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Ontology and signal analysis based fault identification for ultra-precision flycutting machines

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Abstract
The ultra-precision single point diamond flycutting method has many positive characteristics such as high production efficiency, good repeatability, environmente friendly and easy to maintain, it can produce fine optical surfaces directly. But the motion errors which would influence the quality of the machined surfaces are very weak and always coupled, it is hard to achieve the error detection and error source identification for ultra-precision flycutting machines. To solve this problem, different measuring data such as spindle error, feed error, vibrations and temperatures of different components, and compressed air pressure were collected synchronously in real time, and then we established the fault diagnosis method based on ontology and semantic technology to analysis the acquired measuring signals.
The method includes signal analysis and feature extraction of raw data, fault recognition based on continuous Gaussian mixture density hidden Markov model (CGHMM), and semantic mapping technique which relating signal analysis to ontology elements. It combines the advantages of signal analysis and ontology, to identify fault information timely and accurately. Taking the spindle vibration signal of the machine tool as an example. Under different working conditions, feature extraction of the spindle vibration signals were acquired. The fault identification is carried out by CGHMM. Finally, semantic mappings and knowledge reasoning for the identification result can validate the performance of this method, several error souces which can introduce mid-spacial frequency patterns on the machined surfaces were located and solved separately.

Keywords
Fault identification, signal analysis , CGHMM, ultra-precision flycutting

1. Introduction

Large scale optics have excellent optical properties, which are widely used in the military and civilian advanced scientific and technological fields, the demand for high-quality optics is increasing dramatically[1]. The ultra-precision single point diamond flycutting method has received more attention in the field of ultra-precision machining due to its high production efficiency. However, for flycutting, processing accuracy and surface quality are all along affected by the environment and mechanical conditions. To improve the machining quality of workpieces, researches are more on the dynamic characteristics of machine tool currently[2].Thus,monitoring ultra-precision flycutting machine tools(UPF) which is shown in Figure.1, makes it significant to establish relationship between machine tool status and surface quality of workpiece,including vibration, temperature, etc.

Figure 1. (Ultra-precision flycutting machine tools)

The remaining sections are organized as follows. Section 2 introduces the processing methods of the signal. Section 3 provides continuous Gaussian mixture density hidden Markov model (CGHMM). Section 4 constructs the CGHMM and verifies the accuracy of the model. Finally, the paper is summarized and concluded in Section 5.

2. Processing methods of signals

Monitoring the status of UPF, affected by the sensor's accuracy and environmental, the measured signals are usually mixed with irrelevant signals. Meantime, flycutting, as an ultra-precision technology, has weak signal changes. To improve the accuracy of research , feature extraction is used. Fast Fourier transform(FFT) and wavelet transform are two methods widely used currently.

2.1. Signal acquisition

Vibration sensors are installed on UPF, located on the spindle, table and ground. Combining Labview system to acquire signals, collecting signal under different operating conditions.

2.2.Signal processing

Based on the existing researches[3], combined with the characteristics of UPF, 14 features are extracted from time-domain for the vibration signal, and 12 features are extracted from frequency-domain after FFT. As the main tool of signal processing, wavelet decomposition has been increasingly used in the field of mechanical processing. Orthogonal wavelet packet decomposition and reconstruction occur with the generation of wavelet transform. The steps of wavelet packet energy extraction are as follows[3]:

Signal *x(t)*:

$$x(t) = x_{31} + x_{32} + x_{33} + x_{34} + x_{35} + x_{36} + x_{37} + x_{38} \tag{2.1}$$

$$S_{3j} = S_{31} + S_{32} + S_{33} + S_{34} + S_{35} + S_{36} + S_{37} + S_{38} \tag{2.2}$$

Energy of each band:

$$E_{3j} = \int |S_{3j}|^2 \, dt = \sum_k^n |x_{jk}|^2 \tag{2.3}$$

This chapter introduces the application of FFT and wavelet packet theory, introduces the characteristic parameters, and prepares for the subsequent model building.

3. Continuous Gaussian mixture density hidden Markov model

Hidden Markov model(HMM) has developed very quickly in modern scientific research. Fault diagnosis can be simplified into pattern recognition and classification problem. Researchers have introduced the method of HMM pattern recognition into monitoring and fault diagnosis[4], and has achieved some achievements.

HMM contains three parts: evaluation problem based on forward algorithm,identification problem of Viterbi algorithm and learning problem based on the Expectation-maximization.

