A ROBUST METHODOLOGY FOR TOOL CONDITION MONITORING USING SPIKING NEURON NETWORKS

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ABSTRACT
Artificial neural networks of sigmoidal and McCulloch-Pitts neurons have found increasing favour in industry research because of their most attractive features, abstraction of hardly accessible knowledge and generalisation from distorted sensor signals. In recent years experimental evidence has been accumulating to suggest that biological neural networks, which communicate through spikes, use the timing of these spikes to encode and compute information in a more efficient way. In this paper it is presented a simplified version of a Self Organizing neural architecture based on Spiking Neurons and it is shown that this computational architectures have a greater potential to unveil embedded information in tool wear monitoring data sets and that smaller structures, compared to sigmoidal neural networks, are needed to capture and model the inherent complexity embedded in tool wear monitoring data. Additional, it is proposed a robust methodology based on tool wear estimation historical evolution that should improve estimation and predictive capabilities of Tool Condition Monitoring systems.

KEY WORDS
Spiking Neuron Networks; Machining; Condition Monitoring; Tool Wear

1. Introduction

Manufacturing industries' drive for cost savings and productivity improvements have culminated in the creation of minimally manned factories. The late 1990s and early 2000s have witnessed a change from the old practice of changing tools automatically, to the feasibility of instituting tool change procedures based on monitoring the amount of wear on the cutting tool-edges through the implementation of adaptive tool inspection mechanisms. For machine tools these systems are termed tool condition monitors (TCM). The main goal in the application of TCM is to increase productivity and hence competitiveness by maximising tool life, minimising machine down time, reducing scrappage and preventing damage. Thus, appropriate and timely decision for tool change is significantly required in the machining systems. The traditional ability of the operator to determine the condition of the tool based on his experience and senses, i.e. vision and hearing, is now the expected role of the monitoring system. One important strategy to support this goal is sensor-based, real-time control of key characteristics of both machines and products, throughout the manufacturing process.

In order to justify the capital investment associated with the installation of flexible manufacturing equipment it is necessary to achieve the maximum utilisation possible. One of the challenges this poses lies in devising methods for the classification of cutting tool wear. This seemingly simple task has posed considerable difficulty, probably due to the fact that tool wear introduces small changes in a process with very wide dynamic range. The task can be subdivided into a number of stages; sensor selection and deployment, generation of a feature indicative of tool condition and finally classification, i.e. assessing the collected and processed information so as to determine the level of wear on the tool.

This article is subdivided in four main sections: an introductory section to condition monitoring and its present state; an introduction to spiking neuron networks and its feasibility to condition monitoring; a section dedicated to the experimental work and simulation results; and a last section that lays out a robust methodology to aid tool wear estimation and prediction.

2. Condition Monitoring

The need for monitoring in a metal cutting process encompasses monitoring the machine and the cutting process dynamics, cutting tools and workpiece to insure optimum performance of the systems. A tool condition monitoring system can therefore be viewed as serving the following purposes, Byrne et al. [1]:

- Advanced fault detection system for cutting and machine tool,
- Check and safeguard machining process stability,
- Means by which machining tolerance is maintained on the workpiece to acceptable limits by providing a compensatory mechanism for tool wear offsets, and
- Machine tool damage avoidance system.

Several factors have impeded advances in the development of TCMSs including inappropriate choice of sensor signals and their utilisation. The random behaviour can be attributed to the large-scale variation and non-homogeneities that exist in the workpiece. Typically, most metal cutting processes can be classified as having one or more of the following characteristics, Warneche et al. [2]:

- Complex to chaotic behaviour due to non-homogeneities in workpiece material,
- Sensitivity of the process parameters to cutting conditions, and
- Non-linear relationship of the process parameters to tool wear.

