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# Towards Online Health Monitoring of Robotic Arm

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**Abstract:** Robot arms exhibit complex dynamic behaviours as their joints move at different angular speeds, acceleration, torques, and rotation at various angles. These operations differ from that of rotating machines, which often move at fixed continuous speeds. Since the majority of health monitoring strategies have been designed for the latter, it is a challenge to develop a reliable and intelligent health monitoring system for robots that addresses the non-stationary nature of their signals; often requiring synergy of instrumentation, analytical and information technologies with knowledge and experience in design, operation and maintenance. This article presents preliminary findings regarding the extraction of crucial components from data obtained from an industrial robot arm, with the ultimate goal of designing a multi-sensor measurement system for online health monitoring. This approach serves as an alternative to the conventional method that relies on vibration signal analysis for detecting anomalies and predicting remaining useful life (RUL), when integrated with machine learning techniques. The primary aim of the proposed system is the online identification of operational anomalies, deterioration, or damage that may adversely affect the arm's reliability and safety. To achieve this goal, the measurement system can employ wavelet analysis and decision trees to accurately track each joint of the robot arm during operation.

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*Keywords:* Condition monitoring, sensors prediction methods, remaining useful life, machine learning.

## 1. INTRODUCTION

Robot arms face increasing demands on their performance, reliability and product quality [Bi et al. (2020)]. In the course of their development and operation, industrial systems must grapple with the challenge of optimizing productivity while simultaneously accounting for multiple factors, including efficiency, production costs, resource utilization, and energy consumption. This is critical to ensuring that the system meets the sustainable manufacturing requirements of Industry 4.0 [Psarommatis et al. (2022)], that has led to several innovations in sensor research, diagnostics and monitoring processes. Some of these innovations are attributed to time series modelling, Fast Fourier Transform and time-frequency analysis, to monitor the online health of the system and to make Remaining Useful Life (RUL) predictions [Piccoli et al. (2020); Moreira et al. (2018); Gonçalves et al. (2011)]. However, sensors are typically wired, often mounted inconveniently. Another problem is processing the large amount of data collected. As a result, there are two challenges:

- An adequate measurement technique;
- Implementation of fault recovery activities.

Model-based solutions in the digital era require going beyond typical monitoring methods to real-time processing, e.g., by calculating various model coefficients or during the operation [Candy (2005)]. However, for practical purposes, it might be difficult to apply physical process complexities. An alternative is to use data-driven methods for diagnostic systems to make predictions; albeit under some uncertainty [Khorasgani et al. (2018)]. The various aspects described above contribute to what is commonly known as the "information overload problem". While data mining and existing data reduction techniques can address this issue, more sophisticated measurement and data processing approaches are necessary to effectively capture and account for the diverse operating conditions and behaviors of complex industrial systems. Dalzochio et al. advocated that a key component for health monitoring in modern systems requires the integration of the big data revolution with machine learning strategies [Dalzochio et al. (2020)]. To successfully transition from raw industrial big data to knowledge-based executive actions without human intervention, it is necessary to employ various algorithms and methods that can effectively address data-related challenges and bridge the gap between advanced sensor systems. This calls for the development of novel analytical tools, including expert/intelligent systems. In the mechanical domain, the emergence of "fully coupled systems" facilitates the utilization of data analysis and intelligent decision support tools to predict potential failures [Cheng et al. (2019)]. Health management in robot arms can be considered a representative example of such studies. E.g., Vamsi et al. demonstrated the application of a wavelet-based feature extraction technique to process raw signals and simulate the non-stationary load profile experienced by a wind turbine [Vamsi et al. (2019)]. The efficiency

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of this approach was evaluated under both stationary and non-stationary loads using a Support Vector Machine (SVM) as the classification technique. Such investigations verify the diagnostic capabilities of signal analysis. The RUL prediction problem has also been studied by combining SVM and AutoRegressive and Integrated Moving Average (ARIMA) based identification methods for real-time monitoring of manufacturing processes [Kozlowski et al. (2020)]. While the overall objective was condition estimation with uncertainty analysis, sensor data management played an important role to construct the classifier for fault assessment and the RUL prediction. Despite these developments, literature claims that operation-level predictive models are still in their infancy, especially for industrial IoT applications. This is because of: differences in features, the black-box nature of AI, different levels of designer skills, etc., indicating that there is not a universal criterion [Khan and Yairi (2018)]. There is a need for a more effective process, that also considers the dynamic response of the system under different conditions. It should be emphasized that while various articles showcase simulated results that align with experimental measurements, such outcomes are typically obtained under laboratory conditions that do not directly mirror the actual industrial setting.

