Towards Predictive Maintenance: an Edge-based Vibration Monitoring System in Practice

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***Abstract*—Due to the high acquisition and operation cost of industrial machinery, the cost-effectiveness is highly influenced by the quality and continuity of their production. In this context, Predictive Maintenance emerges as a maintenance strategy aiming to maximize uptime by constantly monitoring a quantity related to the machine's health, such as vibration patterns, in order to perform maintenance stops only when strictly required. The implementation of this strategy, however, faces multiple challenges. One of them is related to the design, installation and operation of the sensoring systems required, which are subjected to budget constraints and also technical constraints such as sensor battery lifetime. Another challenge is given by the intelligence required for analysing real-world data generated within uncontrolled industrial environments and producing a machinery health indicator from it. This work illustrates a vibration monitoring system currently operating in a textile manufacturing machine; proposes a versatile Anomaly-Detection-based procedure for the analysis the real-world data produced by such systems and extraction of a machine health indicator from it; and also proposes an extension to the system in order to adapt it to the connectivity requirements set by the current context of Industry 4.0.**

***Index Terms*—Predictive Maintenance, Anomaly Detection, Vibration Monitoring**

I. Introduction

A. The Way to Predictive Maintenance

Here I will include the first few paragraphs of the thesis in a shorter form.

1) Vibration analysis - a glimpse into the condition of rolling machinery: Here we talk concretely about vibration.

B. Associated challenges

This will also be a resumed version of the respective part in the thesis.

C. Industry 4.0 - Enabling Predictive Maintenance

Here we can make a generalization of the term Industry 4.0 to say that it brings not only connectivity but also encompasses the intelligent data analysis philosophy. We can, for example, talk about Anomaly Detection here.

II. Related work

Here I will present some articles and other sources about vibration analysis and talk about their shortcomings which we intend to overcome. I will also write about some cases where PM wa0s sucessfully implemented.

III. Concept - Data analysis techiques

The vibration monitoring solution proposed in this work employs a range of techniques within the realm of data and signal analysis. This Section is dedicated to summarize them.

First, in Section III-A we present a discussion about the field of machine vibration analysis, which is required in order to gain insights into how to interpret the vibration signals and learn which of its features can be correlated to the machine's condition.

In Section III-B we present an overview of the signal processing techniques which must be implemented in the data processing pipeline in order to extract the desired features from the vibration signals.

In Section III-C we discuss the data clustering techniques used to identify and segregate the potentialy multiple operational modes presented by the machine under study.

Finaly, in Section III-D we explore the AD concept and discuss about how to use the Multi-Variate-Gaussian-Distribution to implement AD in the scenario at hand.

Figure 1 presents an overview of the techniques discussed in this Section.

A. Vibration Analysis

In the context of PM of rotating machinery, vibration analysis is widely considered the single most important technique available [1]. It is a powerful method for monitoring the

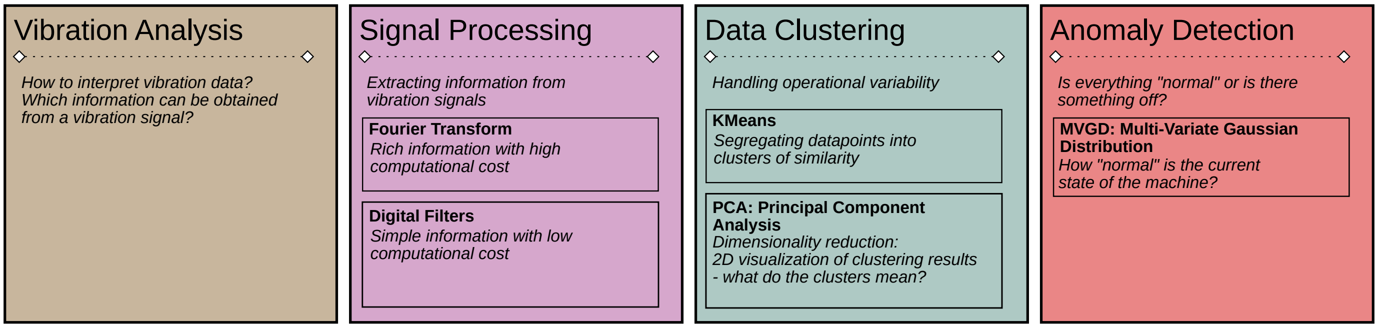

Fig. 1. Overview of the techniques employed in the data analysis.

general health of an equipment by indicating the onset and/or presence of many fault mechanisms, including [1]:

