MULTI-SENSOR CONDITION MONITORING USING SPIKING NEURON NETWORKS

Rui G. Silva
Universidade Lusíada de VN Famalicão
Largo Tinoco de Sousa, 4760-108 Vila Nova de Famalicão, Portugal
rsilva@fam.ulusiada.pt

Steven Wilcox
University of Glamorgan, School of Technology
Pontypridd, Wales UK CF37 1DL, UK
sjwilcox@glam.ac.uk

António A.M.M. Araújo
Universidade Lusíada de VN Famalicão
Largo Tinoco de Sousa, 4760-108 Vila Nova de Famalicão, Portugal
ajmm.araujo@gmail.com

ABSTRACT

The paper presents an intelligent system for on-line monitoring of the cutting process. The monitoring apparatus is developed both in hardware and software. The system is based on a PC which is connected to a set of sensors, via a data acquisition card, for on-line post-processing and classification. The proposed monitoring system takes advantage of most attractive features of neural networks, such as abstraction of hardly accessible knowledge and generalisation from distorted sensor signals, to give a reliable prediction on tool condition. It consists of six components: data collection, feature extraction, multi-sensor integration, pattern recognition, tool wear estimation, and outlier detection. The proposed architecture has a built-in Self Organizing neural architecture component based on Spiking Neurons and it is demonstrated that these 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.

KEYWORDS

Spiking Neuron Networks; Machining; Condition Monitoring; Tool Wear.

1. INTRODUCTION

Manufacturing industries and their customers are now demanding substantial increase in flexibility, productivity, and reliability from process machines, as well as increased quality and value of their products. Many condition monitoring systems have been used to supervise the state of different industrial processes. A condition monitoring system can be viewed as serving the following purposes: advanced machine and process fault detection; verification and protection of machine and process stability; maintenance of process tolerances by providing a compensatory method; protection of machine and process failure. Several factors have retarded advances in the development of condition monitoring systems, including inappropriate choice of sensor signals and their utilization, and their inability to perform robustly in noisy environments.

Artificial neural networks of sigmoidal and McCulloch-Pitts neurons have found increasing support in industry research (Sick, 2002) because of their most attractive features, i.e. abstraction of hardly accessible knowledge and generalisation from distorted sensor signals. In recent years, accumulated experimental evidence has suggested that biological neural networks, which communicate through spikes, use the timing of these spikes to encode and compute information in a more efficient way, providing to the new neural network models additional characteristics that perform better in the modelling of nonlinear data than the traditional models. Besides, in cutting tool processes, the various detected signals hold a rich temporal structure, requiring real-time processing from neural network.

In order to justify the capital investment associated with the installation of flexible manufacturing equipment it is necessary to achieve the maximum possible utilisation. One of the challenges posed by this 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 a very wide dynamic range. The main goal in the application of Tool Condition Monitoring (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 decisions for a tool change are required in 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.

This article starts with an introduction on condition monitoring and its present state (Section 2) and Section 3 presents the current developments on spiking neuron networks, as well as the overall methodology to aid tool wear estimation and prediction. Section 4 is dedicated to the description of the experimental apparatus and cutting conditions used to test the prototype system. Section 5 presents the simulation results of the proposed system based on experimental data collected from experiments. Finally, the main conclusions drawn from the work described in this paper are summarised in the last section.

2. CONDITION MONITORING

Manufacturing industries' drive for cost savings and productivity improvements have culminated in the creation of minimally manned factories. 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 (Byrne, 1995). Much research has been carried out concerning the development of a reliable TCM system, however, none has yet found ubiquitous industrial use (Dimla 2000). One of the primary reasons for the lack of industrial application of TCM systems is due to the fact that TCM systems have been developed based mainly on mathematical models, which require huge amounts of empirical data, reducing therefore their adaptation capacity. 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. The random behaviour can be attributed to the large-scale variation and non-homogeneities that exist in the workpiece. More recently developed nonlinear measures over time series, such as time delay and embedding dimension, characterize other features more reliably than standard information extraction methods, such as Fourier transforms, and should unveil a new dimension of information (Stam, 2005).

