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Short communication

Tool wear condition monitoring using a sensor fusion model based on fuzzy inference system

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Abstract

One of the biggest problems in manufacturing is the failure of machine tools due to loss of surface material in cutting operations like drilling and milling. Carrying on the process with a dull tool may damage the workpiece material fabricated. On the other hand, it is unnecessary to change the cutting tool if it is still able to continue cutting operation. Therefore, an effective diagnosis mechanism is necessary for the automation of machining processes so that production loss and downtime can be avoided. This study concerns with the development of a tool wear condition-monitoring technique based on a two-stage fuzzy logic scheme. For this, signals acquired from various sensors were processed to make a decision about the status of the tool. In the first stage of the proposed scheme, statistical parameters derived from thrust force, machine sound (acquired via a very sensitive microphone) and vibration signals were used as inputs to fuzzy process; and the crisp output values of this process were then taken as the input parameters of the second stage. Conclusively, outputs of this stage were taken into a threshold function, the output of which is used to assess the condition of the tool.

Keywords: Condition monitoring; Drilling; Tool wear; Fuzzy inference system; Sensor fusion

1. Introduction

Online monitoring of the tool wear condition is very crucial in order to improve the quality of the unmanned manufacturing systems employing drilling and cutting processes. Early replacement of a workable tool or late replacement of a worn tool may cause time and/or production loss. Moreover, due to complex structure of tool wear mechanism, unpredictable breakages may occur at any time which might also lead to catastrophic failure affecting other components in the system. By employing effective tool wear condition-monitoring techniques, not only such failures can be avoided but also maximum utility can be obtained from the tools.

A considerable amount of research has been carried out before for the development of reliable condition-monitoring techniques. These techniques can be categorized into two main groups: direct methods and indirect

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methods. Direct methods require direct measurements from the tool, while the indirect methods utilize cutting parameters such as force, vibration, acoustic emission and power measured during the cutting process. Direct measurement of tool wear requires that either the tool be removed from the machine after a certain period time or a measuring device be installed on the machine. However, both of these alternatives are not feasible in automated machining processes and cause downtime and production loss. Therefore, although the direct methods are likely to be more accurate than the indirect methods, the indirect methods have been preferred over the direct methods and most of the research in this field is concentrated on them [1].

Commonly used parameters in indirect methods are cutting forces, vibration, acoustic emission, current, power and temperature. A number of studies have been focused on time series and frequency domain analysis of these parameters. Besides these analysis techniques, pattern recognition [2], statistical analysis [3], Fourier transform [4], wavelet transform, fuzzy logic and artificial neural networks [5–7] have been successfully applied to some extent. These methods have sufficiency and practicability at different degrees with respect to others.

Besides the method used, the parameter choice is also very important to design an effective condition-monitoring system. A parameter that works well for one method might not be the appropriate choice for the other. Hence, diagnosing mechanisms depending on a single sensor may not be able to make reliable results for the condition of the tool. Therefore, it is preferable to employ multiple sensors instead of a single sensor to observe the same process [8]. Liu and Wo [9] detected the tool wear status with high accuracy rates using force thrust and vibration signals in a sensor fusion model.

In this work, a two-stage tool wear condition-monitoring technique based on a fuzzy inference system was developed. In the first stage, statistical parameters such as RMS, standard deviation, mean and maximum values were obtained from the force, vibration and machine sound signals acquired from three sensors. These parameters were then used to develop three separate fuzzy systems. In the second stage, a new fuzzy system was built based on the outputs of the three fuzzy systems built in the former stage. The tool wear condition was assessed according to the decision of this fuzzy system.

2. Experimental setup

Fig. 1 presents the experimental setup used in this study. Drilling operations were selected as a machining process conducted on a four-axis computer numerical controlled (CNC) machining center. The thrust force signals were measured using a dynamometer while an accelerometer was mounted on the tool holder to measure the vibration. Besides the force and vibration measurements, machine sound data were also collected through a microphone placed in the direct vicinity of the workpiece. Finally, signals from these three sensors were recorded to computer using a data acquisition card.

3. Fuzzy inference model

In this paper, a fuzzy system model with 2-stage 4-inference was designed to predict the tool wear condition. The system designed can analyze the signals acquired by three separate sensors as can be seen in Fig. 2.

