A Multi-sensor Based System for Manufacturing Process Monitoring

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Abstract: In order to improve the availability and productivity of manufacturing systems, process monitoring has become an important matter in modern automated plants. The traditional monitoring technologies are based on single sensors and are insufficient, especially for manufacturing processes of highly complicated and automated systems. Instead, multi-sensor based technologies are developing rapidly and are widely used for such monitoring tasks. This paper introduces a multi-sensor based process monitoring system for an existing machining centre. The system can monitor the major manufacturing process faults or abnormalities of the machining centre and provide maintenance planning through measuring and analysing multiple sensor parameters such as power, vibration, temperature and pressure of spindle, feed axes, and hydraulic and pneumatic systems of the machining centre. The general structure of the monitoring system and the implementation of the main steps of the monitoring system development are presented in detail.

Key words: Dynamic systems approaches, Manufacturing system, Process monitoring, Diagnosis, Condition monitoring

1. Introduction

Manufacturing processes represent substantial investments in capital equipment. Automated plant is intended to achieve a high rate of production, but prerequisites for profitable operation include reliable running and efficient maintenance. It is estimated that the annual maintenance cost for automated plant is 10% of the capital cost. When breakdown occurs, rapid fault identification, repair and recovery is paramount, to avoid large losses. Ideally, predictive maintenance or *condition monitoring* avoids on-line failure.

Automated plant is difficult to monitor, because it has many parts linked with complicated processes. The main stream condition monitoring techniques such as vibration, lubricant and thermal analysis have made limited penetration because:

- manufacturing plant has a multiplicity of axis drives and sub-systems;
- speeds and loads vary continuously;
- no single parameter provides an economical solution;
- each plant is different.

Typically, the current best practice extends simple on-line diagnostics provided by the equipment manufacturer for rapid diagnosis after failure. The status of system processes, or the monitoring of certain process variables, e.g. metal cutting, have been used as the starting point. Early monitoring of manufacturing processes relied on the sensing and processing of a single parameter based on a single sensor [1]. Cutting force and other related parameters like spindle torque or main drive current are very popular [2,3,4]. Also several vibration and acoustic emission monitoring schemes have been proposed [5,6]. These single-sensor or single-parameter schemes are only suitable for monitoring of simple manufacturing processes with a single condition or infrequently changed conditions. They have poor usability and will bring about false alarms and incomplete diagnosis if they are used for more complicated manufacturing systems.

Modern manufacturing systems are highly complicated, automated and integrated. Their manufacturing processes are complex and changeable. All relevant parts or components of the processes are closely related to each other. The processes involve a large number of factors and the relationship between these factors and the processes is complex and to some extent is fuzzy. In these cases, the use of traditional single-sensor based monitoring is not suitable. Therefore, multi-sensor based monitoring must be adopted to extract multiple interrelated parameters from every part of the machine so as to reach a significant conclusion.

In recent years, manufacturing process monitoring has attracted many researchers. Many monitoring techniques and prototype systems have been proposed or developed. A multi-sensor approach to drill wear monitoring was proposed by Oklahoma State University [7]. Researchers at Southampton Institute developed a neural network based multi-sensor system for monitoring the conditions of cutting tools [8,9]. Multi-sensor based monitoring of gear tooth fatigue for predictive diagnostics was developed at Pennsylvania State University [10]. Tool wear monitoring of turning operations by neural networks, and expert system classification of a feature set generated from multiple sensors was investigated at the University of Glamorgan [11]. The research, development and application of techniques for monitoring and diagnosis of machine tools have been reviewed [12].

Manufacturing process monitoring has increasing importance. However, all available techniques and systems have their drawbacks. They are not completely effective, and more information is required to describe how real faults develop and exhibit themselves in monitored parameters. This paper presents an implementation of a multi-sensor based manufacturing process monitoring system for an existing machining centre. The general structure of the system and the implementation of some of the main steps in the monitoring system development, including the choice of parameters, feature extraction and decision-making, are introduced in detail. The system has been running on the machining centre for about two years and has achieved good results, which are demonstrated as case studies.

2. General structure of the monitoring system

The monitoring system described was developed for a PFZ1500 machining centre, which is an integral part of a flexible manufacturing system in Zhengzhou Textile Machinery Plant. This is a complicated automated flexible machining centre with a spindle and three feed axes (X, Y, Z). The process monitoring of such a machining centre is important and certainly multi-sensor based.

Figure 1 shows the layout of the multi-sensor based monitoring system. Figure 2 is the monitoring procedure of the system. Because of the complexity of the machining centre and the requirements of real-time monitoring, the essential functional modules in the monitoring system include a fast signal processing unit, a self-adaptive learning/training unit, a process change recognition unit, and a global decision-making unit.

In the development of a multi-sensor based monitoring system, the choice of parameters, feature extraction and decision-making are the three main steps. For a complicated manufacturing system, there are various signal state changes that will happen during operation. Some signals may change abruptly and some gradually. Of the latter, some may change faster than others. The features extracted describe the state changes of the manufacturing process from the monitored multi-sensor signals.

After the features are extracted, decision-making is carried out to analyse and infer the process status according to these signal features and finally reach a significant result from multiple interrelated features. Therefore, an appropriate decision-making strategy is critical to the monitoring result. The models used are further described in a recent paper [13].

