Research on tool condition monitoring system in auto-balancing machines

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Abstract

A drill set working condition monitoring system is introduced and investigated to improve the performance of auto-balancing machine. The experiment setup to acquire data of armature currents of spindle and servo motors is constructed. The features of the armature currents of both spindle motor and servo motor in time domain, frequency domain and time-frequency domain are extracted respectively, and they are fused separately by two distinct RBF ANNs to get the primary fusing results. The primary results are fused by the third RBF ANN to get a comprehensive result. Experiment results demonstrates that the servo motor current have a closer relation with drill set working condition than that of spindle motor, and the two successive fusing operation can achieve much reliable recognition to a correctness of 86.67%.

Keywords: Tool condition monitoring, spindle motor, servo motor, data fusion

1. Introduction

There is an increasing tendency to equip dynamic balancing machine with built-in automatic unbalance correction unit (so called auto-balancing machine), especially for those which are used for balancing mass produced rotors. For auto-unbalance compensation of segmented rotors like fans or die-casting motor rotors, on which the unbalance compensation will be resolved into vectors, removal of weight by drilling is a preferable material removal process compared with milling and grinding. Drilling bit, as an important element in weight removal, its condition monitoring is critical to increase the process productivity and improve the accuracy of unbalance correction as well.

Many efforts have been made in drill set working condition monitoring. S. Braun [1] recognized the tool work state by monitoring the torque drifts force and feed force and has achieved very high recognition accuracy, but this method is difficult to apply in industry for its high cost and complex installation. The vibration and acoustic emission methods are investigated by E. Jantunen [2]. It is claimed that the vibration monitoring method is pretty effective but it is sensitive to environmental noise, and the acoustic emission method needs a special installation position and a stricter environment. Other method includes machine vision, temperature detection and so on, but they are only applicable in laboratory environment [3]. The armature current is the appropriate tool condition related quantity which is easy to detect and not sensitive to environment influence. The armature currents of spindle motor and servo motor have been investigated separately in drill bit condition monitoring [3], but the results are far from satisfactory. The main reason is the features of spindle motor current or servo motor current itself is partial and exparte and can not reflect the tool condition comprehensively.

Sensors data fusion has already been used in tool condition monitoring system. GLittlefair, M.A. Javed, & G.T. Smith have fused signature from AE sensor, dynamometer and accelerometer and have got a satisfactory result. Ismet Kandilli [4] also experimented with sensors from multiple sensors including cutting forces, vibration, current and sound and also got an accurate result. But they all experimented with features in one or two domain. The result was influenced with the cutting condition and the environmental noise. Synthesizing the features in time domain, frequency domain and time-frequency domain is expected to be the method to convey tool working state comprehensively, which will be explored in succeeding sections.

2. Selection and extraction of signal feature

Features in time domain, frequency domain and time-domain are adopted to denote the all-sided drill set condition. For the purpose of tool condition monitoring, the general rule for selecting features should be sensitive to tools conditions and insensitive to cutting conditions.

Signals in time-domain can directly convey the tool working state. Among RMS (root mean square), peak value, wave factor and kurtosis, the last two indexes are not sensitive to cutting condition, such as cutting speed, spindle speed and so on, than the first three, we chose those two as the indicators of drill set working condition in time domain.

With the tools wearing the signal energy of armature current in frequency domain transfers from high frequency range to low frequency range [5]. So the energy's changing in different frequency range can express the tool wearing state. In frequency-domain, we choose signal energy in low frequency range in Welch power spectrum as one of the feature of tool condition, as shown in Fig.1. Meanwhile power peak value and corresponding frequency, barycenter of energy distribution in different frequency range are also selected as indicators of tool working condition.

