Heterogeneous Feature Selection with an Application in Multi-Sensor-Based Condition Monitoring of a Tool Used in Rotary Ultrasonic Machining

Hua BAI¹, Guang-Hui LI² and Hong-Xiang WANG³

¹P.O.Box412, Harbin Institute of Technology, China
²1 South Dahongmen Road, Fengtai District, Beijing
³P.O. Box 424, Harbin Institute of Technology, China

Email: baihua@hit.edu.cn, lisantun@sina.cn, whx@hit.edu.cn

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Abstract. Effective monitoring and diagnosis of tool wear condition plays a critical role in improving rotary ultrasonic machining quality and system reliability. In this study, force and vibration signals were first collected during rotary ultrasonic machining operation, next processed by time/frequency domain analysis or wavelet packet decomposition (WPD) for feature extraction, and then the best features are selected by a newly proposed heterogeneous feature selection method. Physical experiment data of the BK7 glass grinding process are implemented to evaluate the proposed method. The results were shown to illustrate the effectiveness of the proposed methods.

Introduction

Rotary ultrasonic machining is one of the cost-effective machining process available for hard and brittle materials, which feature superior properties of high hardness and wear resistance. Tools wear faster in rotary ultrasonic machining process because of high cutting force and low materials removal rate, causing breakage or wear which may greatly decrease machining quality. Therefore, for rotary ultrasonic machining, effective monitoring and diagnosis of tool wear condition and timely replacement of the tool are really important to improve machining quality and system reliability.

Studies have shown some sensory signals such as forces, power, vibration, and acoustic emission (AE) that highly correlate with the tool condition, are used for machining monitoring system to detect the cutting tool condition. Adam and Bhuiyan reviewed state-of-the-art methods in tool condition monitoring system and facilities implemented respectively[1,2]. Research issues such as sensor system selection[2,3], multi-sensor fusion system[1,4], sensory signal processing and potentially discriminant feature extraction[5,6] are successfully developed by previous researchers. However, The challenging problem of multi-sensor data fusion is the determination of the best feature extraction and selection for combining the multi-sensor data inputs, which are frequently not comparable and sometimes inconsistent, since multi data could be derived from different physical property(such as forces, power, vibration, etc.) describing different features of the subspace associated with the same experimental situation, or from the measurement of the same attribute over a number of different ranges or domains.

Generally, the property of multi sensors which give information on the same environment but from different subsets of the environment is homogeneous, reversely, multi sensors which together perceive the whole environment but which individual only perceive a subset of the environment, and give data with completely different features is heterogeneous. The later is more complementary and redundant, and it may greatly improve the performance of the multi sensor data fusion in accuracy, certainty and completeness. But the time asynchronism, the tremendous boost in data size, and the unmaching problem in data dimension let the heterogeneous sensor fusion more complex and more difficult.
This paper made a study of the aforementioned issues in multi-sensor-based condition monitoring of a tool used in rotary ultrasonic machining. Signal processing methods based on time/frequency domain analysis and wavelet packet decomposition (WPD) are applied for processing heterogeneous sensory signal to extract the potentially discriminant feature; A newly proposed method based on linear combination of sensitivity, dispersion between clusters and in clusters is exploited for feature selection. More details about the heterogeneous feature extraction and selection are briefly described in the following sections.

**Heterogeneous Multi-Sensor Data Acquisition and Feature Extraction**

Ultrasonic 70-5 5-axis milling center of DMG MORI is chosen as the experimental facility. The spindle speed is 4000rpm and the feed rate is 100mm/s in experimental condition. The heterogeneous data acquisition system consists of the force signal acquisition system and the vibration signal acquisition system. As schematically shown in Fig.1, it consists of a computer with a data acquisition card, a Kistler 9256C2 dynamometer and a Kistler 5080A charge amplifier which are used to acquire force signal, and an IEPE accelerometer which is used to online collect vibration signal. The cutting tool was a electroplated diamond drill with a diameter of 6mm and grit mesh size $91\mu m$. The workpiece material was BK7 glass with a size of 60mm×60mm. The tool wear condition is evaluated by analyzing the surface topography of the electroplated diamond drill under a digital microscope and the tool wear diagram is shown in Fig.2.

