Computers & Industrial Engineering 60 (2011) 801–810

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Data mining for quality control: Burr detection in the drilling process ☆

Susana Ferreiro [a,*], Basilio Sierra [b], Itziar Irigoien [b], Eneko Gorritxategi [a]

[a] Fundación TEKNIKER, Eibar, Guipúzcoa, Spain
[b] University of the Basque Country, San Sebastián, Guipúzcoa, Spain

ARTICLE INFO

Article history:
Received 25 March 2010
Received in revised form 24 January 2011
Accepted 27 January 2011
Available online 4 February 2011

Keywords:
Data mining
Machine learning
Drilling process
Burr detection

ABSTRACT

Drilling process is one of the most important operations in aeronautic industry. It is performed on the wings of the aeroplanes and its main problem lies with the burr generation. At present moment, there is a visual inspection and manual burr elimination task subsequent to the drilling and previous to the riveting to ensure the quality of the product. These operations increase the cost and the resources required during the process. The article shows the use of data mining techniques to obtain a reliable model to detect the generation of burr during high speed drilling in dry conditions on aluminium Al 7075-T6. It makes possible to eliminate the unproductive operations in order to optimize the process and reduce economic cost. Furthermore, this model should be able to be implemented later in a monitoring system to detect automatically and on-line when the generated burr is out of tolerance limits or not. The article explains the whole process of data analysis from the data preparation to the evaluation and selection of the final model.

1. Introduction

Nowadays, practically all fields of industrial activities are moving towards automation of their processes. This automation should ensure the quality of the product while minimizing manufacturing cost and optimizing resources.

Drilling is the most important operation for aeronautic industry because it implies a high economic cost. This cost is consequence of the visual inspection and burr elimination tasks. They are non-productive operations, carried out subsequent to drilling and they should be eliminated or minimized to the maximum extent possible. A small or medium size aeroplane has more than 250,000 holes to be inspected and if there is burr, it must be eliminated. It is necessary to eliminate this manual process and change it for a monitoring system able to detect automatically and on-line when there is a burr. The aim of this article is to obtain a model that can be implemented into the machine to predict the burr generation during the drilling process.

The technological centre 'C.I.C MARGUNE', a Cooperative Research Centre for High Performance Manufacturing, patented a monitoring method, experimentally adjusted, able to detect if the size of the generated burr is between aeronautical limits or not (Peña, Aramendi, & Rivero, 2007). This method consists of a conventional mathematical model to burr detection based on the parameters extracted from the whole internal signal of the machine and its percentage of correct classification was 92%.

Nevertheless, this model could not be implemented into the machine and there is currently no monitoring method for burr detection, so most of the research of this article was focused on obtaining a model that could be implemented in a monitoring system to predict automatically the burr generation during the drilling process. This model was derived from a process that extracts useful and understandable knowledge previously unknown from a set of experiments. Fig. 1 shows the communication among different phases of the knowledge extraction process.

The storage, the organization and the information retrieval have been automated thanks to the data base systems and the availability of a huge quantity of information. There are some analytic techniques based on statistics that have been used to analyze this information, but they are cryptic for people who are not very experience with it. Data mining as explained in Michalski, Bratko, and Kubat (1998) and Kaelbling and Cohn (2003) is a multidisciplinary field easy to put into practice and it combines several techniques such as statistics, machine learning, decision-making support systems, and visualization, in order to extract knowledge from a data set. Each phase of the process includes a set of these techniques.

The process is iterative and interactive. It is iterative because the output of any phase may turn back to the previous steps and because some iterations are necessary to extract high-quality knowledge. It needs to explore various models to find the most useful one to solve the problem. In the search of a good model it may be possible to return to previous phases and make changes in the data. Even the problem definition could be modified to give it a different approach. Moreover, the process is interactive because the expert in the problem domain should help in data

☆ This manuscript was processed by Area Editor Satish Bukkapatnam.

* Corresponding author.
E-mail address: sferreiro@tekniker.es (S. Ferreiro).

