Monitoring and Diagnosing Manufacturing Processes Using a Hybrid Architecture with Neural Networks and Fuzzy Logic

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Abstract

The success of unattended manufacturing depends largely on control mechanisms that monitor the current machining state and take means in case of disturbances. Direct methods generally lack on-line capability, whereas indirect methods are difficult to pursue because changes in cutting conditions influence such methods. Knowledge about these changes exists but it is unstructured from the sensor's point of view. In the context of this unstructured knowledge, a hybrid architecture, featuring fuzzy logic and neural networks, is described that copes with the shortcomings of the traditional methods to monitor and diagnose an unattended milling machine. Force, spindle current, and acoustic emission data that were stored in previous experiments are used as input to the neural network after they undergo some signal processing to calculate the membership functions of fuzzy relations. Afterwards, fuzzy logic principles are used to diagnose the system's status with regard to tool wear and chatter. It is shown that the system works reliably in a wide range of operations, correctly renders the current state, and is a viable alternative to existing monitoring methods.

Introduction

The need of manufacturers to come up with reasonably priced products has resulted in increasing use of unattended and/or automated manufacturing systems. One problem so far is how to deal with malfunctions and disturbances of which tool wear, chatter, and tool breakage are among those that occur most frequently. To be on the safe side, manufacturers use conservative operating conditions to prevent these malfunctions (Rangwala and Dornfeld, 1989). However, this results in less efficient, and, therefore, more costly production which stands in contrast to the goal outlined at the beginning.

To cope with that dilemma, manufacturers can consider the use of sensors to control the system on-line. These sensors include temperature sensors (Epstein and Wright, 1991), acoustic emission sensors (Dornfeld, 1986), dynamometers, and current sensors (Agogino, 1988). Since each sensor alone cannot render reliably the state of a lool in changing cutting conditions, integrating the information of various sensors became the major challenge. By using partly redundant information this sensor fusion can provide data for decision making about the process that will yield less uncertainty. Early solutions tried to extract relevant features from those data and then to infer the tool status. Others (Agogino, 1988) proposed the use of expert systems and probabilistic influence diagrams. However, all approaches still suffer from high sensitivity to changing cutting conditions.

This is where neural networks help. Their strengths are the ability to filter out noise and their robustness in changing conditions that were not preprogrammed. Rangwala (1988) introduced a neural network utilizing information from acoustic sensors and force sensors to monitor tool wear. He proposed the use of features gathered by a Fast-Fourier Analysis and used a backpropagation algorithm to train his network. Burke (1989) used the same data but applied it to a classifying clustering algorithm. More recent developments (Leem 1992) suggested the use of Kohonen's Feature map to cluster data and to get a solution by determining into which cluster a data point falls. In other developments, fuzzy logic controllers have been introduced to cope with a variety of different problems. This paper investigates how a hybrid fuzzy-neural system can deal with the problem outlined above. Each method has its strengths and weaknesses and often one method alone does not perform satisfactorily. It therefore would seem sensible to combine the advantages of each system and form a hybrid one.

A milling machine under various operating conditions was selected as the manufacturing environment. In particular,

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tool wear and chatter were investigated in a regular cut as well as entry cut and exit cut Data sampled by three different sensors (acoustic emission sensor, dynamometer, motor current sensor) were used to determine the state of the machine.

Fuzzy diagnosis has proven to be an intriguing way to deal with problems. However, one of the shortcomings has been the inability to design the membership functions a priori or even during test operations. A "heuristic" tuning is necessary in most cases to achieve reasonable results. This unsatisfactory state can be avoided by letting a neural network learn the membership functions which may have a much higher complexity than the handtailored triangular-shaped functions that humans usually start with. The values generated by the neural net are then combined with a value from another neural network that resembles the consequent part of the fuzzy rule to form the complete fuzzy value of diagnosis of the state on chatter and tool wear.

Experimental Setup

Data obtained during earlier experiments (Agogino, 88) were used. They were gathered from a numerically controlled upright Bridgeport milling machine.

