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Big Data Methods for Precision Assembly

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Abstract

Industry 4.0 looks at increasing the availability of data, for example, that resulting from an assembly process. This article explores the application of these concepts to a precision assembly task to maximize the yield and machine uptime. Although traditional methods focus on data resulting from assembly, this paper will look at the full scope of available data. In conjunction with a discussion of this data, a model to describe a precision assembly process will be introduced. This model enables long term errors to be detected as well as the identification of trends enabling predictive maintenance.

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1. Introduction

Precisions assembly is a unique branch of assembly in which the tolerances between the assembled parts are on the range of less than 25 μm. Due to the extreme requirements of these tasks, the initial investment in machine and process development are very high. The tight process tolerances make the processes highly sensitive to change, where any slight deviation can result in unacceptable output. Common practice is to monitor the process output, making sure that the produced assemblies are acceptable. When something goes wrong with the process, additional defect parts need to be created to reproduce and ultimately find the error.

Within this paper a method to find these disturbances well before they become a problem is presented. First a generalized precision assembly task, its components and a brief review of the data they produce is presented. This is followed by data mining techniques and a discussion of which methods are promising to analyze this data in such a manner that deviations can be found before they are a problem. Lastly, these methods are shown on a portion of an assembly task.

The following article is organized as follows. First the available data will be introduced. Next related work and methods within data mining will be explained. This will be transferred to an assembly problem and used in an example process, to show that this approach is functional.

1.1. Data within a Generalized Precision Assembly Task

The data found in a precision assembly task can be broken down into four categories. This includes process data, machine data, environment data, and data about the assembled product. The different data sources are shown in Figure 1. Process covers data which is gathered during the production. An example could the force of setting a handled part on a substrate. One large source of data which should not be overlooked is the machine itself. These data can include the positioning error associated with the actuators, information resulting from self-tests, as well as information resulting from subcomponents connected to the assembly robot. Information about the environment includes such things as the temperature and relative humidity. Last but not least are the assembly data (product), which includes measurements about the quality of the resulting parts or information about their quality before the assembly.

Each of the presented data categories offers a large amount of data, most of which is of little to no use. Although data is becoming cheaper and cheaper to store, it is also important to consider which data do not need to be saved for long periods of time. Amongst this data there are useful elements and it is a matter of to find the useful elements amongst the rest.

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2. Assembly Systems and Data

In the previous section an introduction in available datasets to a precision assembly task was given. To get useable information out of this data, this is followed by an overview of data mining methods. Current methods are then presented, followed by an explanation of the functionality of data mining methods.

2.1. Application of Data Mining Methods

Data mining represents a set of methods which enable the extraction of knowledge from a large dataset. Such methods are not new to assembly and production tasks. The following section presents a brief look at other methods and how they have been applied to assembly processes.

An example of a data mining method is pattern recognition. This method enables trends to be found in large datasets. Based on these trends, it is possible to determine how a process is performing over a long period of time. Extending this to a precision assembly task, a substantial gain can be made if a combination of the correct data and methods can be found, which enable the health of a system to be determined. [6]

The concept of data mining needs to handle two main aspects: which data need to be saved and how to convert the saved data into useful information. In addition to actually saving the data, it is important that the data be saved in a format so that it can be evaluated at a later date, when it for example came to a failure of the product. To understand current methods and their applicability a brief review of data mining methods is presented.

An extensive review of data mining applications for quality improvement in manufacturing industries covering literature from 1997 to 2007 is presented in [9]. The review briefly describes the basic procedure of the knowledge discovery in databases (KDD) and data mining processes. The reviewed application studies are categorized into common quality improvement tasks, such as predicting quality, classification of quality, or parameter optimization. Different application studies refer to assembly processes in metal product manufacturing industries and electronic product manufacturing industries, respectively. Although some of the goals are the same, none have extended the concepts to a precision assembly task.

Using process and product data to determine how well a production process is working is not a novel concept. Other examples include a condition-based maintenance (CBM) system [10] with the main steps: data acquisition, data processing and maintenance decision-making. This paper summarizes the recent research and developments in diagnostics and prognostics of mechanical systems implementing CBM. A log based predictive maintenance strategy build with multiple-instance learning is presented in [13]. This paper presents a predictive maintenance workflow and compares this to competing methods. Further research on knowledge discovery and data mining application is presented in [1]. This paper looks at data mining in a manufacturing environment. It focuses on points like characterization and description, classification in manufacturing, prediction, clustering, and evolution analysis.

Likewise detecting predictive failures can be done by observing systems status, which was shown by [5]. Using online learning methods, a failure forecast method is presented. Here a class of decision trees, where the one with the larges reward value is chosen to predict failures in production. A large training dataset was created to make the analysis functional. It was shown that good prediction accuracy for failures can be reached by such an online system.

In the field of precision assembly, a multi-agent architecture for reconfiguration of precision modular assembly systems has been implemented. The paper developed a framework for reconfigurable and modular equipment modules [2]. This is done by creating sub-modules for each equipment part, where it is possible to combine different sub-modules to create a functional machine offset for a specified production task. Only the needed machine parts can be configured together. It is not a predictive tool but a tool to speed up system configurations in precision assembly by modelling the production process in subdivided modules.

In summery there are already many different tools for data analytics and even for predictive processes in production. But what is still missing, is to consider a production process and a related method to explore data with tight tolerances, where even a measuring error is in the order of the measured production data. Such a precise process work with a very different tolerance range. Other authors started modeling of precision processes, but do not use these models for a forecast of machine failures or necessary maintenance [2].

Another aspect which sets precision assembly apart from other assembly tasks is the comparatively small batch sizes. Consequently, only a very small dataset is available and thus the main challenge here is to create a reliable model out this dataset. This paper explores existing DM methods which can be applied to precision assembly tasks to help predict when maintenance is required.

2.2. Data Mining Methods

As shown in the last section, data mining methods have been applied to different manufacturing and assembly tasks. In addition to these methods, there are other data mining methods which are applicable to the task at hand. Following a presentation of these methods, a summary and discussion of their applicability to precision assembly is presented.

The increasing role of big data has caused continual growth within data mining methods. Some general methods which enable the data to be converted into useful information are investigated here. Tools which enable this include:

- Statistical methods such as linear regression to gain insight into trends within the data
- Clustering methods, which structure big data sets, and finally
- Expert knowledge to explicitly look for effects, for example using a lookup table.