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Procedia CIRP 38 (2015) 53 – 57

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The Fourth International Conference on Through-life Engineering Services

Condition monitoring in the cloud

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Abstract

Due to the very high demands on availability and efficiency of production systems and industrial systems, condition-based maintenance is becoming increasingly important. The use of condition monitoring approaches to increase the machine availability and reduce the maintenance costs, as well as to enhance the process quality, has increased over the last years. The installation of industrial sensors for condition monitoring reasons is complex and cost-intensive. Moreover, the condition monitoring systems available on the market are application specific and expensive. The aim of this paper is to present the concept of a wireless sensor network using Micro-Electro-Mechanical Systems – MEMS sensors and Raspberry Pi 2 for data acquisition and signal processing and classification. Moreover, its use for condition monitoring applications and the selected and implemented algorithm will be introduced. This concept realized by Fraunhofer Institute for Production Systems and Design Technology IPK, can be used to detect faults in wear-susceptible rotating components in production systems. It can be easily adapted to different specific applications because of decentralized data preprocessing on the sensor nodes and pool of data and services in the cloud. A concrete example for an industrial application of this concept will be represented. This will include the visualization of results which were achieved. Finally, the evaluation and testing of this concept including. implemented algorithms on an axis test rig at different operation parameters will be illustrated.

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Keywords: Condition monitoring; algorithms; wireless sensor network; classification

1. Introduction

Due to the very high demands on availability and efficiency of production systems and industrial systems, condition monitoring is becoming increasingly important. The use of condition based maintenance approaches to increase the machine availability and to reduce the maintenance costs, as well as to enhance the process quality, has increased over the last years.

The installation of industrial sensors is very costly and can be demanding due to cable communication issues and access to the component under consideration. These are also too expensive and need additional hardware and software, in order to enable communication, data acquisition and conditioning for additional applications, such as condition monitoring.

Moreover, the condition monitoring systems available in the market are cost-expensive and mostly designed only for application specific use. The implementation of a wireless sensor network for condition monitoring applications can increase the adaptability and flexibility of its use for manifold applications. They will enable the distributed data preprocessing, feature extraction and classification on the sensor node. Furthermore, intelligent algorithms for fault detection and diagnosis can be implemented on the sensor node level, which allows decentralized data processing [1].

In addition, the main industrial sensors available in the market are wired and very expensive, and have normally little or no intelligence. Therefore, the industry sensors are less

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doi:10.1016/j.procir.2015.08.075

suitable for many condition monitoring applications. In comparison, Micro-electro-mechanical systems (MEMS) sensors are cost-effective, highly integratable. Besides, they consume less energy and are highly configurable [2,3].

2. Vibration sensor based on MEMS accelerometer for condition monitoring

The most common technique used for condition monitoring of wear-susceptible rotating components is the diagnosis based on vibration data (e.g. acceleration or acoustic emission) [4,5]. In a research project, a MEMS based wireless sensor network for fault detection and diagnosis was used [6]. A condition monitoring application of a ball screws in industrial plants using wireless sensor concepts is published in [7].

In [8] the suitability of the MEMS for condition monitoring applications was investigated. The results obtained were satisfactory and confirm that MEMS sensors can be used to acquire data for condition monitoring. However, their range of application is limited, for instance, because of the sensitivity to humidity.

Nevertheless, the use of MEMS sensors with associated development board, such as Raspberry Pi 2, Arduino R3 and Beagle Bone Black for monitoring of wear-susceptible rotating components can be an alternative to the very expensive condition monitoring solutions available on the market, which use industrial sensor data.

3. Concept of the wireless sensor network

To increase the machine availability and reduce the downtime as well as the maintenance costs, a wireless sensor network for condition monitoring is installed. It is composed of four individual nodes, which can act independently from each other. Each of these nodes disposes of a MEMS temperature and vibration sensor. A MEMS digital output motion sensor with 3-axes "nano" accelerometer is used. The specification of this sensor is showed in the table 1.

Table 1. The MEMS Sensor specification 1.

MEMS sensor LIS3DH specification	
Measuring accelerations with output data rates from	1 Hz to 5 kHz
Wide supply voltage	1.71 V to 3.6 V
Ultra low-power mode consumption	< 2 µA
Dynamically selectable full-scale	±2g/±4g/±8g/±16g
Data output	16 bit
Operating range	-40 °C to +85 °C
Shock survivability	10000 g
Digital output interface	I2C/SPI

Fig. 1 shows a simplified schematic structure of the wireless sensor network, which is implemented on the axis test rig.