> "Amplified sensor outputs were fed into an analog to digital converter as an add-on board. Data were acquired from four channels, one each for the AE signal, dynamometer X and Y directions, and the current sensor. Data were sampled every 1 millisecond from all four channels, in approximately 750 milliseconds, over the cutting parameters and machining conditions defined by this study.
>
> In order to develop a "real time simulation" that did not compete with daily users for time on the milling machine the data were uploaded from the INTEL 310 to a DEC Microvax computer. The simulation reads the actual sensor data from files on the Microvax as if it were reading them in real time.
>
> Acoustic emission signals were obtained from an Endevco 920A piezoelectric transducer mounted directly on the workpiece. The RMS signal was fed through an A/D converter in the INTEL 310 computer for data acquisition. A Kistler 9257A dynamometer (piezoelectric transducer) was used to measure force in the workpiece. And, lastly, an American Aerospace Controls series 1003AM1 AC current sensor (based on induction measurements) was used to measure spindle motor current.
>
> Chatter is the self-excited vibration that occurs when a machine tool exceeds its stability limit. Acoustic emission can be an important predictive measurement for detecting chatter. If detected, chatter can usually be corrected by reducing the depth of cut or feed rate. When chatter occurs, the AE signal increases dramatically in amplitude. Chatter can also be detected by the frequency content of the dynamometer" (Agogino, 88).

Tool wear can be recorded by the change in force RMS along both X and Y directions because tool wear results in an increase in cutting force. The current sensor reading is also proportional to the cutting force and to the tool wear. More importantly, it is a good detector of die cut state because the entry of the tool into the workpiece produces very high acoustic emissions and force readings which in turn could lead to wrong diagnosis.

A minimal amount of signal processing was performed on the sensor readings. Instead of feeding the raw data into the neural net, the mean of the acoustic emission as well as its standard deviation was used for a window of 0.05s. Also, the mean of the motor current was taken as well as the standard deviation of the upper part of the amplitude of the force readings in the x-direction. The force in the y-direction was not considered because it constitutes basically the same information as in the x-direction. Thus, if we used this data as well, the system would potentially learn more noise than gain new information.

Neural-Fuzzy Reasoning

Reasoning in fuzzy logic is done with IF-THEN relations. Therefore, after the logic is identified the fuzzy membership function has to be established. Initial intuition and/or experience and later tuning might be necessary to obtain a correct relation. This is where the neural networks come into the game. Their task is to learn the fuzzy relations by a simple mapping from clustered input to membership value. No knowledge about the function itself is necessary which gives rise to the hope that this might be a way to successfully diagnose a system at the first try.

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The procedure is divided in several steps (Takagi, 1991). First, the number of rules is determined by dividing the training data into different groups using a standard clustering method. A dendrogram established the clusters utilizing the centroid method. The number of clusters was determined according to their relative distances from each other. Once a certain threshold was reached, the number was fixed. In the remaining clusters, data points from different situations might still overlap. Those clusters undergo a new run through the clustering algorithm. Thus, all known diagnosing situations may be sorted out

The system is subsequently trained with a perfect fit membership value (μ=1) for the cluster it belongs to and no fit (μ= 0) otherwise. This part resembles the IF portion of the fuzzy rule and can be expressed as:

$$NN_{mem}(x_1, x_2, x_3, x_4) \text{ is } A^i \text{ is } m_i$$

where:

$NN_{mem}(x_1, x_2, x_3, x_4)$ is the neural net into which x_1 - x_4 are fed
A^i is a fuzzy number relating to the cluster i that x_1 - x_4 belong to
m_i is the membership value that is learned by this step
x_1 - x_4 are the four different data gathered from the sensors at one time instance

Note that A is a fuzzy number without a specific meaning. It can be thought of as a combination of quantities of the inputs, for example: AE mean LARGE and AE stdev SMALL and me mean SMALL.