A mechanistic model derived from first principles is theoretically the most accurate model that can be developed for any system. Unfortunately, the resources required to develop such a model for even the simplest of systems tends to prohibit their use. To give an idea of the complexity of the cutting process one can simply look at the turning process. Tool wear processes generally occur in combination with the predominant wear mode, dependent upon the cutting conditions, workpiece and tooling material, and the tool insert geometry. For a given cutting tool and workpiece material combination, the tool wear form may depend exclusively on the cutting conditions, principally cutting speed V and the un-deformed chip thickness t, and a combination of the aforementioned wear mechanisms. Ranges of cutting speed where each type of wear is predominant can be identified by considering the product of these values as V.t, which is directly proportional to the cutting speed. Sometimes, the tool life can be considerably reduced if the area of cut, the area swept by the cutting tool, is significantly increased (i.e. by increasing the depth of cut mainly). At low cutting speeds, the tool wears predominantly by a rounding-off of the cutting point and subsequently looses sharpness. As the cutting speed increases the wear-land pattern changes to accommodate the ensuing change with extremely high values, leading to plastic flow at the tool point. Cratering on the other hand depends largely on the cutting temperature than on the cutting speed. Therefore, forecasting in complex systems characterized by poorly understood, noisy and often non-linear can be practically impossible when based on traditional model predictive algorithms, Parlos, et al. [3].

Consequently engineers tend to rely on system identification techniques to establish process models. As with linear models, ANNs provide a description of the relationship between cause and effect variables. The benefit of ANNs over linear models is that they are capable of modelling non-linear relationships. In fact studies have shown them to be capable of modelling any non-linear function to arbitrary accuracy Cybenko [4] and Hornik et al. [5]. Also, artificial neural networks have found increasing favour in manufacturing systems research because of their ability to perform robustly in noisy environments, Balazinski et al. [6]**.** Abstraction of hardly accessible knowledge and generalisation from distorted sensor signals are some of the most attractive features of neural networks when applied to sensor fusion and classification in tool wear monitoring. Nevertheless, although working in certain conditions, most of the previous applications of neural networks have some limitations, as reported by Lennox et al. [7] in an extense study into the application of artificial neural networks in the area of process monitoring and control.

Much research has been carried out concerning the development of a reliable TCMS. However, none has yet found ubiquitous industrial use, Dan and Mathew [8] and Dimla [9]. Several factors have impeded advances in the development of TCMSs including inappropriate choice of sensor signals and their utilisation. One of the primary reasons for the lack of industrial application of TCMSs is due to the fact that TCMSs have been developed based mainly on mathematical models, which require huge amounts of empirical data. Another possible hindrance lies in the nature and characteristics of the utilised sensor signals in general, which tend to be stochastic and non-stationary and therefore difficult to model, Silva et al.[10].

In order to achieve reliable tool wear monitoring it is necessary to incorporate some degree of intelligence into the software and perhaps also utilise multiple sensors, Dimla et al. [11]. Numerous approaches have been described in the open literature ([2], [9], [12]), some studies applied to the turning process ([8], [13]).

3. Spiking Neuron Networks

Computational models for neural systems have often concentrated on the processing of static stimuli. However, numerous biologically relevant signals have a rich temporal structure, and neural circuits must process these signals in real time. In many signal processing tasks, such as audition, almost all of the information is embedded in the temporal structure. In the visual domain, movement represents one of the fundamental features extracted by the nervous system. Hence, it is not surprising that in the last few years there has been increasing interest in the dynamic aspects of neural processing. Processing of real-world time-varying stimuli is a difficult problem, and represents a challenge for artificial models of neural functions, Natschläger and Maass [14]. Simultaneously, in computer science several areas such as computer vision, robotics, and machine learning have also increased their efforts to deal with dynamic real-world inputs.

Models of spiking neurons have been extensively studied in the neuroscience literature [15], in recent years. Spiky networks have a greater computational power than networks of sigmoidal and McCulloch–Pitts neurons, Maass [16], and are able to model the ability of biological neurons to convey information by the exact timing of an individual pulse, and not only by the frequency of the pulses Bugmann [17] and Maass and Ruf [18]. A class of the more detailed models, known as conductance based ones, have their origins in the classic work by Hodgkin and Huxley [19] who have summarised their experimental studies of the giant axon of the squid in four differential equations. Also, pulse coding is computationally powerful [20] and very promising for tasks in which temporal information needs to be processed.

To date all neural network based tool condition monitoring relied on the traditional basic concepts introduced by McCullock and Pitts. However, in recent years experimental evidence has been accumulating to suggest that biological neural networks, which communicate through spikes, use timing of these spikes to encode and compute information. In tool condition monitoring, numerous sensed signals on the process have a rich temporal structure [21], and neural circuits must process these in real time. As suggested, these new computationally architectures of neural networks based on Spiking Neurons, also known as integrate-and-fire neurons, reveal a greater computational power than networks of sigmoidal and McCulloch-Pitts neurons.