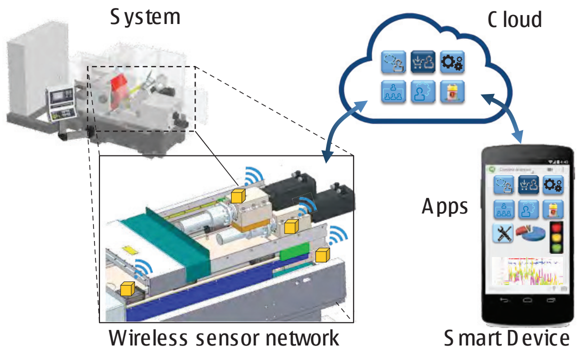


Fig. 1 Wireless sensor network on the production system.

The concept presented in Fig. 1 consists of the wireless sensor network, which includes a MEMS vibration sensor, a minicomputer (Raspberry), the cloud (including services) and a smart device for remote access and visualization.

The data acquisition and processing is realized on the sensor node level. Furthermore, the classification of the features extracted from the diagnosis signal is transmitted to the cloud server. On the cloud server there are applications and services available for maintenance planning, remote condition monitoring, etc.

Via smart device the service technician or maintenance planner can receive the reports generated using a condition monitoring processing unit. This allows remote continuous monitoring of the production system and enables condition-based maintenance decision making of the system concerned.

4. Distributed condition monitoring on wireless sensor network and in the cloud

The steps of pattern recognition on the sensor node include data acquisition, signal preprocessing, feature extraction and selection and classification.

Firstly, the vibration data are collected using a MEMS vibration sensor with a sampling rate of 3000 Hz.

In the second step, the raw data are preprocessed using different methods, such as low-pass filtering and Fourier transform. Then, the features from the preprocessed signals are extracted. Feature extraction can be done by calculating characteristic signal parameters. These are for example, statistical features, such as, variance, Root mean square (RMS) value, kurtosis, skewness, etc. In the next step, suitable features are selected. This step affects the classification results. Therefore, the selection of proper features can increase the Support Vector Machine (SVM) performance, which was implemented for data classification. For this reason, *sequential feature selection* method is used to identify the suitable features [9].

After the classification of the features is successfully completed, the result from each sensor node is transmitted to the cloud. If a component is damaged, it is detected and the service technician will be informed, so that the action needed can be taken. For this purpose, an application for smart devices is developed.

Fig. 2 illustrates the chosen structure of distributed condition monitoring on wireless sensor network and in the cloud using Raspberry and a MEMS vibration sensor.

The concept is designed to monitor all wear-susceptible of the feed drives, such as ball screw, recirculating linear motion roller bearings and guidance of the machine tool. Therefore, each node of the sensor network is responsible for condition detection of one of the components under consideration. The data acquisition, signal preprocessing, feature extraction and selection, and classification will be realized on each node.

In this work, four Raspberry Pi 2 modules are used as wireless senor nodes and an additional Raspberry module is configured as a local server (Cloud). This is realized using Apache HTTP Web Server, PHP5 module and a Database Engine MYSQL, which increase the reliability of the data transfer. Besides, the Raspberry Pi wireless sensor nodes and the local server are connected to the same network [10].

There is a set of rules in the cloud for condition detection of the complete system implemented. Furthermore, several services for different users are (e.g. maintenance planer, service technician) implemented.

For data security aspects, the sensor nodes are protected by a password. In addition, the functionality of the web server and the access to operating system and its files are limited.

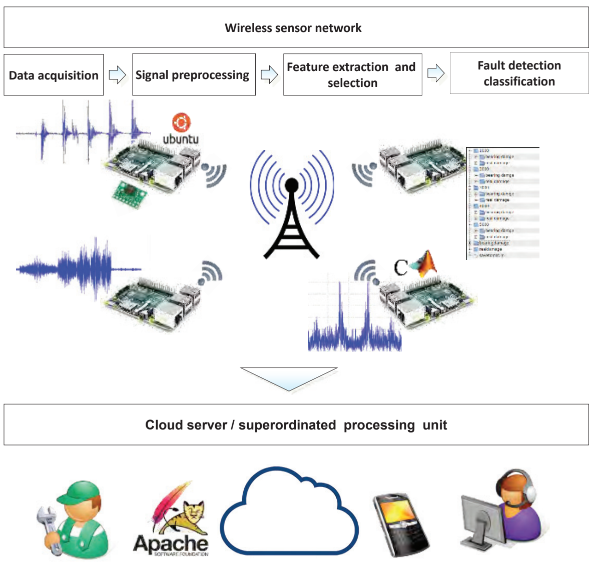


Fig. 2 Structure of distributed condition monitoring on wireless sensor network and in the cloud.

