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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.

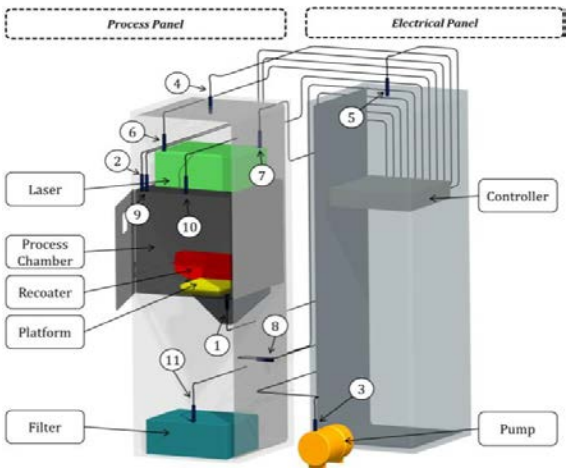

Fig. 1. Machine components and sensors position.

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

analysis of the found clusters was executed and the final results of the work discussed and concluded.

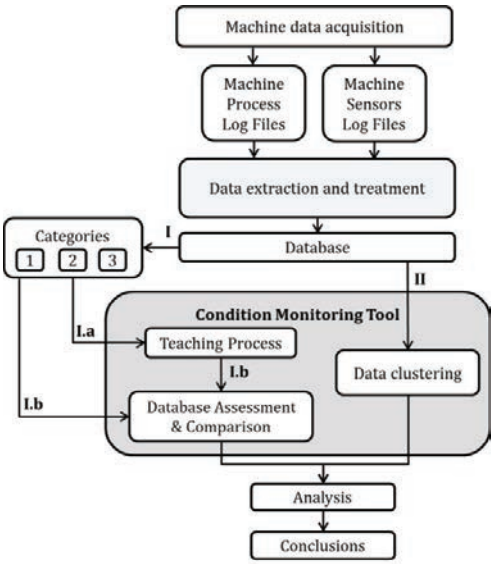

Fig. 2. Experimental approach.

4.2. Process data extraction

In order to obtain the information from the machine data, a self-implemented solution was used to extract and treat the raw data. This software transformed the machine process log files in process information. From these files, the parameters 12 to 16 from table 1 were calculated.

The parameters from 1 to 11 were obtained from the machine sensor log files. The same software read these files in order to verify if they had some data failure. When errors were found they were corrected. This step was important to avoid incorrect interpretation in further steps of the analysis.

4.3. Definition of the categories

According to the machine and process conditions three different categories were defined. They are described as follows:

- **Category 'Finished perfectly'**
  This category represents the workpiece manufacture without any kind of failure or interruption during the manufacturing process. This is assumed as the normal behaviour of the machine.

- **Category 'Finished with errors'**
  This category represents when the manufacturing process is completed, but a failure or interruption occurred during the process. When it happens, there is a possibility that the workpiece quality is worsened.

- **Category 'Not finished'**
  This category means that a severe failure or interruption occurred during the manufacturing process and the machine could not recover from this state. In most cases, the workpiece is not completed and the work is lost.

4.4. Division of the database

Using the categories from the previous section, the database with information of 271 independent manufacturing processes was divided. The database was created with machine data from the process and the sensors during the manufacturing of different workpieces with various geometries, distinct number of layers, and diverse materials (e.g. stainless steel, titanium alloys, aluminium alloys). Then, a dataset was taken from the database, which contains a total of 90 manufacturing processes data (30 from each category).

Table 2 shows how the database was divided and how the processes were distributed among the categories, according to section 4.3. Also, it shows the influence of the dataset 1 on each category and on the entire database.

Table 2. Categorized historical database manufacturing processes and the dataset 1 influence.

Number	Database – Number of processes	Dataset 1 influence (%)
Finished perfectly	103	29,13
Finished with errors	81	37,04
Not finished	87	34,48
Total	271	33,21

4.5. Implemented algorithms for intelligent pattern recognition

With the goal of training the classification algorithms from the tool of the section 3, the patterns of the three categories were taken. All categories comprise the parameters from table 1. First, the parameters from dataset 1 were individually analysed. Each parameter was examined by four different pattern recognition algorithms or classifiers. The used algorithms were Nearest Neighbour, Bayes Classifier, Neural Network, and Support Vector Machine (SVM).

The Nearest Neighbour algorithm is a simple method that can be used for classification of a feature vector to one of the known classes. This algorithm calculates the geometrical distance of the unknown vector (unknown measurement) to several next neighbours [9,10].