- Shaft misalignment
- Rotor unbalance
- Mechanical looseness
- Bear and gearing damage/degradation
- Inadequate reassembly after maintenance

In order to carry out this kind of analysis, the process starts with the aquisition of vibration signals of the machine under test by means of a vibration transducer. Then, the vibration waveforms can be analysed by multiple techniques. In the simplest approach, one takes into account that, in general, vibration in rotating machinery is to be avoided. Although it is physically impossible to have a rotating machine without producing, the intensity of this vibration should be kept within acceptable levels dictated by the mechanical structure of the machine and the environment where it is located. Thus, the Root Mean Square (RMS) value of the vibration signal is a useful indicator of the machine condition.

This approach gives little to no indication of what the root cause of an underlying problem might be. A more sophisticated approach is the frequency analysis of the vibration waveform. The decomposition of the vibration signal into its frequency components is explained in more details in Section 3.2.1. Once the frequency components are obtained, one can associate the amplitudes over the frequency spectra to the frequencies where mechanical problems such as the ones listed in this section are expected to appear. Also, while the frequency indicates the source of the vibration, the amplitude indicates the severity of the problem.

The process of associating specific mechanical problems to a machine's vibration frequency spectra involves knowledge of a plethora of characteristics such as bearing and gear geometry and materials, type of grease, maintenance history and so on.

A basic characteristic is the rotating speed of the motors. A very common type of motor used in industrial rotating machinery is the four-pole three-phase electric induction motor [2]. This type of machine presents a mechanical rotation slightly below half that of its alternate current electric supply. Thus, for a 50Hz network, we expect a peak around 25Hz for rotating machinery which employ such motors. Thus, for the case of machine speed control by means of the motor, the position where the peak around 25Hz appears is directly related to the speed the machine is being operated at. This is specially useful, as the machine's speed can exert a high influence on its vibration pattern, and thus the vibration analysis should take the machine's speed into account [3].

B. Signal Processing

In order to extract the features from the vibration signals, a set of techniques from the realm of signal processing must be employed. In this section, we describe two techniques: the *Fourier Transform* and the *Digital Filters*.

1) Fourier Transform: The Fourier Transform is a mathematical transform widely used to decompose a time-function into multiple sinusoidal functions distributed over a frequency spectrum. The result of this transform is then not based on time, but on frequency [4].

In the discrete-time case, the FT is called Discrete Fourier Transform, which is expressed as:

$$X_k = \sum_{n=0}^{N-1} x_n e^{\frac{-j\omega kn}{N}} \quad (1)$$

Due to the discrete-time nature of the sampled signals used in signal processing, there is a time-difference T_s between any two consecutive samples. Such T_s value is called *sampling time*, and its inverse $f_s = 1/T_s$ is called *sampling frequency*. As stated by the *Nyquist-Shannon sampling theorem*, the highest-frequency component in the image of $G(\omega)$ will have frequency $f_s/2$ [5]. Thus, the sampling frequency f_s of a signal defines the highest frequency component that can be obtained by the Fourier Transform of this signal.

Just like the input signal is of discrete-time, the output signal is of discrete-frequency. The time-resolution of the input signal is equivalent to the sampling time T_s and is thus determined solely by the sampling rate f_s. The frequency-resolution Δf of the output, however, is influenced also by the number N of the samples in the input signal and is expressed Equation 2:

$$\Delta f = f_s/N \quad (2)$$

Rich but expensive information. Explain how to extract a specific range.

2) Digital Filters: Digital filters are algorithms applied to sampled signals to reduce or enhance specific frequency ranges contained in them.

Similarly to the FT, the input to a digital filter is a time-domain signal. The output, however, is another time-domain signal, not a frequency-domain decomposition. This output signal contains, idealy, only the frequency components within specific ranges called cuttoff frequencies, which are embedded in the filter's mathematical description. Briefly explaining, ideal filters work by applying a zero-gain to the frequencies to be removed from the signal, which are called the stop-band, and unity-gain to the frequencies to be preserved, which are called the pass-band.

In contrast to ideal filters, real-world filters presents undesired characteristics such as a transition band, which is a gradual reduction of the gain between the frequencies to be preserved and the ones to be rejected. Other undesired characteristics are ripple and phase distortion. Figure 2 illustrates the transition band and ripple characteristics in a low-pass filter, which is characterised by a single cuttoff frequency, with the stop-band being all the frequencies above the cuttoff frequency, and the pass-band the ones below it.

