Int J Adv Manuf Technol (2010) 50:47–52
DOI 10.1007/s00170-009-2509-6

ORIGINAL ARTICLE

Prognostics for drilling process with wavelet packet decomposition

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Received: 28 December 2008 / Accepted: 28 December 2009 / Published online: 2 February 2010

Abstract On-line tool condition monitoring is highly needed in drilling production process. Input current has been employed to monitor the drilling tool wear by many researchers. But few cases can represent the wear status and recognize the breakage simultaneously. The remaining life of tool has not been discussed sufficiently. This paper presents a strategy of on-line tool monitoring system for drilling machine using wavelet packet decomposition of spindle current signature. A moving window technique is used to extract the real drilling parts of data from sampled data sequence. The wavelet packet decomposition is used to extract features from non-stationary current signal. Critical features are selected according to their ability of discriminating the wear progress under Fisher criterion. Logistic regression combined with autoregressive moving average models are used to evaluate the failure possibility and remaining life of the drill bit. Experimental results show good performance of the proposed algorithm.

Keywords Tool wear · Wavelet packet decomposition · Feature selection · Prognostics

1 Introduction

Drilling is one of the most frequently used machining operations. Drilling tool wear may influence the quality of the surface finish and the dimensions of the parts that are drilled. Tool fracture and wear could damage the process and increase the production cost. Regular tool change could prevent happenings of bad parts, but this methodology is based on conservative tool life estimations, which assumes the worn out time of cutting tool, thus unfortunately losing the potential production time of healthy tool. So, only the on-line tool condition monitoring and prognostics can make use of the whole life of tool economically without causing quality problem of production. Actually, around 80% of the cases return the investment in monitoring system in 1 month or less [1].

Many models have been developed and applied in the monitoring of tool wear. Neural network was proposed to detect the wear [2, 3]. Model-based techniques were used to detect the breakage of drill tool [4]. Statistic approach was also used for tool wear analysis [5]. But from the essence of prognostics, the failure possibility and remaining life (RL) have not been discussed sufficiently. Direct tool wear measuring attempts such as visual inspection or computer vision, etc., have not yet been proven to be very attractive neither economically nor technically [6]. Cutting forces and spindle torque are closely related to the cutting process. It is generally known that cutting forces increase as tool wear increases [7]. In some applications, the installation of a force measuring sensor system is difficult or impossible in industrial production line. Vibration and acoustic emission (AE) were also used in some researches. Vibration and sound are very sensitive to the surrounding noise, which is inherent to the cutting processes [6]. AE methods may suffer from severe attenuation and multi-path distortion [6, 16]. Spindle current is available in almost all modern machining centers or can be easily measured from servo motor driver. Many researchers studied the current signature [8–10]. Many of them used time domain features [9, 10]. Some tested the time-frequency

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features with arbitrarily set filtering frequency or scales [8, 11]. Few of them gave the prediction of the tool's RL.

This paper presents a strategy for on-line monitoring and prognostics of the wear of drill bit. Spindle A.C. servo motor current signal was sampled continually and de-noised through soft threshold with wavelet packet decomposition. Time-scale features were extracted and selected to monitor the status of drill. Logistic regression (LR) and autoregressive moving average (ARMA) models were used to evaluate health status and predict the RL. Experimental results show that monitoring system based on current with proposed prognostic method can indirectly detect the wear and predict the RL of drills.

2 Wavelet packet decomposition

Direct measurements of spindle current signal show that severe interference forms different sources represented in additive model. Firstly we use a low-pass filter (LPF) to preserve the spectral contents of the cutting signal and minimize any spurious data. This LPF cannot eliminate all spurious components, so wavelet packet decomposition was used to de-noise the signal and enhance the current signal corresponding to the cutting force.

The bases of wavelet decomposition are the wavelets $\psi_{a,b}(t)$, generated from a basic wavelet function $\psi(t)$ by dilations and translation.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

Where a is called scaling parameter, b is time translation parameter, and $\psi(t)$ is the "mother wavelet."