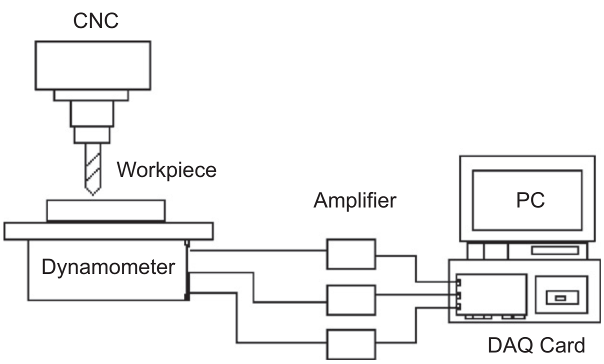

Fig. 1. Experimental setup.

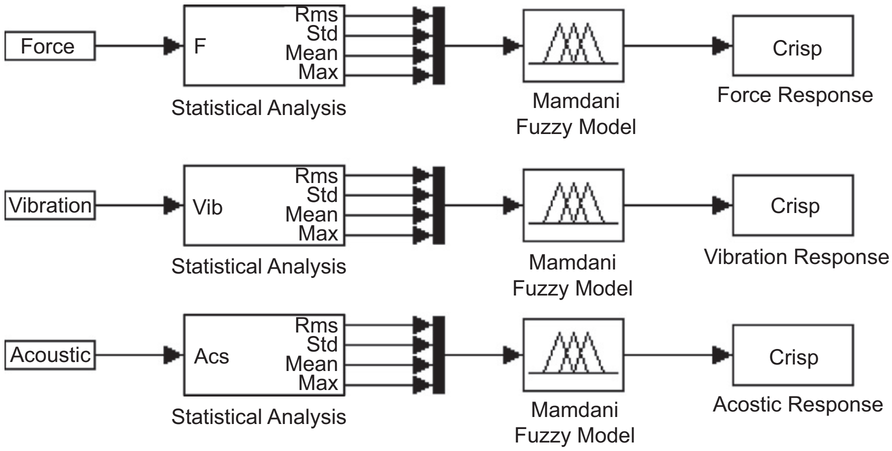

Fig. 2. Fuzzy sensor model: the first stage.

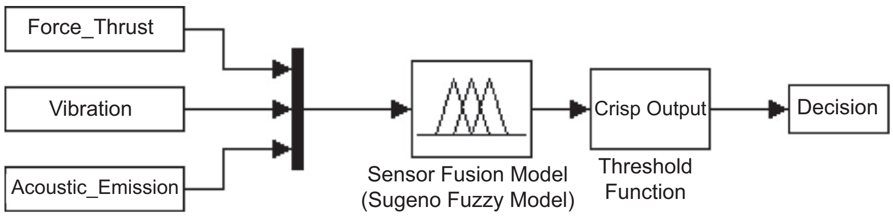

Fig. 3. Sensor fusion model: the second stage.

The entire system consists of two stages. In the first stage, the statistical parameters such as RMS, standard deviation, mean and maximum values calculated from the thrust force, vibration and machine sound signals acquired from various sensors are sent to Mamdani fuzzy inference system. In the second stage, crisp values of the defuzzification of this system are then sent to another fuzzy inference system of Takagi–Sugeno as input parameters. The the most popular centroid calculation method is used for defuzzification. Mamdani and Takagi–Sugeno models are basically similar. The main difference between Mamdani and Sugeno models is that the output membership functions of Sugeno could either be constant or linear while the output membership functions are nonlinear in Mamdani models. 'Takagi–Sugeno' models were preferred because of their ease of use.

Tool wear is detected based on the decision mechanism of the second stage fuzzy system. Raw signals are processed in the first fuzzy system as seen in Fig. 2 with an output of tool wear rate to form an input for the second fuzzy system as seen in Fig. 3. The detailed explanations of the two stages are provided below.

3.1. Fuzzy sensor model

Input membership functions for the Mamdani fuzzy model in this stage are chosen as three pieces of Gaussian functions representing the three states of the tool: sharp, workable and dull. The output membership functions are chosen as nine pieces for smooth response. Input and output membership functions can be seen in Fig. 4.