In light of the aforementioned challenges, this study aims to develop an instrumentation system that integrates wavelets and decision trees for effective health monitoring. The success of this system will depend on its ability to swiftly process data and generate highly-accurate models for assessing the condition of the robot arm. This research is a collaborative effort between the authors and the automotive production industry, which typically incurs high operating costs due to quality control of manufacturing processes. Furthermore, conventional methods of ensuring quality through destructive testing do not offer a definitive guarantee. Hence, the study seeks to explore ways of enhancing the supervision of technological processes by incorporating additional sensors. As robot arms necessitate suitable sensing for positioning and holding components in a workstation, the findings demonstrate the potential of a specialized system for critical health monitoring processes. The following sections describe the theoretical background, data processing and experimental setup. Finally, prediction errors achieved with the use of different signal sources are presented and compared.

## 2. TOWARDS INTELLIGENT HEALTH MONITORING

Robotic systems are tasked with performing a variety of repetitive tasks, resulting in continuously varying loads and speeds on their joints. Addressing this challenge requires a two-stage approach, as depicted in Figure 1. In the first stage, the focus is on capturing the robot's operation and analyzing the resulting vibration signals to extract relevant features. To achieve this, a wavelet-based technique is utilized to identify the condition-sensitive features. Subsequently, threshold levels are determined based on the extracted signals from the robot in a healthy state. This process is repeated for faulty conditions. In the second stage, the focus shifts to diagnosing the type of fault based on the data obtained in the first stage. This study presents a two-stage approach for monitoring and diagnosing faults in robot joints, which are subjected to continuously varying loads and speeds during repetitive tasks. The first stage involves capturing the vibration signals of the robot's operation and analysing them to identify relevant features using a wavelet-based technique. This is followed by the determination of threshold levels based on the extracted healthy state, which are then compared to those obtained from faulty conditions. In the second stage, a decision tree algorithm is trained to classify and diagnose the type of fault from the detected data. To achieve this, the robot is programmed to move each joint independently, and vibration signals are collected and analysed using the Discrete Wavelet Transform (DWT) due to its ability to analyse non-stationary signals. The proposed approach offers a reliable and accurate way of monitoring and diagnosing faults in robot joints.

### *2.1 Analysis with Discrete Wavelet Transform*

Wavelet analysis has been recognized as a valuable tool for detecting singularities or anomalies in signals. One significant limitation of the Fourier Transform (FT) in analyzing signals is its inability to capture the temporal and frequency information of non-stationary signals. This limitation can be illustrated in Fig. 2 by considering a signal with four different frequencies, present at all times, as depicted in the top-left image. The frequency domain response of this signal is shown in the top-right image. In contrast, the bottom-left image in represents the same signal with four different frequencies, but each frequency exists at a different time. The frequency response of this signal is shown in the bottom-right image. Despite the fact that the two signals have the same four frequencies, the FT cannot distinguish between them because it does not provide any information on where in the time series each frequency component exists. In contrast, the DWT decomposes a signal into its sub-bands using a cascade of high-pass (HP) and low-pass (LP) filters, as shown in Fig. 3. This decomposition can effectively capture the temporal and frequency information of non-stationary signals. The accuracy of DWT depends on the choice of basis function employed in the analysis. The commonly used basis functions have two properties that make them useful for health monitoring, as highlighted in [Akujuobi (2022)]:

- Their compact support: Wavelets with compact support have non-zero values only in a finite range, making them computationally efficient and suitable for analyzing signals with localized features;
- Their ability to act as band-pass filters: Wavelets can extract specific frequency components from a signal, which is useful for tasks such as noise reduction and feature extraction. The width of the frequency band that a wavelet can pass is determined by the extent of its support.

