International Journal of Engineering Science Invention (IJESI)
ISSN (Online): 2319-6734, ISSN (Print): 2319-6726
www.ijesi.org ||Volume 10 Issue 4 Series III || April 2021 || PP 46-50

Artificial intelligence systems for tool condition monitoring in machining: analysis and critical review

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Abstract
This paper presents an in-process tool wear prediction system, which uses a force sensor to monitor the progression of the tool flank wear and machine learning (ML), more specifically, a Convolutional Neural Network (CNN) as a method to predict tool wear. The proposed methodology is experimentally illustrated using milling as a test process. The experiments are conducted using dry machining with a non-coated ball endmill and a stainless steel workpiece. The measurement of the flank wear is carried on in-situ utilising a digital microscope. The ML model predictions are based on an experience database which contains all the data of the precedent experiments. The proposed in-process tool wear prediction system will be reinforced later by an adaptive control (AC) system that will communicate continuously with the ML model to seek the best adjustment of feed rate and spindle speed that allows the optimization of the flank wear and extend the tool life. The AC model decisions are based on the prediction delivered by the ML model and on the information feedback provided from the force sensor, which captures the change in the cutting forces as a function of the progression of the flank wear. In this work, only the ML model component for the estimation of tool wear based on CNNs is demonstrated. The proposed methodology has shown an estimated accuracy of 90%. Additional experiments will be performed to confirm the repetitiveness of the results and also extend the measurement range to improve accuracy of the measurement system.

Keywords: *Flank wear, force sensor, milling application, deep learning, convolutional neural network, self-learning.*

I. Introduction

Machining is an industrial process in which metal is sculpted by removal of material. This manufacturing technique is a fundamental method that is expected to still be used in the next decades. However, the technique faces critical problems related to the cutting process such as tool wear and tool failure. As a result, Tool Condition Monitoring (TCM) is gaining more consideration in automated manufacturing processes in recent time [1-2]. Tool wear is well known as it degrades machined surface texture and causes unpredictable inaccuracy in work geometry. It also affects significantly tool life and production cost [2]. From a technical and economical viewpoint, it is therefore essential to design a smart system able to monitor the progression of the tool wear during the machining process. This will allow the identification of a worn tool in order to be replaced. This will allow to increase the accuracy of the cutting process and, therefore, ensure the achievement of the technical specification requested to reach the suitable geometry of the machined components [3].

Tool wear mainly includes the wear on the clearance face (flank wear) and that on the rake face (crater wear). Of these two, flank wear (*VB*) is frequently used as the main indicator to define the end of adequate tool life. Previous studies [4] have confirmed that as flank wear land width (*VBb*) grows to a certain threshold, it influences the surface finish and dimensional accuracy of the workpiece as well as the stability of the machining process [5]. Therefore, tool failure due to flank wear can be evaluated by the maximum value of *VBb* and predicted by a function of time. Based on this statement, this paper focuses only on the progression of the flank wear.

There is a large body of research on tool wear monitoring. Key reasons for building effective TCM systems for high performance machining are to: increase sustainability and promote automation in the cutting process; ensure the required surface roughness and dimensional accuracy; minimize the number of tool changes that, ultimately, impact on valuable production time. Most approaches proposed are based on various types of independent sensors [6-8] such as acoustic emission (AE), forces, accelerations, and measurement of contact resistance between the tool and the workpiece [9]. However, most reported work using an ML model are offline techniques. The novelty of the approach presented here is the combination of the self-learning and self-adaptive components operating simultaneously online as one body to produce an in- process smart tool wear detection and prediction system. The self-learning component allows the system to learn, identify and predict the tool flank wear using the CNN. The self- adaptive component takes into account this prediction and the information delivered by the force sensor to determine the best adjustment to the machining process and extend tool life.

Figure 1 illustrates the architecture of the whole system. The proposed method explores the development of algorithms that can learn from and make predictions on data. Such algorithms, instead of following strictly static program instructions, make data-driven predictions, by building a model from sensors inputs. The methodology also provides the basis for an automatic control system that preserves its operational capability without the intervention of the operator and therefore creates a level of self- awareness.

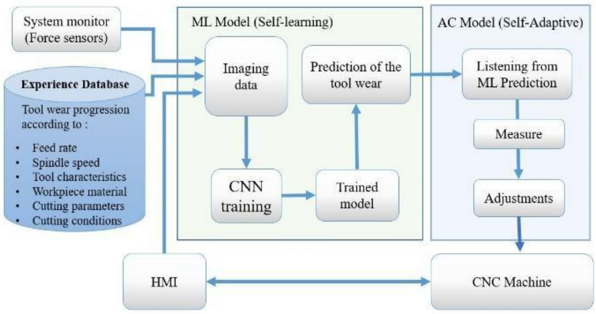

Figure 1. Overview of methodology for in-process tool wear prediction system

II. Methodology

Mechanism of in-process wear prediction system

The in-process wear detection system uses the experience database to train the CNN to recognize the behavior of tool and workpiece through force measurement. After training, the CNN is able to predict the wear. The adaptive control will then take the feedback from the CNN and apply the necessary adjustments between feed rate and spindle speed to reach the desired force. The goal of the combination is to create:

1) Self-learning: learn from the machining experience will deliver an accurate prediction.
2) Self-adaptive: maintain the needed force predicted by the CNN, in order to optimize tool life and improve surface finish. By satisfying these two conditions, the system will provide the basis for an automatic control system that preserves its operational capability under conditions of unexpected change.

