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Process Segmented based Intelligent Anomaly Detection in Highly Flexible Production Machines under Low Machine Data Availability

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Abstract

Anomaly detection is a key feature to monitor production systems an avoid downtimes, which has still not been implemented holistically. Especially in highly flexible plants or special process machines, conventional approaches like neuronal network classification or intelligent autoencoder fault detection are not suitable firstly due to the small amount and secondly due to the lack of labeling of data for each process. In this paper a novel concept is presented to segment different processes intelligently in the first step to find fine granular process patterns across process boundaries. Based on these patterns, anomaly detection and further classification are performed. A special feature is the integration of user knowledge, so that classification is possible even with a small amount of data. This approach is validated on an assembly line for electric motor production as well as in a handling robot. This paper shows results from real test series and thus demonstrates the practical suitability of the novel approach.

Keywords: fault detection; condition monitoring; machine learning; machine tools

1. Introduction

The failure of machines as unscheduled machine downtime is still one of the largest cost factors in production [1]. A machine failure can lead to a standstill in production and thus the loss of supplies. Furthermore, defects in machine components can also lead to quality problems of the finished products [3]. Monitoring systems are therefore used to detect faults in the machine or in the process [2,4]. Monitoring systems for process monitoring, for example, and the associated increase in plant availability and quality have become established in production in recent years [5]. In addition to conventional monitoring systems, which are based on user-defined intervention limits, new machine learning applications are also being introduced [5]. The best known representative of monitoring systems is anomaly detection [6,7], which can be executed both unsupervised [8] and supervised. Anomaly detection, which makes anomalies visible, is the precursor to condition monitoring. The goal of these applications is the detection of abnormal behavior of the machine and the feedback of this information to the user. Instance maintenance strategies, such as predictive maintenance [9], can then be connected to this process. Supervised anomaly detection, which is based on classification methods, usually requires a large amount of data for training. For this reason, these methods are often used in large series or on rigid production lines where only small process deviations can be tolerated [10]. Especially in small series production, down to single part production, often only a few data points exist which can be used for training. In addition, there is a great heterogeneity of the data, due to the constantly changing requirements of the components [11]. In general, measurement data is recorded via additional implemented sensors at the corresponding effective point in the machine. Additional acceleration or force sensors are often used [12,15].

The mentioned heterogeneity of processes for small batches or in highly flexible production machines is one of the biggest

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problems when using anomaly detection [13,23]. Usually, the amount of available data from one process is not sufficient for robust training of the algorithms. When using conventional rule-based approaches for anomaly detection, fixed defined rules can become very complex for highly flexible production machines and are not applicable for fast and efficient response [14]. Furthermore, industrial anomaly detections require the use of external sensors in the machines [15]. Especially in brown field applications, the use of expensive additional sensor technology is often not economical. Also, the heterogeneous machine architecture and the lack of standardization of data formats and control access in the brown field is a major challenge in the application of anomaly detection in flexible production systems [16].

In this paper, a novel approach is presented to apply anomaly detection in flexible manufacturing plants. The core of this work is the upstream segmentation of processes and their characteristics in an entire data stream [14,17]. Based on this segmentation, anomaly detection is performed to find faults in various production plants. The anomaly detection is based on already existing data of the plant. The functionality of the approach was demonstrated within the scope of an experimental validation on a highly flexible handling robot and an assembly process in electric motor production.

2. State of the Art and Research Deficit

In the field of intelligent anomaly detection, many publications are released [9]. In research papers, a distinction is usually made between Brown Field and Green Field applications. The biggest challenge regarding Brown Field anomaly detection is the data acquisition and data provision from different types of machines and controllers [16]. Especially the high-frequency data supply of e.g. motor currents of the axes or process forces and torques has not been standardized so far. In addition, a heterogeneous machine park has different wear levels of machines and their components, which results in a significant increase in signal variance [18].

Pattern Recognition & Anomaly Detection

Pattern recognition as a means of identifying identical machining segments represents a young field of research and has only received attention in literature since the turn of the millennium. However, the interest and intensity of research activities have been exceptionally high since then [19].

Approaches for extracting and recognizing patterns of a fixed pattern length and a variable pattern length must be additionally subdivided. Exact algorithms possess the disadvantage of being designed for a fixed pattern length and due to high computational complexity, are not considered applicable for variable pattern lengths [20]. In addition to pattern prediction approaches, deep learning methods have also been proposed for time series classification based on approaches such as Long Short Term Memory (LSTM) or Convolutional Neural Networks (CNN) [21].

The consideration of multivariate time series, as they are usually found in production machines, is required. This aspect is considered in some works, but has not been the focus of pattern recognition research so far.