4. Preliminary Experimental Work

Based on the above considerations experimental background work was conducted on the turning process to collect tool wear data. In this work a set of tool wear cutting data was acquired by machining a block of mild steel under realistic production conditions that consisted of a cutting speed of 350 m/min, a feed rate of 0.25 rev/min and a depth of cut of 1 mm, with a coated cemented carbide tip. The set of sensors used were; an accelerometer for measuring vertical vibration, a microphone for recording the sound emission, a strain gauged tool holder for force measurement and a meter for the spindle current of the CNC machine. The turning operation was carried out on an MT 50 CNC Slant Bed Turning Centre. The analogue signals were sampled at 20 kHz with tool wear and sensor data being acquired at intervals of 2 min, taking into account an expected tool life, for each insert, with a typical value of 15 min. Sample data were recorded for 6 inserts. The length of each sample was 512 points, and these were acquired approximately in the middle of the bar.

Each 512 point record was processed to generate the features used in the classification stage. A total of 12 features were extracted from the sound and vibration data: absolute deviation, average, kurtosis, skewness and the energy in the frequency bands (2.2-2.4 and 4.4-4.6 kHz) obtained from the spectra. Two additional features were presented from the means of the feed and tangential forces. Results have sown that tool wear classification is difficult in the presence of such noisy data and it is therefore required that classification is made by a method that can resolve the complex interrelation between features to produce a robust wear classification. Also the use of multiple sensors should prove to be of great value towards tool wear evaluation since the noisy character of each sensor alone would lead to certain failure of the monitoring system [11].

5. The Spiking Neuron Network (SNN) Model Implementation

Despite the current popularity supervised learning algorithms, its need for a correct estimate of tool condition in every training sample limits its successful application to online tool wear monitoring systems. The implication of requiring correct tool condition is that the machining operation must be interrupted so as to acquire information about tool condition and, as there are numerous combinations of tools, work materials, and cutting conditions (e.g. cutting speed and feed rate), which the eventual monitoring system should handle, a supervised learning procedure is undesirable. For a practical and reliable on-line monitoring system, it is desirable to have a neural network using “unsupervised” training samples without tool wear information, thereby allowing the interpretation of the resulting self-organisation with the fewest number of “supervised” samples. Also, unsupervised learning can be used to validate features´ trustworthiness in the sense that there is no prior knowledge of what is being classified. In this sense the network creates clusters that should allow classification of input patterns into classes of wear states. Therefore, the combination of unsupervised learning with artificial spiking neurons should resemble a more realistic description of unsupervised learning.

As shown by Maass [16] leaky integrate-and-fire neurons can compute weighted sums in temporal coding, where the firing time of a neuron encodes a value in the sense that an early firing of the neuron represents a large value. The basic output neuron, in a typical spiking neuron network, receives a weighed contribution from each input neuron. Each output neuron fires as long as some threshold is reached, firing time correlates to a class of input patterns. Competitive learning is centred in the first fired output neuron so that it gets gradually representative of such a class of patterns. Unsupervised learning follows a scheme by which a set of n-dimensional input vectors are randomly presented to the input neurons. Assuming that the input vector is normalized then this weighted sum represents the similarity between the two vectors with respect to the Euclidean distance. Hence the earlier v_j

fires, the more similar is its weight vector to the input vector [22].

Self organisation of topologically close neurons is realised taking into account that initial neurons that are topologically close together have strong excitatory lateral connections whereas remote neurons have strong inhibitory connections.
Taking into account what was previously discussed, and based on the above indications, the algorithm will be presented step by step as it was built for the simulation.

Step 1. Initialise weights from the inputs i to the total output nodes j, to small random values.

Step 2. Present an input vector s_i^l randomly selected from the training set – time is embedded in the feature vector.

Step 3. Compute the weighted sum between the input S_i and each output node v_j, at each time step δ, using the following equation,

$$Pot_j = \sum_i w_{ij} s_i^l$$

Step 4. Select the firing neuron, the ones which cross a threshold θ (chosen experimentally so that classification could occur, data dependent), and update all weights according to the following rule,

$$\Delta w_{ij} = \eta(1 - t_j)(s_i^l - w_{ij}),$$

where t is the firing time of the output neuron j and η the learning rate, η linearly decreasing with time.

Step 5. Repeat for each time step, by going to Step 3.

Step 6. Repeat by going to Step 2

The implementation consists of three major components; input vector normalisation, training, and test data interpretation. Upon training, the weights start to stabilise until there is no significant change in their value. Interpretation of the output results was achieved by analysing the firing times of the output neurons, the earlier they fire the closer they match a group classification.

