are performed manually during scheduled maintenance and are highly dependent on the experience of maintenance personnel. This not only is prone to human error, but also limits large scale deployment in semiconductor fabrication. The proposed solution automates this process by monitoring the vibration signal patterns, continuouslyin real-time, to proactively identify robots that are at risk of failure. The vibration signals are captured using tri-axial accelerometers placed near the bearings in the arms of the robot.

The proposed method analyzes specific parameters of the vibration signal and generates alerts for maintenance, before the uncontrolled vibrations affect production. Identifying parameters which are correlated to failures ischallenging. This work presents four such indicative parameters, determined based on time and frequency domain analysis of the vibration data collected from good and faulty robots. The proposed method based on outlier detection is an Edge /Cloud architecture for remote monitoring and alerting.

Keywords: Robots, Condition Monitoring, Anomaly Detection, Semiconductor Fabrication Units

Introduction
Robots are used in practically every industry ranging from food industry, packaging, automobile, and electronics, including several applications related to inspection and remote monitoring. One big area of robot deployment is semiconductor fabrication industry. Robots are deployed specifically for jobs that require precision, such as pick and place in chip and automobile assembly lines, and jobs that are repetitive in nature, to reduce human errors and fatigue. Any malfunctioning of these robots affect the quality of the product and result in yield loss, as in the case of fabrication units.Malfunctioning of wafer handling robots causes particle contamination, wafer slip and wafer break, resulting in production yield loss, equipment down time and factory throughput. Presently, wafer handling monitoring instruments diagnose vibrations of a robot at end-effector. Detection of anomaly in these vibrations are performed manually during scheduled maintenance and are highly dependent on the experience of maintenance personnel. This not only is prone to human error, but also limits large scale deployment in semiconductor fabrication industries with thousands of inline robots, besides causing disruptions in production due to unscheduled maintenance.

This paper presents a method to automate this process by monitoring the vibration signal patterns, continuously in real-time, to proactively identify robots that are at risk of failure, thus alleviating human intervention and enabling large scale deployment of condition-based maintenance. The method reduces downtime of the equipment as any anomaly or indication of degradation is addressed proactively before catastrophic failure. By driving predictive maintenance, the method reduces maintenance cost, besides enabling efficient and cost effective inventory or lean inventory. Furthermore, by proactive sensing of anomalous functioning of the robot, the proposed method maintains a very high quality of wafers produced, reducing waste and increasing yield. The method also enables efficient and real-time remote monitoring and alerting as it has both Edge and Cloud components. The proposed method is based on highly reliable parameters from both time and frequency domains of the vibration signal, minimizing false alarms. The methodis capable of identifying any anomaly in the robots, addressing a wide range of failure modes.

Unlike most of the existing methods which are cloud-based, and hence require high and costly data transmission bandwidth for sending sensor data to Cloud, the proposed method extracts parameters from the sensor data at the Edge of the equipment, analyzes the data and generates alerts. The parameters are sent to the cloud for further advance analytics, thereby reducing the amount of data required to be transmitted and reducing the reaction time for fault detection. This also enabled raw sensor data to remain on factory premises, alleviating privacy and security concerns associated with Cloud-based solutions[1-8].

Materials and Methods

The solution is composed of three major analytic blocks as shown in Figure 1:

Figure 1: Major Analytic Blocks

Sensor data preprocessing

This module will be responsible for preprocessing of the vibrations data captured from the sensor, like noise reduction, filtering, converting from time series to frequency domain (FFT).

Feature extraction

Time domain features, i.e. variance and RMS, and frequency domain features, i.e. energy and median frequency, are extracted from the vibration signals. These parameters were found to be more sensitive to changes in equipment health.

Statistical Process Control (SPC)/Outlier Detection

This is the block/module that does the final analysis based on the outlier detection algorithm. It determines if the features have deviated from normal condition, based on thresholds that was set to detect the anomaly.

Figure 2 shows a simple block diagram of the end-to-end solution of the predictive maintenance system showing a single edge gateway connected to few devices that are monitored with sensors on them. The other end of the gateway is hooked up to cloud based server(s). Details on each block of the edge analytics with in the gate are described in detail below

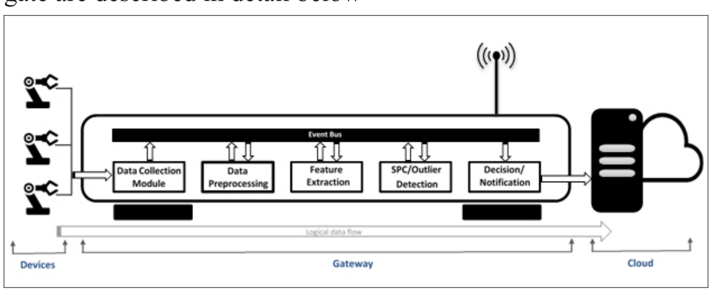

Figure 2: Block Diagram

Data Collection Module

This module established a link between the gateway and the sensor node/hub. This module will either directly or indirectly use the software SDK provided by the sensor vendor to establish communication, configure the sensor and the base, and ingest the sensor data. If this module uses the SDK directly then the protocol used to communicate will depend on the SDK; otherwise any protocol communication such as MQTT, CoAP, AMQP, DDS, & HTTP, may be used based on the applications' requirements.