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 the systems tends to prohibit their use. Also, 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.,* 2000). Consequently engineers tend to rely on system identification techniques to establish process models. As with linear models, Artificial Neural Networks (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, 1989). In many signal processing tasks, such as audition, almost all of the information is embedded in the temporal structure (Natschläger and Maass, 2002). It becomes clear that neither biological neurons nor biological synapses are modelled well by the "neurons" and "synapses" of common artificial neural network models that ignore the inherent temporal dynamics of their biological counterparts. The selected training data-set should capture the characteristics of the tool wear process and this imposes significant computing burdens which may result in complex identification model hampering the feasible application of neural networks (Salgado and Alonso, 2006). Once the signals that will be used in monitoring have been chosen, the fundamental problem to be overcome in order to achieve effective monitoring would be to extract information that is correlated with tool wear (Figure 1). The stochastic and non-stationary nature of the signals, which may be due to the heterogeneity of the workpiece, the sensitivity of the features being measured in the process to changes in cutting conditions, and the non-linear relationship of these features to tool wear, makes this no trivial task. Hence, current interest is focused on investigating such tools as time series techniques that allow valuable information to be extracted. It is felt that the combination of these two approaches, a non-linear time series analysis and a temporal sequence processing using Spiking Neuron Networks, will generate new methodologies for tool wear monitoring. Also, it will certainly give a different perspective on the subject of tool wear monitoring and understanding of the cutting process itself.

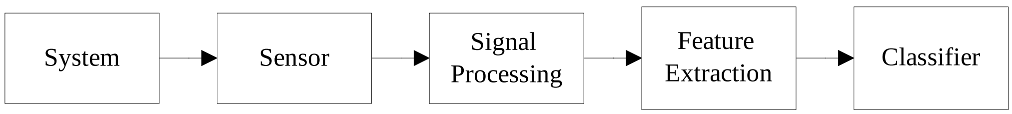

Figure 1 – Tool Condition Monitoring Methodology

3. CONDITION MONITORING BASED ON SPIKING NEURON NETWORKS (SNN)

Models of spiking neurons have been extensively studied in the neuroscience literature (Gerstner, 1999) in recent years. Spiky networks have a greater computational power than networks of sigmoidal and McCulloch–Pitts neurons (Maass, 1997), 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, 1997; Maass and Ruf, 1999). A class of the more detailed models, known as conductance based ones, have their origins in the classic work by Hodgkin and Huxley (1952), who have summarised their experimental studies of the giant axon of the squid in four differential equations. To date all neural network based tool condition monitoring relied on the traditional basic concepts introduced by McCullock and Pitts (Sick, 2002). In TCM, numerous sensed signals on the process have a rich temporal structure (Silva *et al*., 1998) and neural circuits must process these in real time.

Despite the current popularity of 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. 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 (1999) 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 neuron v_j fires, the more similar is its weight vector to the input vector, Ruf and Schmitt (1997).

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. Given that our features represent analogue signals they have to be encoded in such a way as to reflect linear changes, known as delay coding. Delay coding arises from the observation of real world neuron response, which suggests that highly stimulated neurons tend to spike sooner.

Taking into account what was previously discussed and based on the above indications, the basic structure of 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 randomly selected from the training set with delay coding;
Step 3. Compute the weighted sum between the input Si and each output node v_j, at each time step δ, the Posts Synaptic Potential (PSP), $PSP_j = \sum_i w_{ij} s_i^l$
Step 4. Select the highest post synaptic potential among neurons and update all weights in a similar fashion as the one used in Self Organizing Map neural networks, $\Delta w_{ij} = \eta\left(s_i^l - w_{ij}\right)$, where η is the learning rate.
Step 5. Repeat for each time step, by going to Step 3.
Step 6. Repeat by going to Step 2

The implementation of the SNN module 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 post synaptic potential of the output neurons, the higher their values 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.

