Tool Condition Monitoring Method in Milling Process Using Wavelet Transform and Long Short-Term Memory

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Abstract
Industrial automation is a promising move to fulfill today's competitive manufacturing industry demands by lowering operation costs, increasing productivity and quality. Monitoring the production process is one of the important steps toward total autonomy of manufacturing plants, which reduces routine checks, enables proactive maintenance and reduces repair costs. This research investigates tool wear as one of the most common faults in milling process during cutting of the D2 high speed steel as a hard to cut material using Carbide Walter End Mill Protostar tool. Vibration signal is chosen to represent the system status due to its applicability in industry. Signals are transformed into time-frequency domain using Wavelet Transform method to reveal both time domain and frequency domain features of the signal simultaneously. In order to model the complex and non-linear relations between tool wear and vibration signals under varying cutting parameters, a deep learning based algorithm, Long Short-Term Memory (LSTM) Artificial neural networks (ANNs) is employed. Deep learning algorithms are getting lots of attention recently within the diagnosis and prognosis community because of their exceptional performance in exploiting information in big data to solve complex problems. LSTM network is a type of recurrent ANNs that have some internal cells that act as long-term or short-term memory units, which is most suitable for sequential data and time series like vibration signals in our analysis. After designing the system, performance of the monitoring method is validated using experimentally acquired data with K2X10 Huron high speed CNC machine in LIPPS and Dynamo labs of ETS.

Keywords
Deep Learning, Tool Wear, Wavelet Transform, Condition Monitoring, Time-Frequency Transformation, Machining Process

1. Introduction

Machining processes are key components of industrial manufacturing, which requires higher productivity, parts quality, workers safety and lower operational costs. Therefore, there is growing demand to make the machining operation autonomous. Along with other initiatives in automation, online monitoring of machining process is beneficial to assure the production safety and quality. Tool wear is one of the most common and costly defects of the machining process, which is caused by excessive, contact forces and friction between cutting tool and workpiece material, high temperatures in the cutting surfaces and pressure of the chips on the tool. It may deteriorates the surface finish or causes damage or breakage to the tool, workpiece or machining center if is not detected and fixed on time [1]. Therefore, designing a reliable and robust online automatic tool condition monitoring (TCM) system is in high demand to actively monitor the cutting process and provides actionable reports of tool condition status.

TCM systems can be divided into two main sub-categories: direct and indirect methods. Direct methods involve a procedure to directly measure actual value of faults with a laser, optical or ultra-sonic sensor. This could be costly and causes interruption in the manufacturing process for the measurements. Indirect methods in contrast employs physical parameters of the system such as force, vibration, etc. to indirectly reflect the status of the system [2]. Indirect methods can be used to fulfill TCM requirements as an alternative to indirect methods with accurate results and acceptable cost[3]. Another advantage of this approach is that the same sensor can be used for multiple monitoring purposes.

Force, vibration, acoustic emission, current and power signals are among the applicable and most common signals for TCM application in the literature. Li et al. studied TCM using force signals to reveal tool faults in turning[4]. Fourteen time-domain features of the signal are extracted and fed into a v-support vector regression model to developed flank wear prediction model. Force signal shows high accuracy to represent tool wear variations, however, it is also dependent on other operating conditions and relatively costly for industrial application [3]. Vibration sensors are practical in industrial environments and can represents the tool wear with appropriate performance. Harun et al. studied tool condition during deep twist drilling process using time and frequency domain fault features and compared vibration and force signals in this application. They concluded that both sensors are acceptable for this application, however they recommended vibration signal [5]. Acoustic emission is another efficient signal for TCM which is highly used in the literature [6] . Power and current sensors are also cost effective and applicable for industrial environment. In and study, current signals of the spindle of the milling machine is used to investigate tool wear. S-transform is used to transform the signals to time-frequency domain [7]. Sensor fusion is another approach to increase the accuracy and reliability of the monitoring. In an study, Segreto et al. combined information of the force, acoustic emission and vibration signals for tool condition monitoring of the turning process [8].

In the next step, signals are processed to magnify the effect of monitoring variables and reducing the effect of the noise in the signals. Time, frequency and time-frequency domain analysis are most common methods for signal processing in TCM [9]. Time-frequency analysis is appropriate for this application as it investigates both time variant and frequency dependent characteristics of the signal simultaneously, although it has higher computational costs [10]. In a study s-transform as a powerful time-frequency transformation method is used by Rehorn et al. to generate a feature called selective regional correlation, for machining condition monitoring [11]. In another study, a comparative analysis is conducted among common time-frequency transformation methods for the purposes of TCM in milling operation [12].

