Development of a Cyber-Physical System based on selective Gaussian naïve Bayes model for a self-predict laser surface heat treatment process control

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Abstract. Cyber-Physical Systems (CPS) seen from the Industrie 4.0 paradigm are key enablers to give smart capabilities to production machines. However, close loop control strategies based on raw process data need large amounts of computing power, which is expensive and difficult to manage in small electronic devices. Complex production processes, like laser surface heat treatment, are data intensive, therefore, the CPS development for these type of processes is challenging. As a result, the work described in this paper uses machine learning techniques like naïve Bayes classifiers and feature selection optimization, in order to evaluate its performance during surface roughness detection. Additionally, the feature selection techniques will define optimal measuring zones to reduce generated data. The models are the first step towards its future embedding into a laser process machine CPS and bring *self-predict* capabilities to it.

Keywords: CPS, machine learning, naïve Bayes, laser heat treatment, self-predict, Industrie 4.0

1 Introduction

Nowadays, laser applications are growing in many sectors like medicine, metrology, telecommunications and industrial applications [1]. However, industrial applications represent near 63% of the global market ($1.671 million last year), where high-power lasers used for macro-processing are the most interesting due to their potential of applicability in the manufacturing industry. Near 75% of these applications are related to sheet metal cutting and the remaining 25% is related with other processes like drilling or heat treatment [2].

As result of this, laser technologies have been evolving to allow their applicability in the manufacturing sector, where robustness, repeatability and reproducibility are key factors. Accordingly, process monitoring technologies have been developed in order to enable in-process quality control.

For a laser surface heat treatment process control, the main objective is to regulate the amount of energy deposited over the treated surface by the laser

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beam source [1]. The aim of this energy addition is to increase surface temperature and modify the mechanical properties of the surface, the physical phenomena has being essentially thermal [3] [4] [5].

Basically, laser surface quenching occurs when a high-density laser beam is focused on a small area where it causes the heating. In the case of steels, this involves its temperature to the austenite region. When the laser beam is moved, the area is immediately quenched by heat conduction to the surrounding metal [6].

Because of the thermal behaviour, laser process monitoring systems are mainly based on temperature reading, where contactless pyrometers and thermal cameras are often used. Additionally, if the monitoring systems seek to ensure the in-process quality, with low latency control loop, pyrometers are the most used option [7].

However, in a surface heat treatment the process area is larger than the area covered by the pyrometer, that increases the risk of losing critical information to effectively control the process. Costly analysis processes have to be carried out in order to estimate the optimal measuring point. Particularly, in the process of this study, the treated area is more than fifteen times the pyrometer range, so that trying to cover the complete area adding pyrometers is unmanageable.

As a result of the above mentioned problem, new developments towards the use of thermal cameras and image processing tools to cover wider areas are found in the literature [8]. Basically, these developments are based on thermal image processing in order to obtain a matrix of temperatures over the treated surface, which can be analysed and used as a matrix of pseudo-pyrometers.

Nonetheless, the control of the process based on this technology has an important drawback regarding the latency of the system. Due to the large amount of information analysed every process cycle, computing power may compromise the latency of the system, which is directly related to the size of the image and sampling time. This high latency prevents the use of this control strategy for in-process quality control.

Therefore, the objective of this work is to take advantage of cyber-physical systems (CPS) capability to handle large amounts of information integrated with processing capabilities [9] [10] [11] that will reduce the need of computing power to decrease the latency of a thermal camera control process. Additionally, using available monitoring technologies (in this case thermal cameras) complies with some Industrie 4.0 basic recommendations which explains that is not about putting more sensors inside processes [12] [13], but about extracting information from the actually available systems.

As a result of this latency reduction, the monitoring system will have in-process quality control capabilities. Machine learning techniques are used to identify patterns inside the thermal image during the process that can be classified in order to detect fluctuations during the process. This fingerprint of each fluctuation will be used to develop predictive models to control the laser power without the need of a complete pseudo-pyrometer matrix analysis every sampling time.

2 Methodology

Because laser beam energy deposition efficiency is strongly related to surface roughness due to its reflectivity, process parameters have to be adjusted. That is, lower roughness produces higher reflectivity which means that less laser energy is absorbed. Therefore, one of the main purposes of heat treatment process control is to be able to give the required amount of energy regardless of the surface roughness.