5. Evaluation

5.1. Installation of the axis test rig

In order to evaluate the solution implemented, vibration data using MEMS sensor was acquired on an axis test rig from a CNC-controlled centerless grinding machine. This test rig incorporates a top slide, an inside slide and a machine bed. Futhermore, two asynchronous motors drive the ball screws, which move the slides along the unloading axis X4, and the infeed axis and recessing axis X1 in steps of 0.2 µm. Fig. 3 shows a schematic representation of the axis test rig.

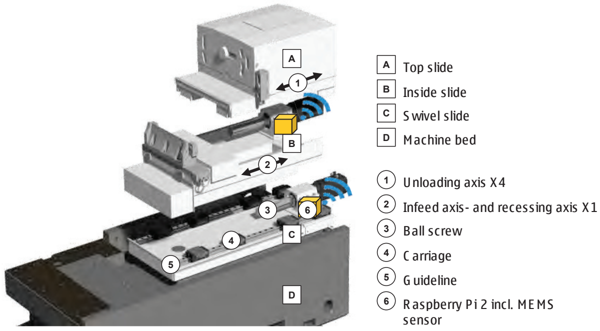


Fig. 3 Schematic representation of the axis test rig.

5.2. Data acquisition

A design of experiments was developed for the acquisition of training data in order to evaluate the implemented algorithms. For this purpose, reproducible damages were created using the Laser powder cladding method. A five-axis Trumpf TruLaser 7020, with various laser spot diameters, was used to create the faults on the surface of the spindles. In addition, a fault was created on the needle roller/axial cylindrical roller bearing spindle.

The acceleration of the spindles was measured on the axis test rig using different operating parameters during the experiments. They were conducted repeatedly under exactly the same conditions. Therefore, a CNC test program was developed.

The vibration data were measured using a MEMS sensor with a sampling rate of 3000 Hz. Fig. 4 shows the collected vibration data at 1000 mm/min and at 3000 mm/min for three different classes. It also shows the measured vibration data using MEMS sensor at the axis test rig at different operation speed.

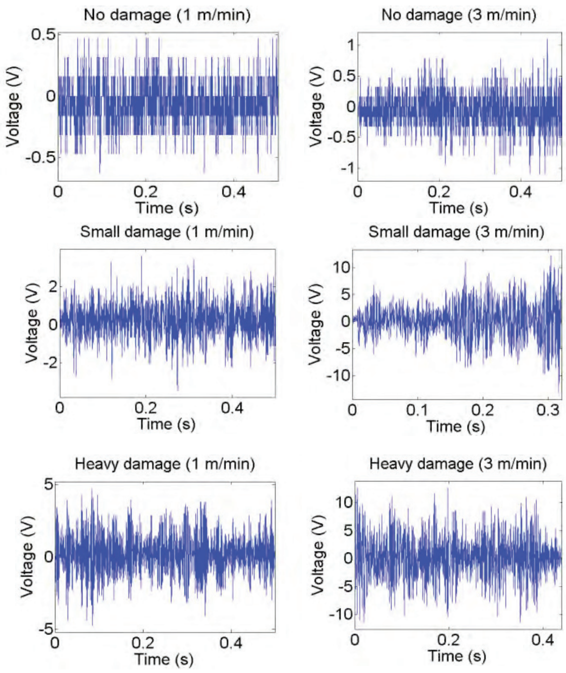


Fig. 4 Measured vibration data using MEMS sensor.

5.3. Data classification with Support Vector Machine

The feature extraction using Python is realized on the Raspberry. Python was selected to be used for this application because it is a fast programming language widely used in the field of data analysis using machine learning methods. To enable the feature calculation and classification on the Raspberry, extensions to the Python programming language such as Numpy, SciPy, Matplotlib, and Scikit-learn were used.

For the calculation of the selected features, such as statistical values (variance, mean and kurtosis) the Scipy library is used. It includes the functions for the calculation of the statistical values.

For the classification of the features extracted, a support vector machine algorithm is implemented [11]. SVM is a computational learning method based on the statistical learning theory. This function acts as an expert system SVM is based on the Vapnik-Chervonenkis (VC) Theory [12], which has recently emerged as a general mathematical framework for estimating dependencies from finite samples. VC theory combines fundamental concepts and self-consistent mathematical theory, well-defined formulation and principles related to learning. SVM is used successfully in many classification problems like text categorization, image classification, and bioinformatics.