Many different approaches to anomaly detection in time series can be found in literature. Both k-Nearest-Neighbor--based methods and neural network approaches are used in recent research [21]. However, the approaches considered there do not fulfil the requirements in the context of online anomaly detection on highly flexible production systems like machine tools or robotic kinematics. Major deficits are:

- Streaming data: A concept is needed that can process the streamed sensor data.
- Real-time capability: It must be possible to process the streamed data in real time and online
- Multivariability: it must be possible to analyze not only univariate but also multivariate time series in the form of sensor data.
- Transient and continuous anomalies: The approach must be able to detect both transient and continuous anomalies.

3. Approach of Intelligent Anomaly Detection

The aim of the intelligent anomaly detection approach is to develop an online-capable algorithm which identifies recurring machining segments and classifies them as a reference. This means there are at least two recurring signal courses. In this way, the algorithm should detect faults during machining or a component loss in the robot handling application. These faults are reported back to the user. The algorithm presented in this section is composed of four steps. Figure 1 shows the structure of the intelligent anomaly detection.

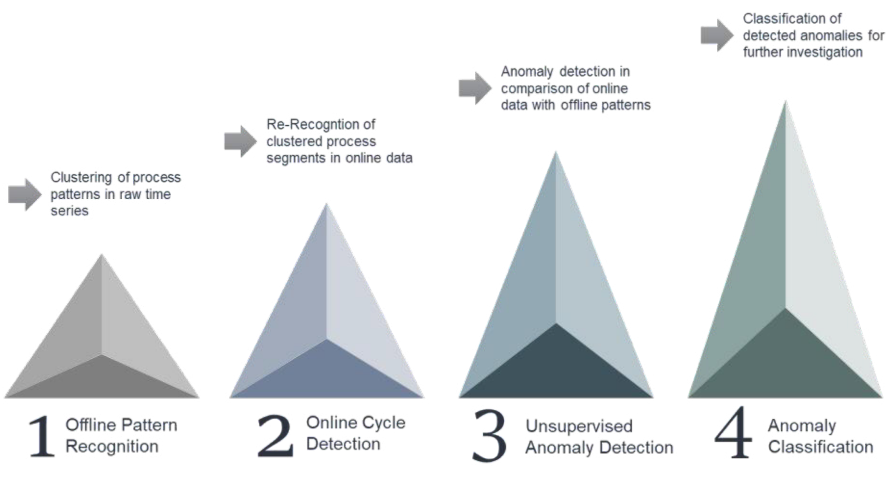

Figure 1: Structure of the intelligent anomaly detection (cf. [17])

In the first step, the raw unlabeled data from the production line is read into the so-called Offline Pattern Recognition (OPR) [17]. There, the relevant processes in the production machine are represented by splitting them into subsequences and a density-based clustering procedure using mean shift clustering. The core of the clustering method is the optimal selection of the cluster settings or the step size parameter bandwidth. An optimization procedure is used to determine the optimal parameter selection of the cluster algorithm. Based on the coverage of similar sequences, the calculation of a parameter is done with formula (1). This parameter represents the deviation:

$$representive\ deviation\ (RD) = \frac{1}{m}\sum_{j=1}^{m}\frac{1}{n}\sum_{i=1}^{n} d(\theta_{R,j}, \theta_{i,j}) \tag{1}$$

With $d(\Theta_{R,j}, \Theta_{i,j})$ as the distance between the cluster representative $\Theta_{R,j}$,the associated cluster participants $\Theta_{R,j}$, m as the number of clusters and n for the number of cycles in the associated cluster. This is initially determined for each cluster and computed in a subsequent optimization procedure. The optimal clustering is then calculated according to formula (2):

$$h_{opt\_coverage} = \frac{1}{m}\sum_{i=1}^{m} \Big[\min_{RD} \max_{n_C \to n_{C_{ref}}} h(n_C, RD)\Big]_m \tag{2}$$

With m as the number of patterns, n_C for the number of clusters, $n_{C_{ref}}$ as the number of reference patterns which are computed in a commissioning step. Therefore $n_{C_{ref}}$ equals m initially. After the various processes from the flexible production plant have been calculated using offline pattern recognition, the actual anomaly detection is performed on the basis of these patterns. The first step is the retrieval of the process occurring in the online signal via a score value [17,25]. The score value describes the deviation of the windowed area in the online signal to the patterns found in the clustering. After the correct process clusters have been selected, anomaly detection is performed. This is mainly based on the alignment of two signals by a relative comparison [14]. In this process, the online signals of the drive parameters, such as motor current, force and torque are compared with the multivariate signals already found from the clustering. Depending on the variance of the process, anomalies are output by frequency and absolute error and made available to the user via a Graphical User Interface (GUI). Subsequently, the unsupervised anomalies are classified and trained using a hybrid approach consisting of a support vector machine and an autoencoder. With this approach, anomalies found unsupervised can be classified and an anomaly label can be issued to the user. This can be used for troubleshooting as well as a feedback loop into the machine. Classification is only possible after a few anomalies have been found.