The Bayes Classifier is based on the Bayes decision theory. This statistical approach is widely used in the field of pattern recognition in various industrial fields, such as image and text recognition [11,12].

The use of Neural Network in the research environment is widespread. It is composed of three layers and each layer can include more than one neuron. A large number of training methods for neural network can be found and deployed for specific applications [13,14,15,16].

SVM is a modern approach in the field of machine learning, which the learn methods are based on the statistical theorems [17]. It is also a common method in condition monitoring field, as can be seen in [18,19].

After the feature extraction step, the best suitable features for the concrete application were proposed. For this purpose, the tool disposes an approach for selecting these best features depending on the categories used for the training step. This approach evaluates the separability of the different categories in the feature space with the chosen features [8].

The next step selected the features and used them as an input to train the classification algorithms. The output of the classification algorithms is the percentage of the correct classification of the unknown data to test the algorithms. The test data is part of the identified categories, which were not used to train the algorithms, i.e., the rest of the database.

4.6. Assessment of the database

After training the CMT tool each category of the parameters from table 1, an assessment of the whole database was carried out. The database was evaluated with the algorithms from section 4.5 in order to separate the processes automatically. The results are shown in section 5.1.

4.7. Data clustering

In order to verify if there were any unknown patterns in the raw database, a complete data clustering was performed. Data clustering is an important analysis to confirm if the manually identified categories were correctly separated. The cluster analysis was carried out by using the k-mean algorithms [20].

The number of expected categories in the database can be used as a parameter for the algorithm (in this case, three categories). If the number of categories is known, the algorithm provides the minimum number of groups that can be identified.

5. Results

5.1. Classification

Fig. 3 shows the classification results using four different parameters and the classifiers introduced in section 4.5 for the 'Finished perfectly' and 'Not finished' categories. The parameters 'Optical Bank' and 'Platform Time' were considered the worst ones, while 'Process Oxygen – O_2' and 'Idle Time' were considered the best ones amongst the 16 parameters.

By observing Fig. 3a, it can be noticed that the best classification was the 'Finished perfectly' category for the process parameter 'Idle Time'. On the one hand, both Bayes Classifier and SVM algorithms resulted in almost 100%. On the other, Neural Network had a result of 90% of recognition and Nearest Neighbour about 70%.

However, considering the classification for the 'Not finished' category in Fig. 3b, the parameter 'Idle Time' was not the best. With all four algorithms, the best parameter was the 'Process Oxygen – O_2' (blue column in the same figure). Although the latter was better recognized in this category, the results for all parameters were similar. The biggest difference was the 'Platform Time' using the Bayes Classifier, which reached only 22% of accuracy.

In summary, the classification from sensor and process parameters of the 'Finished perfectly' category was more successful in comparison to the 'Not finished' category. According to Fig. 3, all classification methods reached classification accuracy smaller than 60% for the 'Not finished', while the accuracy for 'Finished perfectly' was around 100%. This means the 'Not finished' category alone is not suitable enough for the process monitoring using these parameters.

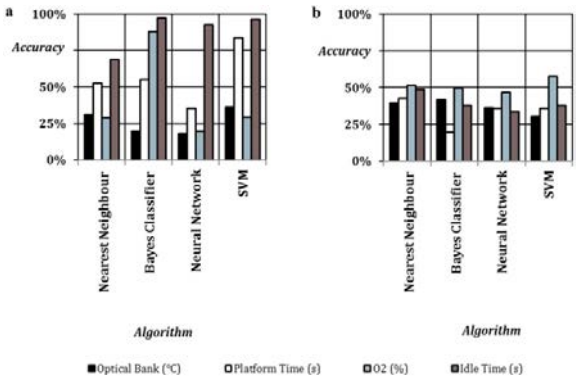

Fig. 3. (a) best and worst results for 'Finished perfectly' category; (b) best and worst results for 'Not finished' category.

In order to decide which parameter was more suitable to be used, the average value from each category together with the algorithms was obtained for the 16 parameters from table 1. The best two results and the worst two results are shown in Fig. 4a. The best parameter was the 'Idle Time' and, therefore, it was chosen to monitor tasks of the entire SLM machine.

Moreover, it was necessary to investigate what algorithm would match with 'Idle Time' to achieve the best results. Thus, the average of the final values from each algorithm was calculated regarding 'Idle Time', ignoring the categories. The results were plotted and they are shown in Fig. 4b.