For fault detection and diagnosis in industrial applications, SVM is developed for recognizing pattern in the collected sensor data. These are classified to predefined fault condition of the considered component [13].

The most significant benefit of SVM is higher efficiency in high dimensional nonlinear classification problems while other statistical classifiers often fail in achieving it. The idea is to maximize the margin between hyper plane and the training examples.

This can be done by finding the optimal hyper plane which has maximal margin.

After signal preprocessing, the statistical features are extracted. For the purpose of classification appropriate data is selected. The implementation of the SVM algorithm on the Raspberry is done in Python. The feature extraction and SVM algorithm was previously implemented and tested in MATLAB environment. Fig. 5 represents selected features for the classification step.

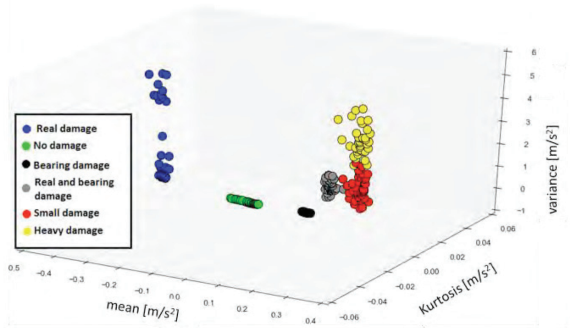
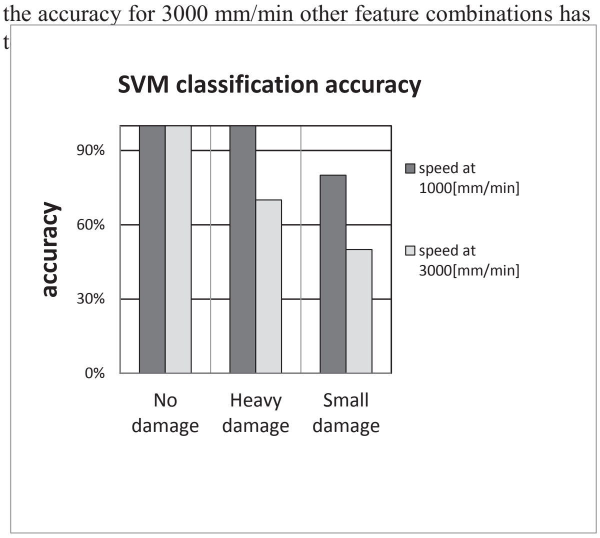


Fig. 5 Presentation of the suitable feature for the classification on the feature space.

Fig. 5 shows, that the features selected (mean, kurtosis and variance), for the classification step of the data at 1000 mm/min are correctly chosen.

The classification accuracy using different test data at 1000 mm/min and 3000 mm/min is also illustrated in Fig. 6. This displays that the features selected for the classification (Fig. 4) for all test data at 1000 mm/min is 100%. In contrast, the accuracy of SVM classification of the test data at 3000 mm/min did not reach 100% for all tested classes. To increase the accuracy for 3000 mm/min other feature combinations has t



6. Conclusion and future work

The concept presented in this paper was implemented to enable embedded data acquisition and signal processing, using Raspberry Pi 2 and MEMS vibration sensor. This allows the realization of condition monitoring solutions for different applications. Moreover, the use of this concept to design a wireless sensor network for condition monitoring applications can be used to increase machine availability and optimize the maintenance planning. In particular the use of MEMS sensors to acquire the diagnosis signals with suitable minicomputer, such as Raspberry allows quick and simple adaptation of a wide variety of industrial applications.

Furthermore, it enables decentralized data preprocessing, feature extraction and selection, as well as classification on the sensor node level. This concept can be configured for a variety of industrial applications to realize condition monitoring of components.

The concept for the wireless sensor network realized and illustrated in this paper will be installed at different machine tools with the feed axis in the Fraunhofer IPK test field, in order to validate it under several working conditions. In addition, another vibration MEMS sensor with higher sampling rate is planned to be used.

In the future research activities the implementation of different classification and clustering algorithms on the sensor nodes will be addressed. This will enable the condition monitoring steps (signal preprocessing, feature extraction and classification) of the acquired data direct on the node.

The installation of the wireless sensor network using Raspberry Pi 2 modules and MEMS vibrations sensors will reduce the costs of the installation of industrial sensors allowed an easy adaptability to different specific applications by decentralized data preprocessing, feature extraction and selection and classification on the sensor nodes and mobile provision of evaluations.

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