The continuous wavelet transform of signal $x(t)$ is defined as

$$W(a,b) = \int x(t)\psi_{a,b}{}^{*}(t) \tag{2}$$

In order to calculate $W(a,b)$ with computer, parameters (a,b) must be discretized. Dyadic discretization is the most popular method where $a=2^n$, $b=k2^n$, k, $n\,Z$, discrete wavelet transform coefficients in level n are calculated as

$$c(k) = \int x(t)\psi_k{}^{*}(t) \tag{3}$$

Mallat [12] has proved that there exists a unique function $\varphi(t)$ for $\psi(t)$, If we define $\varphi_k = 2^{-\frac{1}{2}}\varphi\left(\frac{t-2k}{2}\right)$, then

$$d(k) = \int x(t)\varphi_k{}^{*}(t) \tag{4}$$

With Eqs. 3 and 4, signal $x(t)$can be decomposed to wavelet approximation signal coefficients $c(k)$ (k=1,2,....) and detail signal coefficients $d(k)$ (k=1,2,.....). We can repeat this decomposition operation to signal $c(k)$ and $d(k)$. For level n decomposition, there will be 2^n signals $m_l(k)(l=1,2,...2^n)$. Similarly the inverse wavelet packet can reconstruct the original signal from the wavelet packet spectrum. The basic idea of de-noising with wavelet decomposition is wavelet packet coefficients from signal and noise have different behaviors, while larger coefficients carry more signal and smaller carry less. So the approach of de-noising is to reduce the size of detail coefficients with thresholding method. The de-noising includes three steps:

1. Signal decomposition. Select level N, compute $m_l(k)$ $(l=1,2,...2^n)$ for each level. $n=1......N$.
2. Shrink the coefficients. Change the wavelet coefficients in $m_l(k)(l=1,2,...2^n)$ according to a certain thresholding strategy.
3. Signal reconstruction. Recover signal from the modified coefficients $m_l(k)(l=1,2,...2^n)$ in step 2.

Apparently, step 2 is the key point of the process. The choice of threshold directly influences the effectiveness of the de-noising algorithm. Donohon [17] proposed the universal or minimax threshold rule to detect the sparse impulse, but the wavelet representation is not very sparse in this application; it is observed that Stein's unbiased risk estimator threshold rule perform better in such case [18]. This technique calls for setting the threshold T to $T = \sqrt{2\log_e^{\left(s\cdot \mathrm{lon}_2^s\right)}}$, where s is the length of the signal.

After the LPF and de-noising with wavelet packet decomposition, a cleaner current signal will be obtained. In order to find best features to indicate wear status, we need to extract the corresponding information from current signature.

3 Feature extraction and selection

We decomposed the cleaner current signature again from level n=1..to..N. In this study, the energy of wavelet packet signal node $[n,l]$ was used as feature

$$E_{n,l} = \sum_k m_{l,k}^2, (l = 1, 2., ...2^n) \tag{5}$$

where n is the decomposition level, $(l=1,2,...2^n)$ is the sequence number of the nodes in level n, and k is the coefficient number in signal $m_l(k)$ of node $[n,l]$.

Feature selection is to select the feature components that contain discrimination information and discard those feature components, which provide little information. In the process of every hole drilling, a current signature was obtained; thus, wavelet node energy $E_{n,l}$ in each node (n,l)

was calculated, so $E_{n,l}$ will form a sequence with the drilling time (or drilled hole numbers). Provided with the available feature components $\{f_j | j = 1, 2, ...\}$, we can select the most discriminating ones according to the criterion

$$J(f_{z1}) > J(f_{z2}) > ...... > J(f_{zM}) \tag{6}$$

where $J(f_{zi})$ is a criterion function of measuring the discrimination ability of the feature f_{zi}. Here Fisher's function was used as in [13]

$$J(f_j) = \left(|u_{j1} - u_{j2}|^2\right) \Big/ \left(\delta_{j1}^2 + \delta_{j2}^2\right) \tag{7}$$

where u_{j1} and u_{j2} are the mean values of the feature f_j for classes 1 and 2 (class1 indicates a sharp drill, and class 2 refers to the case when the tool is worn), and δ_{j1}^2 and δ_{j2}^2 stand for the variance of the feature f_j for classes 1 and 2. According to Eqs. 6 and 7, features with larger $J(\cdot)$ values will be selected to evaluate the drill health.