Inputs for each Mamdani fuzzy system consist of four pieces as seen in Fig. 4. Mean value, standard deviation, RMS and maximum values of force thrust, vibration and machine sound signals are taken as inputs for each system. Each input leads to the related output membership function (MF) by Table 1. MF-1 states the sharpest tool while MF-9 states the dullest. The remaining seven functions are used to get the transient states between the sharpest and the dullest. S, W, D abbreviations are used for sharp, workable, dull states,

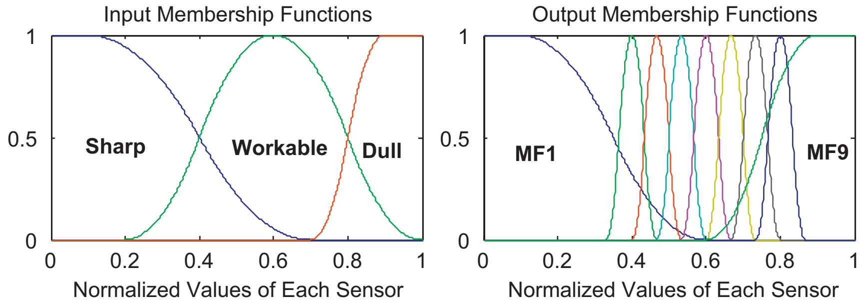

Fig. 4. Input and output membership functions for the first fuzzy model.

Table 1
Rules used in the first fuzzy model

Max	Mean	Standard deviation			Standard deviation			Standard deviation		
		S	W	D	S	W	D	S	W	D
Sharp	Sharp	MF1	MF1	MF2	MF4	MF4	MF5	MF7	MF7	MF8
	Work	MF3	MF3	MF4	MF5	MF6	MF7	MF8	MF9	MF9
	Dull	MF6	MF6	MF6	MF9	MF9	MF9	MF9	MF9	MF9
Work	Sharp	MF2	MF2	MF3	MF5	MF5	MF6	MF8	MF8	MF9
	Work	MF3	MF4	MF5	MF6	MF7	MF8	MF9	MF9	MF9
	Dull	MF7	MF7	MF7	MF9	MF9	MF9	MF9	MF9	MF9
Dull	Sharp	MF3	MF3	MF4	MF6	MF6	MF7	MF9	MF9	MF9
	Work	MF4	MF5	MF6	MF7	MF8	MF9	MF9	MF9	MF9
	Dull	MF8	MF8	MF8	MF9	MF9	MF9	MF9	MF9	MF9
RMS		Sharp			Workable			Dull		

respectively. A sample rule is shown below that is used in the first fuzzy model:

$$\text{IF (RMS} = \text{sharp) AND (max} = \text{dull) AND (mean} = \text{workable) AND}$$
$$\text{(std.deviation} = \text{workable) THEN output} = \text{MF5}$$

Mathematical cost (Z) of this rule is calculated by the following equation:

$$Z = M^P + N \tag{1}$$

In this equation, M and N stand for the number of input and output membership functions, respectively; while P represents the number statistical parameters used. As it can be seen in Eq. (1), the cost of the process grows exponentially with the number of input membership functions. Thus, this equation shows the importance of the selection of input parameters and membership functions.

3.2. *Sensor fusion model*

In the second stage, defuzzicated output values of the first fuzzy model are directly used as the input parameters for the Takagi–Sugeno fuzzy model. Fig. 5 illustrates the inputs for the Takagi–Sugeno fuzzy model. The most important point in determining the decision rules in this stage is deciding on the weights of the outputs of the three models in the first stage. As seen from Table 2, the decision responses based on the machine sound signals are chosen more effective when the cutting tool goes into a dull condition. Similarly, when the tool is still in sharp condition, the decision responses based on the force signals are provided to be more dominant. Besides, vibration signals make the decision responses smoother.

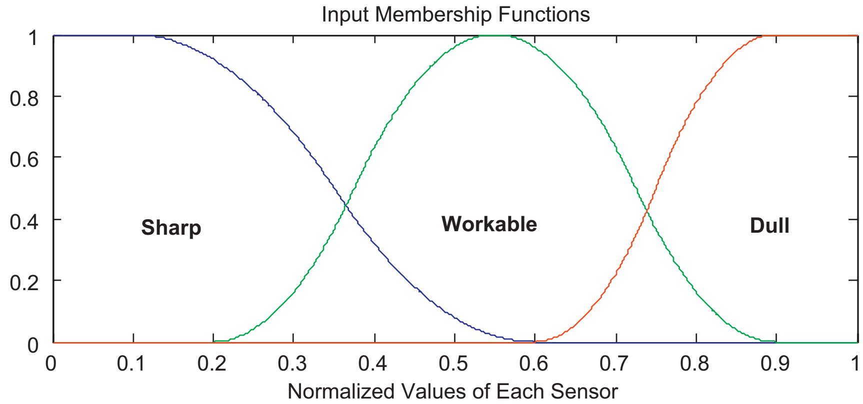

Fig. 5. Input membership functions for Takagi–Sugeno model of sensor fusion technique.