Because of this, for experimentation two scenarios arise: ground and unground workpiece surfaces. Consequently, machine learning techniques are used to classify the workpiece surface type within an acceptable limit of time. This time will have a strong influence over the laser beam control in order to modify the power input to correct the energy needs to achieve the optimal process temperature.

Therefore, the experimental setup is oriented to gather real data from a laser heat treatment process and evaluate the machine learning techniques performance in order to enable their application within a CPS device. Accordingly, data acquisition system and machine learning model are explained in the following sections.

2.1 Laser Heat Treatment Data Acquisition

As mentioned before, the laser heat treatment parameter to control the process is the amount of energy deposited over the surface, i.e., the process is mainly thermal. In a real control strategy of a laser process, the power needed from the laser beam source to achieve the heat treatment temperature is the parameter to be controlled, and, the quantitative input variable needed is the treated surface temperature during the process.

In order to gather the surface temperature, experimentation has been carried out over 12 real workpieces (6 ground and 6 unground) that are simplified as one set of cylinders with dimensions described in Table 1. Each set contains 4 cylinders type M and 6 cylinders type P. In order to get the process temperature, a FLIR A655sc 25^{o} thermal camera with 640 x 480 pixels at 25/12.5 Hz has been used to record each cycle. The cycle time is between 20 to 25 seconds, depending on the cylinder size.

In order to extract the temperature data from each frame, an image processing software, developed in collaboration with Vicomtech-IK4, has been used to deploy over the laser heated zone a 3 x 5 matrix of *virtual* pyrometers. The treatment zone size is 20 x 10 mm. Therefore, the measurements taken from the *virtual* pyrometer array are stored in a CSV file for further manipulation. The complete process is described in Figure 1.

Table 1. Cylinder sizes and quantities

Cylinder Type	Diameter [mm]	Height [mm]	Ground Surface Cyl.	Unground Surface Cyl.	Total Cyl.
M	67.85	19.19	24	24	48
P	56.60	15.24	36	36	72

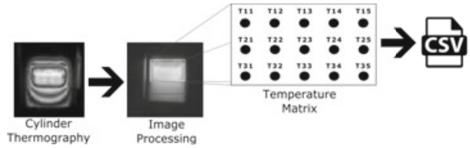

Fig. 1. Data acquisition process.

2.2 Machine Learning Experimental Setup

From a machine learning viewpoint, for each type of cylinder described in Table 1, a naïve Bayes model will classify its surface type based on the information given by the variables, i.e. temperature values, contained in each thermography frame. Therefore, the percentage of correctly and incorrectly classified instances will be used as a quantitative measurement for the classifier performance.

A *naïve Bayes classifier* is the simplest Bayesian classifier. It is built upon the assumption of conditional independence of the predictive variables given the class. Although, this assumption is violated in numerous occasions in real domains, the paradigm still perform well in many situations. The most probable *a posteriori* assignment of the class variable is calculated as prediction.

$$c^* = arg\,\max_c p\,(c|x_1,\ldots,x_n) = arg\,\max_c p(c)\prod_{i=1}^{n} p(x_i|c)$$

Consequently, in order to evaluate the minimum time required by the classifier to detect the surface type of the cylinder, an incremental amount of frames will be given to the model. Each frame represents a specific amount of time, depending on the video speed used by the thermal camera, i.e. 12.5 Hz is equivalent to 80 ms and 25 Hz is equivalent to 40 ms. Therefore, if the classifier needs 1 frame to reach the desired accuracy, it will mean that the model can give a result in 80 ms at 12.5 Hz. As a result, experiments have been carried out for cylinders Type M and P from 1 frame to 20 frames, which is between 0.8 and 1.6 s depending on the frame rate used in the camera.

After running experiments for each type of cylinder, 3 different types of feature selection (FS) techniques have been carried out to increase the classifier accuracy. These FS techniques will assist classifier models to deal with large amounts of irrelevant information [14].