The relations between extracted features of the signals and tool wear is non-linear and complex, especially under varying cutting parameters such as depth of cut and feed rate which makes the monitoring task difficult. Therefore, a solid algorithm is necessary to accomplish the decision-making requirements. Machine learning algorithms such as artificial neural networks (ANNs), support vector machine (SVM) and Bayesian networks are common in the literature to fulfil this need. ANNs method is employed by Patra et al. to investigate tool wear of the micro drilling process [13]. In another study, a sound based system is developed using discrete wavelet transform (DWT) and SVM algorithms in face milling operation for TCM [14]. Tobon-Mejia employed Baysian network for the prediction of remaining useful life (RUL) of the tool in machining process [15].

Recently, deep learning algorithms draw attention of researchers in different fields due to their promising capabilities to solve complex challenges [16]. Deep learning refers to machine learning algorithms with deep multiple layers which enable them to learn highly complex patterns from even low-processed to raw signals [17]. In the era in which sensors are continuously producing enormous amounts of data, such techniques are in need to make the most information out of this data. These algorithms are less dependent on applications and frameworks and they are most efficient to outperform other methods when the relationship between the input data and desired outputs are complex [18]. Despite this potential, they are relatively new in the field of machinery fault monitoring. In an study, Jing et al. developed a Convolutional neural network based algorithm for gearbox condition monitoring [19]. Zhao et al. conducted a study to investigate the researches using deep learning methods in machine health monitoring [20]. Further research is crucial to examine deep learning algorithms applicability with different signals and levels of signal processing in TCM applications.

In this study, a TCM system is proposed using LSTM ANNs as a powerful and state of the art deep learning algorithm. Vibration signals from ETS experimental dataset are used to develop the monitoring system. Signals are processed using Wavelet method to transform them to time-frequency domain. Afterwards, the frequency bands energies calculated in the previous step is fed to the LSTM network as the features to construct the monitoring system. The algorithm accuracy is compared with a baseline Multi-Layer Perceptron (MLP) ANNs. This paper is organized as follows: Section 2 represents the formulation and backgrounds of the techniques of the paper. The proposed methodology is elaborated in Section 3. Results and discussion are presented in Section 4 and Section 5 is devoted to conclusion.

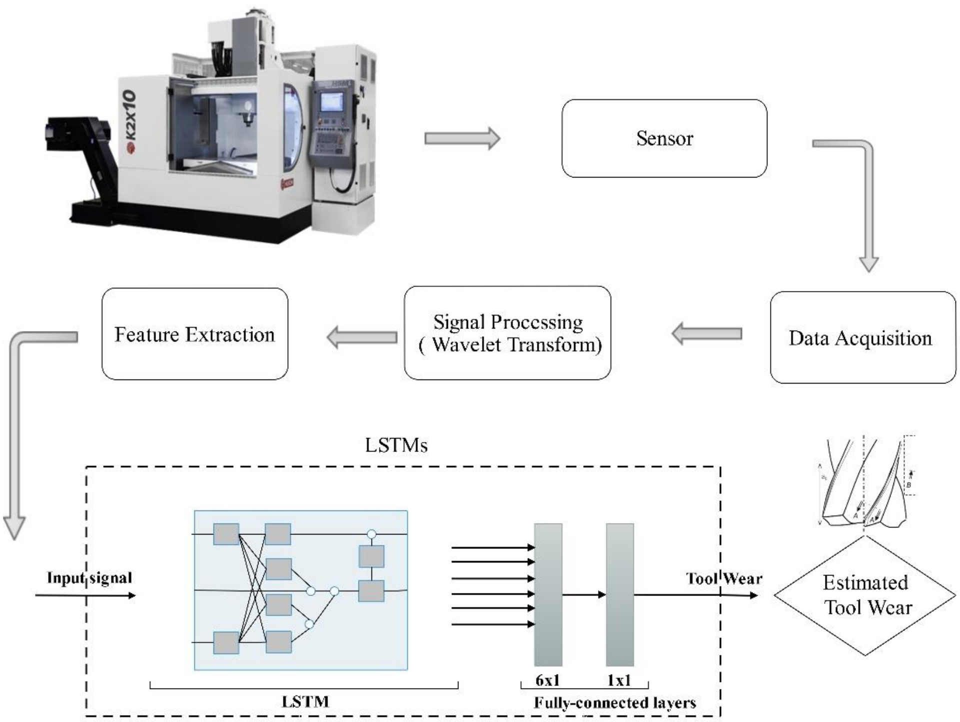

Figure 1.The monitoring system framework

2. Background of methods

2.1. Wavelet Transform

Wavelet transform is one of the widely used algorithms for fault diagnosis and health condition monitoring. In wavelet transform, wavelets are used as the basis instead of sinusoidal functions that are used in fast Fourier transforms which is the main difference between wavelet transform (WT) and Fast Fourier Transform (FFT). It is famous for transient signal analysis as well as time-frequency localization because it introduces a scale variable in addition to the time variable in the inner product transform. It has a better time localization but a lower frequency resolution for higher frequency components. In contrast, for lower frequency components, the frequency resolution is higher while the time localization is worse. Following equation describes the formulation of the continuous wavelet transform [10].

$$WT_x(t,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(u)\psi\frac{(u-t)}{a}du$$

where wavelet $\psi\frac{(u-t)}{a}$ is derived by dilating and translating the wavelet basis \$ $\psi(t)$, and $\frac{1}{\sqrt{a}}$ is a normalization factor to maintain energy conservation and $a > 0$.