4 Health evaluation and remaining life prediction

We can use the current features of drilling process to deduce the failure possibility of drill bit. The cutting process condition description from daily maintenance records/logs is a dichotomous problem (either normal or failed), which can be represented using logistic regression function [14]. The goal of logistic regression is to find the best fitting model to describe the relationship between the categorical characteristic of dependent variable (the probability of an event is constrained between 0 and 1) and a set of independent variables. The logistic function is

$$\Pr\text{ob}(\text{event}) = P(\mathbf{x}) = \frac{1}{1 + e^{-g(\mathbf{x})}} = \frac{e^{g(\mathbf{x})}}{1 + e^{g(\mathbf{x})}} \tag{8}$$

The logistic or logit model is

$$\begin{aligned} g(x) &= \log[\Pr\text{ob}(\text{event})/\Pr\text{ob}(\text{no.event})] \\ &= \log\left(\frac{P(\mathbf{x})}{1 - P(\mathbf{x})}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_h x_h \end{aligned} \tag{9}$$

where $g(x)$ is a linear combination of the independent variables $x_1, x_2, ..x_h$.

The pre-condition for figuring out $P(\mathbf{x})$ is determining parameters α and $\beta_1, \beta_2, ...\beta_h$ in advance. Due to the fact that the dichotomous-dependent variable makes estimation using ordinary least squares inappropriate, rather than choosing parameters that minimize the sum of squared errors, estimation in logistic regression chooses parameters of α and β_1, $\beta_2, ...\beta_h$ using the maximum likelihood method [14]. Then, the probability of failure for each input vector $\boldsymbol{x}=[x_1, x_2, ...x_h]$ can be calculated according to Eq. 9.

The essence of prognostics is to estimate the residual life in the future that may influence the decision of tool changing. After drilling a hole, we need to know the failure time of current drill bit. ARMA model can be used to predict the degrading process with the past failure possibility known from the logistic regression module. If y_t is the possibility of failure at moment t, the ARMA (p,q) will be

$$y_t - \varphi_1 y_{t-1} .... - \varphi_p y_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + ... + \theta_q \varepsilon_{t-q}$$

where p and q are the orders of the autoregressive part and the moving-average part, respectively. ε_t denotes the series of errors. p and q can be determined using AIC rule, and the model parameters can be identified based on the Yule–Walker equation [15]. The failure possibility in the future can be predicted on-line based on the dynamic ARMA model.

5 Experiment setup

The schematic diagram of the experimental setup is shown in Fig. 1. A Mori Seiki TV30 machine center was used, and drill diameter is 6.35 mm (1/4 in.). A force sensor was also installed for convenience of comparison except a closed-loop current sensor. NI PCI 6240E card and Labveiw software were used to acquire the current signature and cutting force data.

6 Data analysis

Table 1 shows the value of spindle and feeding speed used in two tests.

For on-line monitoring system, data were sampled continually without knowing the start or stop point of drilling process as shown in Fig. 2a, so there must be a lot

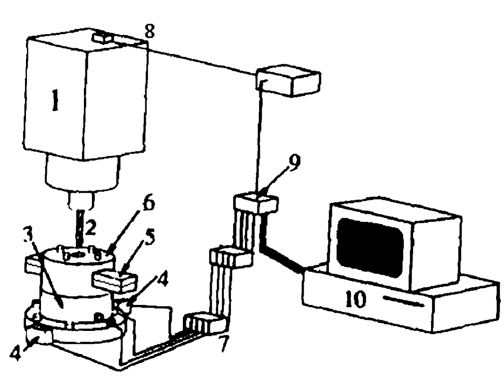


Fig. 1 Experimental setup of the drilling process: *1* spindle motor, *2* drill bit, *3* four component drilling dynamometer, *4* piezoelectric strain element, *5* workpiece, *6* fixture, *7* charge amplifiers, *8* current sensor, *9* data acquisition screw terminal board, *10* personal computer