Table 2
Output functions and the rules used for the Takagi–Sugeno fuzzy model

Vibration	Machine sound	Force thrust		
		Sharp	Workable	Dull
Sharp	Sharp	1	1	2
	Workable	1	2	2
	Dull	2	2	3
Workable	Sharp	1	2	2
	Workable	1	2	3
	Dull	2	2	3
Dull	Sharp	1	2	2
	Workable	1	2	3
	Dull	2	3	3

4. Experimental results and discussion

The desired decision response of the Takagi–Sugeno model should be a monotonically increasing function which is not realizable because of the measurement noise and the varying parameters for various experiments. However, the fuzzy-controlled sensor fusion technique used in this work aims to develop efficient results.

The force, vibration and machine sound signals for a sharp and dull condition of a sample tool are shown in Figs. 6–8, respectively. These figures clearly reveal that the signals change drastically as tool wears. However, tool wear cannot be easily determined by visual analysis of the raw signals during the transient states between the sharp and dull states of the tool. The fuzzy rules given in Table 2 are constituted based on this fact.

A normalized output response for the Takagi–Sugeno model is shown in Fig. 9. As explained before, this is a monotonously increasing function that shows the status of the tool between 0 and 1 that correspond to degree of the wearness of the tool. As the value goes to 1, it means the tool gets more worn or about the breakage.

Outputs of the Takagi–Sugeno model are used as the input to the threshold function which forms the certain decision whether the tool is worn or not. Decision results for two selected tools are shown in Fig. 10.

In this study, tool wear monitoring was based on multiple sensor inputs and sensor fusion technique in order to increase the reliability of the proposed scheme. Monitoring techniques based on a single sensor may not be accurate. Because, tool wear is a very complex process and dependent upon diverse machining factors

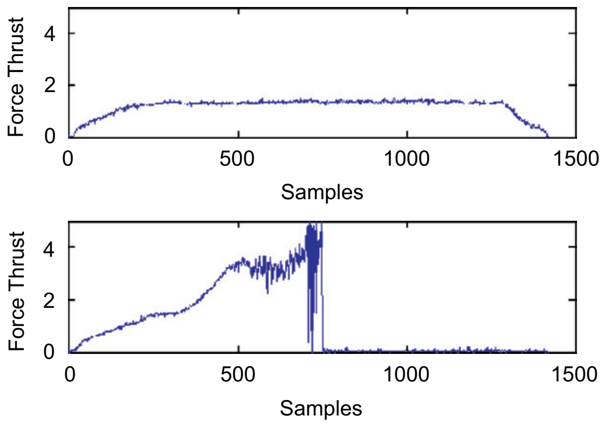

Fig. 6. Raw signals from the force thrust sensor for a sharp and a dull tool.

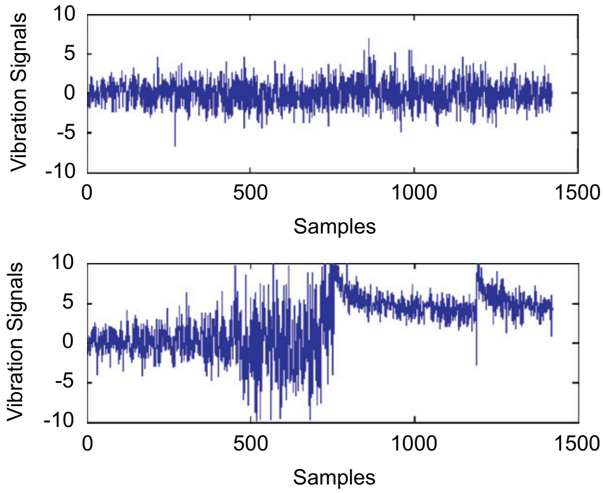

Fig. 7. Raw vibration signals for a sharp and a dull tool.

