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Intelligent pattern recognition of a SLM machine process and sensor data

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Abstract

Selective Laser Melting is an additive manufacturing process, in which the research has been increasing over the past few years to meet customer-specific requirements. Therefore, new manufacturing parameters have been monitored raising the number of sensors in the machines. Consequently, it leads to a bigger amount of data and difficulties to perform manual data analysis. In order to improve the analysis, this paper illustrates a possibility of pattern recognition using a different historical process and sensors data from a SLM machine. The results are evaluated using an intelligent tool for algorithms configuration and data analysis developed at Fraunhofer IPK.

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Keywords: Pattern recognition; data analysis; SLM; additive manufacturing; sensor data

1. Introduction

The demand for flexible and innovative manufacturing technologies at the industrial sector is increasing [1]. The Selective Laser Melting (SLM) manufacturing process has received much study in the recent years due to its capability of manufacturing metallic functional workpieces with more complex geometries than the conventional methods. Such advantages are used by companies to meet the industrial-specific requirements. By using SLM technology, the workpiece is built layer by layer, basically with metal powder and a laser device.

In order to assure the quality of the workpiece and the process, high precision sensors and actuators are used to monitor and to control important process parameters. These devices provide data from the whole manufacturing process, which can be used to understand its behaviour as a system and how each parameter behaves in different situations. However, although understanding these data is a challenging area, a major focus is given in how to produce components with new materials [2] and also in how to improve the mechanical properties of the produced components [3,4].

Using data from machines, trends can be identified and knowledge used to improve the entire process. Examples of intelligent pattern recognition can be found in [5,6,7]. In [5] an application was developed to allow analysts to detect technical problems that are evolving and to launch appropriate counter measures in terms of condition-based maintenance.

Observing such advantages, it is noticed that more work is needed in this area. Few researchers have addressed the problem of recognizing data patterns of a SLM machine. Previous analysis performed at Fraunhofer Institute for Production Systems and Design Technology (IPK) in Berlin, Germany, showed that the manual assessment is time-consuming and technically difficult to perform, but still possible to be realized.

The purpose of this work is to answer two main questions. The first one is to know if it is possible to assess automatically the condition of the machine using only one of the several monitored variables in the process, taking into account three pre-defined categories of the machine conditions. The second question is if it is possible to identify patterns (i.e. clusters) in the entire database, in absence of pre-defined categories. These assessments are performed using a tool developed at Fraunhofer IPK, which contains different data mining algorithms implemented. The results can be used to predict the machine's behaviour and to avoid future failures during a

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component manufacturing, improving, thus, the quality of the component and the process reliability.

2. Selective Laser Melting

2.1. Selective Laser Melting principles

SLM is a three-step layer-based process using a metal powder bed to manufacture a workpiece. In the first step, a thin layer of metal powder is placed on a platform using a mechanical coating system. In the second step, a focused laser beam selectively melts the top-most layer of the powder bed. Then, in the third step, the platform is lowered and the cycle begins again. Due to this particularity, complex workpieces can be built up using thousands of layers.

2.2. Parameters under observation

The monitored parameters and their units are shown in table 1. A total of 16 parameters were chosen. Parameters such as 'Platform Temperature', 'Optical Bank Temperature', and 'Process Oxygen' are the key elements of the SLM process due to their substantial influence on the layer quality.

Table 1. The chosen parameters and units.

Number	Parameter	Unit	Number	Parameter	Unit
1	Platform Temperature	°C	9	Process Oxygen	%
2	Process Chamber Temperature	°C	10	Process Pressure	mBar
3	Pump Temperature	°C	11	Filter Conditions	%
4	Process Panel Temperature	°C	12	Total Layer Time	Seconds
5	Electrical Panel Temperature	°C	13	Layering Time	Seconds
6	Optical Bank Temperature	°C	14	Idle Time	Seconds
7	Collimator Temperature	°C	15	Recoater Motion Time	Seconds
8	Environment Temperature	°C	16	Recoater Filling Time	Seconds

Other parameters influence more the time to manufacture the workpiece than the layer quality. These are considered important to the process behaviour. For instance, the 'Total Layer Time' is the parameter that measures the total time spent when manufacturing one single layer. It includes the laser time to melt the layer geometry, the time for layering (number 13 of the table 1), and the time the machine may have been stopped. The latter was called 'Idle Time' (number 14 from table 1) and plays an important role to identify whether an error occurred during the manufacturing process.

The position of the considered sensors and monitored machine components are shown in Fig. 1. The numbers are according to table 1.

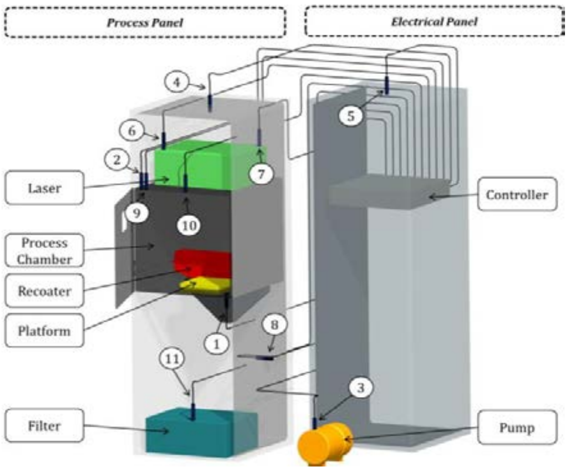

Fig. 1. Machine components and sensors position.

3. The Condition Monitoring Tool (CMT)

The CMT is a condition monitoring tool that permits an intelligent configuration of pattern recognition algorithms for fault detection and for diagnostics applications [8]. It was developed at Fraunhofer IPK and it has a modular design, which allows the user to interactively configure the algorithms via user interface. CMT composes the needed steps for a successful pattern recognition application, such as: signal pre-processing (e.g. filtering), features extraction and selection (e.g. statistical values), and classification or clustering algorithms.

4. Methodology

4.1. Overview

The performed methodology is shown in Fig. 2. At first, the raw data from the process and the sensors were acquired. Using self-implemented software, information from the process data was extracted and the sensor data was treated in order to build the database of the SLM machine.

From this point, two paths were followed. The first path, (symbol 'I' in Fig. 2) was performed to manually divide the database into three different behaviour categories. Then, a subset from each category was randomly chosen and called 'dataset 1' ('I.a' in Fig. 2). This dataset was used to train the algorithms implemented in the CMT tool described in the previous section. After training the tool, the entire database was assessed in order to observe if it was possible to classify the patterns according to the categories ('I.b' in Fig. 2). From this assessment, the results of each algorithm were compared to the manual categorization and evaluated.

The second path was to assess the machine database using the same tool (symbol 'II' in Fig. 2). Differently from the path 'I', no category was defined at this step. This was performed to observe the possibility of identifying general patterns in the database without any process knowledge. After that, an