In real-time, the only available information concerning a configuration's success will reside in its training performance. The ideal policy will recommend employing a neural network exhibiting "good" sample set classification. The testing to be performed will assess the validity of such a policy for competitive learning, i.e. it will observe its generalisation ability. In addition, testing will identify the configurations which typically yield good results, and mark them as good candidates for the application. Two policies exist for training pertaining to weight update. In this work the policy dictating that weights freeze after "sufficient" training is followed because this provides better control over test classification.

6. Simulation and Results with the SNN

Simulation was performed with an artificial neuron network algorithm, similar to the above description, using 16 input neurons (one for each feature extracted from experimental data) and a variable number of output neurons. Training was performed on experimental data from 4 cutting inserts representing several wear stages. Classification tests were conducted on unseen experimental data from 2 cutting inserts.

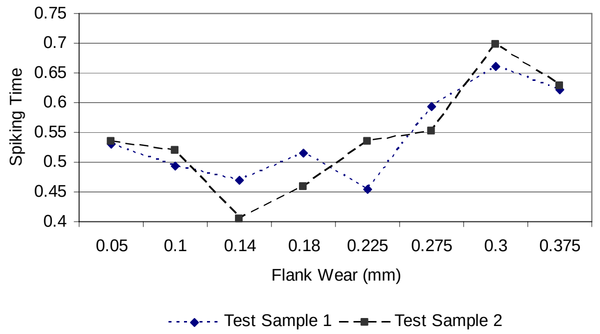

Figure 1 – characteristic Spiking time response on unseen cutting data

Self organisation occurs and it is depicted a classification pattern by the timing of neurons burst. Tests have shown that initially nearly all neurons react strongly, i.e. fire early on each input, whereas after learning only few neurons, being topologically close, react on a certain input pattern. In response to this observation simulations were conducted by reducing the output layer up to only one neuron. It was observed that learning still took place and the resulting classification was the reflex of neuron firing time, as in Figure 1. Therefore, classification is possible based on the timing neurons potential cross a threshold and fire.

It can be observed that for an early stage of wear there is no clear classification reflecting a gradual increase in the wear state. It is though clear that above a flank wear of about 0.27 mm classification is possible based on the spiking time of the output neuron, and undoubtedly recalls a worn state of the tool.

7. Robust Estimation and Prediction

It is well known that industrial processes are characterized by noisy environments and therefore pose a challenging task for monitoring strategies. Also, most methodologies fail to be successful because of their incapability to cope with random and spurious events that may cause or lead to doubtful decisions concerning tool wear estimation.

Further, tool wear evolution is a continuous process that has a predetermined growth nature.

Given the above considerations, and in order to improve the performance a tool condition monitoring system, past experience can be taken in to account for each tool life. This consists of keeping track of classifications and then using a number of classifications to assess the consistency of classification. Through the use of historical data the system becomes aware of previous performance and can judge its reliability, therefore system 'awareness' provides a certain degree of "intelligence" which enables the system to know, according to the "past", what the "present" may or may not be. This methodology resembles, to a certain extent, the cognitive process of the operator when confronted with doubtful information and enables the "machine" to make more reliable decisions. To aid this task regression can be used to model tool wear evolution and give predictive capabilities to the monitoring system.

8. Conclusion

This paper described the implementation of a prototype decision support system for tool wear monitoring based on Spiking Neuron Networks. It was shown that the modelling technique proposed is highly effective for the classification of wear levels of tool inserts using apparently weak features.

The results show that time coding have an enormous impact on the structure of the network required to perform this classification task. The reduction in size allows for a fast and realistic learning in real-time, and possibly on-line. These results show that such an adaptation can result in grate improvements if compared with previous approaches using traditional artificial neural networks.

The proposed methods have shown the adequacy of spiking neuron networks for tool condition monitoring implying that this approach is feasible for industrial applications where only noisy data is available. It is shown that the combination of these two approaches, a non-linear time series analysis and a temporal sequence processing using Spiking Neuron Networks, is a promising new methodology for Machine Condition Monitoring. Robust estimation and prediction should also prove to contribute to the success of this approach.

9. Acknowledgement

Research for this article was partially supported by FCT – Fundação para a Ciência e a Tecnologia, Portugal. Project Reference POCTI/EME/59491/2004.

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