3. Choice of parameters

Manufacturing process monitoring usually requires some specific parameters that quantitatively indicate the process status. From these parameters the process status can be deduced. Appropriate choice of these parameters is critical to a multi-sensor based monitoring system. Generally the choice of parameters should satisfy the following requirements:

- sensitivity: a small status change must lead to a big enough feature parameter change;
- stability: the parameters should not be affected by sensing conditions (such as sampling frequency, sampling length and start point, signal-to-noise ratio, the sensitivity of sensing devices) and the machine working conditions (load, rotational speed, etc.);
- correspondence: the correspondence between parameters and the process status should be good, ideally a single parameter representing a single status; this is impossible in many situations - a parameter may correspond to multiple abnormal statuses;
- computation: complicated computation should be minimised in the processing of these parameters; in particular for automatic monitoring, minimal computation is an important advantage;

- adjustable control limits: for the given parameters, clear control limits should be set; these control limits should be adjustable during the machine operation;
- small database capacity: the choice of parameters should make the database capacity as small as possible; this will reduce the complexity of computation.

When considering the monitored parts or components in a manufacturing system, the parameters may include a selection of the following:

- vibration: acceleration, velocity and displacement;
- noise: noise pressure, noise intensity;
- acoustic emission (AE): AE event counting rate, accumulative counting and AE energy;
- force: stress, torque, axial thrust, vertical component, horizontal component;
- temperature: motor temperature, oil temperature;
- pressure: hydraulic pressure, pneumatic pressure;
- power: voltage, current.

A manufacturing system is a complicated assembly of machines, with appropriate management and control components and software. It is impossible to contemplate the monitoring of all parameters [12]. Consequently, a limited choice has to be made. Usually the following parameters are chosen:

- feed and spindle drive current;
- mains voltage;
- hydraulic and pneumatic pressure;
- acceleration of spindle and feed motors;
- temperatures of the spindle box, control box, spindle motor, feed motors, and hydraulic oil.

In most manufacturing systems, transducers will be available for the measurement of current and voltage, but sensors must be retro–fitted to measure pressure, temperature and acceleration. Some other parameters are sometimes chosen for monitoring purposes, such as:

- acceleration time for the spindle motor;
- tool change time;
- oil filter degree of purity;
- number of slide movements.

In addition, there is sometimes a need in the practical situation to monitor parameters such as door closure, tool presence, and work-piece presence.

Considering the sensitivity and ease of acquisition, the system for the PFZ1500 machining centre in the study monitored power, vibration, temperature, and pressure. In detail, the parameters are as follows:

- power parameters: voltage (U), spindle drive motor current (I_s), X-axis drive motor current (I_x), Y-axis drive motor current (I_y), Z-axis drive motor current (I_z); power (P) is calculated by $P=UI$;
- vibration parameters: accelerations of the spindle and the three feed axes (X-axis, Y-axis, Z-axis) in three directions (X, Y, Z);
- temperature parameters: spindle motor (T_s), oil in the spindle box (T_b), feed drive motors in three axes (T_x, T_y, T_z);
- pressure parameters: pneumatic supply for clamping devices (P_c), hydraulic oil for rotating devices (P_r) and feed drives (P_f).

4. Feature extraction

In order to describe the operating state of the machining centre, the monitoring system must be able to extract signals that indicate the essential features of its process status from many available parameters. A common and normalised feature extraction rule is adopted here, which is based on the classification of the signals into slowly changing signals and fast changing signals. For slowly changing signals, an energy related feature such as amplitude, variance or sum of squares is extracted, which is represented as $E(k)$. For fast changing signals, two kinds of features are extracted. They are:

- a feature that indicates the instantaneous rate of change of the process status, represented as $\Delta\Phi(k)$;
- a feature that indicates the changing trend of the process status at the moment, represented as $\sum(k)$, such as energy, divergence, distributed matrix and average variance.

Essentially $\Delta\Phi(k)$ uses the previous status to check the current status. Suppose $\Phi(k)$ and $\Phi(k-1)$ are parameters indicating the process status at time k and $k-1$ respectively, then

$$\Delta\Phi(k)= \Phi(k)-\Phi(k-1) \tag{1}$$

Generally speaking, $\Phi(k)$ is related to the information at several previous instances. Suppose $\{x\}$ is the array of signals to be checked, then

$$\Phi(k)=f\{x(k), x(k-1), \dots, x(k-n)\} \tag{2}$$

$$\Phi(k-1)=f\{x(k-1), x(k-2), \dots, x(k-n-1)\} \tag{3}$$

$$\Delta\Phi(k)=f\{x(k), x(k-1), \dots, x(k-n-1)\} \tag{4}$$

If the representations of the common items in equations (2) and (3) are the same, i.e. they are not affected by time, then

$$\Delta\Phi(k)=f\{x(k), x(k-n-1)\} \tag{5}$$

An increase in relative status change increases the magnitude of $\Delta\Phi(k)$. The machining centre is considered to have a significant event if the status change exceeds a fixed pre-set limit.

The auto-regressive (AR) model for a self-adaptive Kalman wave-filter is suitable for the description of the signal features [14]. Its adaptability is well suited to the principles of feature extraction. Therefore, it is used to describe the fast changing signal features. The AR model is:

$$X_k = X^t(k) \cdot \Phi(k) + \omega_k \tag{6}$$

where $\Phi(k)=\{-a_1, -a_2, \ldots, -a_n\}$ is the model parameter, $X(k)=\{x(k-1), x(k-2), \ldots, x(k-n)\}^t$ is the sample array, and ω_k is white noise with an average value of 0.

Parameter estimation by the AR model is defined by:

$$\Phi(k) = \Phi(k-1) + \sigma_w^{-2}[X_k - X^t(k)\Phi(k-1)]P(k)X(k) \tag{7}$$

$$P(k) = P(k-1) - \frac{P(k-1)X(k)X^t(k)P(k-1)}{\sigma_w^2 + X^t(k)P(k-1)X(k)} \tag{8}$$

where $P(k)$ is the co-variance matrix for parameter estimation, and σ_w is the residual.