To improve system’s reliability, given the noisy characteristic of sensor signals, it is proposed the use of an outlier detector to reject abnormal classifications. The mechanism used hereby takes advantage of the statistical leverage of samples and allows for a better judgement on the neuron network classification results. The first stages of wear are ignored – up to 0.15 mm of flank wear – giving place to a rising importance of the polynomial regression as an outlier detector, given established intervals of confidence whereby it is possible to reject/accept a given classification. The effectiveness of this approach should reveal of great importance in an on-line monitoring system, given the abundance of classification results and consequent importance of statistical data.

4. APPARATUS AND FEATURE EXTRACTION

Based on the above considerations, experimental background work was conducted on a 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.

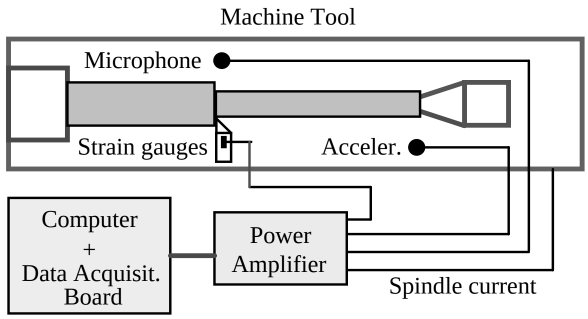

Figure 2 Experimental apparatus

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 (Figure 2). 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.

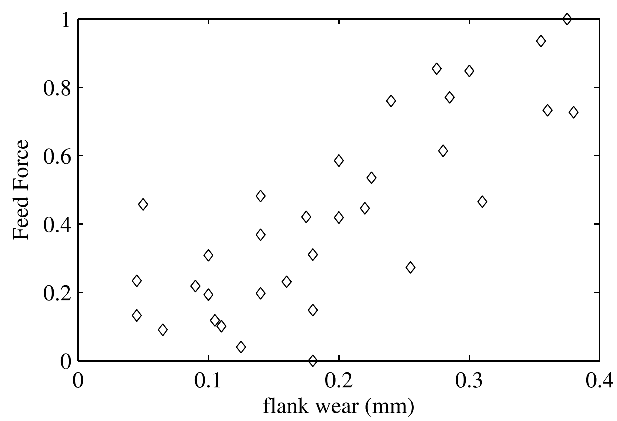

Figure 3 - Feed Force

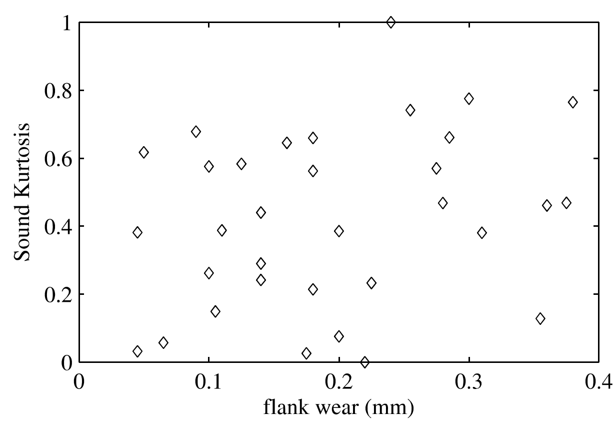

Figure 4 - Kurtosis of Sound

Each recorded 512-point sample 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 showed 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 (Dimla *et al*., 1997; Sun, 2006).

As shown by the example presented in Figure 3, both tangential and feed forces show an increase with tool wear, which is consistent between tools. The remaining features (absolute deviation, mean, kurtosis, and skewness of both sound and vibration) exhibited little correlation with flank wear data points (Fig. 4), appearing to be randomly distributed through the entire space. Although the statistical parameters did not present any obvious relation to tool wear evolution, it is not possible at this stage to judge their importance for tool wear monitoring due to the complexity of the process. The second part of this paper, however, shows that such data can still be used in monitoring the cutting process.