In practical terms, the DWT decomposition method is capable of examining local variations in a signal across multiple frequency bands and scales. For example, if there is high-frequency noise with a large amplitude superimposed on a low-magnitude shift over a longer period, the transform can effectively separate these two scales and detect the baseline shift. In contrast, many other techniques

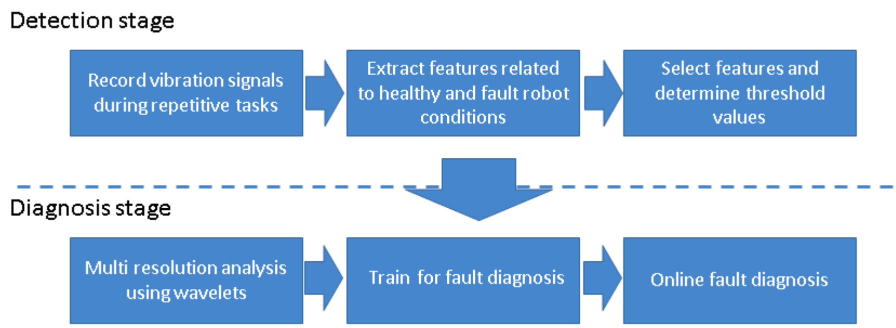


Fig. 1. The proposed strategy for intelligent health monitoring

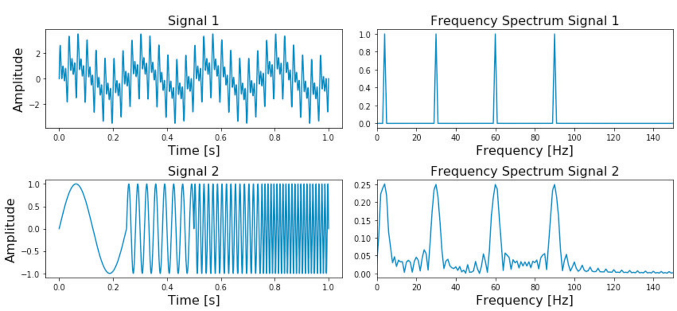


Fig. 2. The figures illustrate waveforms consisting of four frequencies that are constantly present (top), and four frequencies that occur at distinct time intervals (bottom), along with their corresponding frequency spectra.

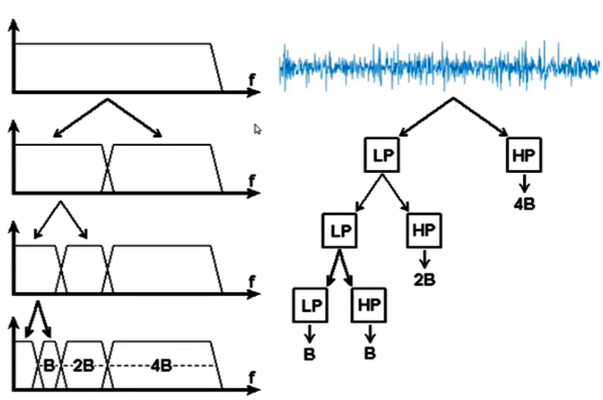


Fig. 3. Using wavelets on a time series

are unable to detect such a shift, which could indicate an important event for the analyst. Therefore, the ability of the DWT method to detect and separate signals at different scales and frequency bands makes it a powerful tool for signal analysis in various applications, including health monitoring. In contrast to methods that solely rely on frequency analysis, the compact support of the DWT makes it well-suited for processing non-stationary data. By applying the DWT, specifically the variant known as the 'Maximum Overlap DWT' or 'shift invariant DWT', to a dataset, it becomes possible to detect anomalies or change points. The lower-frequency sets of coefficients are analyzed to identify significant shifts in the baseline, indicating the occurrence of a long-term change under any noise. This feature makes the DWT an effective tool for detecting changes in non-stationary data, where conventional frequency-based methods may not suffice.