Therefore, $\Delta\Phi(k)$ can be calculated according to any of the following equations:

$$\Delta\Phi(k) = \|\Phi(k)\| - \|\Phi(k-1)\| \tag{9}$$

$$\Delta\Phi(k) = \|P(k)\| - \|P(k-1)\| \tag{10}$$

$$\Delta\Phi(k) = \Phi^t(k)P(k)\Phi(k) - \Phi^t(k-1)P(k-1)\Phi(k-1) \tag{11}$$

$\|\mathrm{x}\|$ represents the norm of “x”.

Another feature, $\Sigma(k)$, is described by variance:

$$\Sigma(k) = \sigma^2(k) = \frac{1}{n}\sum_{t=0}^{n-1}[x(k-t) - \overline{x(k)}]^2 \tag{12}$$

where

$$\overline{x(k)} = \frac{1}{n}\sum_{t=0}^{n-1} x(k-t) \tag{13}$$

Here the changing rate of variance is not chosen for $\Delta\Phi(k)$, and the parameter estimation by the AR model is not chosen for $\sum(k)$. This is because the process status can be represented more efficiently through different feature parameter composition, and integration of multiple parameters can be achieved.

For slowly changing signals, the feature chosen is:

$$E(k) = \frac{1}{n}\sum_{t=0}^{n-1} x^2(k-t) \tag{14}$$

Parameters like current and voltage can also be processed using the same methods for rapidly changing signals. Their features are:

$$\Delta\Phi(k) = U(k) - U(k-1) \tag{15}$$

$$U(k) = \frac{1}{n}\sqrt{\sum_{t=0}^{n-1} [x(k-t) - \overline{x(k)}]^2} \tag{16}$$

$$\sum(k) = \frac{1}{n}\sqrt{\sum_{t=0}^{n-1} x(k-t)^2} \tag{17}$$

where n is determined according to the sampling frequency and the rotational speed of every axis. It is usually less than the number of the measured signal points within a cycle of rotation of a monitored part/component. This parameter as well as the order of the model can be adjusted during real-time monitoring.

In addition, a normalised processing strategy is employed for state changes caused by the shape of the work-piece and the time sequence of the process. Because the time sequence of abruptly occurring faults is much shorter than usual process changes, a normalised feature parameter $\delta(k)$ is introduced to process $\Delta\Phi$ further.

$$\delta(k) = \frac{|\Delta\Phi(k)|}{\sqrt{[\Delta\Phi^2(k-1) + \Delta\Phi^2(k-2) + \cdots + \Delta\Phi^2(k-n)]/n}} \tag{18}$$

Thus for each monitored part/component, the extracted features include: U, $\sum(P)$, $\Delta\Phi(P)$, $\delta(P)$, $\sum(I)$, $\Delta\Phi(I)$, $\delta(I)$, $\sum(a_x)$, $\Delta\Phi(a_x)$, $\delta(a_x)$, $\sum(a_y)$, $\Delta\Phi(a_y)$, $\delta(a_y)$, $\sum(a_z)$, $\Delta\Phi(a_z)$ $\delta(a_z)$ and T. In addition, the temperature feature T_b, and three pressure features P_c , P_r, P_f are also extracted. In total, 72 features (17×4+4=72) are extracted in the monitoring system.

5. Fuzzy decision-making

The purpose of manufacturing process monitoring is to determine the area, type and scale of the possible faults or abnormalities, so as to provide the necessary knowledge for process control, planning and scheduling. Having extracted the signal features that describe the signal states and state changes, further work is required to transfer these signal features into relative fault or abnormality information at the part/component level. The following fuzzy decision-making model can achieve this.

5.1 Basic principle

Suppose there are two finite sets:

$$W = \{w_1, w_2, \ldots, w_m\} \quad \text{and} \quad V = \{v_1, v_2, \ldots, v_n\} \tag{19}$$

A fuzzy set on W can be expressed as a m-dimensional vector, $\boldsymbol{A}$,

$$\boldsymbol{A} = [a_1, a_2, \ldots, a_m]^{\mathrm{T}} \tag{20}$$

Similarly, a fuzzy set on V can be expressed as a n-dimensional vector, $\boldsymbol{B}$,

$$\boldsymbol{B} = [b_1, b_2, \ldots, b_n]^{\mathrm{T}} \tag{21}$$

If there exists a fuzzy matrix, R,

$$R = [r_{ij}]_{n\times m}, \qquad 0\leq r_{ij} \leq 1 \tag{22}$$

which satisfies

$$\boldsymbol{B} = R \otimes \boldsymbol{A} \tag{23}$$

then R is called the fuzzy relationship between $\boldsymbol{A}$ and $\boldsymbol{B}$. This kind of relationship is also called the fuzzy transformation from W to V. R is usually normalised, i.e.

$$\sum_{j=1}^{m} r_{ij} = 1 \tag{24}$$

The fuzzy logic operator "⊗" in equation (23) has two different operations according to practical situations. When any two of the elements in $\boldsymbol{A}$ are interrelated to each other, it will operate as follows:

$$x \otimes y = x + y - xy \tag{25}$$

Otherwise, it will operate according to the usual matrix multiplication rule.

In manufacturing process monitoring,

- W is the signal feature set;
- V is the fault or abnormality set;
- $\boldsymbol{A}$ is the vector for the state description of the extracted signal features;
- $\boldsymbol{B}$ is the vector for the possibilities of faults or abnormalities;
- R is the fuzzy matrix of the relationship between $\boldsymbol{A}$ and $\boldsymbol{B}$.

Therefore, the meanings of their elements are as follows:

- a_i is the description of, or the degree of, the process fault or abnormality reflected by the i-th feature;
- b_j is the fuzzy probability or possibility of the j-th fault or abnormality;
- r_{ij} is the fuzzy probability or possibility that the i-th fault or abnormality will occur when the j-th feature is abnormal. It is also called the fuzzy Grade of Membership (GoM), i.e. the degree that the j-th feature will reflect the i-th fault or abnormality.