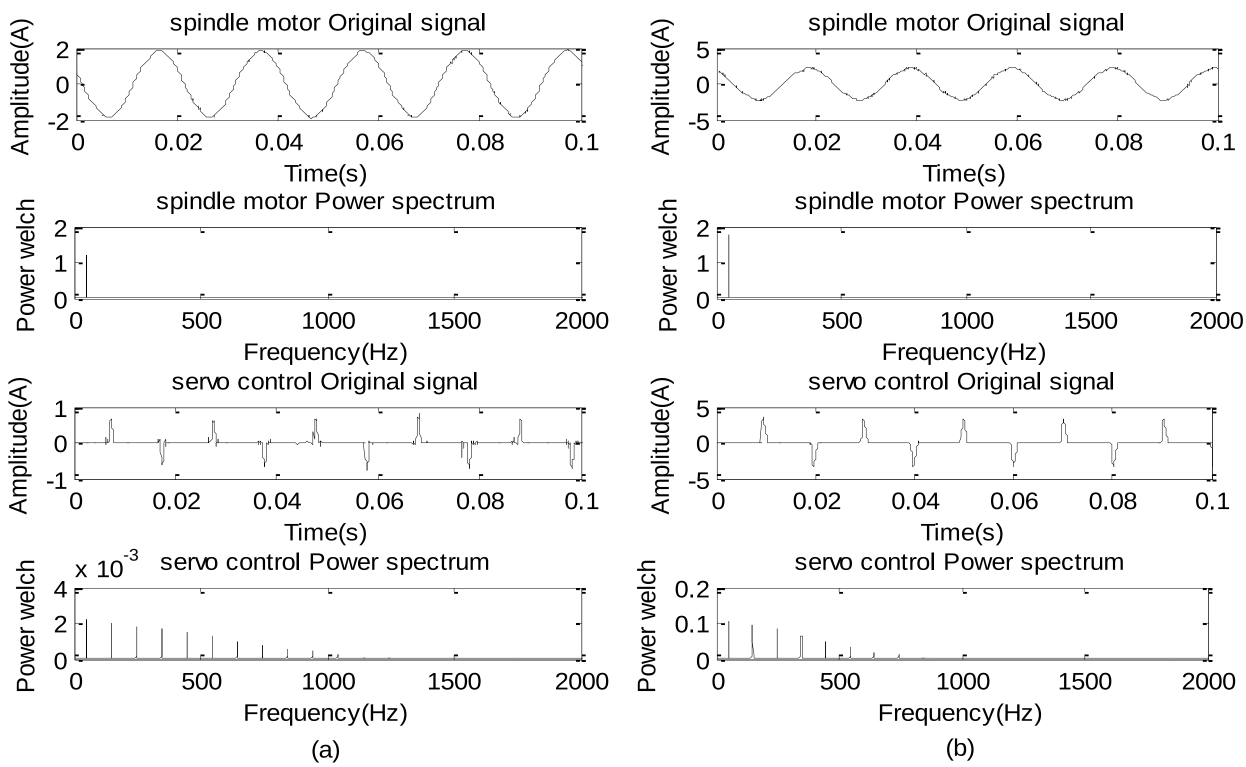

Fig. 1. (a) The time and frequency signature from spindle and servo motor current when tool is sharp
(b) The time and frequency signature from spindle and servo motor current when tool is worn out.

The wavelet package is introduced to our design due to its ability of extracting information in frequency domain at different frequency bands. The decomposed current signature can express the drill set working condition [5]. As discussed above that the energy distribution of power spectrum changes with the drill bit wearing. The energy in frequency domain transfers from high frequency bands to low frequency bands [6]. So we adopt the ratio between energy of different frequency bands and the whole energy as the feature conveying the drill set working condition.

The signals in our experiment have been decomposed to three layers using db5, the node is denoted by (3, 0), (3, 1)… (3, 7) as shown in Fig.2. Denote the energy of corresponding node as E_{3j} , it can be expressed as :

$$E_{3j} = \int \left| S_{3j}(t) \right|^2 dt = \sum_{k=1}^{n} \left| x_{jk} \right|^2 \tag{1}$$

Where S_{3j} is the reconstructed signal by node (3, j) (j=0, 1…7), x_{jk} is the amplitude of S_{3j}

For handling different diameters of drill set, the normalized process is introduced; the feature vector can be expressed as

$$T = [\frac{E_{30}}{E}, \frac{E_{31}}{E}, \frac{E_{32}}{E}, \frac{E_{33}}{E}, \frac{E_{34}}{E}, \frac{E_{35}}{E}, \frac{E_{36}}{E}, \frac{E_{37}}{E}] \tag{2}$$

Where E_{3j} is the energy of node (3, j) (j=0, 1…7) and $E = (\sum_{j=0}^{7} \left| E_{3j} \right|^2)^{1/2}$.

The wavelet node energy in each frequency segment undergoes considerable change when the cutting tool fails. So the energy of in each of the frequency segment is chose be one of the feature vectors.