The non-idealities of a filter implementation can be reduced by increasing the filter's complexity, at the cost, in the digital case, of more computations required. Other trade-offs are presented by the filter's topology, as this choice can result, for example, in a narrower transition band at the cost of a higher phase distortion.

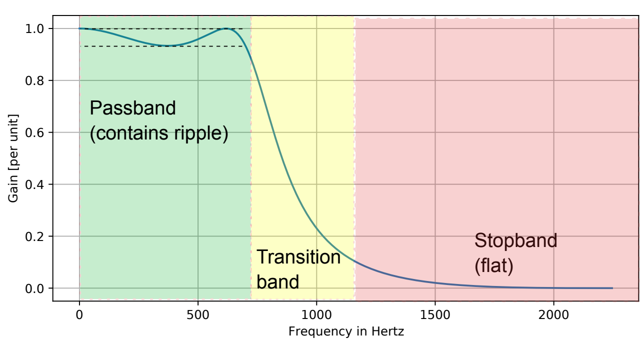

Fig. 2. Example of a frequency response of a non-ideal low-pass filter

C. Clustering

In statistical data analysis, the term "clustering" refers to the task of dividing a group of data points into subgroups, also called clusters, of data points which are considered similar according to some specification.

In this context, the concept of "similarity" can be defined in different forms. A simple and intuitive method is the Euclidean distance between the data points, meaning that points located close to each other are considered similar.

As already explained in Section 1.1, industrial machinery usually presents different operational modes. These different types of operations produce differences in vibration signals which must be taken into account in the analysis of the acquired signals. This work then makes use of clustering techniques in order to identify aggregation patterns in the vibration signals which can be associated with different operational modes.

This section then describes two specific techniques employed in the clustering task in this work: the K-Means algorithm and the Principal Component Analysis.

1) K-Means: K-Means is a simple and popular technique within the realm of data clustering. This technique works, in essence, by identifying a certain number of positions around which the data points tend to aggregate themselves and then labeling the data points according to the closest of the positions of aggregation identified.

Figure provides an intuition for the working principle behind this technique. It illustrates a toy example with multiple datapoints which aggregate themeselves in two clusters. The objective of K-Means is to find points C_A and C_B, namely the centroids, which minimizes the WCSS, which is determined as per expressed in Equation 3:

$$WCSS = \sum_{i=1}^{m} l_i^2 \tag{3}$$

where m is the number of points in the dataset and l is the Euclidean distance between each point p_i and the nearest centroid to it, as per Equation 4:

$$l_i = min(dist(C_A, p_i), dist(C_B, p_i)) \tag{4}$$

The K-Means technique does not specify the number of clusters in the data. This is an information that must be given as an input to the problem. However, this information is usually not known beforehand, and figuring out how many clusters the underlying patterns in the data present is actually part of what is expected of a data clustering procedure. The Principal Component Analysis, presented in the next session, comes into play in this task by facilitating that humans apply their expertise to identify patterns visually.

2) Principal Component Analysis: Principal Component Analysis is a data dimensionality reduction technique widely used to represent data with more than three dimensions in a graphical way in two or three dimensions. This enables humans to use their sense of vision to try to find insights in the data.

The intuition behind this technique can be explained as applying a change of basis in the data, where this new base is composed of vectors that point in the directions of maximum variance in the data. These vectors, also called Principal Components, are hierarchically sorted based on how much of the total data variance they explain.

Such principal component vectors are equivalent to the eigenvectors of the data's covariance matrix, and the variance explained by them is directly related to their associated eigenvalues [7]. Thus, the math behind PCA can be summarized by building a linear transformation matrix with the eigenvectors of the covariance matrix and then applying this linear transformation to the data in question.

The data's covariance matrix C, of dimensions $m \times m$, where m is given as per Equation 5:

$$C = \frac{1}{m} \sum_{i=1}^{m} (x^{(i)} - \mu)(x^{(i)} - \mu)^T \tag{5}$$

D. Anomaly Detection

Anomaly Detection (AD) is a term used to refer to a number of mathematical techniques which aim to detect outliers in datasets.

These techniques can be summarized in two basic pillars:

1) Providing a mathematical model that captures the underlying patterns in a dataset
2) Using this model to declare if a given datapoint conforms to the model-associated pattern or not, that is, if it is a normal or an anomalous point

1) The Multi-Variate Gaussian Distribution: The Multi-Variate Gaussian Distribution is an extension of the Gaussian Distribution in which the data-points have more than one dimension, in addition to taking to account the correlation of the variables in the dataset for the determination of the probability that the point belongs to the distribution.