According to equations (20) – (23),

$$b_i = \sum_{j=1}^{m} r_{ij} a_j \qquad i = 1, 2, \cdots, n \tag{26}$$

where m is the number of extracted features in the monitoring system, and n is the number of possible faults or abnormalities.

5.2 Feature description

The description of the extracted signal features, i.e. vector $\boldsymbol{A}$, is very important, because it directly affects the decision-making result. According to the different requirements of monitoring speed and diagnostic precision, vector $\boldsymbol{A}$ can be described by the following three different methods:

5.2.1 0–1 rule

In the 0-1 rule, the state of a feature is described as "1" if the value of this feature is larger than a pre-set limit, otherwise it is described as "0". A vector $\boldsymbol{A}$ generated like this is composed of "0"s and "1"s.

Feature description using the 0-1 rule is simple and clear. Decision-making based on this kind of feature description is also fast. The full cycle of the monitoring process, from data acquisition to decision-making, can operate in real time, i.e. a couple of seconds or less.

5.2.2 Fuzzy GoM function

Methods for the determination of the fuzzy GoM include:

a) *Evaluation and inference*. The GoM or GoM function is determined by experts on the design, manufacture and maintenance of the machining centre, through evaluation and inference, based on their experience, intuition and skills. This kind of GoM or

GoM function determination method is outwardly subjective, but it is essentially objective and can be revised and improved adaptively in practical operations.

b) *Fuzzy statistics experiment*. This method first determines a domain E, and then considers an active ordinary set F^* on E. The boundaries of F^* are changeable and the meaning of F^* itself is not clear and definite. In an experiment, the result of every observation is a fixed element e_0 of E, i.e. $e_0 \in E$. During k experiments, this element may or may not be subordinate to F^*. Therefore, the GoM of e_0 to F^* can be calculated by:

$$\mu(e_0) = \lim_{k \to \infty} \frac{\text{times } e_0 \in F^*}{k} \tag{27}$$

c) *Weighted statistics*. This is a comprehensive evaluation method based on multiple factors such as statistical data, mechanism analysis results, clarity of fault signatures and ease of acquisition of signatures in the field. The corresponding GoM can be obtained according to the set of recorded points and set of weights for each signature.

d) *Ordering by contrasting two elements*. This method contrasts every two elements and puts them in order, so as to determine the approximate distribution of GoM's. Currently there are several methods such as relative comparison, contrastive averaging, and ordering according to the priority relationship.

e) *Function construction*. The GoM is described by a specific distribution curve. The function for the curve is normally in multiple segments. This is the most popular feature description method used by researchers. The GoM function and an element of vector $\boldsymbol{A}$ are normally chosen to be

$$\mu(x) = e^{-k(x-c)^2} \qquad (k > 0) \tag{28}$$

$$a_i(x) = 1 - \mu_i(x) \qquad i = 1, 2, \cdots, m \tag{29}$$

where c is the average value of learned/trained signal features in a normal state, x is the value of a feature, and k can be adjusted according to different signal features so that the GoM of every feature function is more appropriate to the practical situation. For signals with a bigger fluctuation, k is given a smaller value. In fact, this parameter is acquired automatically in monitoring systems.

Suppose t^- and t^+ are the lower and upper limit values of the learned/trained signal features in a normal state. If the GoM is 0.3 when $t^- = t_0$ and $t^+ = t_1$ (t_0 and t_1 are constants), i.e. a_i=0.7, then k can be obtained from:

$$e^{-k(x-c)^2} = 0.3 \tag{30}$$

In fact, the 0-1 rule is a special case of GoM description, i.e.

$$\mu(x) = \begin{cases} 1 & t^- \le x \le t^+ \\ 0 & x < t^-, x > t^+ \end{cases} \tag{31}$$

The GoM description method is more accurate and objective than the 0-1 rule, but the monitoring process using this kind of description is longer. The detailed implementation steps include

- after the monitoring system has learned/trained and obtained the lower and upper limit values of all the signal features in a normal state, k_i is calculated when the GoM is 0.3, and an expression is obtained for μ_i;
- after monitoring is started, the array of features is obtained and μ_i is calculated for each feature;
- the vector $\boldsymbol{A}$ is calculated by

$$\boldsymbol{A} = \{1-\mu_1, 1-\mu_2, \ \ldots, 1-\mu_m\} \tag{32}$$

5.2.3 Interrelationship model

This model introduces the concept of Grade of Interrelationship (GoI) which means the degree that a feature is interrelated to another. GoI's can be appropriately revised according to the practical situation of the machining centre, so as to obtain a more accurate signal feature description.

For a specific monitored part/component, suppose the vector for signal features in a normal state is

$$\boldsymbol{X}_0 = [x_0(1), x_0(2), \ \ldots, x_0(n)]^{\mathrm{T}} \tag{33}$$

and the vector for signal features in an unknown state is

$$\boldsymbol{X} = [x(1), x(2), \ \ldots, x(n)]^{\mathrm{T}} \tag{34}$$

then the GoI, S_j, of the j-th feature in an unknown state to its corresponding feature in a normal state can be defined as:

$$S_j = \frac{\min |\Delta x(j)| + \xi \cdot \max |\Delta x(j)|}{|\Delta x(j)| + \xi \cdot \max |\Delta x(j)|} \tag{35}$$

where $|\Delta x(j)|$ is the deviation of every signal feature in an unknown state with respect to its corresponding signal feature in a normal state, $|\Delta x(j)|=|x(j)-x_0(j)|$, $\max|\Delta x(j)|$ and $\min|\Delta x(j)|$ represent the maximum and minimum values of $|\Delta(x(j)|$ respectively, and ξ is the distinguishing coefficient. $\xi\in(0, 1)$, which is normally set to be 0.5.