Table 1 Experiment parameters

Test name	Spindle speed (rpm)	Feeding speed (mm/min)
Test 1	500	24
Test 2	1,250 for first 24 holes	30
	500 for after 24 holes	30

of useless data sampled at idle time. Because current signature were sampled continually at fixed frequency 250 Hz, before any analysis, we need to extract the exact parts of data related to hole drilling, and all data related to idle time should be discarded while evaluating drilling performance. For a certain depth hole drilling, if the feeding speed is fixed, number of useful data points collected while drilling should be equal for every hole. For example, if feeding speed is 24 mm/min, the depth of work piece is 18 mm, the number of useful data during one hole drilling is $18/24 \times (250 \times 60) = 1,1250$. Because the absolute value of drilling data is much higher than those in idle time, so we use a moving window whose width is 11,250 to smoothly pass from the start of data sequence. If the root mean square value of sub-group data inside the window reaches a peak value, then this sub-group data are exactly the part of real drilling data. Figure 2b shows the real drilling data extracted from original data in Fig. 2a.

After obtaining the drilling data, we can perform the low-frequency filtering and wavelet packet decomposition. At each decomposition level n=1,..,N, for example, if N=5, there will be a total of 64 features $E_{n,l}(l = 1, 2, ...2^n, n = 1, ..., 5)$. For each feature, Eq. 7 was used to evaluate its ability of

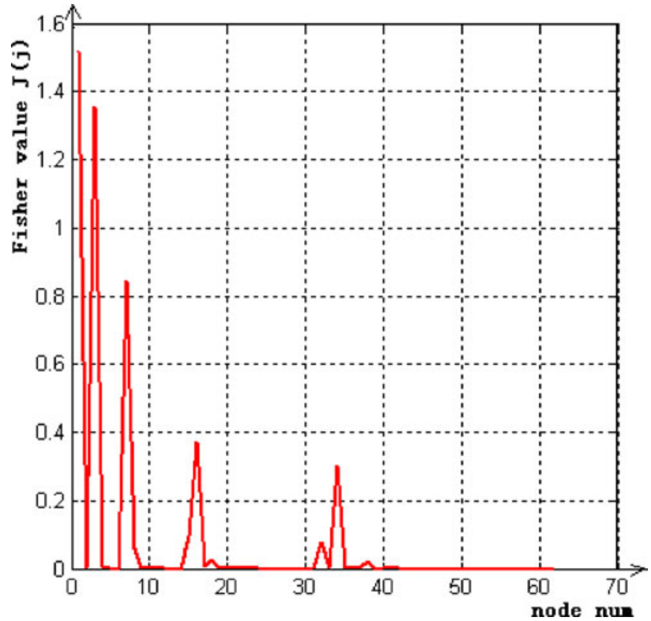


Fig. 3 Discrimination intensity of different features

discriminating tool wear stage. Figure 3 shows feature intensity value $J(\cdot)$ with the feature number k. From Fig. 3, 10 features were selected according to Eq. 6.

For each drilling process, a 10-dimension feature vector was inputted into LR model for training of assessment LR model. Based on the data of 10 holes (five holes of good condition versus five holes of dull condition), the LR parameters α and β_1,β_2,...β_{10} were estimated using maximum likelihood method. The trained LR model was used to evaluate the possibility to fail for all stages. In test 1, the