4. Experimental Validation on a Handling Robot

In the context of the validation of the described approach, an experimental setup with a handling robot is realized. The aim of the validation is to prove the functionality of the approach consisting of segmentation of the process and detection of an anomaly. Figure 2 shows the schematic setup of the handling robot including an end effector with part fixture. On the right side the movements of different tasks are shown.

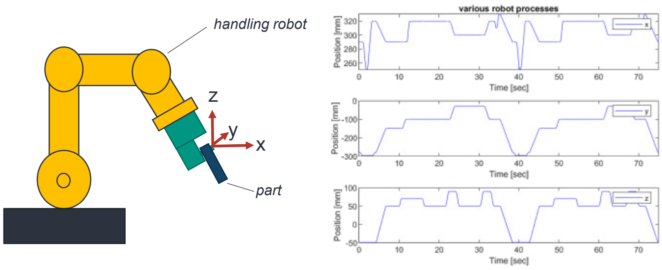

Figure 2: (left) handling robot for experimental validation, (right) position movements of the handling robots in X, Y, Z

In the experiment, 10 different movements with different velocities in X, Y and Z direction were performed. After performing 10 x 10 movements without part loss, arbitrarily selected processes were performed again but with part loss at an undefined position. The loss of the component was realized by a manual interaction at the end effector. The weight of the component (2 kg) was significantly less than the maximum load (6 kg) of the robot. Data acquisition was done via an OPC UA interface on the robot. It was possible to record 50 parameters from the respective drive motors with a sampling rate of 50 Hz. The position set values from axes 1-3 were used to determine the process via offline pattern recognition. Anomaly detection was performed on all remaining parameters, using the motor current and the calculated values of force and torque of the axes.

Results

In this validation, the functionality of the algorithm was successfully demonstrated. All parts of the algorithm were successfully executed and the component loss could be detected by the anomaly detection in the signals.

Figure 3 shows the motor torque measuring of different processes. It can be seen, that there are different signal tolerances based on different tasks of the robot. There is a part drop, which is detected by the intelligent anomaly detection automatically.

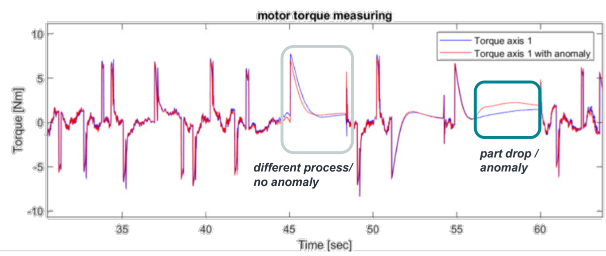

Figure 3: measured motor torque without anomaly (blue) and with part loss anomaly (red signal in green rectangle)

It can be seen that the anomalies are only very local and due to the high variance of the processes, fixed intervention limits could not be derived. The anomalies can be detected in the drive signals. The algorithm is able to investigate multivariate drive signals after matching the online data with the references from the cluster process [14]. The part drop was found independently at two points in the process and output to the user via the GUI.

The experiment shows that the approach is able to detect anomalies in highly flexible systems without complex training.

5. Experimental Validation on an Assembly Line for Electric Motor Production

To ensure generalizability and also the applicability to transfer the approach to other machines, a further validation is described. The novel approach is implemented in an electric motor production process. The machine is essentially characterized by the assembly of subcomponents in an interlinked system. The critical process step is the pressing of the magnets into the stator. Here, a joining unit from Fa. Promess [24] presses several permanent magnets into the stator. Up to now, this system has only been monitored via fixed threshold values, which a user has to set individually. The novel approach is able to ensure high availability of the system as well as to detect faults in the pressing process and to inform the user regarding quality issues. Figure 4 shows the setup of the joining unit. Synchronous position and force time series are available for monitoring the system.

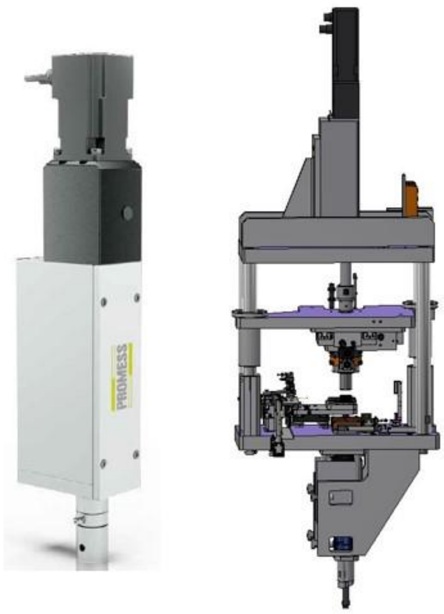

Figure 4: (left) Fa. Promess pressing unit, (right) construction figure of the magnet pressing station [24].