Data Preprocessing

This module will be responsible for any type of preprocessing that needs to be done on the sensor data: i.e., noise reduction and Fourier transform.

Feature Extraction

Dimension reduction, converting vibration data into parameters/ features: i.e. mathematical moments. Normalization is also carried out at this stage.

Statistical Process Control (SPC) is closelyrelated to univariate outlier detection methods. It considers the case where the univariable stream of measurements represents a stochastic process, and the detection of the outlier is required online.Outlier detection methods aim to identify observation points that are abnormally distant from other observation points. A univariate outlier is an occurrence of an abnormal value within a single observation point. This detection method can be parametric, i.e. assume a known underlying distribution for the data set, and defines an outlier region such that if an observation belongs to the region, it is marked as an outlier.

Decision/Notification

The configurable rule-based notification functionality is provided by this module; criteria are set to indicate when the anomaly has occurred, and can be updated to reflect system-level changes. This module can also detect false positives and is configured to not generate false alarms/notifications. This module also has the knowledge of the protocol and configuration to effectively communicate with the server, either to send the notification or the data.

Data collection

The raw acceleration (g) data was collected using a high-precision triaxial MEMS accelerometer placed on the device under test (DUT) such as industrial robot arm. The data were collected with the sensor specification shown in **Table 1**.

Table 1: Accelerometer specifications

Measurement range	± 2 gstandard
Accelerometer bandwidth	0 Hz to 500 Hz
Accuracy	10 mg
Resolution	12 bit
Sampling rate	Continuous sampling rate of 512 Hz

Two sets of data was collected, one set was from a known good robot and another set from a known anomalous robot.

Preprocessing

It's been noted that frequency spectra are more sensitive to changes related to machine condition. Since the data collected were raw acceleration data which are in the time domain, we convert the time series data into frequency domain using fast Fourier Transform (FFT). The FFT sampled input data size and the output bin size was set to 1024, with a 50% overlap window on the sampleddata. Since the sampling rate was 512Hz only frequencies up to half this sample rate can be accurately measured.

Features examined

The following features shown in Table 2 were examined to select the best set of features that were indicative of the health of the robot. Because of the non-stationary nature of the vibration signal, we took averages (Avg) of the features over 100 running windows of 1024 points per window, explained in detail in this section.

Table 2: Time and Frequency domain features examined to selectthe most indicative features

1	Mean	10	Mean of 'Median frequency'
2	Minimum	11	Std. deviation of 'Median frequency'
3	Maximum	12	Mean of 'Avg. Energy'
4	Variance	13	Std. deviation of 'Avg. Energy'
5	Std. deviation	14	Mean of 'Avg. Mean frequency'
6	Median	15	Std. deviation of 'Avg. Mean frequency'
7	Mean of 'Energy'	16	Mean of 'Avg. Median frequency'
8	Std. deviation of 'Energy'	17	Std. deviation of 'Avg. Median frequency'
9	Mean of 'Mean frequency'	18	Root Mean Square

Features selected

Table 3 presents the selected features proposed in this paper, based on their discriminative power between good and bad robots.

Table 3: Selected set of features

	Known Bad Device	**Known Good Device**
Variance	Higher	Lower
Median Frequency	High amplitude lower median frequency	Low amplitude higher median frequency
Root Mean Square	Higher	Lower
Energy	Higher	Lower

Median frequency (mf), which is a measure of skewness in power spectrum, is defined as the frequency that divides the power spectrum into two equal parts and is obtained as follows:

$$\sum_{i=1}^{m} I_i = \sum_{i=m+1}^{n} I_i$$

where n is the total number of frequency bins (0.5*512=256), obtained using FFT, Ii is the amplitude or intensity of spectrum at the i^{th} bin and median frequency (mf) = f(m), i.e., frequency of spectrum at mth bin.

Energy: Spectral Energy of the signal **Spectral energy** is obtained as follows:

$$\text{Spectral energy} = = \left(\frac{1}{n}\right) * \sum_{i=1}^{n} I_i^2$$

Root Mean Square (RMS) is the square root of the arithmetic mean of the squares of the values.
In the case of a set of n values { x 1, x 2, … , x n}the RMS (x_{rms}) is

$$x_{\mathrm{rms}} = \sqrt{\frac{1}{n}\left(x_1^2 + x_2^2 + \cdots + x_n^2\right)}$$

Variance

A physical quantity which informally measures how far a set of data are spread out from their mean, is the average of quadratic summation, which sums the square value of the difference of each datum point and the mean.