5. SIMULATION RESULTS

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 four cutting inserts, representing several wear stages. Classification tests were conducted on unseen experimental data from 2 cutting inserts. Neuron network classification output is given in terms of Postsynaptic Potential (PSP).

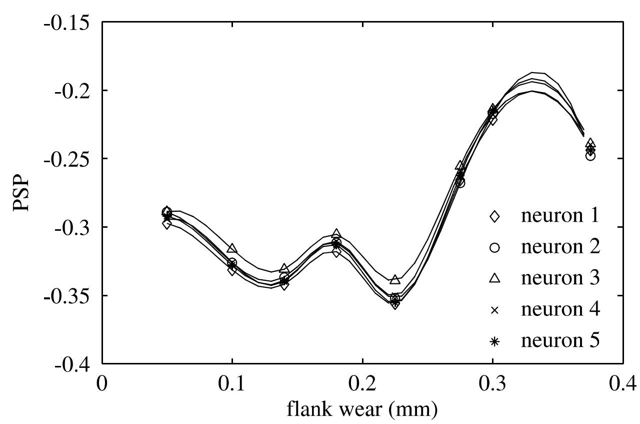

Figure 5 – Characteristic PSP response on unseen cutting data – constant learn rate

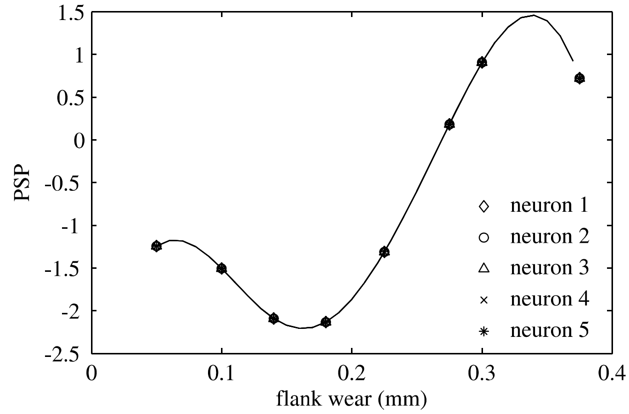

Figure 6 – Characteristic PSP response on unseen cutting data – linearly reducing learn rate

Classification of unseen data is possible and can clearly be depicted from Fig. 5 and Fig. 6 where all neurons give the same result. During the first stages of tool wear there is insufficient data to train the neural networks and classification is not clear giving place to very distinctive worn stages towards the end of tool life, as the tool beds down. Worn stages of tool wear are identified clearly progressively between 0.2 mm and 0.3 mm of flank wear – it should be noted that according to standards, a tool flank wear above 0.3 mm is regarded as worn tool. Given similar responses from all output neurons, tests were also conducted by reducing the output layer up to only one neuron. It was observed that learning still took place, and the resulting classification was a reflex of neuron response. The learning rate has a great impact on results, and it is shown that for a linearly reduced learning rate, classification is improved, Fig. 5 versus Fig. 6.

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 post synaptic potential of the output neuron, and undoubtedly recalls a worn state of the tool. The results presented here, using spike neuron networks, exhibit a clear improvement on classification if compared to those obtained using a Self Organizing Map, as in Silva *et. al* (1998). This algorithm is faster, more accurate and, has a higher capability to model noisy and apparently random tool wear sensed data.

6. 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 delay coding, combined with the capabilities of spiking neuron networks to encode information have an enormous impact on the structure of the network required to perform this classification task. It should be noted that the size of the simulated networks is reduced to 16 input neurons, and one output neuron and, consequently, classification is achieved many times faster. The reduction in size allows for a fast and realistic learning in real-time.

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, showing better results than sigmiodal like neural networks, is a promising new methodology for Machine Condition Monitoring. Also, the polynomial regression approach for outlier detection adds an improved reliability preventing the system from reacting erroneously to spurious data.

Further research is currently underway to implement a prototype system in complex industrial facilities and to develop new strategies for tool wear state forecasting.

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