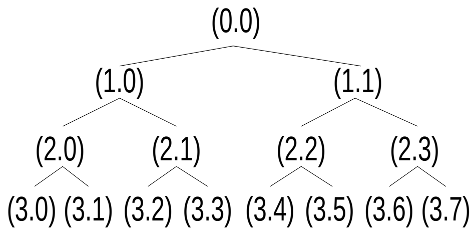

Fig. 2. Decomposition tree of current signature using wavelet packet transform.

3. Cutting data fusion and tool state recognition

The advantage of ANN (Artificial neural network) is their strong ability to describe the highly non-linear characteristics existing in complex processes. In drill set condition monitoring, different features have highly non-linear mapping relations with tool working state. Radial Basis Function neural network featured with simple structure, strong ability to approach real value on the whole and easy and quickly to training is selected for information fusing in this research.

The detected armature current signals of both spindle motor and servo motor, after feature abstraction in time domain, frequency domain and time-frequency domain are used as the input vectors of two distinct ANN to get the primary fusing results. Then the primary results are fused by the third RBF ANN.

We choose Gauss radial basis function (3) as kernel function of ANN because its monotonicity with the Euclidean distance between x and c_i, center of sample data. The features from time domain, frequency domain and energy distribution of wavelet package constitute the input vector of the ANN. During the training process, the output of ANN is the drill set wear degree expressed by the blade width, 0.2mm means that drill sets are sharp, 0.5mm means workable and 0.8mm means worn out.

$$k_i(x) = \exp(-\frac{\| x - c_i \|^2}{2\sigma_i^2}) \tag{3}$$

Where x is a point in a space and c_i is a center point in space.

The number of training sample is 60. After training, the deviation between results of ANN and goal has minimized to 7.44801e-005 and the number of neurons is 57 for spindle motor current signal. And the deviation is 4.22164e-030, the neurons number is 60 for servo motor. The results of first round of feature fusing operation are used as the input of the third RBF ANN with 60 neurons. The final deviation is 2.85808e-030 and the convergence procedure is showed in Fig 3.

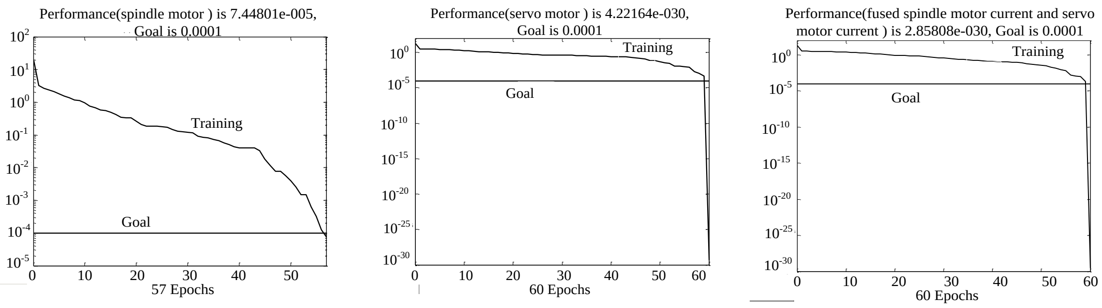

Fig. 3. The RBF ANN's convergence of spindle motor features, servo motor features and synthetical features.

4. Experimental setup and results

The schematic diagram of drilling based auto-balancing machine and its TCMS is shown in Fig. 4. The AC asynchronous servo motor drives the drilling set move forward via the ball screw. The current of spindle motor and servo motor are acquired by close-loop Hall current sensors and sampled at 33 KHz respectively by PCI-DAC (data acquisition card) in PC [7], the drill set external working condition is listed in Table 1.

We have chose 7 different sized drill (7mm, 8mm, 9mm, 10.2mm, 11.5mm, 12.1mm, 13mm) sets and 3 cutting speed in our experiment

When fusing features by RBF ANN, 60 vectors were used for training, and another 15 vectors were used for testing. The output result is listed in Table 2. Summary and comparison between features from both motor currents is presented in Table 3.

