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Effect of different features to drill-wear prediction with back propagation neural network

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ABSTRACT

In this paper, a back propagation neural network (BPNN) has been applied to predict the corner wear of a high speed steel (HSS) drill bit for drilling on different workpiece materials. Specially defined static and dynamic features extracted by a wavelet packet transform (WPT) from the resultant force converted from thrust and torque together with the cutting conditions (workpiece material, spindle speed, drill diameter, feed rate) are used as inputs to train the network to obtain a better output, drill corner wear. Drilling experiments have been carried out over a wide range and, features newly defined and conventional ones, features extracted from different frequency bands are compared.

1. Introduction

This paper is concerned with the prediction of drill wear with features extracted from the static and dynamic components of the resultant force of converted thrust and torque by wavelet packet transform (WPT) using back propagation neural network (BPNN).

The sequence of activities in sensor monitoring of machining process conditions can be surmised as: process variables, sensorial perception, data processing, feature extraction, cognitive decision making and action by Teti et al. [1].

Previous literatures in drill wear prediction have taken the thrust and torque as independent physical quantities without taking the information of the relationship between them into account [2]. Dynamic components of the resultant force of principal force and feed force were used to indicate the adhesion of tool–chip interface and predict the surface finish successfully [3]. Therefore in this paper, a conversion method of thrust and torque is discussed and based on which the newly defined static and dynamic features are defined.

The features are extracted by an n level WPT. Signals are decomposed into 2^n sets of coefficients generating many frequency bands which provides opportunities to find useful signal features (SFs) [4].

Then the extracted features along with drilling conditions such as workpiece material, drill diameter, spindle speed and feed rate are used to train the BPNN.

Panda et al. [5] compared back propagation neural network (BPNN) and radial basis function network (RBFN) in predicting of drill flank wear using features such as average and root mean square (RMS) of thrust force, torque and vibrations which proved that BPNN was better in the prediction accuracy. And relations between these conventional features and drilling conditions were discussed.

Different results are obtained using new features and conventional features, and features extracted from different frequency bands.

2. Definition and extraction of the static and dynamic features

In this paper, the thrust (Fz) and torque (Mz) monitored by the dynamometer during the drilling process are converted into the equivalent thrust force (Ft) and the equivalent principal force (Fp) by Eqs. (1) and (2):

$$Ft = \frac{Fz}{2 \times \sin(\varphi/2)} \quad (1)$$

$$Fp = \frac{2Mz}{d} \quad (2)$$

In which φ means the point angle and d means the diameter of the drill bit.

Then a rectangular coordinate is applied with the horizontal axis as Fp and vertical axis as Ft. Therefore, any point in this rectangular

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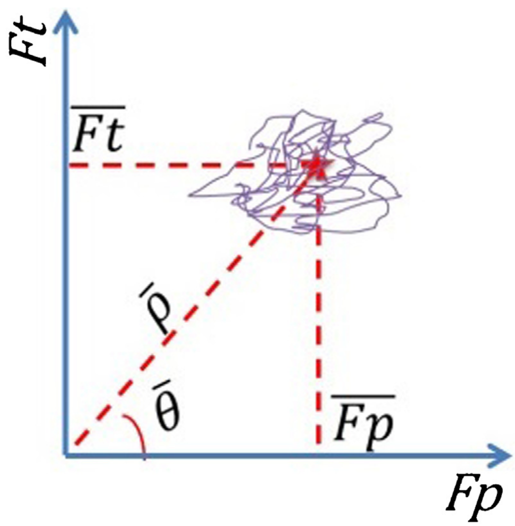

Fig. 1. Definition of static features.

coordinate represents the resultant force of *Fp* and *Ft*. Thus the data sampled and processed from experiments is turned into a series of the resultant force vectors in time sequences and then into the trajectory of the resultant force.

As shown in Fig. 1, $\overline{Ft}$ and $\overline{Fp}$ are the mean values of *Ft* and *Fp* respectively, and they comprise the static features together with $\overline{\theta}$ and $\overline{p}$ which can be described by Eqs. (3) and (4):

$$\overline{\theta} = \frac{1}{n}\sum_{i=1}^{n}\theta_i \tag{3}$$

$$\overline{p} = \frac{1}{n}\sum_{i=1}^{n}\rho_i \tag{4}$$

In which n means the total number of points in the data set, and θ_i, ρ_i are the 2 parameters of data point i in a polar coordinate.

ΔFt and ΔFp are the fluctuation ranges of *Ft* and *Fp* and $\Delta\theta$, $\Delta\rho$ indicate the variation range of the resultant force in polar form as shown in Fig. 2. And the root mean square (RMS) values of *Ft* and *Fp* are also frequently used features in previous papers [6,7]. Similarly, RMS values of θ and ρ are also calculated for comparison.