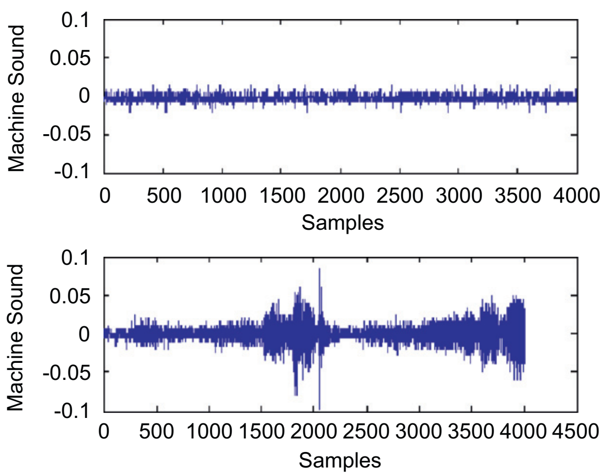

Fig. 8. Raw machine sound signals for a sharp and a dull tool.

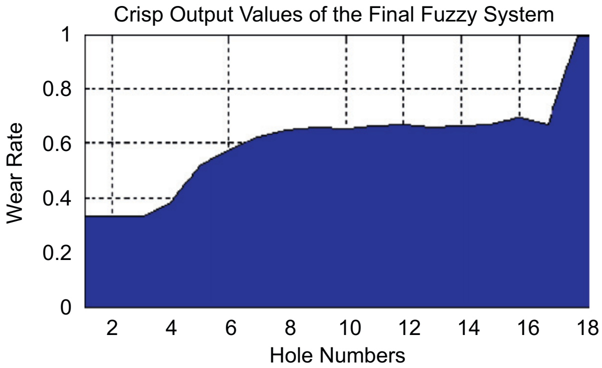

Fig. 9. Takagi–Sugeno model output of the system before threshold function.

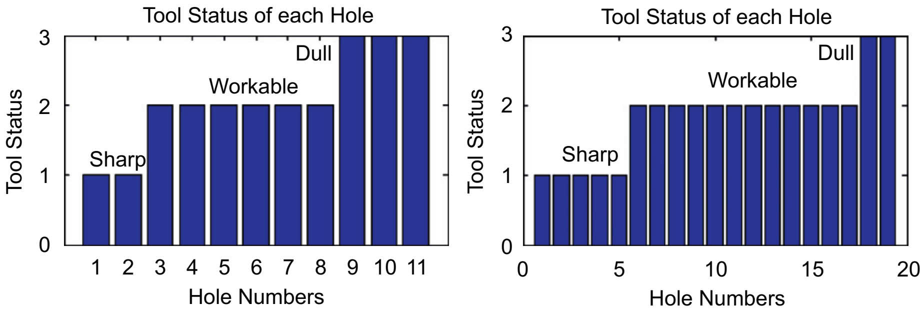

Fig. 10. Eventual results for selected tools.

such as cutting velocity and feed rate which affect the reliability of detecting tool wear and failure. For example, cutting forces are a function of cutting velocities and in the case of significant change of cutting velocity, thrust changes remarkably. This may not result in meaningful information on the tool condition monitoring. Hence, other sensor outputs must be used to correctly assess the condition of the tool.

Cutting force, vibration and machine sound signals were combined in this work in a sensor fusion technique in order to take the advantages of all measurements. For instance, force signals are good to monitor tool wear while the machine sound signals outperform others in detecting tool breakage. When only one sensor output was used to detect tool wear, the resulting output functions obtained from the models were not monotonically increasing and thus did not identify tool wear as good as in the multiple sensor case. Similarly, a single-phase fuzzy model did not perform as reliable as the double-phase one.

5. Conclusions

In this paper, statistical parameters derived from experimentally measured force, vibration, and machine sound signals were used to develop a fuzzy-logic-based sensor fusion method for estimating the cutting tool wear. Sensor fusion was utilized for optimizing the decisions made by the fuzzy logic inference system.

The goal of this study was to match the expert decision (based on visual analysis of the tool) by analyzing the signals acquired throughout the experiment. The decision rules were based on the statistical values of the experimental data acquired from various sensors and the corresponding expert decision.

The performance of the suggested model could be improved by handling the problem as a classification problem with three inputs: force, vibration and machine sound and using various classifiers that were proven to get superior performances. The performance could further be enhanced through the use of electric motor current as the fourth input parameter to the fuzzy system.

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