Development of a condition monitoring system using visual information and statistical data by application of analogue acoustic and magnetic sensors

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Abstract
Digitalization is increasingly transforming the working world. The demands on employees and entrepreneurs increase and change in this process. This process also imposes special requirements on the future generation of measuring systems. In the future, production will be largely automated and monitored in terms of quality. Easy operability, fast access to results, communication skills, self-learning and decision routines of measuring systems, and processing of big data are in the focus. The paper shows the expected changes in workplaces, developments that will result for the future generation of measuring instruments, and solutions which have already been implemented by the authors.

1. Introduction

The advent of digitalization into production poses a challenge for both entrepreneurs and employees. Companies need to adapt and evolve to be prepared for the future. This includes improvement of hardware infrastructure, use of state-of-the-art production technologies and further training for employees. Measurement systems play an important role in this development, because they represent an interface-link between production and data created by sensors and actuators. Seen in this light, they are one of the foundations for the Internet of Things (IoT) and present an opportunity for big data analysis [1]. Measurement systems also have to be prepared for the future, but mostly these systems do not meet the prospective requirements. Many measurement systems are developed to visualize their results or reduce them to a human understandable level, but do not provide access to the underlying raw data because of, for instance, missing interfaces or limitations in processing and storing large amounts of data.

The patented High-Frequency-Impulse-Measuring (HFIM) is suitable for future challenges. It allows to calculate a short-time Fourier transformation (STFT) and thus to perform a spectral analysis of a signal in real-time and is suitable for analogue data. The Fourier-transformed data is visualized in a 3D diagram with time, frequency and amplitude displayed on the axes. This way it is possible to monitor selected frequency ranges relevant for the respective production process. Mathematical algorithms allow to process and transform the raw data stream to extract information and to reduce the high data rate. This method is applicable for every signal coming from different sensors obtained in a certain range of applications. In this paper we show applications using acoustic (piezoelectric) and magnetic sensors (Barkhausen noise).
2. Initial situation

The digitalization of production does not only mean the use of computers as a decision-making aid. Rather, it is a combination of current techniques to connect machinery, storage systems and resources to a Cyber Physical System (CPS). This can be helpful to reduce the own production costs by increasing capacity utilization and also enables open customer interfaces for the production of individual products (Smart Factory) and the provision of a service on demand. Implementing these factors well can help a company to strengthen their label. There are many challenges for workers and companies concerning digitalization. As operating processes will change it is mandatory for companies to

- develop education programs to qualify workers for non-planned production,
- create the prerequisites so that production, development and planning can grow together,
- change their company structure to decentralized managing,
- combine human abilities and little technical helpers like apps, panel PCs or smart watches,
- strengthen the creativity and flexibility of their workers [2].

Moreover, entrepreneurs have to invest in their infrastructure. In addition to hardware, interfaces and modern production controls, measurement systems play an important role. Sensor and actuators produce an already vast, but still growing amount of data concerning products, machinery and facilities, which can be used for product monitoring, wear detection and optimization of supply chains. Unfortunately, many current measurement devices do not meet these prospective demands. There is a lack of adaption to

- the increasing complexity of products,
- complexity of value added chain,
- faster methods engineering [3].

The main problem is that actual measurement devices do not offer raw data for big data analysis. The provided information is restricted to 2D diagrams, tables and reports and is reduced to a human intellectual level. There is a need for the following adaptions for measurement systems in companies, for initial and further training on the subject of digitalization:

- Advanced data science and cooperation with data scientists,
- Scalable data analysis systems and superior statistical analysis,
- High data rate and innovative filter methods as well as data interfaces,
- Algorithms for automated strategic decision making,
- Identification of relevant and important data (minimizing human factor),
- Combination of data analysis, visualization of data and decision methods,
- Pattern recognition or classification methods for data sets,
- Use of real-time data [2].
3. State of the art

Based on parallel computing and Field-Programmable-Gate-Arrays (FPGA) the patented HFIM is able to transform analogue data by short-time Fourier transformation (STFT) in real-time. After A/D conversion, the incoming signal is sampled at up to 100 MHz. Every 1,024 samples the corresponding frequency spectrum comprising 512 discrete values is calculated. With the use of multiple oversampling one spectrum is computed every 43 µs. The short-time Fourier transform is visualized using a 3D diagram with time, frequency and amplitude displayed on the axes. This method can be applied to monitor production processes with piezoelectric or magnetic sensors [4][5][6].