Lastly, the THEN part of the rules is determined and the amount of diagnosing value for each rule trained. This is done by introducing as many additional neural nets as there are rules. Input is the sensor data, output the diagnosis for a rule. This relation can then be expressed as:

$$y_i=NN_i(x_1, x_2, x_3, x_4)$$

where:

y_i is the diagnosis value for a rule
$NN_i(x_1, x_2, x_3, x_4)$ is the neural net for rule i

The overall diagnostic output is obtained by taking the weighted average of membership values with the diagnostic value of each rule. The relation for the defuzzification for the diagnosis can be expressed as follows:

$$\beta^* = \frac{\sum y_i \mu_i}{\sum \mu_i}$$

where:

β^*= overall control value, in this case for tool wear and chatter
μ_i = membership value of rule i

The system is then ready to run. Since we deal with a network of neural nets instead of a single one the architecture is as shown in fig. 1.

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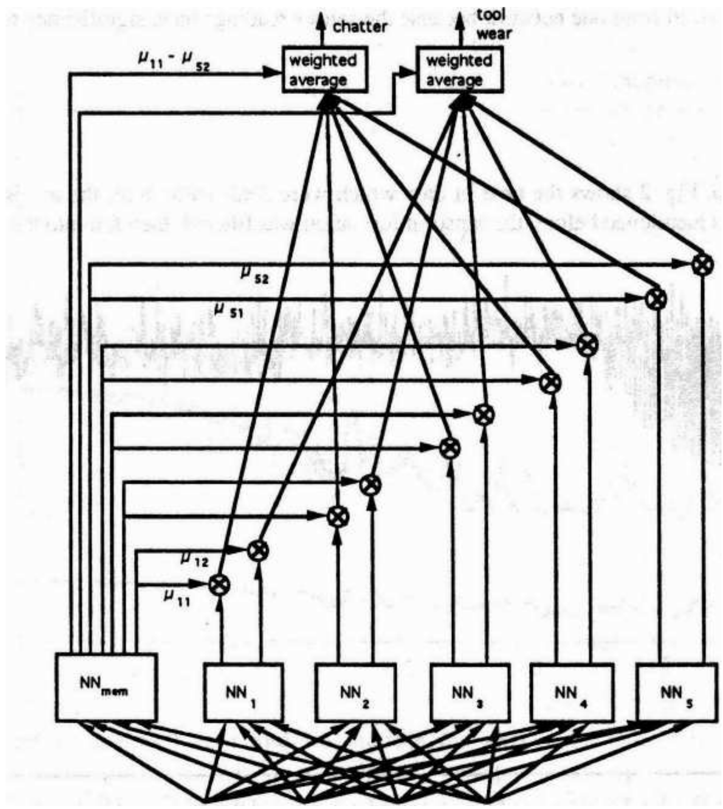

Fig. 1: Architecture of the neuro-fuzzy system

For the neural net for the membership function (NN_{mem}), a 4-9-5 net was used. NN_1 - NN_5 used a 4-5-2 net each. Training data were chosen from different process conditions, mixing a variety of conditions with and without tool wear and chatter. Furthermore, the case of entry/exit cut was observed. The number of learning data was varied between 20 and several hundred to check for the effect on the result. A minimum amount of signal processing was conducted over a window of 0.05 s in considering the average and the standard distribution of the acoustic emission and the average of the motor current and the upper amplitude of the dynamometer. Only three of the four sensors were used, omitting the reading of force in the y-direction because it was felt that it contained the same information as the data from force in the x-direction.

The network and its fuzzy logic components were programmed in the standard programming language C, developed on a general purpose workstation using a standard operating system (UNIX) to allow for integration and support of an Open-Architecture Machine Tool.