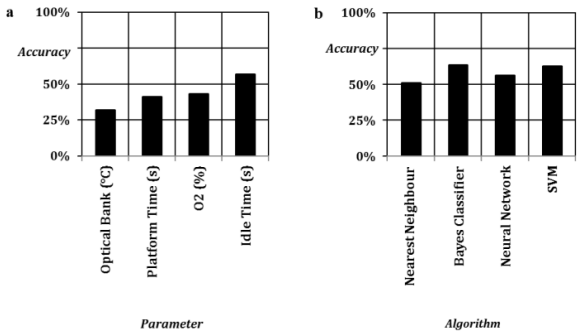

Fig. 4. (a) accuracy average related to the parameter; (b) accuracy of the algorithms related to 'Idle Time'.

The best algorithms were the Bayes Classifier and SVM, reaching both an accuracy average around 60%. The other two algorithms achieved accuracy results of 50%. Although the results from Fig. 4b were slightly close to each other, the best algorithm was the Bayes Classifier. Therefore, the pair ('Idle Time', Bayes Classifier) was considered the most appropriate to be used in the machine.

5.2. Clustering

As mentioned in section 4.7, clustering algorithms separates the amount of data in groups that have some common pattern. Several parameters for the algorithm were used to calculate the feature matrix (such as statistical values) and then to cluster. In general, four different results were achieved with various categories. The average of the identified categories was 3.5, a close value to the pre-defined number of categories from section 4.3.

An example is shown in Fig. 5 below. It presents a diagram from the condition monitoring tool with the clustering results for the process data. In this case three categories were found. Some points from categories 1, 2 and 3 are close to each other, what could cause possible misunderstandings in the data interpretation. Possible reasons for such proximity are either how the database was split or the data quality.

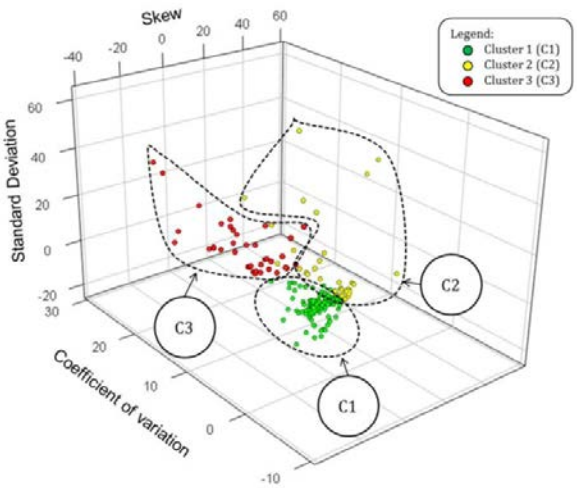

Fig. 5. Cluster example for process data.

6. Conclusions and Overview

This work presented the possibility of classifying and identifying patterns of a historical database from a SLM machine by using a tool developed at Fraunhofer IPK. The results helped to answer the two questions made at the beginning of this paper.

The chosen parameter and algorithm to identify the pre-defined categories were the 'Idle Time' (parameter 14 of table 1) and the Bayes Classifier, due to the achieved accuracy of 63%. It showed that an automatic classification for the SLM machine is possible.

Some problems were faced during the training step. They were related to the categories 'Finished with errors' and 'Not finished.' Several results were considered not reliable and they would have impacted the understanding of the process. Thanks to prior knowledge of the machine behaviour, those problems were identified before concluding this work.

The above mentioned errors came from the 'Process data extraction' step (section 4.2). One part originated in the self-implemented solution and the other from the files of the machine. Only the errors from the tool could be corrected. Subsequently, the experiments were repeated and results revalidated. The machine files should still be improved.

Regarding the clustering, patterns in the database were found using the k-mean algorithm without any pre-defined categories. The average of 3.5 identified categories can be considered as a confirmation of the machine conditions described in section 4.3

Furthermore, the database size was big for the tool. The algorithms found patterns in most cases. Better results can be achieved with more improvements on the CMT tool for pattern recognition in order to better filter useless data.

Future works will address the implementation of the found patterns in the machine software. It will be performed to identify on a real-time basis the parameters trend before the failure happens, avoiding disturbance in the manufacturing process. Consequently, the workpiece quality can be assured.

Moreover, other analysis will be performed in order to detect correlations among the parameters from table 1 and also among new observed variables. By detecting correlation, the prediction of the machine behaviour while manufacturing a workpiece can be optimized. Also, the life cycle from machine components can be studied and the failures anticipated. This would increase the reliability of the machine and the quality of the built workpiece.

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