Because there are differences between features in nature, dimension, measurement criterion, quantity level and change of speed, it is unreasonable to use equation (35) directly to obtain S_j through calculating $|\Delta x(j)|$. Therefore, the features must be normalised. For example, $|\Delta x(j)|$ can be replaced by the fuzzy GoM, i.e. $|\Delta x(j)|=1-\mu_j$. For the deviation of every feature, the dimensionality is removed and it is limited to the range (0, 1).

5.3 Evaluation of the decision-making result

The above fuzzy decision-making will result in a vector ***B*** which is composed of fuzzy GoM's of all the faults or abnormalities. In manufacturing process monitoring, this vector represents the possibility of every process fault or abnormality. The possible fault or abnormality can be determined by the following two methods.

5.3.1 Maximum GoM

By this method, the possible fault or abnormality is the one that corresponds to the maximum GoM in vector ***B***, which is the only decision-making result. Suppose F is the set of faults or abnormalities, then

$$F = \{ f_i \mid f_i \to_j^{\max} b_j \} \tag{36}$$

This method only considers the contribution of the element with a maximum GoM in vector ***B***. It neglects the contribution of other elements with a smaller GoM. Using this method to evaluate the decision-making result, sometimes it may be difficult to get a correct answer if there are multiple elements with the same or very close GoM to the maximum. Meanwhile, it will lose a large amount of information.

5.3.2 Threshold

According to experience or experimental results, a threshold τ is given to the GoM's in vector ***B***. If a GoM is greater than or equal to the threshold, i.e. $f_i \geq \tau$, the fault or abnormality corresponding to this GoM will be thought to exist. Then the decision-making result is:

$$F = \{ f_i \mid f_i \geq \tau \} \tag{37}$$

6. Implementation of multi-layer decision-making

In the manufacturing process monitoring system for the PFZ1500 machining centre, a multi-sensor monitoring strategy was adopted and a large number of signal features were extracted. If the traditional one-layer fuzzy decision-making strategy is used, it will be difficult to assign a reasonable weight for each element in the fuzzy relationship matrix R. Even if they are determined, the assigned weights of each signal feature must be very small because the sum of the weights of all the signal features for a specific fault or abnormality must be 1. Furthermore, the precision of vector $\boldsymbol{B}$ must satisfy a fixed requirement. After decision-making, the contribution of those signal features with a smaller weight to the result may be neglected, so it is hard to get a satisfactory result. Therefore, it is necessary to divide the signal features into some sub-feature groups at multiple layers, and then make decisions layer by layer.

6.1 Signal features classification

The 72 signal features are divided into multiple sub-feature groups at three layers, according to categories. Firstly, according to the different parts/components that are monitored, the whole signal feature set $W=\{w_1, w_2, \ldots, w_{72}\}$ is divided into five large feature groups. These are:

- the spindle related group W_1, containing 18 power, vibration and temperature signal features;
- the X-, Y- and Z-axis related feature groups W_2, W_3, and W_4, each containing 17 power, vibration and temperature signal features;
- the pressure related feature group W_5, containing three pressure signal features, P_1, P_2, P_3.

These satisfy

$$\bigcup_{i=1}^{5} W_i = W \tag{38}$$

Obviously, the intersected set of any two different feature groups is empty, represented as ϕ, i.e.

$$W_i \cap W_j = \phi \qquad (i \neq j) \tag{39}$$

Secondly, each of the feature groups, W_1, W_2, W_3 and W_4, can be further divided into three smaller sub-feature groups according to the natures of their signal features, i.e. power feature group W_{i1}, vibration feature group W_{i2} and temperature feature group W_{i3}. They also satisfy

$$\bigcup_{j=1}^{3} W_{ij} = W_i \qquad (i = 1, 2, 3, 4) \tag{40}$$

$$W_{ij} \cap W_{ik} = \phi \quad (j \neq k) \tag{41}$$

Specifically,

$$\begin{aligned} W_{i1} &= \{U, \Sigma(P_i), \Delta\Phi(P_i), \delta(P_i), \Sigma(I_i), \Delta\Phi(I_i), \delta(I_i)\} \\ W_{i2} &= \{\Sigma(a_{ix}), \Delta\Phi(a_{ix}), \delta(a_{ix}), \Sigma(a_{iy}), \Delta\Phi(a_{iy}), \delta(a_{iy}), \Sigma(a_{iz}), \Delta\Phi(a_{iz}), \delta(a_{iz})\} \end{aligned} \tag{42}$$

For the spindle, $W_{i3} = \{T_s, T_b\}$, while for the X-axis, Y-axis and Z-axis, W_{i3} only contains a motor temperature feature, T_x, T_y or T_z.

So far, the classified layers of all the signal features are as shown in Figure 3.

6.2 Decision-making layer by layer

According to the monitored parts/components and the extracted features, the faults or abnormalities of the PFZ1500 machining centre can be divided into 11 fault areas. These 11 fault areas are the spindle, spindle motor, tool/work-piece, X-axis, Y-axis, Z-axis, X-axis motor, Y-axis motor, Z-axis motor, main voltage, pneumatic and hydraulic sources. Multi-layer fuzzy decision-making determines the fault possibilities of the 11 areas by making decisions layer by layer.