Variance of a set of n equally likely values ($x_1 \ldots x_n$) can be written as:

$$\mathrm{Var}(X) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2,$$

whereµ is the expected value, i.e.,

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i .$$

To further reduce the noise considering the non-stationary nature of the vibration data a rolling window average of size 100 was used on each of the features. These features are input data for the outlier detection algorithm and since the fundamental requirement for this algorithm is that the input data need to be normalized, the computed features data are normalized.

Univariate Outlier Detection

The Intel® Data Analytics Acceleration Library (DAAL) is utilized in this study. The DAAL implementation of the Univariate Outlier Detection takes in the array of the data for outlier detection and an initialization procedure for setting initial parameters of the algorithm i.e. vectors of means, standard deviations, and limits defining the outlier region for which the z-score is given in units of how many standard deviations it is from the mean. The output of the algorithm is the *n x p* table of zeros and ones. A value of 0 in the position (*i, j*) indicates an outlier in the i^{th} observation of the j^{th} feature.

Results and Discussion

Figures 3 shows the difference in the Median frequency values under healthy conditions (Post Repair) and faulty conditions (Pre Repair). We observe that the Median frequency reduces in the Pre Repair robot, as the robot develops low frequency components due to wobbly motions, caused due to the fault. **Figures 4-5** show the data distribution of Variance, Median frequency, Average Energy and RMS under healthy and faulty states. We observe that the selected parameters clearly distinguish the healthy and faulty states of robot.

The anomaly detection method monitors the selected parameters continuously at real time, using statistical process control methods and generates alerts once the values of the above mentioned parameters cross 2 sigma and 3 sigma limits.

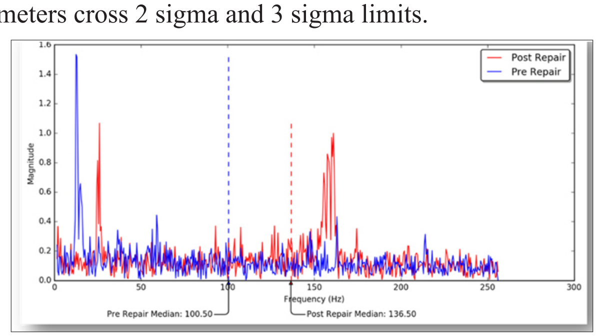

Figure 3: Anomalous robot (Pre Repair) has higher low frequency components, hence lower Median frequency

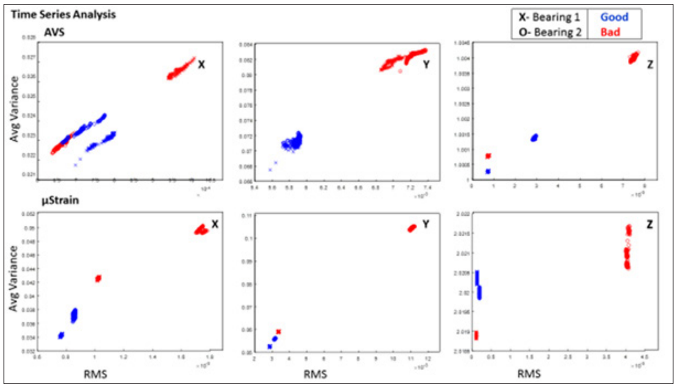

Figure 4: Robots with good bearing have lower Average Variance values in all axis

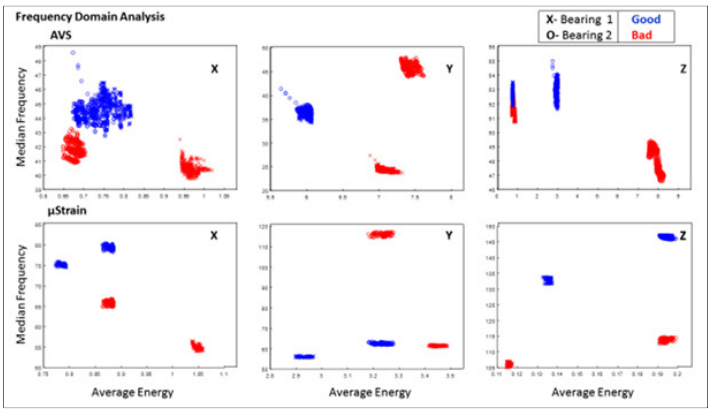

Figure 5: Good robots show higher median frequency values in X and Z axis

Conclusion

We developed a method that enables efficient and real-time remote monitoring and alerting of robot failures. This new method is based on highly reliable parameters from both frequency and time domains of the vibration signal, minimizing false alarms. The method has advantages over existing cloud-centric method in areas including minimized data latency and protection of IP sensitive production data. The application of this method is not limited to detecting anomaly in semiconductor robots, it can be applied to any industrial robot of interest.

A patent application has been filed on this work (U.S. Application No. 15/721,473). Patent pending.

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