The methodology behind DWT signal classification is based on the concept of dividing a signal into various frequency sub-bands using DWT. If the different types of signals exhibit distinct frequency characteristics, then this difference in behaviour should be manifested in one or more of the frequency sub-bands. After computing the approximation and detail coefficients to various levels of decomposition, the features related to the frequency bands in each level, such as mean and standard deviation, can be extracted by reconstructing the coefficients. These features can then be used as input for a classifier, such as a Decision Tree, Neural Network, or Random Forest, which can be trained to distinguish between different types of signals. The choice of wavelet family and the order of the mother wavelet can significantly affect the outcome of DWT-based signal processing. Different wavelet families have different properties, such as the number of vanishing moments, frequency localization, and regularity. In vibration signal analysis, the Daubechies wavelet family is a popular choice as it has good frequency localization, smoothness, and a finite number of vanishing moments. The order of the mother wavelet determines the number of filter coefficients that are used in the decomposition process. In this context, the Daubechies order 2 mother wavelet, which has four filter coefficients, has been found to be particularly sensitive to robot faults. Jaber et al. (2018) demonstrated that this wavelet was effective in detecting different types of faults in robot joints, such as gear and bearing faults, using vibration signals. Therefore, it is a reasonable choice for the current study that aims to diagnose robot faults using vibration signals through DWT analysis [Jaber and Bicker (2018)].

## 3. EXPERIMENTAL SETUP

The Yaskawa GP series robot arm, depicted in Figure 4, was employed in this investigation. These arms are intended for high-speed assembly, packaging, and general handling tasks, and have a variety of movements. The arm is divided into three sections: the hand, the forearm, and the upper arm. This model, specifically, has a vertical multi-joint (6 degrees of freedom) with a horizontal and vertical range of approximately 700mm and 1300mm, respectively. Its maximum payload is around 8 kg, and it is outfitted with a 3-kg gripper tool that is included in the payload. The elbow joint is an essential component of the robot arm as it serves as the connection point