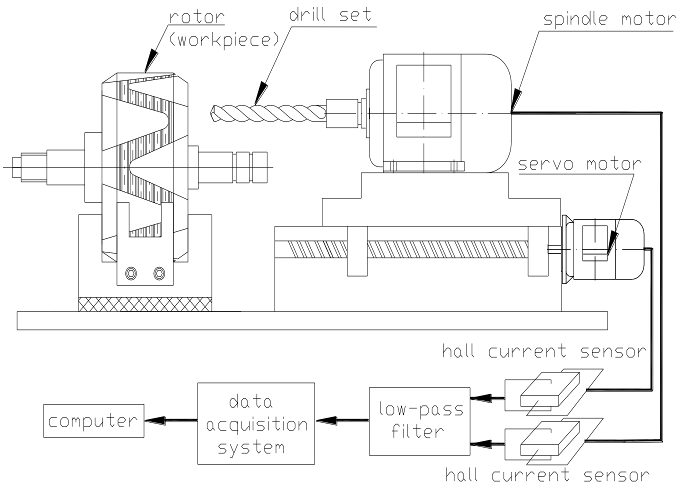

Fig. 4. Schematic diagram of the experiment setup.

Table 1. The experimental condition.

Tool	HSS-drill
	Diameter 7,8,9,10.2,11.5,12.1,13mm
	Tool material high-speed steel
Cutting condition	Spindle speed 500r/min
	Feed rate 83.3mm/min, 58.5mm/min, 52.1mm/min Without coolant
Workpiece	45# quench steel
Sensors	Close-loop Hall current sensor (0-12A)
	Ration: 2:1000, frequency: 0-100KHz
Data acquisition card	12 bit resolution, Sample range ±10V
	Sample rate at 66KHz of two channels, 33KHz respectively

From Table 2 and Table 3, we can see that the monitoring accuracy from spindle motor current and servo motor are 53.55% and 66.67% respectively. That means the synthetical features in time domain, frequency domain and time-frequency domain have a close correlation with drill set working condition. After further fusing, the accuracy can improve to 86.67%.

Table 2. The fusing results.

Diameter (mm)	Cutting speed(m/min)	Feedspeed (mm/rev)	Wear (mm)	Experiment result from spindle motor	Experiment result from servo motor	Experiment result from synthetical features
7	10.9956	0.1042	0.5	0.462665(workable)	0.496510(workable)	0.450993(workable)
8	12.5664	0.1190	0.5	0.497155(workable)	0.507679(workable)	0.501332(workable)
8	12.5664	0.1042	0.5	0.499576(workable)	0.497610(workable)	0.499803(workable)
9	14.1372	0.1190	0.5	0.555948(workable)	0.451636(workable)	0.491397(workable)

12.1	19.0066	0.1190	0.5	0.116679	0.194441	0.185904
9	14.1372	0.1667	0.2	0.165427(sharp)	0.179152(sharp)	0.177153(sharp)
9	14.1372	0.1190	0.2	0.038654	0.161671(sharp)	0.182995(sharp)
10.2	16.0221	0.1190	0.2	0.159688(sharp)	0.218326(sharp)	0.165047(sharp)
11.5	18.0642	0.1190	0.2	0.160434(sharp)	0.181420(sharp)	0.164928(sharp)
13	20.4204	0.1042	0.2	0.093685	0.447136	0.235731(sharp)
8	12.5664	0.1190	0.8	0.467210	0.723330(worn out)	0.716093(worn out)
8	12.5664	0.1042	0.8	0.258278	0.442890	0.159921
9	14.1372	0.1667	0.8	0.053255	0.529739	0.697535(worn out)
10.2	16.0221	0.1042	0.8	0.750549(worn out)	0.587625	0.730085(worn out)
11.5	18.0642	0.1190	0.8	0.425738	0.740245(worn out)	0.759988(worn out)

5. Conclusion

The synthetical features adopted in time domain, frequency domain and time-frequency domain have a better correlation with drill set working condition. Meanwhile the same conclusion that the features of the armature current of servo motor is more correlated than that of spindle motor to drill set condition, which has been reported by S. Braun [1], is also achieved in our experiments.

The more important result is the fused result from multiple sensors is a more reliable one to recognize the drill set working condition.

Table 3. Summary of experimental results.

	Features of pindle motor current		Features of servo motor current		Features of both spindle and servo current	
5sharp	3	60%	4	80%	5	100%
5workable	4	80%	4	80%	4	80%
5wornout	1	20%	2	40%	4	80%
	53.33%		66.67%		86.67%	

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