3.1. CGHMM

Generally, the HMM considers that the observations in a certain state are discrete fixed signals,while the observations follow a continuous Gaussian probability density function distribution, it is called continuous Gaussian mixture density hidden Markov model. The parameters of CGHMM can be expressed by five-tuples $\lambda = (\pi, A, B, \mu, U)$,

π:Initial probability distribution vector,

A: State transition probability matrix,

B: Observation probability density function,

μ: Mean vector,

U: Covariance matrix

Using CGHMM for fault diagnosis, the extracted feature parameters are directly used as the observation sequence;the feature parameter sequence is not processed, and the fault recognition rate is high.Meantime, the output probability of the model is described by a Gaussian mixture density function, which reduces the model's storage space and computational complexity, and makes it more convenient and reliable to diagnose fault.

Comparing CGHMM with neural network and other research methods, we can find that CGHMM has better monitoring performance and diagnostic effect[4].

4. Application of CGHMM in fault diagnosis of UPF machine

4.1.Signal acquisition and feature extraction

Aiming at UPF, determine the sensor installation positions, install acceleration vibration sensors on the spindle, table and ground.The sensor sensitivity is 10,000Mv/g, and the sampling frequency is 1000Hz.

Based on UPF for processing KDP crystals, considering the surface quality detection parameters of the workpiece, the number of hidden states of CGHMM is eight. Take 1 minute data as a sample, and get a total of 800 samples (100 samples for each state).

According to section 2, the experiment chooses 14 time-domain features, 12 frequency-domain features and 8 wavelet packet energy as the characteristic features. The 34X3 eigenvalue matrix obtained after processing of each sample is used as the observation vector matrix of CGHMM. Taking a sample signal as an example, the observation vector matrix is as follows:

$$X_{34\times3} = \begin{bmatrix} -4.75e-05 & -1.60e-05 & -4.05e-05 \\ \cdots & \cdots & \cdots \\ 0.176 & 0.104 & 0.034 \end{bmatrix} \tag{4.1}$$

4.2.CGHMM training

Using multiple sets of samples to establish CGHMM model for each state, not only increase the generalization characteristics of the model, but also facilitate the re-evaluation of each model parameter. Training with the EM algorithm, the initial model parameter state probability distribution vector and state transition probability matrix are randomly generated. After training the samples in 8 states, the CGHMM parameters of each state are obtained.

Taking a sample signal as an example,the CGHMM parameters are as follows:

$$\pi_{1\times3} = [0,0,0,0,0,0,1,0] \tag{4.2}$$

$$A_{8\times8} = \begin{bmatrix} 0.498 & 0.024 & \cdots & 0 & 0.239 \\ 0 & 0 & \cdots & 0 & 0 \\ \cdots & \cdots & & \cdots & \cdots \\ 0 & 0 & \cdots & 0.726 & 0.183 \\ 0 & 0 & \cdots & 0.251 & 0 \end{bmatrix} \tag{4.3}$$

$$C_{2\times8} = \begin{bmatrix} 0.478 & 0.499 & 0.731 & 0.657 & 0.999 & 0.333 & 0.909 & 0.749 \\ 0.522 & 0.501 & 0.269 & 0.343 & 0.001 & 0.667 & 0.091 & 0.251 \end{bmatrix} \tag{4.4}$$

Besides, μ is the mean matrix with specification of 34X8X2; U is the covariance matrix with specification of 34X34X8X2.

The relationship between the log-likelihood probability value of each iteration of each CGHMM model and the number of iteration steps is shown in Figure 2.

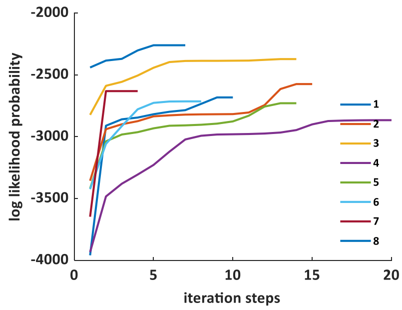

Figure 2. (The CGHMM training curve)

4.3.CGHMM identifying

The 100 sample observation series obtained in each state of UPF were input into the CGHMM model of 8 states, and the log-likelihood probability values under each model were calculated. The model state corresponding to the maximum value is the state recognition result of UPF.

5. Conclusion

In this article, CGHMM is applied to fault diagnosis of UPF. First, feature extraction is extracted from the vibration signals of UPF, and the corresponding surface quality of workpieces are input into the CGHMM, training model to obtain 8 states of CGHMM, establishing the relationship. However,due to fewer types of signals, the accuracy is poor. Next, we should increase pressure and temperature signals to training model for improving the accuracy of CGHMM. Experiments verify the validity of the model and prepare for subsequent researches.

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