Using a piezoelectric sensor as uniaxial vibration sensor, HFIM reflects process behavior in different frequency ranges. These provide information about acoustic behavior of process or machinery (< 20 kHz), friction behavior of tool-component contact (up to 400 kHz) and also high-frequency friction during plastic deformation (up to 1,000 kHz). Even crack events in components during production can be monitored as impulse-like signals with frequency-broadband behavior and a high amplitude during the first few milliseconds. Fig. 1 shows data recorded during a cutting process for car body components. The sensor is mounted to the lower tool. Measurement was started as soon as tool and blank holder were closed and finished after reaching bottom dead centre. The upper part of Fig. 1 shows the signal prior to short-time Fourier transformation, with time displayed on the horizontal and amplitude on the vertical axis. It is not easily possible to detect the abnormality in the last third of the process because the high-frequency signal indicating tool breakage is superimposed by the low-frequency machine noise. After STFT certain frequency ranges corresponding to, e.g., background or unwanted machine noise can be filtered out and thus the signal to noise ratio (SNR) can be increased significantly. Other applications that can be monitored are straightening and bending, wire drawing, plastic injection molding, welding, tool wear and many more [7][8].

Fig. 1: Top: Amplitude vs. time diagram sampled with 100 MHz with a low SNR. Signal data come from a cutting process with tool breakage in the last third of the process. Bottom: The same signal after STFT. Spectral analysis facilitates filtering out the low-frequency machine noise and thus facilitates detection of the high-frequency signals indicating the defect.

Condition monitoring using a magnetic sensor is based on the principle of magnetic Barkhausen noise. An alternating magnetic field interacts with domains of a
ferromagnetic material. These elements are separated by so-called Bloch or Neél walls and describe areas of a homogeneous magnetic moment, which are also areas of the same magnetic direction. If the external alternating magnetic field reaches a distinctive strength, it causes different magnetic effects. The magnetic moment of already well-oriented areas aligns with the orientation of the outer field. Equally oriented areas grow by shifting the Bloch or Neél walls. This growth leads to a superposition of the external and the internal increasing magnetic field, because more and more areas are in the same orientation. The total magnetic field is strengthened until all areas are equally oriented (saturation). The movement of Bloch or Neél walls causes an inductive electric current that is recorded by the sensor. The strength of the electric current depends on the density of effective magnetic imperfections. These imperfections are types of carbon distribution in the crystal lattice, grain size or residual stresses. Fig. 2 illustrates the effect of the outer magnetic field in form of the magnetic hysteresis and the resulting changes in magnetic domains.

![Figure 2: Magnetic hysteresis loop and corresponding changes in a ferromagnetic material due to the alternating external magnetic field \( H_T \). Right: Barkhausen noise signal and the same signal after STFT.](image)

### 4. Data analysis tools

Piezoelectric and magnetic sensors generate huge amounts of measurement data (the original signal data as well as the Fourier-transformed signals) on potentially multiple channels if, e.g., several piezoelectric sensors are attached to different parts of a machine or tool at the same time. Moreover, there is information from the actuators and occasionally video data that allows for aligning the sensor data with the process. In order to evaluate the measured data appropriately and particularly to establish condition monitoring for a new type of production process further data is required. For instance, if the objective is to identify damaged work pieces based on acoustic sensor data, information about process quality like the current scrap rate, results of visual inspection of individual work pieces and/or findings of a laboratory analysis are needed. These are related to the sensor data and provide clues as to which signal characteristics indicate faulty process behavior. For machine or tool wear detection, information about the machine state, adjustment of machine parameters, if the machine has been serviced, if parts were replaced etc. is needed and compared with long-term trends in the sensor data. For determining the hardness of materials using magnetic sensors and Barkhausen
noise analysis the hardness (for example Vickers or Rockwell) of at least two reference work pieces is required for calibration.
In sum, heterogeneous data from many different sources, which in part might arrive delayed (e.g., results of laboratory analyses) need to be collected, organized, stored in a data base and made available in a format suitable for further analyses.

4.1 Condition monitoring using piezoelectric sensors

In order to establish condition monitoring, relevant features of the sensor data that indicate anomalies or are related to certain kinds of errors or defects in the production process need to be identified. This on the one hand requires knowledge and experience of experts who can provide detailed information about the sequence of actions in the process, typical defects and their possible sources, relevant frequency ranges or any confounding variables that have an influence on the signal data recorded by the sensors, but are not directly related to the defect of interest. On the other hand, a close cooperation to statisticians or data scientists is needed who, using design of experiments (DoE) and state-of-the-art data mining and machine learning tools, can help to gain new insights into the process. The QASS measurement system provides many tools for pattern recognition and is equipped with a visual work- and data-flow design software that allows for quickly building a data analysis chain tailored to the process at hand (cp. Fig. 3).

It offers many pre-processing options for the measurement data, which is an important first step in the analysis. These include filtering out or diminishing the intensity of the signal in certain frequency ranges, calculating compressions to reduce the amount of sensor data while preserving the information and smoothing methods such as moving averages in time and frequency to reduce the variation in the data.