0360-8352/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.cie.2011.01.018

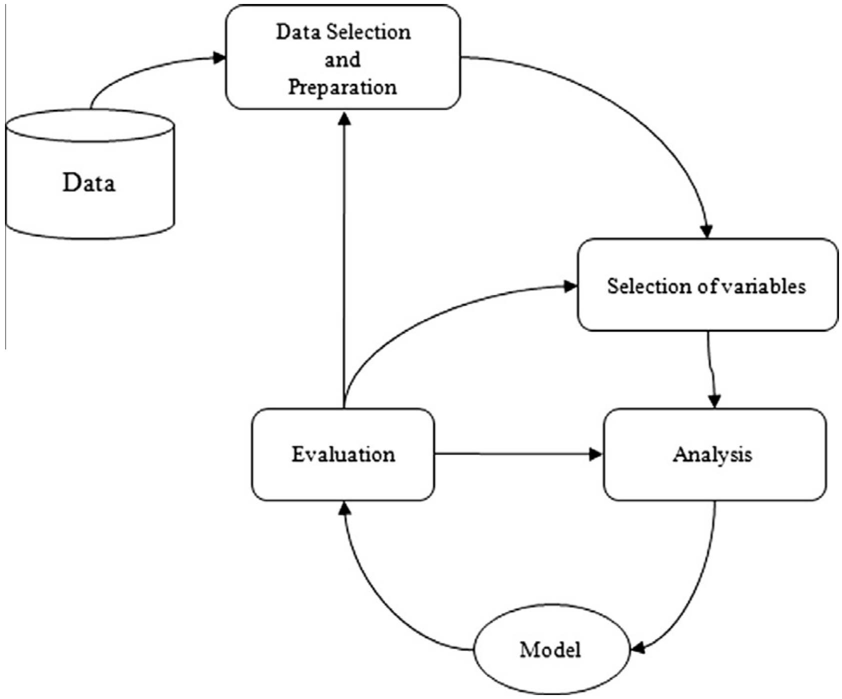

Fig. 1. Data analysis process.

preparation and evaluation. The evaluation is one of the most important phases in this process and it needs to have well-defined training and validation stages to decide which model offers better performance and accuracy. The idea is to estimate (train) the model with a subset of the dataset (training dataset) and then validate it with the rest of the dataset (test dataset).

The main contribution of this article is to explain the usefulness and benefits of the data mining techniques to obtain a robust, accurate and reliable model that can be implemented into a monitoring system and used to predict burr generation during the drilling process as shown in Fig. 2.

The rest of the article is organized as follows. Section 2 presents a review of related and previous works in the use of other data driven models in machining, and the position of the present work in the context of previous ones. Section 3 shows the experimental dataset, characteristics of the process, and data selection and preparation. It defines a clean and reliable dataset. Section 4 briefly describes the concept of machine learning. Next, Section 5 explains the results of the analysis and evaluation in order to obtain the best final model for detecting burr generation: application of machine learning algorithms without selection of variables, then with selection and combination of algorithms, and finally, makes a change of strategy to eliminate false negatives (cases in which the model predicts no burr but burr is generated. And finally, Section 6 closes the article with the most important conclusions.

2. A review of related works

Aeronautic industry, as well as other industrial sectors must modify some of its manufacturing processes and maintenance strategy. Considering maintenance strategy, it is necessary to minimize the cost of maintenance and to increase operational reliability, replacing the traditional "fail and fix" method with "predict and prevent" as explained in Ferreiro and Arnaiz (2010). And with regard to manufacturing, the major need is to increase productivity and to optimize and automate certain processes while ensuring the quality of the product. In both, manufacturing and maintenance, it is essential to explore new technologies, and a lot of works have been published looking into monitoring and diagnosis.

Bukkapatnam, Kumara, and Lakhtakia (1999) presents a methodology based on chaos theory, wavelets and neural networks for analyzing AE signals. It evolves a thorough signal characterization, followed by signal representation using wavelet packets, and state estimation using multilayer neural networks. Bukkapatnam, Kumara, and Lakhtakia (2000) develops a methodology for accurate and algorithmically simple neural network estimation by exploiting the properties of the underlying machining, dynamics and its interactions with flank wear dynamics. Kamarthi et al. (2000) investigate a flank wear estimation technique in turning through wavelet representation of acoustic emission (AE) signals. The effectiveness of the wavelet representation of AE signals for flank wear estimation is investigated by conducting a set of turning experiments on AISI 6150 steel workpiece and K68 (C2) grade uncoated carbide inserts. In these experiments, flank wear is monitored through AE signals. A recurrent neural network of simple architecture is used to relate AE features to flank wear. Using this technique, flank wear estimation results are obtained for the operating conditions that are within in the range of those used during neural network training. In Pittner and Kamarthi (2002) the work deals with the assessment of process parameters or states in a given application using the features extracted from the wavelet coefficients of measured process signals. Sick (2002) describes the 'state of the art' with 138 publications dealing with on-line and indirect tool wear monitoring in turning by means of artificial neural networks. The article compares the methods applied in these publications as well as the methodologies used to select certain methods, to carry out simulation experiments, to evaluate and to present results. Rangwala and Dornfeld (2002) present a scheme that uses a feedforward neural network for learning and optimization of machining operations. The network learns by observing the effect of the input variables of the operation (such as feed rate, depth of cut, and cutting speed) on the output variables (such as cutting force, power, temperature, and surface finish of the work-