This calculation is based on the covariance matrix C, already presented in Equation 5. The data-point's probability is given by Equation 6:

$$p(x|\mu, C) = \frac{1}{(2\pi)^{n/2}|C|^{1/2}} \exp\left(\frac{1}{2}(x-\mu)^T C^{-1}(x-\mu)\right) \tag{6}$$

IV. Hardware implementation - Data aquisition setup

The vibration monitoring hardware and software infrastructure used in this work was developed by the company DELTA Systems and is installed in a textile manufacturing plant in the city of Malatya in Turkey.

The hardware setup consists in a set of 85 wireless vibration sensors, which are all installed in a same machine and communicate with 2 gateways over radio. Figure 3 depicts one of the sensors attached to the referred machine.

The wireless electronic sensors are embedded systems controlled by a microcontroller. The microcontroller program is written in C language, and the compiled machine code is stored in the microcontroller itself. The system also comprises an external flash memory used to store vibration measurements for later analysis and/or transmission.

An important challenge related to the operation of the sensors is their energy autonomy. Due to the small form factor of their sensors, the space available for their battery supply is limited, so that the sensor operation, defined by their firmware application code, must ensure that energy-intensive operations, such as the radio communication, are used as seldom as possible.

Fig. 3. Textile machine with electronic sensor attached (Source: DELTA Systems GbR).

The gateway modules are embedded computers with a linux operational system. They run an application written in Python, which is responsible for interacting with a SQLite database, communicating with the field sensors over radio, and also providing a graphical user interface which can be accessed via TCP/IP based connection from a desktop computer connected to the same network.

An overview of this hardware, firmware and software infrastructure available to the vibration monitoring setup is depicted in Figure 4.

V. Results and discussion

A. Data Exploration

Explain vibration signals: Length, sampling rate, axes.

B. Clustering: Segregation of Operational Modes

C. Approach to Anomaly Detection

D. The Way to the Internet of Things

VI. Conclusion

Acknowledgment

Who should we thank?

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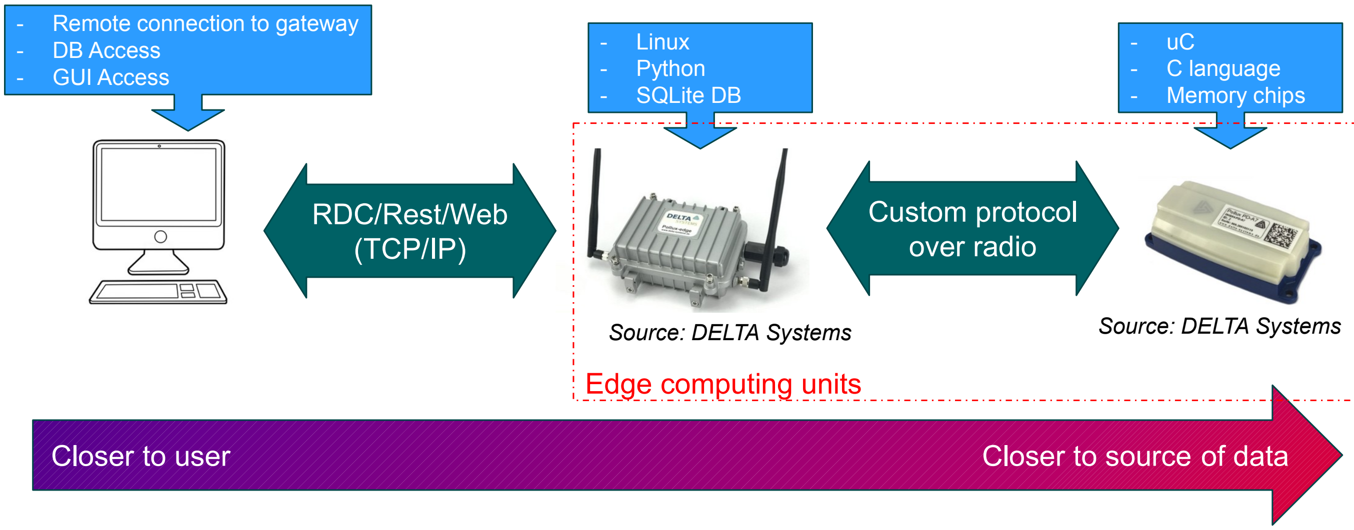

Fig. 4. Overview of the system's architecture.

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