The clustering algorithm identified five different clusters and its corresponding diagnoses values. Then the NN_{mem} was trained. Each data point was assumed to make a perfect fit within its clusters (μ = 1). The other values were 0 for no fit, accordingly. The only thing left is to determine the amount of diagnosis due to each rule. That is, data from each cluster had to be matched with a certain situation, i.e. chatter or no chatter, tool wear or no tool wear. In this manner, the nets for the THEN parts of the rules (NN_1 - NN_5) were trained. In this project, three different cases were considered:

- no tool wear, no chatter
- tool wear, no chatter
- no tool wear with chatter

Each of the cases considered was also observed in the entry/exit cut condition. Therefore, actually six different cases were dealt with because of the very different nature of the entry cut compared to the normal steady cut. It is clear that there are actually many more cases, however, to get a first impression as to whether or not this system is feasible, this amount of data is sufficient. When the system is run, it reads in four sensor readings every millisecond and outputs the result in real-time. The output is the diagnosis for chatter and for tool wear. It shall be shown that

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multiple states can be derived from one network because the sensor readings have significance for tool wear as well as for chatter.

Results

The system worked well. Fig. 2 shows the type of data which were dealt with; here, the acoustic emission for an entry cut is displayed. As mentioned before, the sensor information was filtered, then fed into the neural network.