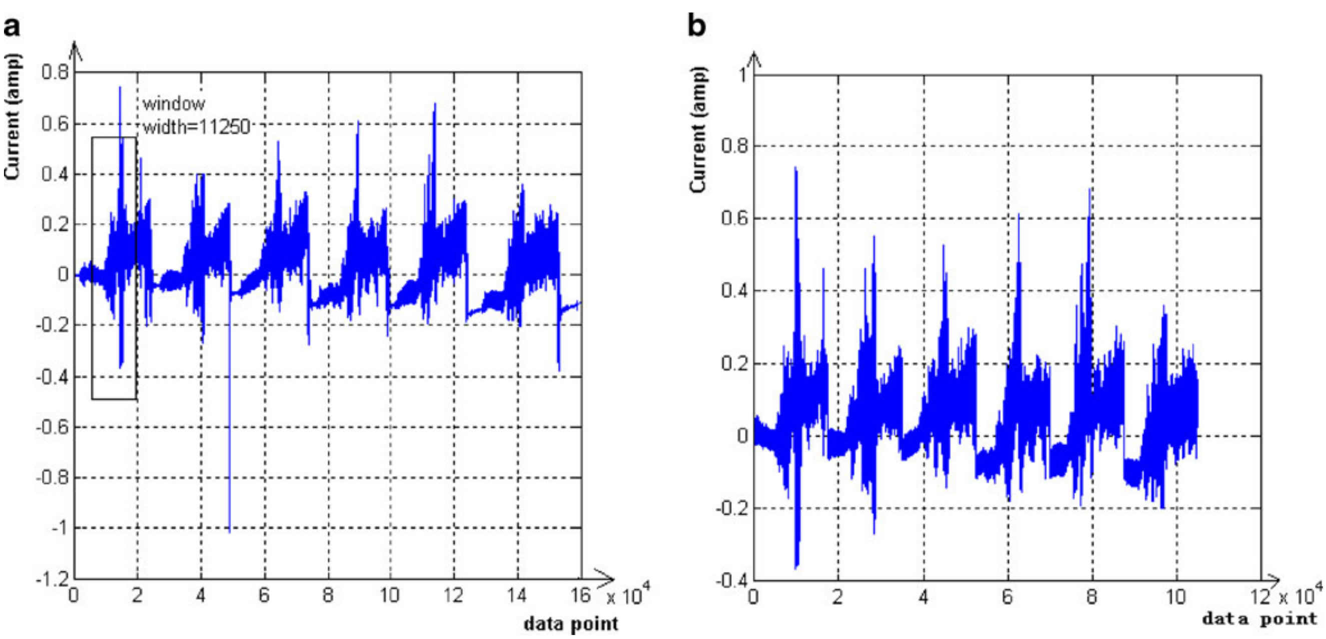


Fig. 2 **a** Original sampled data, **b** drilling data extracted with moving window