Therefore, *filter techniques* assess the relevance of the variables, in this case, the temperatures inside the defined matrix, by looking only at the intrinsic properties of the data. In this experimentation, two types of filter have been used: Correlation-based feature selection (CFS) was introduced by [15]. CFS seeks for a good feature subset, that is one that contains features highly correlated with the class, yet uncorrelated each other. More formally, denoting by $\mathcal{S}$ a subset of the predictive features $\mathcal{X}$, CFS looks for $\mathcal{S}^* = \arg\max_{\mathcal{S}\subseteq\mathcal{X}} r(\mathcal{S}, C)$, where

$$f(\mathcal{S}) = r(\mathcal{S}, C) = \frac{\sum_{X_i\in\mathcal{S}} r(X_i, C)}{\sqrt{k + (k-1)\sum_{X_i,X_j\in\mathcal{S}} r(X_i, X_j)}}$$

measures the correlation between the selected features and the class variable, k is the number of selected features, $r(X_i, C)$ is the correlation between feature X_i

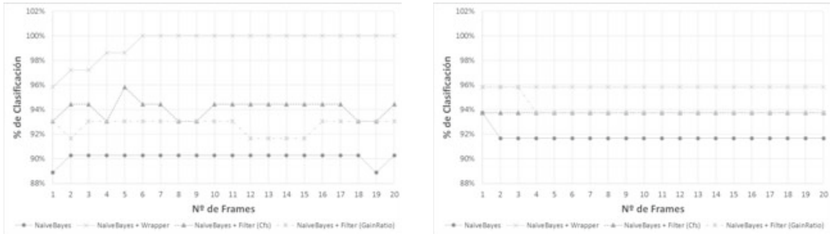

Fig. 2. Classifier accuracy for Type P (left) and M (right).

and the class variables C, and $r(X_i, X_j)$ is the inter-correlation between features X_i and X_j.

The other type of filter used is Information Gain Attribute Evaluation (Gain Ratio). The *information gain* between two variables X_j and C:

$$f(X_j) = \mathbb{I}(X_j, C) = -\sum_{i=1}^{r_j} \sum_{c=1}^{r_0} p(x_i, c) \log_2 p(x_i, c)$$

measures the reduction in the uncertainty of one of them (variable C for example) once the value of the other variable (X_j for example) is known. For Type P test-pieces, the ranked level threshold selected is 0.40, which means that all variables below this value are removed. For Type M, the selected ranked level is 0.92. The thresholds where selected based on the maximum value where the accuracy of the classifier starts to be negatively affected.

Additionally, *wrapper methods* [16] evaluate each possible subset of features with a criterion based on the estimated performance of the classifier built with this subset of features.

The complete experimentation for classification has been run over Weka, which is a collection of machine learning algorithms for data mining [17].

3 Results

The classifier accuracy for Type P cylinders is shown in Figure 2 (left), with and without feature selection techniques applied. For experiments with the naïve Bayes classifier, with only 1 frame the model is able to achieve near 89% of accuracy. Then, with 2 frames and more, the classifier is stable at 90.2% accuracy. This means that the classifier will be able to detect ground and unground surfaces in 160 ms with an accuracy of 90.2%.

On the other hand, for Type M cylinders shown in Figure 2 (right), the naïve Bayes classifier alone achieves 93.8% for 1 frame, decreasing to 91.6% for 2 frames or more. This situation shows a better behaviour than Type P cylinders, getting better accuracy with the same time needed.

However, applying FS techniques, the classifier performance increases for both types of test-pieces, except for CFS in Type M. Regarding the results for Type P for naïve Bayes plus Gain Ratio filter, the accuracy using 1 frame is 93% which remains stable with more frames, expect for 2 frames and from 12 to 15 frames. Nevertheless, using Gain Ratio for Type M, increases the accuracy to

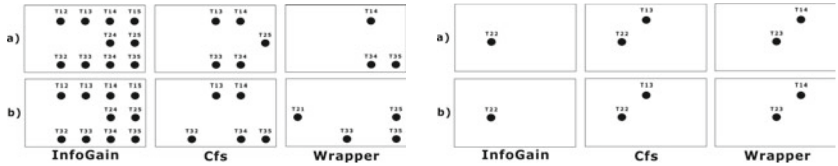

Fig. 3. Selected temperatures for a) one frame and b) two frames. Type P (left) and M (right).

95.8% remaining stable until 3 frames. These results are similar to naïve Bayes filtered with CFS technique.