6.2.1 Decision-making at the first layer

As shown in Figure 3, there are thirteen feature groups at the first layer, i.e. W_{ij} (i=1, 2, 3, 4; j=1, 2, 3) and W_5. For the feature groups related with the spindle and the three feed axes, the fuzzy vector $\boldsymbol{A}_{i1}$ is composed of values of all the signal features in W_{i1}, i.e.

$$\boldsymbol{A}_{i1} = [a_{i1,1}, a_{i1,2}, \ldots, a_{i1,7}]^{\mathrm{T}} \tag{43}$$

According to the relationship between the elements and the fault possibilities of the 11 fault areas, each element is given a weight. These weights comprise a fuzzy relationship matrix R_{i1}

$$R_{i1} = [r_{ij}]_{11\times7} \tag{44}$$

Each element r_{ij} of R_{i1} is usually determined through experts' experience or a GoM function. They satisfy the condition that the sum of all the elements at each line of the matrix must be 1. Hence, by decision-making the fuzzy vector, composed of the fault possibilities of the 11 fault areas, can be obtained by

$$\boldsymbol{B}_{i1} = R_{i1} \otimes \boldsymbol{A}_{i1} = [b_{ij}]_{11\times1} \tag{45}$$

$\boldsymbol{B}_{i1}$ represents the fault possibilities of all the fault areas resulting from the power features of an axis (spindle, X-axis, Y-axis, Z-axis). By doing so, $\boldsymbol{B}_{11}$, $\boldsymbol{B}_{21}$, $\boldsymbol{B}_{31}$ and $\boldsymbol{B}_{41}$ are obtained.

Similarly, the fuzzy vector $\boldsymbol{A}_{i2}$ in the feature group W_{i2} is

$$\boldsymbol{A}_{i2} = [a_{i2,1}, a_{i2,2}, \ldots, a_{i2,9}]^{\mathrm{T}} \tag{46}$$

which represents the degree of abnormality of the signal features in W_{i2}. The fuzzy relationship between $\boldsymbol{A}_{i2}$ and $\boldsymbol{B}_{i2}$ is

$$R_{i2} = [r_{ij}]_{11\times9} \tag{47}$$

Thus, the fuzzy vector representing the fault possibilities of the fault areas is

$$\boldsymbol{B}_{i2} = R_{i2} \otimes \boldsymbol{A}_{i2} = [b_{ij}]_{11\times 1} \tag{48}$$

This is the result of the vibration features of an axis (spindle, X-axis, Y-axis, Z-axis). Hence $\boldsymbol{B}_{12}$, $\boldsymbol{B}_{22}$, $\boldsymbol{B}_{32}$ and $\boldsymbol{B}_{42}$ are obtained.

Similarly the vectors $\boldsymbol{B}_{13}$, $\boldsymbol{B}_{23}$, $\boldsymbol{B}_{33}$ and $\boldsymbol{B}_{43}$ can be obtained, which represent the fault possibilities of the fault areas representing the temperature features of each axis. In addition, vector $\boldsymbol{B}_5$ for the pressure feature group W_5 can also be obtained.

So far, the fault possibilities of all the areas resulting from the signal feature groups at the first layer have been obtained. These are the reflection of the fault possibilities of areas specified by the different feature groups of each axis (spindle, X-axis, Y-axis, Z-axis) and the system pressure feature group, including the following conclusion groups:

$$\{\boldsymbol{B}_{11}, \boldsymbol{B}_{12}, \boldsymbol{B}_{13}\}, \{\boldsymbol{B}_{21}, \boldsymbol{B}_{22}, \boldsymbol{B}_{23}\}, \{\boldsymbol{B}_{31}, \boldsymbol{B}_{32}, \boldsymbol{B}_{33}\}, \{\boldsymbol{B}_{41}, \boldsymbol{B}_{42}, \boldsymbol{B}_{43}\}, \boldsymbol{B}_5$$

The decision-making at this layer is performed within a feature group, so it is calculated according to the usual matrix multiplication rule.

6.2.2 Decision-making at the second layer

The importance of the power, vibration and temperature feature groups of each axis to the fault possibility of each area is different. Hence, a specific weight must be assigned to each of them according to their importance while considering their comprehensive contribution to the possibilities of the fault areas. Then the contribution of all signal features of each axis to the possibilities of the fault areas can be calculated using the fuzzy decision-making algorithm. This is the decision-making at the second layer.

For each axis, the fuzzy vector $\boldsymbol{A}_i$ is composed of fuzzy vectors $\boldsymbol{B}_{i1}$, $\boldsymbol{B}_{i2}$ and $\boldsymbol{B}_{i3}$ obtained from the first layer decision-making results, i.e.

$$\boldsymbol{A}_i = \begin{bmatrix} \boldsymbol{B}_{i1}^T \\ \boldsymbol{B}_{i2}^T \\ \boldsymbol{B}_{i3}^T \end{bmatrix} = [a_{ij}]_{3\times 11} \tag{49}$$

The fuzzy relationship matrix R_i is composed of weights of three kinds of signal features of each axis, i.e.

$$R_i = [r_{i1}, r_{i2}, r_{i3}] \qquad (i=1, 2, 3, 4) \tag{50}$$

Considering the contribution of all the signal features of an axis to every fault area, the fuzzy vector $\boldsymbol{B}_i$ is obtained by

$$\boldsymbol{B}_i = R_i \otimes \boldsymbol{A}_i = [b_{ij}]_{1\times 11} \tag{51}$$

By doing so, the degree that each of the feature groups (W_1, W_2, W_3 and W_4) affects the possibilities of the fault areas can be obtained. The corresponding fuzzy vectors are $\boldsymbol{B}_1$, $\boldsymbol{B}_2$, $\boldsymbol{B}_3$ and $\boldsymbol{B}_4$.

The decision-making at this layer is performed according to equation (25), because the decision-making is between feature groups. The decision-making based on the important factors is supported and enhanced by the less important factors.