Measurement method of forces and flank wear

Cutting force is an important feature in milling application, closely related to tool design geometry. Monitoring the cutting force could deliver a fundamental reference for wear identification as well as information that helps to set the required cutting parameters or cutting tool selection. Therefore, the tool wear monitoring method used in this study is based on forces analysis, using a Kistler piezoelectric dynamometer 60kN, Type 9255C, where F_x, F_y and F_z represent the three orthogonal components of forces exerted during the dry milling process. These were sampled at 50 kHz/channel.

The force signals transmitted during the cutting process are filtered and amplified. The amplifier has been calibrated to the sensitivity of the piezoelectric sensors, which takes into consideration the value of the applied mass or force. These signals are sent to the data acquisition system cDAQ 9191 via the implemented module NI 9215 and then monitored using NI Signal Express. The data is stored in the experience database that will be used to train the CNN model. Each test was carried out as follows: one horizontal cut along the y-axis direction was done using a down milling operation. After one line was completed, the cutter was retracted to another start point to perform another horizontal cut. This was repeated until the whole surface was completed. The cutting parameters of the machining operation were as follows: Spindle speed=10,400RPM, Feed rate = 1555mm/min, Depth of cut in Y direction DOCy= 0.125mm, and in Z direction DOCz= 2 mm. Using a 6 mm Uncoated ball endmill with substrate of tungsten carbide. After each cutting phase, the cutter's flank wear was measured using a digital microscope.

Tool wear prediction method using CNNs

Most data-driven methods that have been used for tool wear prediction are based on machine learning, particularly Artificial Neural Networks (ANN) [10, 11] and Support Vector Machines (SVM) [12, 13]. These techniques, however, are limited in their ability to process natural data in their raw form. Their success relies on the features that are extracted during data pre-processing. The proposed learning module is based on deep learning, which will allow to discover intricate structures in high dimensional data without the need of any hand-crafted features. Deep learning has made major advances in fields such as image and speech recognition [14, 15], natural language processing [16] among others [17]. One successful deep learning architecture for the classification of images has been the Convolutional Neural Network (CNN) [18], which has been further developed to handle time series data classification [19]. The CNN presented here extends those attempts by encoding multivariate time series data collected from the sensor as 3 channel images and using those images as inputs to train the CNN. The imaging process serves as an encoding procedure, meaning the original time series can be re-created from the image, without losing information. Reformatting features of time series as images allows machines to "visually" recognise, classify and learn structures and patterns, capturing the temporal dependencies on data [19]. The training process will be able to find the intrinsic structures on the time series data that link the sensor data to the wear condition of the tool.

2.3.1 Architecture of the CNN

A typical simple architecture of a CNN starts with a convolution layer, which applies a number of filters to the raw input (image). A *ReLU* layer follows, which introduces non- linearity and allows to speed up the training. This layer is then followed by a pooling layer which downscales the output of the convolution. Finally, a multilayer perceptron is connected to the last convolution/pooling to perform the classification. This 3-layer structure can be repeated (stacked) several times. How many should be used depends on the complexity of the data. The architecture implemented here is based on the Tensorflow model for classifying the CIFAR-10 dataset, as it has been proven to work successfully for multi-channel (RGB) image classification [20]. This CNN model has two convolution layers stacked with their corresponding ReLU and pooling layers. Each convolution applies 64 filters.

III. Result & Discussion

As this module was developed in parallel with the machining experimental setup described in the previous section, the CNN was initially trained and tested with a data set obtained from the 2010 PHM Data Challenge [21, 22]. This data set was chosen as it was close to what could be acquired with the machining setup described here. This data set consists on seven signal channels, including cutting force, vibration, both on *x*, *y* and *z* dimensions, and acoustic emission data, from six 6mm ball nose tungsten carbide cutters. This data was acquired on real time while performing 315 cutting tests on a 3-axis high-speed CNC machine for each of the six cutters. As the machining setup is currently designed to take cutting force measurements (*Fx*, *Fy* and *Fz*) only, these three variables were selected from the PHM data set to train the CNN. The aim at this stage was to do a proof of concept of the learning module, whereby given the current measured forces on three dimensions, the state of the cutting tool could be determined. From the PHM data set, the measurements that corresponded to one of the cutters only were taken (cutter 6 as labelled in the challenge) and, using the measured wear in mm at each removed layer, the data was labelled into three classes, namely rapid initial wear, uniform wear and failure. Typically the wear regions for a specific cutter would be defined based on a wear progression curve as the one shown in Figure 2. However, different cutters will exhibit different wear progressions for the same cutter parameters. Therefore, to support the generality of this proof of concept, the wear regions were arbitrarily defined. The current class definition shown in Figure 2 represents a worst case scenario for the learning model

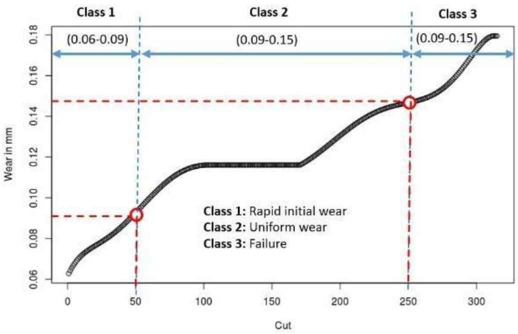

Figure 2. Flank wear progression according to the number of cut, and the wear classes.