2.2. LSTM Neural Networks

LSTM ANNS have recently demonstrated a great success in many machine-learning tasks, such as regression, prediction, etc. While conventional machine learning models can only map from input data to outputs, LSTM is capable of building multi-directional connections and it is effective at capturing long-term temporal dependences and keeps a memory of previous inputs to in the network's internal state, which makes it ideal for sequential data. The following equations is the hidden layer function that give the update for a layer of memory cells [20][21]:

$$\begin{aligned}
g_l^{(t)} &= \theta(W_l^{gx}h_{l-1}^{(t)} + W_l^{gh}h_{l-1}^{(t-1)} + b_l^g) \\
i_l^{(t)} &= \sigma(W_l^{ix}h_{l-1}^{(t)} + W_l^{ih}h_{l-1}^{(t-1)} + b_l^i) \\
f_l^{(t)} &= \sigma(W_l^{fx}h_{l-1}^{(t)} + W_l^{fh}h_l^{(t-1)} + b_l^f) \\
o_l^{(t)} &= \sigma(W_l^{ox}h_{l-1}^{(t)} + W_l^{oh}h_{l-1}^{(t-1)} + b_l^o) \\
s_l^{(t)} &= g_l^{(t)} \odot i_l^{(i)} + s_l{}^{(t-1)} \odot f_l{}^{(t)} \\
h_l^{(t)} &= \theta(s_l^{(t)}) \odot o_l^{(t)}
\end{aligned}$$

where σ is an element-wise application of the sigmoid function, θ is the $tanh$ function, and $\odot$ is the element-wise product. g is the input node with a $tanh$ activation function and i , o and f are the input, output and forget gates, respectively.

3. Proposed Methodology

The proposed methodology of this paper is elaborated in this section. In the signal acquisition step, an accelerometer is used to capture vibration data of the machine spindle for further processing. The framework of the monitoring system of this research is presented in Figure1.

Signals are processed after the acquisition step to extract informative fault indicators and remove noise. Time-frequency analysis is used for this step because of its superior potential in revealing the time variant characteristics of the signals in frequency domain using Morlet wavelet transform method.

In the next step, a set of features are extracted from the wavelet transform to describe the fault properly. The signal energy in different frequency bands are used as the monitoring features. Therefore, minimum pre-processing is implemented to explore the capability of LSTMs in eliminating unnecessary information and magnifying relevant features. In contrast to other hand-crafted feature learning models, deep learning methods are capable to provide an effective prediction tool for fault detections by learning robust feature representations directly from input signals.

A deep LSTMs model is proposed in this paper to accurately predict the faults in machining process. A simple yet effective architecture as shown in Figure 1 is considered due to the constraints of tool condition monitoring system. The keras deep learning library is employed [22] with tensorflow as the back-end [23] to implement the proposed model. The proposed architecture of the paper involves an LSTM with four neurons in the first hidden layer. then the output is fed into two fully-connected layers. The fully-connected layers are responsible to compute the softmax activation with a matrix multiplication followed by a bias in order to produce the prediction value. Mean Absolute Error (MAE) is chosen as the loss function. The model is fit during 2000 training epochs.

4. Results and discussion

4.1. ETS Experimental Dataset

A set of experiments are performed to measure tool flank wear during machining of hard to cut materials. K2X10 Huron high speed CNC machine of the LIPPS laboratory at ETS is used to perform the experimental tests. A tri-axial accelerometer was mounted on the spindle of the machine with a sensitivity of 100mV/g for measuring acceleration.

D2 high speed tool steel is selected as the workpiece material with hardness of 60-62 HRC due to its high wear resistance in order to investigate tool wear in machining hard material with dimension of $200 \times 54 \times 4$. Carbide Walter End Mill Protostar H50 Ultra tool with 6 teeth is selected as the cutting tool with 50 degrees of helix angle. Different cutting speeds of 2500 rpm and 6000 rpm and feed rates of 0.12 mm/tooth and 0.05 mm/tooth with 4 mm depth of cut and tool wear were measured at different intervals which results in 63 cases with different tool wears and cutting conditions. Figure 2 demonstrates this experimental setup.