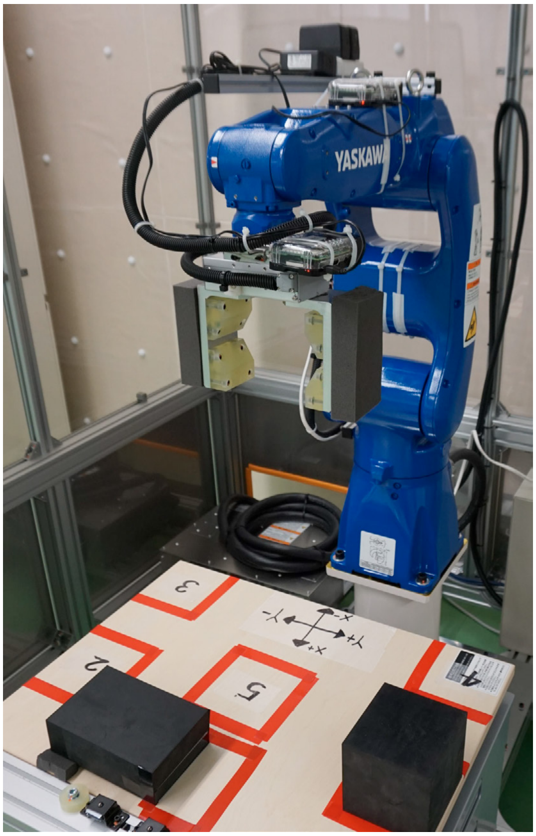

Fig. 4. The robot arm

between the forearm and upper arm. It allows the robot to perform various tasks by regulating the direction and speed of rotation. The joint's performance, however, may deteriorate over time due to a variety of factors, such as poor teeth contacts, noise, and external vibrations. When these issues arise, they can impact the overall performance of the joint, resulting in unwanted movements and errors in the robot's output. One common issue is the degradation of gears, which can lead to momentary jerks whenever the shape of the gears changes. These jerks cause differences between the robot's output and input commands, leading to movement errors. Therefore, it is important to monitor and detect any degradation in the gears or other components of the elbow joint to ensure the robot's optimal performance. The introduction of a fault in a system can occur when the system is subjected to a particular task for a prolonged period of time. Eventually, a fault is developed. However, this process is time-consuming and inefficient for experimental purposes. To simulate faults in the robot arm's joints, controlled faults are introduced by adding weight and removing gear teeth to create stiffness. The reduction in contact between gears is expected to cause an increase in vibration levels. This approach allows for the controlled introduction of faults, which can be observed and analyzed for fault diagnosis and prognosis purposes. To examine the vibration patterns in both healthy and faulty states, the robot arm is fitted with three accelerometers, one each on the hand, forearm, and upper arm. Signals are recorded while the arm carries a payload through six predetermined locations, as indicated in Figure 4. One complete cycle of this motion consists of the following steps:

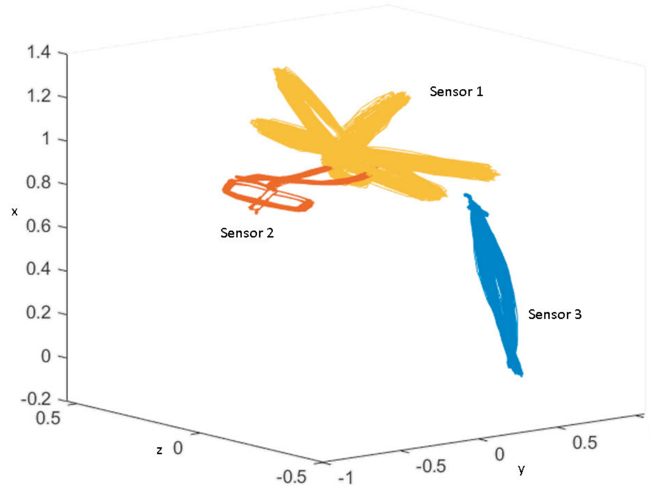


Fig. 5. Sensor data

(1) Lift the payload at place A.
(2) Drop the payload at place B.
(3) Lift the payload at place B.
(4) Drop the payload at place A.

During the pick and place task, the data is collected with two types of anomalies: a physical anomaly, which is introduced by adding weight and removing the gear tooth to simulate stiffness, and a configuration change, which is achieved by manually changing the joint angles. The data collected with and without these anomalies is summarized in Table 1. The primary objective of collecting this data is to have a sufficient amount of data that represents the robot's operation in both healthy and faulty conditions. This data can be used to develop and train a machine learning model that can detect anomalies and classify them as healthy or faulty conditions.

Table 1. List of data collected during the pick and place task

| Type | Description | |
|---|---|---|
| Physical | added weight | 1200 grams to upper arm |
| | | 1200 grams to lower arm |
| | Change payload | 2200 grams |
| | | 600 grams |
| | | 0 grams |
| | Joint Gear tooth | 0% removed |
| | | 25% removed |
| Configuration | Change program | Position (30 cm) |
| | | Trajectory (straight) |
| | Base angle | +90 degree |
| | | -90 degree |
| | Gripper tool weight | 8000 grams |
| | | 0 grams |

## 4. ANALYSIS AND FEATURE EXTRACTION

In order to establish some boundary limits for the healthy state, the pick and place task was repeated multiple times. Various features were computed from the collected signals, such as root mean squared, standard deviation, and kurtosis. These features have been commonly used in the literature and are known to be sensitive in detecting changes in signals. A comparison was then made among these features to identify the sensitive one for this particular study

[Arfaoui et al. (2021)]. In Fig. 5, the vibration behavior of the healthy robot arm is depicted, where sensors 1 and 2 are highly influenced by the robot's motion, while there is no significant horizontal motion detected by sensor 3. This implies that the acceleration caused by the rotation of the forearm and upper arm generates high-frequency vibrations, whereas the angular movement of the forearm produces centripetal acceleration in the Y direction, affecting the Y-axis signal. To investigate the effects of faults on the vibration behavior of the robot arm, Figs. 8-10 display the healthy and anomalous responses of the three sensors when the gear tooth is removed by 25%.