As the time series that corresponds to one layer can be up to 219,000 measurements, a representative portion of the series was taken by selecting a subsequence of 2,000 measurements from the middle of the layer. To prepare the time series data of the cutter for training and testing of the CNN, each time series *Fx*, *Fy* and *Fz* corresponding to a removed layer were encoded as three separate images. To do this, the Gramian Angular Summation Fields (GASF) method proposed by Wang et al. was implemented [19]. The method, as shown in Figure 3, performs two main steps. First, the time series is normalised and transformed into a polar coordinate system. Then, the angular perspective is exploited by considering the trigonometric difference between each point to identify the temporal correlation within different time intervals. Given a time series or vector of size *n*, the resulting image will be a matrix of $n \times n$. For large time series, a Piecewise Aggregation Approximation (PAA) reduction [23] can be applied to reduce the size and smooth the time series while preserving the trends. Once separate images for forces *Fx*, *Fy* and *Fz* that corresponded to a layer were generated, these were reduced from a size of 2k×2k pixels into images of 512×512 pixels using PAA. They were then combined into a 3-channel image. The associated wear class to this image would be determined by the wear value that was measured when the layer was removed.

Time series represented in polar coordinates

Segment of forces measured on Z axis – Wear: 0.179mm

Resulting Image for forces on Z axis

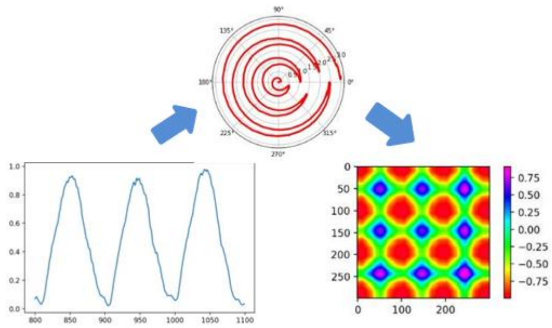

Figure 3. Imaging of. time series using GASF

The imaging process produced 315 3-channel images. These capture the transition of the tool through the different wear stages, showing more circular shapes as the tool wears out. This set of images was divided 70% for training and 30% for testing. The CNN was trained for 1,000 steps using the softmax regression method, learning rates of 0.1 and 0.01 and a decay factor of 0.1. Once the model was trained, it was evaluated on the test set. Table 1 presents a confusion matrix with the results obtained.

Table 1. Confusion matrix showing the classification results on the test set.

N=95	Actual Rapid initial wear	Actual Uniform wear	Actual Failure region	
Predicted Rapid initial wear	14	2	0	**16**
Predicted Uniform wear	3	62	3	**68**
Predicted Failure wear	0	2	9	**11**
	17	**66**	**12**	

Based on the test set, the estimated accuracy of the model is 90%. As illustrated in Table 1, "Uniform wear" cases were correctly classified for most instances (68 predicted against 66 actual). Moreover, the number of incorrect predictions suggests the number of cases for "Rapid initial wear" and "Failure wear" might need to be increased. This was expected, as currently only one cutter (315 images) was used to train and test the model and these particular regions are smaller in the wear curve, so less samples are available. To develop a successful online TCM system, the detection of the second transition is fundamental since it leads to optimal utilization of the tool life. An increase on the number of cases within these classes will be crucial to achieve a more homogeneous accuracy across all classes and that predictions are reliable enough to feed into the Adaptive Model. The overall results, nevertheless, are promising, taking into account no feature selection occurred. This provides a proof of concept, showing that the CNN was capable of capturing the intrinsic structures of the sensor data.

IV. Conclusions

This paper presents an in-process tool wear prediction method based on deep learning. The experimental results indicate that the CNN is capable of identifying the existing correlation between the forces produced during the cutting process and the tool flank wear. This is achieved without the need of feature selection or filtering the signals acquired. This method is applicable for any type of workpiece material or cutting tool provided that appropriate data is available during the training process. In other words, to apply this method the learning component needs to be trained on the behaviors of the combination of the selected tool and workpiece.

From an economic point of view, the cost of the presented solution is high due to the type of sensors used in this experiment, but it reveals the ability of the CNN to identify the variations on the forces as the tool wears out, which provides various advantages. First of all, the simplicity of the implementation. Secondly, the accuracy of the prediction.

Future work will consider a more extensive experimentation using different cutting tools as well as other sensors such as vibrations and acoustic emission therefore increasing the size of the training and test sets. Further changes to the CNN will be done as well, to compare different architectures. Finally, integration of the self-adaptive component will be undertaken.

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