6.2.3 Decision-making at the third layer

Through the above two layers of fuzzy decision-making, fuzzy vectors $\boldsymbol{B}_1$, $\boldsymbol{B}_2$, $\boldsymbol{B}_3$, $\boldsymbol{B}_4$ and $\boldsymbol{B}_5$ have been obtained, which represent the possibilities of the fault areas related to feature groups W_1, W_2, W_3, W_4 and W_5 respectively. In order to obtain the final possibilities of all the fault areas, the five results should be combined.

Like the decision-making at the second layer, weights are assigned to the features in the five groups, which comprise the fuzzy relationship matrix R, i.e.

$$R = [r_1, r_2, \ldots, r_5] \tag{52}$$

The fuzzy vector $\boldsymbol{A}$ is composed of vectors of possibility that each of the five groups reflects the possibilities of fault areas, i.e.

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{B}_1 \\ \boldsymbol{B}_2 \\ \boldsymbol{B}_3 \\ \boldsymbol{B}_4 \\ \boldsymbol{B}_5 \end{bmatrix} = [a_{ij}]_{5\times 11} \tag{53}$$

Then the final vector $\boldsymbol{B}$ can be obtained by

$$\begin{aligned} \boldsymbol{B} &= R \otimes \boldsymbol{A} \\ &= [r_1, r_2, \ldots, r_5][a_{ij}]_{5\times 11} \\ &= [b_1, b_2, \ldots, b_{11}] \end{aligned} \tag{54}$$

The decision-making at this layer is also performed between feature groups, so the operation of "⊗" is as the same as at the second layer.

7. An example monitoring result

As described above, the monitoring system was developed for a PFZ1500 machining centre which is an integral part of a flexible manufacturing system in Zhengzhou Textile Machinery Plant in China. In this case study, the machining centre was milling the surface of a work-piece along the X-axis direction. When the milling feed increased suddenly, the monitoring system alarmed because the vibration, current and power features of spindle and X-axis and the temperature of X-axis feed motor exceeded their pre-set limits. The values of the extracted 72 features from the multi-sensor parameters are shown in Table 1.

For each axis there are 18 features as described above, at the end of section 4. The higher values for the spindle and the X axis may indicate a problem in known locations, certainly when compared to the Y and Z axes, but must be interpreted after weighting in accordance with the algorithm.

After decision-making, the result vector of fault possibilities is as shown in table 2. If the threshold evaluation method is used, and the threshold set to be 0.5, then it is possible to conclude that the tool/work-piece area is faulty or abnormal. Further diagnosis can be carried out using experiential reasoning or other analysis methods, including inspection of the area.

8. Conclusions and Further work

Manufacturing process monitoring is a key technique for modern automated plants. Its purpose is to guarantee the manufacturing systems operate reliably and efficiently, and complete their tasks in an unmanned environment.

The multi-sensor based manufacturing process monitoring system introduced in this paper provides an adaptive solution which overcomes many of the problems associated with traditional single parameter monitoring systems. The multi-layer decision making model deals with the inconsistencies in data type and in differing levels of uncertainty, while capitalising on available expertise and models.

The system has been customised for, and tested upon, a PFZ1500 machining centre in a textile machinery production plant in China, with excellent results. The system can monitor the major process faults or abnormalities. The application of the system has improved the availability and productivity of the machining centre and has solved many problems by accelerating diagnosis. The model and monitoring techniques can be customised to suit many other monitoring tasks.

There are several areas of further work which have been identified. In many instances there are signals which are available but which are not used. There is great scope for the use of on-board microcomputers now being built into the machine and process controls. Signals for warning and diagnostics, which are already available on machines, are under utilised. The monitoring techniques can be adapted to predict faults, and not simply diagnose them after the event.

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Notation

a_i description of, or the degree of, the process fault or abnormality reflected by the i-th feature;

$\{-a_1, -a_2, \ldots, -a_n\}$ Kalman filter model parameter array;

b_j the fuzzy probability or possibility of the j-th fault or abnormality;

c average value of learned/trained signal features in a normal state;

e_0 result of observation, element of E;

f_I individual fault;

k general variable: number of experiments, GoM adjustment parameter;

m number of extracted features in the monitoring system;

n general variable, representing number of samples (determined according to the sampling frequency and the cycle of revolution of every axis) or number of possible faults or abnormalities;

r_{ij} the fuzzy probability or possibility that the i-th fault or abnormality will occur when the j-th feature is abnormal, or fuzzy Grade of Membership (GoM);

t_0, t_1 constants for limit values;

t^-, t^+ lower and upper limit values of learned/trained signal features;

x value of a feature;

$\{x\}$ array of signals to be checked;

$\boldsymbol{A}$ fuzzy set expressed as a m-dimensional vector $[a_1, a_2, \ldots, a_m]$, state description of the extracted signal features;

$\boldsymbol{B}$ fuzzy set expressed as a n-dimensional vector $[b_1, b_2, \ldots, b_n]$, possibilities of faults or abnormalities;

E domain of fuzzy statistics experiment;