In order to gain insight into a new type of production process and to better understand the structure of the emitted signals we can monitor the energy in the Fourier-transformed sensor data and identify subsequences where an energy threshold is exceeded. The detected energy patterns can then be subjected to further analyses like clustering. Clustering on the one hand helps to find frequent patterns in the sensor data that reflect typical process behavior, also known as motif detection [9], and on the other hand identify outliers and anomalies that warrant further investigation. Fig. 3 shows the result of clustering energy patterns found in a deep-drawing process based on their length and energy using the OPTICS algorithm [10], which reveals three abnormal patterns. If the acoustic emissions of a production process are already well understood we can perform a targeted search for signals that are known to be related to defects. As an example we discuss crack detection, which for instance plays an important role in straightening. The formation of a crack causes an impulse-like signal, i.e., a sudden increase in amplitude over a broad range of frequencies, followed by a slower decay. In straightening of steel shafts, the typical length of a crack signal pattern is about 20 ms, with the high-amplitude phase taking about 3-8 ms. A simple recipe for crack detection is to monitor the energy in all frequency bands and alarm if a certain threshold is exceeded for a specific time over a broad range of frequencies. However, there can occasionally occur electric or other disturbances that also manifest themselves as broadband signals in the 3D landscape and thus might not be distinguishable from cracks by simple energy monitoring.

In order to improve crack detection, it is beneficial to search the data stream for sequences that not only match a crack signal in energy and length but also in shape. Pattern search works via a sliding window approach that continuously compares the Fourier-transformed
data in the window with the reference pattern of interest and returns a normalized similarity in the range from 0 to 100%, cp. Fig. 4. The calculated similarity is invariant towards deviations in length and amplitude up to a user-specified level in order to account for fluctuations in process speed and loudness. The sensitivity of the pattern search can be controlled through a similarity threshold, which must be exceeded in order to consider a pattern as detected.

Fig. 3: Left: Visual program for energy detection in a data stream. Right: Clustering of patterns identified by energy detection in data from deep-drawing processes showing three abnormal results.

For crack detection we typically search for one or more crack signal patterns (to account for further variations in shape not covered by time and amplitude scaling) and optionally one or more noise patterns that correspond to known disturbances. Based on the results of the pattern search the decision about whether an alarm is issued is made as illustrated in Fig. 5.

Fig. 4: Pattern search of a crack signal. Stored reference pattern (top) and matching sequences identified in the data stream (bottom)

In the four graphs in Fig. 5 similarity, energy and length of detected crack (NOK) and noise (OK) patterns are plotted as indicated by the axis labels. The red regions mark ranges where an alarm is triggered, while green regions correspond to regular process behavior.

- If only one of the crack signal patterns is found its energy and length are checked (chart 4). If these are in a typical range for a crack signal (red area) an alarm is issued.
• If only a noise pattern is detected it merely causes an alarm if it has unusual energy and length (chart 1).
• If both types of patterns, crack and disturbance, are found at the same time (as illustrated in Fig. 5) the similarities are compared in a first step (chart 2) to decide about the type of signal (crack or noise). The final decision whether an alarm is triggered is then based on either chart 1 or chart 4, depending on the result from chart 2.

The decision boundaries can be edited and in this way it is easily possible to integrate expert knowledge.

Fig. 5: Decision process for detection of cracks.

Additional to searching for crack signal patterns and known disturbances an energy analysis (see Fig. 3) can be performed. If an energy pattern is found at the same time as one or more of the already known patterns it is simply ignored. If in contrast no known pattern is detected at the same time, energy and length of the energy pattern are plotted to chart 3 in Fig. 5 and an alarm is triggered if these are in an unusual range. This enables the system to get to know previously unknown process emissions.

Moreover, when establishing condition monitoring at a new machine, initially known crack signal patterns and noise patterns coming from a different plant or machine are used as reference objects in pattern search. Under certain conditions, e.g. if a found pattern is confirmed to be a crack or noise event, it can be appended to the list of reference patterns or replace one or more of the default patterns in order to fine-tune the pattern search to the process at hand.

4.2 Hardness testing and anomaly detection using magnetic sensors and Barkhausen noise analysis

The sensor measures the inductive current caused by Barkhausen noise. After short-time Fourier transformation there result regular bumps in the 3D landscape as shown in Fig. 2. For hardness testing the energy of each bump is computed after filtering out noise bands and related to the hardness of the material. Given that other material parameters remain unchanged there is a linear relation between the calculated energy and the surface hardness. In order to learn this linear mapping at least two reference work pieces with
known hardness are required. After calibration the surface hardness can be determined for further work pieces. Additionally, a number of qualitative analyses are possible, for instance testing for mixed-up components or detection of heat treatment defects like grinding burn on the surface of a work piece.

5. Conclusion and outlook

We presented background information and future demands on measurement devices, challenges for entrepreneurs and employees and a survey of data analysis tools for condition monitoring using acoustic (piezoelectric) and magnetic sensors. Our measurement system efficiently processes large amounts of sensor data and offers access to the raw data as well as any kind of results. While for the most part analysis and monitoring run automatically, there are still adjustments (e.g. specifying the similarity threshold, allowed scaling factors, energy threshold, settings in data preprocessing) that need to be made manually and require expert knowledge. Future work will entail to optimize those values automatically.

References

4. DE 101 37 364 A 1 (Patent specification)