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Comparison of Bayesian networks and artificial neural networks for quality detection in a machining process

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ABSTRACT

Machine tool automation is an important aspect for manufacturing companies facing the growing demand of profitability and high quality products as a key for competitiveness. The purpose of supervising machining processes is to detect interferences that would have a negative effect on the process but mainly on the product quality and production time. In a manufacturing environment, the prediction of surface roughness is of significant importance to achieve this objective. This paper shows the efficacy of two different machine learning classification methods, Bayesian networks and artificial neural networks, for predicting surface roughness in high-speed machining. Experimental tests are conducted using the same data set collected in our own milling process for each classifier. Various measures of merit of the models and statistical tests demonstrate the superiority of Bayesian networks in this field. Bayesian networks are also easier to interpret that artificial neural networks.

1. Introduction

Quality is defined as the extent to which a product conforms to the design specifications and how it complies with the requirements of component functionality. For some industries, such as automotive and aeronautical sectors, the quality of their parts is very important given the high requirements to which they are subject.

However, difficulties arise from the fact that a measure of quality can only be evaluated "out-of-process", resulting in losses because there is no alternative to removing defective parts from the production line. Therefore, it is necessary to incorporate machine learning methods that provide in-process solutions to predict quality from some measured variables.

Nowadays, many papers have been published about modelling the machining process and, more specifically, about the prediction of surface quality in machining processes. Researchers have approached the problem from different points of view and using different techniques. The most frequently used are artificial neural networks (ANNs) (Huang & Chen, 2003; Samson & Chen, 2003; Tsai, Chen, & Lou, 1999) and linear and multiple regression (Aboulatta & Mádl, 2001; Feng & Wang, 2003; Kirby, Zhang, & Chen, 2004). However, their models focus on very reduced environments and with limited experimentation.

In Correa, Bielza, Ramírez, and Alique (in press), we have recently proven the advantages of using Bayesian networks (BNs) as a successful solution for predicting surface quality in high-speed milling. As an important added value, the current research includes the influence of the geometry of the workpiece and the hardness of the material to be machined as key variables in the model construction aimed at a particular subdomain that contains a range of aluminium hardnesses used in automotive and aeronautical pieces. This is a landmark in this application domain, since it extends and generalizes the scope of the experimentation, which is no longer confined to a single test profile.

BN models were learnt from data. These data were collected in our laboratory using experimental design to guarantee statistical validity. Besides BNs, we constructed ANNs, known to be a strong competitor widely used in this field, to make a comparison and to demonstrate the superiority of BNs. As far as we know, there have been no comparisons of how well these two techniques solve this kind of problem.

Obviously, these two models have already been compared in other contexts like e.g. modelling manufacturing processes (Perzyk, Biernacki, & Kochański, 2005), discriminating plants, weeds and soil in color images (Marchant & Onyango, 2003), and modelling the response time of service-oriented systems (Zhang

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& Bivens, 2007). The two have been used in a combined fashion (Antal, Fannes, Timmerman, Moreau, & de Moor, 2003).

Our paper aims to compare the two approaches (BNs and ANNs) in the context of a practical industrial problem, the prediction of *surface roughness* in high-speed milling. The proposed models are target the automotive and aeronautical industry using some typical geometric features and a number of aluminium alloys giving a wide range of hardness.

The remainder of this paper is structured as follows. Section 2 presents the difficulties for measuring quality in a high-speed milling process, how surface roughness is inspected and which techniques and data we have used for surface roughness monitoring, since this is a variable that is very difficult to measure in-process. Sections 3 and 4 summarise the main principles of BNs and ANNs, respectively, and introduce the models on which our comparison is based. Section 5 focuses on the quantitative comparison of the two models and, in particular, on the knowledge engineering aspects of both. Finally, Section 6 concludes with our most important findings.

2. Quality in a machining process

The quality of a component is often associated with its surface aspect and appearance. However, this can be misleading in the sense that the surface may contain features that are not reflected in its appearance. Beyond aspect, a machined surface may contain imperfections and deviations from the nominal expected surface that compromise the quality of the component. Hence, it is necessary to clearly define a measure of surface roughness.

