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Tool wear control through cognitive paradigms

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Abstract

In the modern manufacturing systems, machining parameters are fundamental to achieve efficiency for the whole production process. The feed rate, the cutting speed and several other parameters affect significantly the machining efficiency; furthermore, the selection of an appropriate cutting tool results fundamental to set-up, in the possible best way, the other parameters. This problem is one of the most complex in machining processes and it refers directly to the quality of the finished product. The life of the selected cutting tool, under the conditions given by the other parameters, is crucial in term of efficiency and it should be estimated as accurately as possible and permanently kept under control. An optical monitoring process (video camera) can observe the tool wear development. The images give the opportunity to drive the process in achieving the target of zero defects manufacturing but there is the need to firstly elaborate and homogenize them, in order to standardize the control and predict the tool wear. By the use of a DNA Based-Computing method, the influence of user-settings on the elaboration of a set of images will be investigated.
In order to supply a direction for the development of methodologies for real-time tool wear recognition and prediction in a complex and high automated environment, this paper proposes an approach for the identification of the tool wear defection. The methodology designs an artificial Neural Network (NN) for automatic tool wear recognition: a set of images are standardized in grayscale and then processed in order to extract features for NN training phase. By the use of a DNA Based Computing method (DBC), the influence of user-settings on the elaboration of a set of images will be then investigated. It will be a crucial point for the development of a new method for the real-time tool wear recognition that will be based on the information provided by the DBC.

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Keywords: Tool Wear; Neural Network; DNA Based Computing

1. Introduction

The modern age of the manufacturing processes is oriented to achieve results of efficiency, decrease of waste and, above all, the target needs to be a zero defect production. In order to achieve such goals, the right choice of the cutting tool and its working parameters are fundamental and must be related to the machining in progress. Several hidden and random factors might have a strong influence on the success of manufacturing processes and they need to be predicted.

To obtain a high quality product, one of the main fundamental element is the cutting tool: its quality and the management of its life cycle refers directly to the efficiency of the entire manufacturing process and not only to the quality of the finished product. The choice of the right cutting tool directly influences the parameters related to the production, such as feed rate, cutting speed and depth of cut, as well as the workpiece and its material, and the type of process.

The conditions of the machining process and the tool wear are parameters to be kept constantly under control [1]. The choice of the tool wear is influenced by the above cited parameters; it plays a major role in the manufacturing process and its wear recognition is fundamental in the optimization of the machining process.

This paper proposes a methodology that, by the use of artificial Neural Network (NN), supplies the users with information on the tool wear trend and provides a real-time prediction. Further, a DNA Based Computing (DBC) method with its functionalities on the tool wear understanding is illustrated. The comprehension of the DBC features is important to develop a robust system based on cognitive paradigms.

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2. Machining experiments

A set of machining (quasi-orthogonal turning) experiments were been conducted to obtain the tool wear variability trend. The work material was a bar made of stainless steel of the grade AISI 1045. The cutting tools were P3-type tungsten carbide inserts. The machining operation was stopped after each minute, and the pictures of the worn-zone of the cutting tool along with a reference copper wire of diameter 0.25 mm were taken.

Table 1: Cutting parameters for quasi-orthogonal tests.

Cutting speed [m/min]		Feed Rate [mm/rev]		Depth of cut [mm]	
a	100	d	0.06	h	1
b	150	e	0.12	i	1.5
l	250	f	0.19		

The cutting parameters, which give the values to each set of images as shown in Table 1. From those values, 14 cutting combinations were selected and named as "adh", "aeh", "aei", "afh", "afi", "bdi", "beh", "bfh", "bfi", "ldi", "leh", "lei", "lfh", "lfi".

Images, however, were not homogeneous. Contrast, definition, size and position of the cutting tool vary from one image to another. Standardization procedure of the cutting tool images was reported in [1].

3. Image processing through Neural Network

3.1 NN tool wear recognition

As described in previous work [1], in order to predict the residual tool life before the wear limit and the width of the crater wear, Back Propagation Neural Networks (BP NN) can be utilized to produce a mapping from input vectors to output value.

The starting point of the study was the choice of the tool wear value, which should be compared with the output given by the NN: the tool wear zone was characterized by several measurements, such as width of crater wear [mm], flank wear [mm], and shape of burr. In this paper, it was decided to pay more attention to the estimation and prediction of the crater wear width: the observation and measurement (by using a microscope) of the crater wear was chosen as output of the feature vectors for the training of the NN and as the value to be predicted.

3.2 Neural Network implementation

In order to train a BP NN, the first step to carry out is to choose its parameters and main characteristics, such as number of layers of input&output neurons, transfer functions, input array or matrix, output array or matrix [2].

The BP NNs were created by the use of the "newff" MatLab function:

Net = newcf(p', t', [S1 S2...S(N-l)], {TF1 TF2...TFN}, BTF, BLF, PF, IPF, OPF, DDF);

Where:

- Newcf: to create a cascade-forward BP network;
- p': to transpose input matrix or array: R x Q1 matrix of Q1 sample R-element input vectors;
- t': to transpose target matrix or array: SN x Q2 matrix of Q2 sample SN-element input vectors;
- Si – number of input and output layers: size of i^{th} layer, for N-1 layers;
- TFi: to transfer function of ith layer;
- BTF: BP newtwork training function;
- BLF: BP weight/bias learning function;
- PF: performance function;
- IPF: roll cell array of input processing functions;
- OPF: roll cell array of output processing functions;
- DDF: data division function.

The "newcf" function returns a 3-layer cascade-forward BP network [1], with five nodes in the hidden layer, tangent sigmoid as transfer function between input layer and hidden layer, linear function between hidden layer and output layer and gradient descent.

The series of vectors for the NN training was firstly an input matrix (*p*) given by all the images of a series minus one, and a vertical vector (*t*) with the values of the crater of each image.

The second step was to create a variable with the matrix to test (*ps*): the image chosen to predict the output value, was not included in the training set (leave-k-out method). After training the NN with the command line as above written, a first simulation was performed. Since it was chosen to retrieve only one value of output layer, the outcome output was only one value representative of the entire matrix image [1].

Since a NN reads inputs per rows, a further step was to train the NN not by the use of a set of matrix as input but with relevant features extracted the images, giving as input a set of vectors.

3.3 First sample processing

For a real time prediction of the tool wear trend, the gap between the measured output and the estimated one was too wide (more than 3mms) and so considered as not acceptable. Furthermore, the processing time (more than 10 minutes per elaboration) could not be considered passable. In order to have a more accurate tool wear recognition and reduce the training time for retrieving the NN output, it was necessary to reduce the matrix order to a [1, n] matrix. To construct that single row vector, the relevant features of the tool wear image data were considered [4].

A first set of sample images was used to have an initial approach to the process: a standardization of the images resulted fundamental to stand out the crater wear zone and overshadow the remaining tool area and the image background. The images were re-sized and adjusted in brightness, by the use of the *Microsoft Office Word* tools for images (see Figure 1).

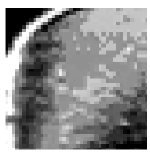

Figure 1: AEH060, after a first processing step.