The offline pattern recognition used the position time series to determine the process. Anomaly detection was performed on the force time series.

Results

The functionality of the algorithm was also demonstrated in this validation successfully. All parts of the algorithm were executed successfully and the fault during the machining was detected by the anomaly detection in the force time series. Figure 5 shows the process of offline pattern recognition. A section of the position time series that was used for the offline pattern recognition is shown on the left. The relevant segments of the time series found by the algorithm are highlighted in grey. On the right the calculated representative of these segments is shown.

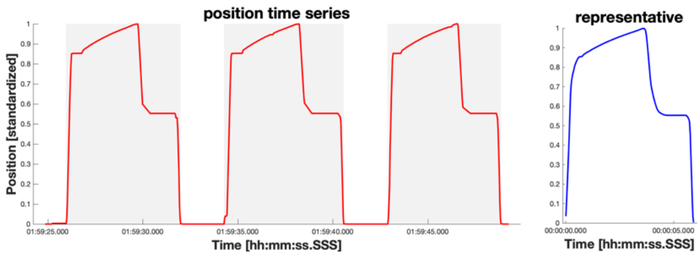

Figure 5: offline training position time series (red), relevant segments (grey), calculated representative (blue)

For each representative the algorithm calculated the process specific system limits for the force data intelligently. The system limits are enhanced by user knowledge. This led to sharp system limits even with a very small set of training data.

The online anomaly detection analysed the test data correctly. It found the calculated representatives in the position time series and checked for the force exceeding the system limits. Figure 6 shows two force time series that were mapped to the representative of Figure 5. The grey envelope shows the calculated system limits, whereas the blue line indicates the run in the force time series that was used for the anomaly detection. On the left a regular run is shown where the force signal always stays inside the envelope of the system limits. On the right the force signal of the detected anomaly is shown. The anomaly occurred in the real machine data. It was not produced by a manual interaction. In the anomaly shown, it can be clearly seen that the force signal leaves the envelope of the system limits.

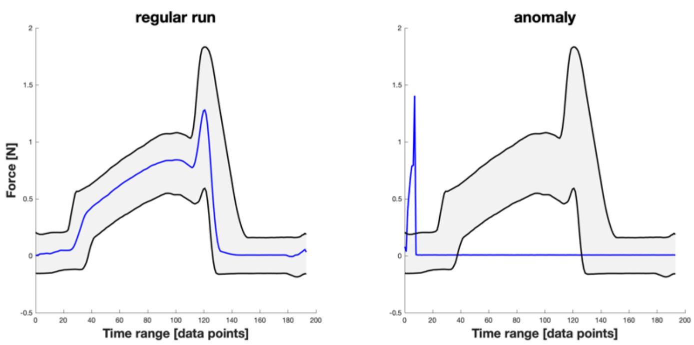

Figure 6: anomaly detection: regular run (left) and detected anomaly (right)

The results show that the algorithm is capable of detecting the occurring anomalies in the force data. The anomaly was detected and output to the user through the GUI.

This verifies the approach on real machine data. The algorithm detected the anomaly and was able to analyse the critical part in the time series exactly and correctly. It can be concluded that the algorithm can be used flexibly in different production environments.

6. Outlook & Conclusion

The research field of anomaly detection is a much studied area with many new publications currently appearing. However, research is focused on green field applications and generally on medium to large scale production. The deficit in Brown Field applications as well as in heterogeneous machinery is hardly explored.

This paper presents the validation of an approach [14,17,18,23,24,25] to realize intelligent process segmentation with subsequent anomaly detection in Brown Field applications.

Major challenges for an industrial application in this approach were identified. One is calculating multivariate signals in real-time, where specialized databases are needed as the basis for a real-time capable data pipeline, which must be developed first. Another one is the determination of the sensitivity of the anomaly detection a-priory, which is highly dependent on the noise of the signals.

Further investigations are planned to increase the computational performance as well as the latency in real-time applications. Further validation experiments on handling robots as well as machine tools are planned to ensure the generalization of the system. This will focus on finding collective anomaly types of different machines and assigning them to each other. Furthermore, classification of detected anomalies, to give recommendations for actions in the context of condition monitoring, is a field of ongoing study.

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