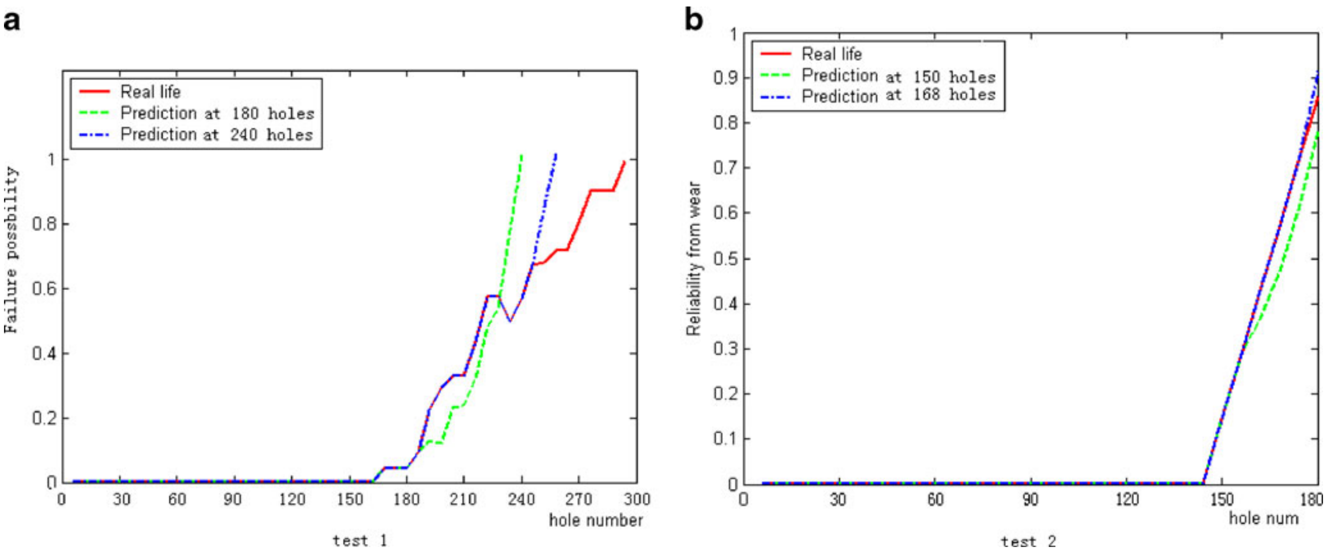


Fig. 4 Failure possibility of drill bit

drill bit broke after drilling 49 holes. Figure 4 shows failure possibility analysis result. The solid line is a real failure possibility acquired from the real drilling data. The dashed line shows failure possibility predicted when drilled 180 holes. We can see that if we drill 50 holes more, the possibility to fail is 60%, which is quite consistent with the real life. The error will be larger when a longer period is predicted. In fact, we will modify the ARMA model every time one more hole is drilled. So we only need to predict whether the drill bit will fail several holes later and not to try to predict condition with long delay.

The same procedure can be applied in test 2. When we predict the failure possibility after 150 holes drilled, from Fig. 4b, 70% failure possibility will be achieved at 175 holes (dashed line), and the reality is it happened at 170 holes.

Besides these two tests, many other tests also give acceptable results, except when the spindle speed or feed speed is too low. In the lighter cutting such as micro-drilling, the current feature is not very sensitive to the wear. The disturbance existing in power supply undulates the change in the current signature.

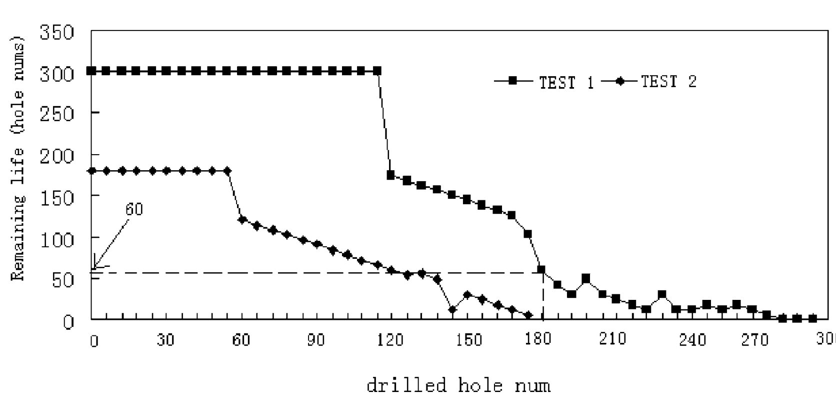
From the predicted failure possibility, the RL of the drill bit may also be calculated. Figure 5 is the predicted RL expectancy. We suppose that when the failure possibility achieves 85%, the tool will fail and must be changed. From Fig. 5, if we predict in test 1 when the tool might fail after 180 holes has been drilled already, we know that 60 holes (the RL) later, the tool will fail and must be changed, which will remind the operator to prepare to change the tool.

7 Conclusion

Spindle current is sensitive to the wear in medium and heavy cutting conditions. In this paper, we presented an application of prognosis of drilling process condition based on the spindle current signature.

The real data corresponding to hole drilling were extracted from sampled data sequence with a moving window technology. The wavelet packet decomposition was used to de-noise the original current signature and extracted time-frequency feature. The energy of the

Fig. 5 Remaining life prediction for tests 1 and 2



decomposition node of current signature was used as evaluation feature. Features with the best distinguishing ability were selected under Fisher criterion.

LR was used to obtain failure possibility of the drill bit. With ARMA model, the residual life was predicted, and the experimental results showed that the algorithms presented in this paper successfully predicted the failure possibility of drill bit and gave out caution of tool changing.

Acknowledgments This research was directed by Professor Jun Ni in Wu Shing Ming Manufacturing Research Center in University of Michigan. I am very thankful to Prof. Ni and other colleagues in Wu Center.

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