Upon analyzing the sub-signals obtained from the DWT, we found that the approximation signals obtained for sensor 3 were primarily associated with the motion of the robot arm, rather than its vibration components. As a result, the approximation signals were found to be of little value in providing useful information about faults in the robot. However, in the case with sensor 1 and 2 for the 25% broken gear tooth, the DWT sub-signals revealed a difference in amplitudes, where the faulty conditions produce lower values. This finding suggests that the sub-signals from sensors 1 and 2 could be used to extract features such as statistical values (e.g., standard deviation and mean) and used for classification purposes. However, instead of extracting statistical features from each signal, the DWT-specific frequency bands are isolated to identify their fundamental frequencies. These frequencies are then analyzed and compared to the baseline frequency observed in the healthy state. The hypothesis is that any deviation in the computed frequencies would indicate the presence of a fault in the system. To achieve this, an FFT is computed for each frequency band generated by the three sensors for different robot scenarios. The resulting frequencies produced in all bands are then analyzed and compared to the frequencies observed in the healthy state. Any differences in the frequencies can then be used as an indication of a fault being present.

## 5. CONCLUSION

This article presents a preliminary study on the development of an integrated health monitoring solution for robotic arms using 3-axis sensors. The collected data is used to study the behaviour of the robotic arm under both healthy and faulty conditions. While several datasets have been created, this paper only presents the analysis of the healthy state and a scenario where a gear tooth is removed by 25%. The objective is to identify the key sub-bands of the DWT, which can be used as features for classification using decision trees or other neural networks. The study confirms that the proposed approach is suitable for monitoring robotic arms with various sensors to study their motion and detect changes between normal and non-stationary conditions. The results demonstrate the potential for isolating faults using DWT-based subband analysis. Furthermore, the study highlights the applicability of the proposed approach for analyzing non-linear behaviours. Possible future work includes expanding the analysis to include other fault scenarios and evaluating the effectiveness of the proposed approach for a wider range of robotic arm configurations.

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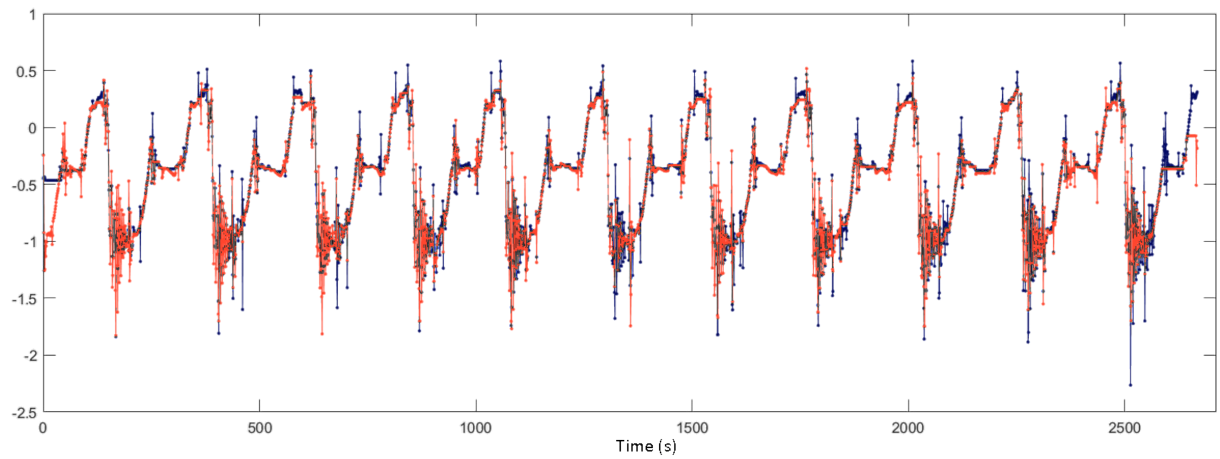


