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Detection of Disturbances of Variable Length in Periodic Processes by Intelligent Systems

Masterarbeit

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1 INTRODUCTION

1.1 INTRODUCTION

This thesis is part of a series of experiments, to develop a method for the reliable detection of anomalies in the operation of assembly line modules. The detection of anomalies in operations of all kinds of systems plays a major role in industrial practice today. Under the keyword predictive maintenance it is an important application for Data Science processes in industrial production. By applying the predictive maintenance approach, both time-consuming routine checks and expensive preventive material renewals should be avoided. Instead, the actual condition of the plant is always monitored by a data-driven process monitoring system. This insight allows, in the best case, maintenance work to be scheduled early on in the production process. This minimizes production downtimes caused by outages or even avoids them completely by combining them with setup procedures. An important aspect that contributes to the current propagation of predictive maintenance procedures is the increasing availability of real-time machine data. They form the basis for live monitoring of the running processes and thus for early detection of wear or defects. The foundation for this data-driven process monitoring is the increasing interconnection of production plants as well as advances in sensor technology.This enables advanced applications for continuous monitoring.

There are many different approaches in research to detect anomalies. Chandola et al. [8] assign the procedures to one of three main groups. When using supervised procedures, a training record with labels for normal and abnormal data is used. On this basis, a forecast model is trained to classify unseen data points. But this method has some disadvantages. One is that anomalies are rare in most cases and therefore often are under-represented in the training data. This can lead to an underestimation of the anomalies when using machine learning methods and therefore to problems in detection [32]. Moreover, it is often a problem to create such a labelled training data set. To realize a reliable anomaly detection all possible errors would need to be known and labelled. To avoid this problem, often semi-supervised procedures are used. In this case only the normal data is labelled. The trained model should reproduce the normal behaviour of the system as accurately as possible. If major deviations from this model occur during operation, an anomaly is assumed. If an unsupervised method is used, no training data is required. This approach is therefore most generally applicable. It is based on the assumption that normal behaviour occurs far more frequently than anomalies. One possibility is to assume, that changes in an otherwise constant process are always considered to be anomalous.If the assumption of rare anomalies does not apply, a high false alarm rate will occur.

This approach to anomaly detection is the origin of the present work. A model that reproduces the behaviour of the system as accurately as possible, will reach its limits when the behaviour that is considered normal changes frequently, or is too complex to be modelled appropriately. To solve this problem, a divide and conquer approach will be tested, in which the current operating state is first determined by an upstream detection algorithm, and then malfunctions are detected by means of a state-specific anomaly detection. The state specific anomaly detection was already investigated in a previous master thesis where an anomaly detection method was developed based on an autoencoder network. The present thesis therefore deals with the comparison of different methods for the automated recognition of occurring patterns in dynamic processes.

1.2 RESEARCH PROBLEM

The present paper, therefore, focuses on the design of a multi-stage architecture to analyze the operating conditions of a belt conveyor module. The goal is to design an overall architecture that allows detecting anomalies during operation despite varying operating states of variable length. To realize this objective based on the already developed autoencoder module for anomaly detection in a fixed operating state, an experiment for the detection of operating states of a conveyor module was carried out in chapter 4. Initially, it is to be determined whether it is possible to distinguish between the operating states that occur during the operation of the module by applying clustering procedures. The corresponding investigation was carried out in section 4.4. The next phase of the proposed architecture is the assignment of the current operating state to one of the identified states by classification. This was examined in section 4.5. The research is completed by a definition of all used procedures in chapter 2 and a discussion of related scientific work on time-series clustering and the detection of operating states in chapter 3.

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CONCLUSION AND FUTURE WORK

This thesis has investigated the detection of operating states and a subsequent classification using the example of a conveyor belt module. Successfully all configured operating states of the demonstrator were detected by using time-series clustering. Furthermore, it was proven that it is possible to assign the current operating state of the system to one of the defined states without errors even under the influence of anomalies by using a random forest.

In further work it must now be investigated whether the results obtained can be reproduced in a real plant. Moreover, the functionality of the presented multi-stage architecture in its entirety has to be examined, first in the laboratory environment and then in a practical installation. The methods investigated in this work have to be combined with the findings obtained in the previous work for the detection of anomalies based on autoencoders. On this foundation, the performance of the overall system and the functionality of the presented architecture can then be examined. Further research could also be conducted on a system for adaptive detection of new operating states to solve the limitation of the fixed number of states analysed in section 5.2. Another opportunity might be to transfer research results to another problem domain and combine them with current research of related papers. For example, Liu et al.[30] have presented a method to detect the operating states of a solar system based on time-series analysis in their current work. They were able to distinguish a fault condition directly based on time-series clustering. Further investigations could reveal whether a detection of more subtle anomalies in the detected states would be possible by applying the multi-level architecture presented in this work.