4.2. Tool wear estimation using vibration signals from ETS dataset

The monitoring system is developed as per the methodology described in the previous section. Also another system without the LSTM layer with just fully connected layers of ANN is developed as the baseline. Fully connected layers can be considered as multi-layer perceptron ANNs which are widely used in this application as a common ANN technique. Data is divided into two categories, training and testing with 70% and 30% of the data respectively. For evaluating the performance of monitoring systems, average accuracy in percentage (the differences between predicted and actual tool wear value divided by average of tool wears) and RMSE are calculated as representative of the performance from the Scikit-learn machine learning performance analysis toolboxes.

Figure 2. Experimental set up

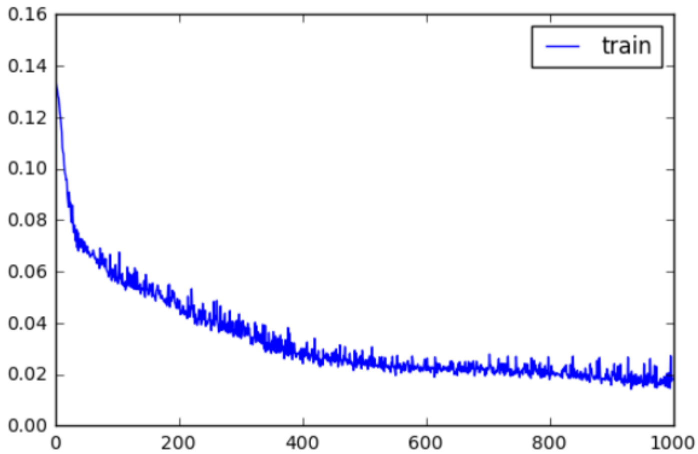

Figure 3. Loss function during training process

Figure 3 reports the loss values of the LSTM training method, which shows it is converging close to zero during the epochs of the training step. Table 1 presents the results of tool wear estimation using test dataset for two different algorithms.

Table 1. Comparison Between regression results

Regression Algorithms	Average Accuracy %	RMSE Test	RMSE Train
LSTM ANNs	92.37	0.00015	0.0001
MLP ANNs	82.21	0.00264	0.00139

Based on the results, LSTM has higher accuracy (92.4%) and lower root mean square error (RMSE) which are acceptable for most industrial applications. Figure 4 illustrates the predicted versus actual tool wears using the LSTM based algorithm for two tools from the no wear (VB=0) state up to the high tool wears. It is observed based on the diagrams and table that LSTM has a promising performance in this application.

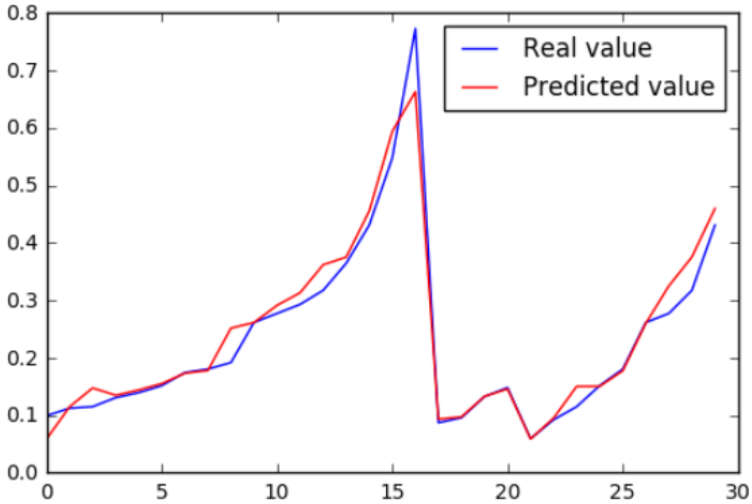

Figure 4. Estimated and real tool wear values using vibration signals

5. Conclusions

A robust tool condition monitoring method is proposed and validated in this research with ability to tolerate changing cutting parameters. Spindle vibration signals from the ETS dataset are used as the fault indicator. Wavelet transform time-frequency transformation method is employed for the signal processing step due to its great applicability to process signals and reveal rich information in both time and frequency domain simultaneously and its proven performance in this application. A deep LSTM based ANNs method is also implemented as the last step to model the complex relationships between extracted features and tool wear.

Time frequency step of the research revealed information on both time domain and frequency domain characteristics of the signals and the study confirms its performance and effectiveness in tool wear monitoring. Table 1 report the comparative results of the LSTM ANNS based proposed methodology of the paper versus MLP ANNs which is one of the most common and widely used ANNs in the Literature. Based on the results, LSTM outperforms MLP with above 10% in accuracy and it has a significantly lower RMSE for both training and test results. So it proves the applicability of LSTM for tool wear estimation.

As the next steps of this study, the results will be validated with other common sensors in this application, especially more economic and applicable sensors such as power and current sensors. In addition, sensor fusion techniques will be investigated at different levels of analysis to increase accuracy and robustness of the system.

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