Fig. 6. Sensor 1 data: healthy response (blue) and anomaly 25% tooth removed (red)

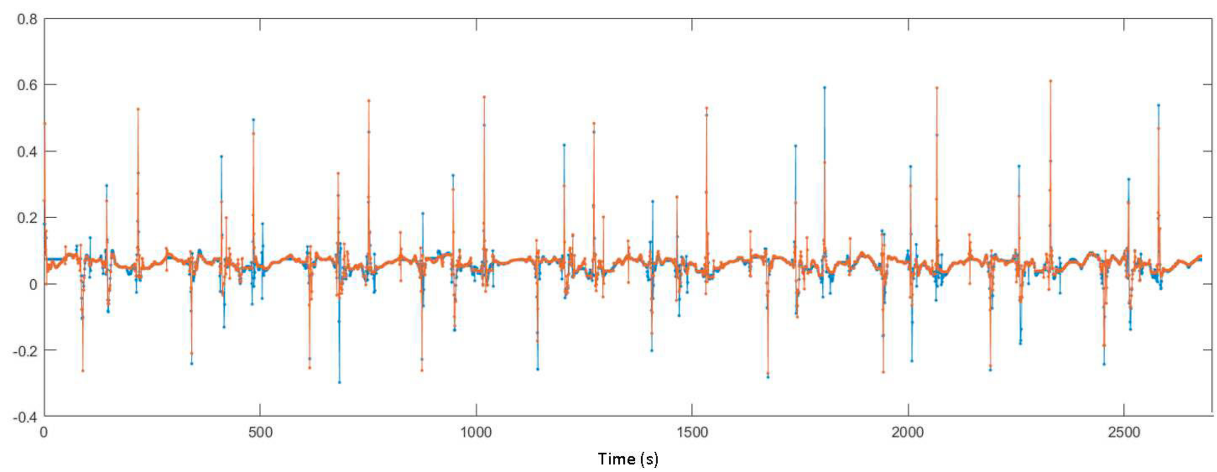


Fig. 7. Sensor 2 data: healthy response (blue) and anomaly 25% tooth removed (red)

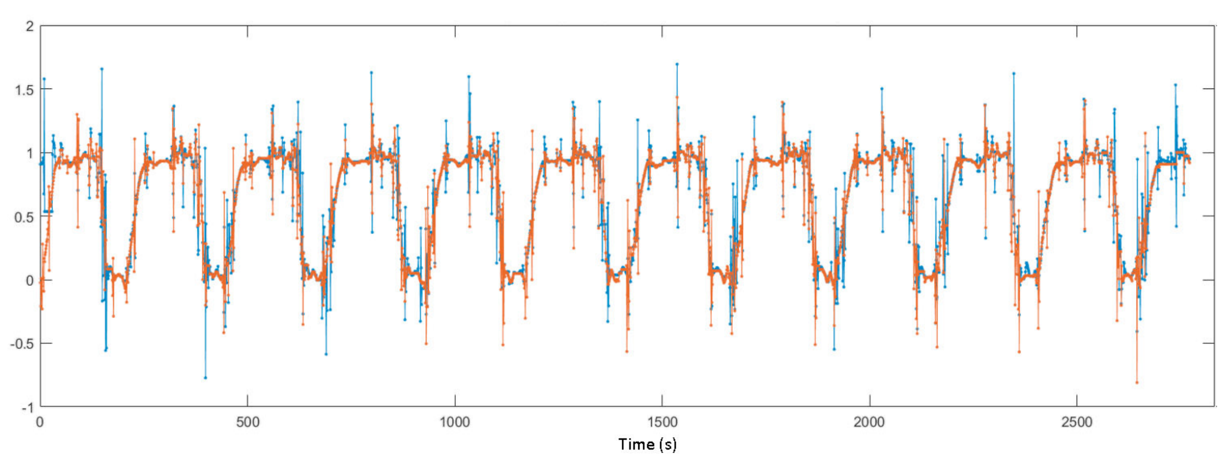


Fig. 8. Sensor 3 data: healthy response (blue) and anomaly 25% tooth removed (red)