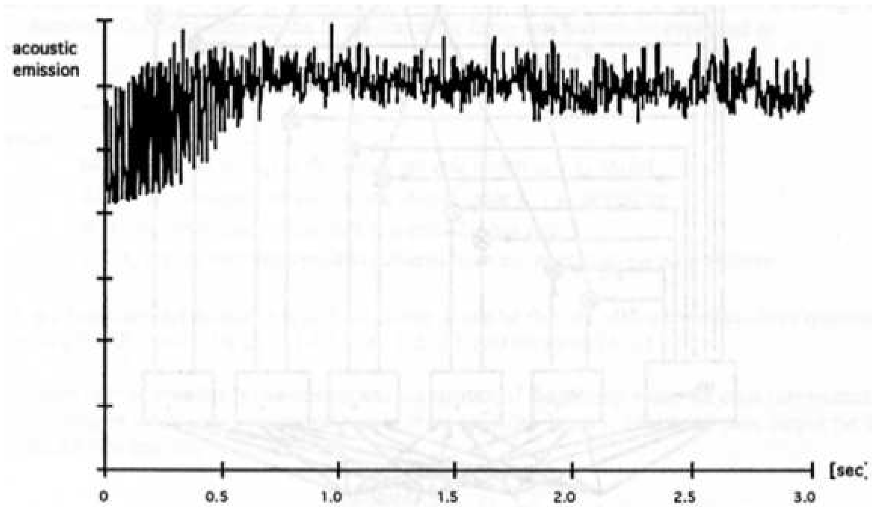

Fig. 2: acoustic emission for worn tool, no chatter, during entry

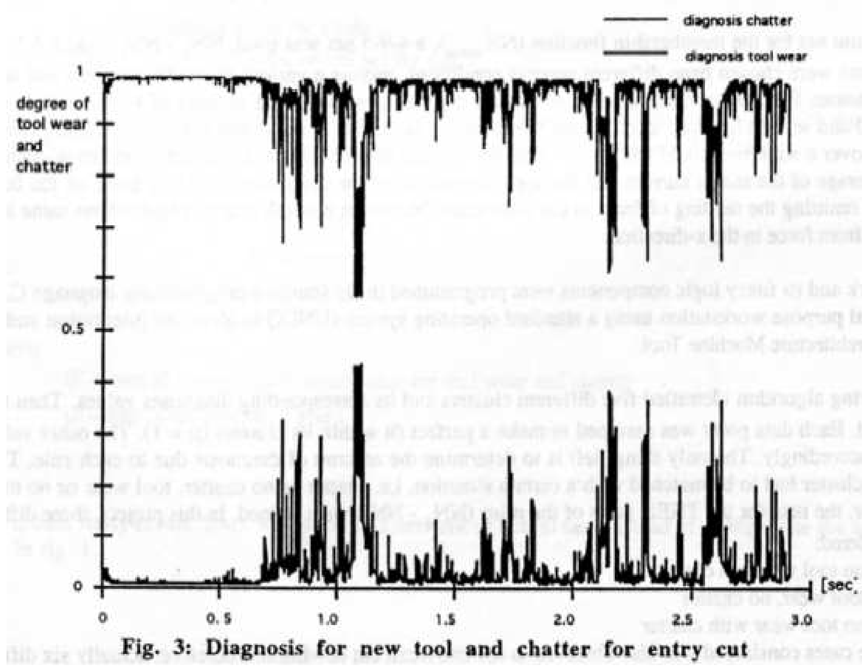

Fig. 3: Diagnosis for new tool and chatter for entry cut

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Fig. 3 shows the diagnosis for chatter and a new tool during entry cut. The diagnosis is very good. Most remarkably is the fact that the diagnosis is corrects from the very beginning. This implies that a tool can be changed even before serious damage has been done to a workpiece because the malfunction is detected right away.

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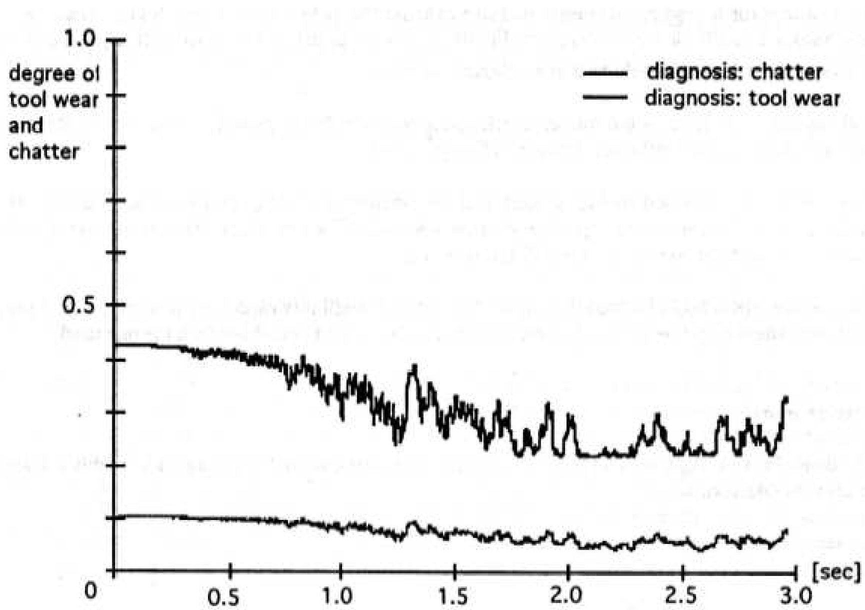

Fig. 4: Diagnosis for new tool and no chatter for entry cut with few training data

The diagnosis works well with a very small number of training data as well. Taking altogether only 20 points from all different cutting situations, the system still gives reasonable answers. Fig 4. shows a new tool and no chatter for an entry cut. Clearly, the diagnosis is not optimal, (nor do we expect it to be) but it still lingers in the correct region.

Further tests were conducted which showed similar promising results for cases with tool wear without chatter.

Discussion and Conclusion

The hybrid fuzzy-neural system performs very well, especially given the nonlinear behavior at entry. Some peaks show that certain regions were not fully covered by training data. More learning data would improve the results.

Further investigations looked at the problem of learning noise. A backward elimination method was used that considered only three out of four sensor readings and checked the error after a given number of epochs. This is done in turn for all sensors and the error is compared. Sensor inputs that just contribute noise to the results could thus be eliminated. However, in this case no superfluous sensors were found apart from the one sensor that was ruled out at the beginning.

Different algorithms using a pure neural net and using a pure fuzzy logic system were developed to check the performance of the neural-fuzzy system. The results demonstrate that the method introduced here is indeed superior. However, if the system were less complex, a neural net alone would do the job as well. The fuzzy-neural net is only justified for a relatively complex system.