2.1. Surface roughness

There are many parameters for characterizing surface roughness, but the most used measure in industry is roughness average, *Ra*, representing the arithmetic mean of the absolute ordinate values $f(x)$ within a sampling length (L), see the following equation:

$$Ra = \frac{1}{L}\int_0^L |f(x)|\mathrm{d}x \tag{1}$$

The unit of measurement of roughness is the micrometre (μm), and, according to ISO:1302 4288:1996, machining processes are able to produce ranges of *Ra* from 0.006 μm to 50 μm. This parameter is primarily used to monitor the production process, which may gradually change the surface due, for example, to the wear of the cutting tool. As *Ra* is an average, the defects on the surface do not have much influence on its results. Hence *Ra* is not used for defect detection. However, roughness is of significant interest in manufacturing because it correlates strongly with the friction interaction with another surface. The roughness of a surface defines how that surface feels, how it looks, how it behaves in a contact with another surface, and how it behaves for coating or sealing. For moving parts, roughness determines how the surface will wear, how well it will retain lubricant, and how well it will hold a load.

Surface roughness can be measured by contact or non-contact methods, but all the methods are based on recording the surface height profile. We selected contact methods because of their reliability, although they are a *post-process* control and do not allow immediate corrective actions. Robust models to predict the surface roughness from experimental data can be very helpful for solving this problem, i.e. to guarantee surface quality *during* the machining process. These models would serve as virtual sensors acting while the machining process is taking place to optimize the final surface roughness. Some of the most recent proposals adopted by researchers to predict surface roughness are presented below.

The most commonly used artificial intelligence (AI) techniques within this context are ANNs with different training algorithms. Backpropagation is the most tried and tested algorithm. It provides very good results in the milling process, as investigated by one of the authors (Correa, 2003).

In the last 10 years, Iowa State University has conducted detailed research on topics like prediction and control in machining targeting tool state and surface roughness. The group led by J. Chen has published several studies on this topic for turning and milling. These works included ANNs and neuro-fuzzy nets (Lou & Chen, 1997, 1999; Lou, Chen, & Li, 1999).

Tsai et al. (1999) presented a surface roughness prediction system for the milling process, where they innovated and included spindle vibration and rotation – VAPR (vibration average per revolution) – in the roughness recognition system. Most of the sensors they used were developed for turning. To find the predicted *Ra* value, they developed two statistical models of multiple regression, and one ANN model based on off-line trained backpropagation. The three models were tested in an end-milling operation using 6061 aluminium, and four-flutes tools. The criterion used to judge the model is efficiency and ability to predict average roughness values was the percentage roughness deviation. The results showed that ANN model predictions are much closer to the real *Ra* values than using the multiple regression model.

Feng and Wang (2003) focused on the development of an empirical model for predicting surface roughness in turning, comparing a linear regression model with an ANN using the same input/output variables in both models. They used the geometric roughness model of Boothroyd and Knight (1989) to predict surface finish: $R_i = f^2/32r'$, where R_i is the arithmetic mean expected of surface roughness (μm), f is the feed rate (mm/rev) and r' is the tool nose radius (mm). The model took on a relatively large radius and a slow velocity. One conclusion of this study was that the ANN and regression models are quite similar with respect to the errors. Both models have a statistically satisfactory behaviour from the modelling point of view.

Benardos and Vosniakos (2003) reviewed the state of the art of the prediction of surface roughness in machining, emphasizing two main problems: (1) determination of the values of the process parameters that produce the desired quality product (technical specifications); (2) maximization of the manufacturing system performance using available resources. One conclusion was a recommendation to use a combination of AI research approaches. Another contribution of this paper is a fishbone diagram of the set of parameters that are believed to influence surface roughness.

Yang, Chen, Chow, and Lin (2006) proposed an adaptive surface roughness control system for end-milling operations. This system was based on the neuro-fuzzy training scheme proposed by Chen (2000). The fuzzy regions were defined for each parameter: cutting speed, feed rate, resulting force on the cutting plane (*Fxy*), normal force to the cutting plane (*Fz*), *Ra* deviation (*DRa*) and feed rate deviation (*Df*). The system has two subsystems, one for predicting in-process *Ra* and another to control the feed rate (*Df*) that is adapted based on the predicted *Ra*.

Kirby et al. (2004) published the development of a surface roughness prediction system using accelerometers in a turning operation with multiple regression techniques. In 2006, the same authors (Kirby, Chen, & Zhang, 2006), developed an adaptive control system that uses the same technique proposed by Chen (2000) and developed for milling by Yang et al. (2006). These models require more flexibility to be adapted for use in industry.

2.2. Experimental procedure and data collection

Because experiments can be very expensive in terms of costs and time, our data collection was based on two designs of experiments