Additionally, using CFS in Type P, the accuracy is similar to Gain Ratio for 1 frame. However, there is an improvement to 94.4% when 2 frames are used. In this case, the selected variables are reduced to 5 instead of 10 with Gain Ratio for 1 frame and 5 instead of 21 for 2 frames.

For Type M workpieces, the same accuracy using 1 frame is found for CFS as the classifier without selected features, nonetheless, it remains stable at 93.75% of accuracy independently of the number of frames given. Consequently, the number of selected variables is 2 compared to 1 using Gain Ratio for both: 1 and 2 frames.

On the other hand, using wrapper technique in Type P, the accuracy is relatively higher than filter techniques, having near 96% of accuracy for 1 frame increasing to 97% for 2 frames. It is important to stress that from 6 frames, the classifier is able to reach 100% of accuracy, meaning that from 6 frames up, the problem is linearly separable. In Type M, the accuracy is the same as Gain Ratio technique, outperforming other FS techniques from 3 frames.

The selected variables positioned within the pyrometers matrix, for 1 and 2 frames, are shown in figure 3.

4 Discussion

As seen in the previous section, feature selection techniques are able to increase the classifier accuracy in average by 9% for Type P and 4% for Type M. In general, the naïve Bayes classifier with wrapper has the best behaviour regarding its accuracy for both scenarios. Nevertheless, the comparison between models and the physical position within the matrix of the selected variables can bring more information regarding the physical behaviour of the temperature. This is relevant in order to develop an accurate but fast control system for the laser surface treatment.

As a result, in Figure 3 where the *virtual* pyrometers within the frame matrix are shown temperature measurement positions are selected at least by two techniques independently of the number of frames used, for example, T14, T34 or T35 for Type P and T22 in Type M. It is understandable, that those positions are relevant for the process as they are always selected.

From these positions, from the process point of view, that right leading (T14) and right trailing edges (T34 and T35) of the laser spot, in Type P scenario, are more sensitive to surface roughness variation which is expressed by an emitted temperature difference easier to detect by the classifier.

Nevertheless, for Type M, the most sensitive point is near the center of the matrix. This situation is interesting due to the fact that the only difference between each test-piece is its size, as process parameters are exactly the same for Type P. However, the number of selected temperature positions are significantly lower.

Therefore, it is expected that selected variables are the best descriptors of temperature differences between ground and unground surfaces. Therefore, in order to increase CPS ability to process information as fast as possible, reducing the amount of information given to it, the temperature measurements should be carried out in zones where best describers are located. Moreover, only pixels of interest within the frame can be gather, transmitted and processed, reducing computing power needs.

In the other hand, the time that the classifiers needs to detect the difference between temperature patterns at an acceptable accuracy is adequate, being always below 160 ms. However, this value depends on the thermal camera frame rate, so that, it is expected that data needed to classify might be obtained in less time, increasing the camera frame rate. In a control model, this situation would reduce the CPS latency.

5 Conclusion

The main conclusion of this paper is that the application of machine learning into CPS is key enabler to give decision capabilities to the analysed kind of devices. Those decisions can be implemented to the control system, adding self-adaptation capabilities to a real production process. In this case, high accuracy levels obtained from classifiers, even without feature selection, are able to detect differences between surface roughness, key condition for *optical* processes like laser heat treatments.

This experimental work only has provided results for two types of surface roughness. However, it is one of the most difficult boundary condition to be detected by machine operators due to small differences between temperatures. In this case, the model only needs information at least from the first two frames of process thermography, which, as explained before should be reduced if the thermal camera speed is higher. This situation opens new application boundaries to integrate machine learning models to control laser surface treatment process.

Therefore, because of the positive results found in this work, further experimentation on the application of machine learning for a cyber-physical system that controls laser surface heat treatment is oriented to detect and adapt the process to different surface roughness values. In this case, due to the results obtained, the classifier model will be able to relate surface reflectivity (directly related to roughness) and temperature values gathered by thermography.

Other applications for future investigation enabled by this work are to detect and alert about surface crack generation and monitor laser scanning system mechanical degradation to give the process predictive maintenance capabilities, all of them part of what is considered, a Cyber-Physical System.

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