The interpretation of fuzzy logic applied to tool wear is the amount of wear at the tool. This is an advantage over other approaches because this method enables us to predict a wear limit if we monitor the tool constantly. As a consequence, an exchange tool can be provided at the correct point of time with no loss in time and money due to failure, poor surface finish, or exchange of a tool that was still functional. However, this interpretation is not so feasible for chatter. Introducing a threshold might circumvent it if we demand control action from the diagnosis.

The choice of binary values as diagnosis values for NN_1 - NN_5 is not very satisfactory. More rules should be

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introduced to allow for a gradual diagnosis to fully exhaust the potential of fuzzy logic. Also, the choice of membership values 1 and 0 for the training data in NN_{mem} seems to defeat the spirit of fuzzy logic. A neural na that could cluster the data itself would be a more elegant solution.

Future work should investigate in the role of overlearning and overfilling as well as the size of the neural net to determine to which extent they influence the result (Takagi, 1991).
Also, data that is not preprocessed should be used to check whether satisfying results can be obtained. Although ID this particular project the amount of signal processing was held to a minimum, there is always the danger that features are chosen that have no relevance in a different setting.

Different neural net types should be tried. Recurrent nets are one possibility especially in view of the general pattern of entry/exit cuts which might be more easily recognized by this type of neural net than the one used.

Acknowledgement

The authors thank Prof. A. Agogino and Prof D. Dornfeld for making available sensor data for this research and Dr. Takagi for his valuable advice.

References

Agogino, A.., and S. Srinivas "Multiple Sensor Expert System for Diagnostic Reasoning, Monitoring and Control of Mechanical Systems," Mechanical Systems and Signal Processing, Vol. 2, No. 2, 1988.

Agogino, A. M., and K. Ramamurthi "Real Time Influence Diagrams for Monitoring and Controlling Mechanical Systems," Influence Diagrams, Belief Nets and Decision Analysis, Ed.: Oliver, R. M., and J.O. Smith. J.R. Wiley & Sons, Ltd. 1990.

Burke, L. I. "Automated Identification of Tool Wear States in Machining Processes: An Application of Self Organizing Neural Networks," PhD thesis, UC Berkeley, 1989. Dornfeld, D.A. "Acoustic Emission Process Monitoring for Untended Manufacturing", proc. Japan-USA Symposium on Flexible Automation, JAACE, Osaka, Japan, 1986.

Epstein, H.A., and P.K. Wright "Intelligent Machine Tools: An Application of Neural Networks to the Control of Cutting Performance" Applications of Artificial Intelligence in Engineering VI", Ed.: Rzerski, G., and R.A. Adey. Computational Mechanics Publications, Southampton, 1991.

Hertz, J., A. Krogh, and R.G. Palmer "Introduction to the Theory of Neural Computation", Addison Wesley Publishing Company, Redwood City, 1991.

Leem, C.S. "Input Feature Scaling Algorithm for Competitive Learning Based Cognitive Modeling with Two Applications", PhD thesis, UC Berkeley, 1992

Rangwala, S.S. "Machining Process Characterization and Intelligent Tool Condition Monitoring Using Acoustic Emission Signal Emission Signal Analysis", PhD thesis, UC Berkeley, 1988.

Rangwala, S.S., and D.Dornfeld "Learning and Optimization of Machining Operations Using Computing Abilities of Neural Networks", IEEE Transactions of Systems, Man & Cybernetics, Vol. 19, No. 2, March/April 1989.

Takagi, H., and I. Hayashi "NN - Driven Fuzzy Reasoning", International Journal of Approximate Reasoning 1991,5: Elsevier Science Publishing Co., New York, 1991.

Tlusty, J., and G.C. Andrews "A Critical Review for Unmanned Machining", Ann. CIRP, 32 (2), 1983.

Wright, P.K., and D.A. Bourne "Manufacturing Intelligence", Addison Wesley Publishing Company, 1988.

Zimmermann, H.-J. "Fuzzy Set Theory and its Applications", Kluwer Academic Publishers, Boston, 1991.

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