The 3 specially defined dynamic features in this paper are "*ConvHullArea*", "*STDEV*" and "*TrackLength*". Intuitively, the concentration of the distribution of data points directly indicates the stability of the resultant force. Therefore, "*ConvHullArea*" is defined as the area of the convex hull of the discretely distributing data points as shown in Fig. 2. "*STDEV*" is defined as the average distance from each trajectory point (Ft_i, Fp_i) to the center point $(\overline{Ft}, \overline{Fp})$ by Eq. (5) and, "*TrackLength*" is defined as the path length of the resultant

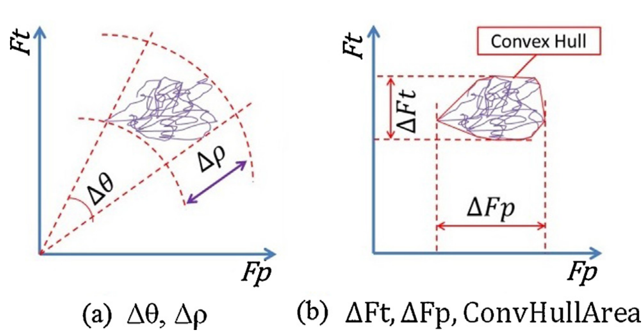

Fig. 2. Definition of dynamic features.

Table 1
Grouping of static and dynamic features.

	Static features	Dynamic features
Group 1		ΔFt, ΔFp, RMS of Ft, Fp
Group 2	$\overline{Ft}, \overline{Fp}, \overline{\theta}, \overline{\rho}$	$\Delta\theta$, $\Delta\rho$, RMS of θ, ρ
Group 3		*ConvHullArea*, *STDEV*, *TrackLength*

force trajectory in unit time (t_0), i.e. the velocity of the resultant force track in the previously declared coordinate illustrating by Eq. (6):

$$STDEV = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(Ft_i - \overline{Ft})^2 + (Fp_i - \overline{Fp})^2} \tag{5}$$

$$TrackLength = \frac{1}{t_0}\sum_{j=2}^{m}\sqrt{(Ft_j - Ft_{j-1})^2 + (Fp_j - Fp_{j-1})^2} \tag{6}$$

In Eq. (5), n means the number of data points during the whole sampling period; while in Eq. (6) m indicates the number of data points in the period of t_0.

So in all, 4 static and 11 dynamic features can be obtained and, they are divided into 3 groups according to the definition of dynamic features as shown in Table 1. Dynamic features in groups 2 and 3 are newly defined in this paper. Features in different groups will be used as inputs to train the neural network separately and their performances will be evaluated.

For features extraction, a 3 level WPT is employed which decomposes the original signals into 8 series of coefficients, the same as elaborated in [8]. However, other than choosing the first packet having the highest energy in many previous researches, 8 sub signals of different frequency bands are reconstructed being converted into time domain according to the coefficients as shown in Fig. 3. The original sampling frequency is 20 kHz, so each of the frequency bands is 2.5 kHz varying from 0–2.5 kHz to 17.5–20 kHz. At last, the features of each frequency band are calculated according to the features definition discussed before.

3. Experimental set up and signal processing

The experiments were conducted on a Mitsubishi CNC machining center with a Kistler 9365B dynamometer, a Kistler 5073 charge amplifier (frequency response 20 kHz) and a Yokogawa DL750 scope recorder. The drill bits used were Mitsubishi SDD series standard uncoated HSS drills. Four different workpiece materials cast iron, S45C, SUS304 and Titanium alloy (Ti-alloy) were used. And for each material, 64 different experiments were carried out with 4 drill diameters, 4 spindle speeds and 4 feed rates. Altogether, 256 distinct groups of feature values have been extracted from the experimental data.

The signal processing first starts with the 2 channels of raw electric quantity signals of thrust and torque generated by the dynamometer. Then they are amplified and converted into 2 voltage signals by the amplifier and then, the scope recorder completes the A/D conversion and digital data recording. After that, the

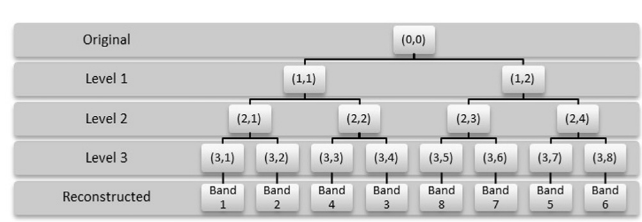

Fig. 3. Signal decomposition and reconstruction by WPT.