F^*	active ordinary set in fuzzy statistics experiment;
$E(k)$	energy-related signal feature;
F	set of faults or abnormalities;
I_s, I_x, I_y, I_z	drive motor current of the spindle, X-axis, Y-axis and Z-axis;
P	Power ;
P_c, P_r, P_f	pressure of the pneumatic supply for clamping devices, the hydraulic oil for rotating devices, and the hydraulic oil for feed drives;
$P(k)$	co-variance matrix for parameter estimation;
R	fuzzy matrix $[r_{ij}]_{n\times m}$, $0\le r_{ij} \le 1$
S_j	Grade of Interrelationship (GoI) of the j-th feature in an unknown state;
T_b, T_s, T_x, T_y, T_z	temperature of the oil in the spindle box, the spindle motor, and of the feed drive motors.
U	voltage;
V	finite set $\{v_1, v_2, \ldots, v_n\}$, fault or abnormality set;
W	finite set $\{w_1, w_2, \ldots, w_m\}$, signal feature set;
$W_{i,j}$	feature groups
$X(k)$	sample array;
$\boldsymbol{X}_0$	vector for signal features in a normal state $[x_0(1), x_0(2), \ldots, x_0(n)]^T$;
$\boldsymbol{X}$	vector for signal features in an unknown state $[x(1), x(2), \ldots, x(n)]^T$;
X, Y, Z	machine axes;
$\delta(k)$	normalised feature parameter;
$\mu(x)$	Grade of membership (GoM) function;
ξ	distinguishing coefficient, $\xi\in(0, 1)$;
σ	standard deviation;
σ_w	residual;

τ	fault threshold;
ω_k	white noise with average value 0;
$\lvert\Delta x(j)\rvert$	deviation of signal features in an unknown state with respect to corresponding signal features in a normal state;
$\Delta\Phi(k)$	instantaneous rate of change of the process status;
$\sum(k)$	feature indicating the changing trend of the process status;
$\Phi(k)$	process status at time k;
$\lVert x \rVert$	norm of "x"
ϕ	empty set;
$\otimes$	fuzzy logic operator.

Figures and Tables

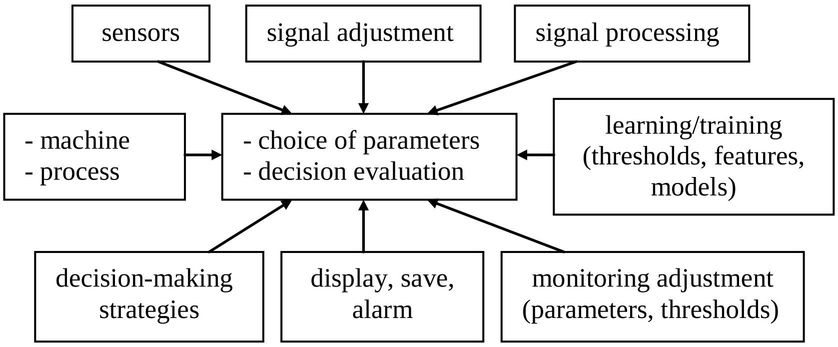

Figure 1 Layout of the Monitoring System

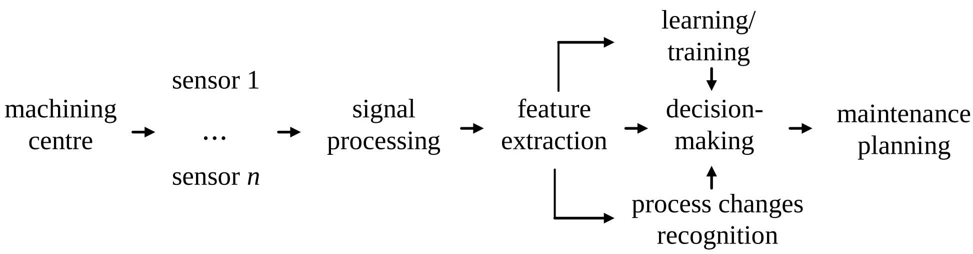

Figure 2 The Monitoring Procedure

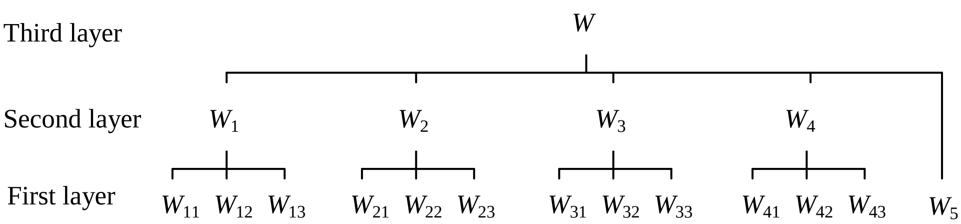

Figure 3 Layers of Signal Features

Table 1: Extracted values from the multi–sensor parameters

	Spindle	X axis	Y axis	Z axis
U	0.00	0.00	0.00	0.00
$\sum(P)$	0.24	0.64	0.00	0.00
$\Delta\Phi(P)$	0.13	0.27	0.00	0.00
$\delta(P)$	0.00	0.00	0.00	0.00
$\sum(I)$	0.65	0.06	0.00	0.00
$\Delta\Phi(I)$	0.22	0.67	0.01	0.00
$\delta(I)$	0.00	0.00	0.00	0.00
$\sum(a_x)$	0.62	0.10	0.00	0.00
$\Delta\Phi(a_x)$	0.03	0.06	0.00	0.00
$\delta(a_x)$	0.00	0.00	0.00	0.00
$\sum(a_y)$	0.39	0.24	0.00	0.00
$\Delta\Phi(a_y)$	0.35	0.03	0.00	0.00
$\delta(a_y)$	0.00	0.00	0.00	0.00
$\sum(a_z)$	0.12	0.42	0.00	0.00
$\Delta\Phi(a_z)$	0.00	0.39	0.00	0.00
$\delta(a_z)$	0.00	0.00	0.00	0.00
	T_s 0.00	T_x 0.72	T_y 0.00	T_z 0.00
	T_b 0.00	P_1 0.00	P_2 0.00	P_3 0.00

Table 2: Result vector of fault possibilities

spindle	0.23
spindle motor	0.29
tool/work-piece	0.68
X-axis	0.25
Y-axis	0.00
Z-axis	0.00
X-axis motor	0.44
Y-axis motor	0.00
Z-axis motor	0.00
main voltage	0.00
pneumatic and hydraulic sources	0.00