Numerous experimental analysis indicate that the tool will be worn out gradually when the tool grind along the work piece edge back and forth. Take the vibration signal as an example, the acquired data which derived from three typical wear stages can be converted into wavelet packet decomposition time-frequency coefficient. As is shown in Fig.3, almost no difference can be found in raw signal representations; to the contrary, the wavelet packet decomposition derivation yields significant discrepancy. It implicates the transient features of tool wear in time-frequency diagram, but more effective feature extraction and selection method need to be developed to conduct quantities analysis.

**Figure 1. Experimental setup.**

**Figure 2. Tool wear diagram.**

**Figure 3. Wavelet packet decomposition time-frequency coefficient.**

Slight wear stage (derived from the first grind circle)
Intermediate wear stage (derived from the thirty grind circle)

Severe wear stage (derived from the sixty grind circle)

Figure 3. Vibration raw time domain signal and wavelet packet decomposition time-frequency diagram.

The data derived from disparate sensor can delineate different tool wear characteristics in various aspects. For the same sensory data, each signal processing technology will yield part of the attributes of the tool wear condition. In this research, some signal processing method, i.e. time domain analysis, frequency domain analysis, and wavelet transform, are used for characterizing the measured vibration and force signal. Features extracted are symbolized in table 1. Matwork’s Matlab signal processing function are conducted for time domain analysis and frequency domain analysis.

Table 1. Summary of the feature symbols in time/frequency domain.

<table>
<thead>
<tr>
<th>Symbol type</th>
<th>Name</th>
<th>Mean value</th>
<th>Root-mean-square error (RMS error)</th>
<th>Variance</th>
<th>Kurtosis</th>
<th>Skewness</th>
<th>Mean square frequency deviation</th>
<th>Variance of frequency</th>
<th>Centroid frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vibration signal</td>
<td>vibMean</td>
<td>vibRMS</td>
<td>vibVar</td>
<td>vibK</td>
<td>vibAlpha</td>
<td>vibMSF</td>
<td>vibVF</td>
<td>vibFC</td>
<td></td>
</tr>
<tr>
<td>Cutting force signal</td>
<td>xfMean</td>
<td>xfRMS</td>
<td>xfVar</td>
<td>xfK</td>
<td>xfAlpha</td>
<td>xfMSF</td>
<td>xfVF</td>
<td>xfFC</td>
<td></td>
</tr>
<tr>
<td>Y</td>
<td>yfMean</td>
<td>yfRMS</td>
<td>yfVar</td>
<td>yfK</td>
<td>yfAlpha</td>
<td>yfMSF</td>
<td>yfVF</td>
<td>yfFC</td>
<td></td>
</tr>
<tr>
<td>Z</td>
<td>zfMean</td>
<td>zfRMS</td>
<td>zfVar</td>
<td>zfK</td>
<td>zfAlpha</td>
<td>zfMSF</td>
<td>zfVF</td>
<td>zfFC</td>
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</tr>
</tbody>
</table>

For the measured vibration signal, the multilevel wavelet pocket decomposition function, \( \text{wpdec} \), available in Matlab is chosen by specifying db3 Daubechies wavelet with \( n=4 \). The energy of each decomposed component is then computed. The energy of a signal is the sum of the squares of its coefficient values. For \( n \) levels of decomposition the WPD produces \( 2^n \) difference sets of coefficients. Therefore, a total of 16 sets are obtained for the feature vector to describe part characteristics of the measured vibration signal. In the same way, for the measured force signal, a total of 8 sets are obtained from 3 levels of wavelet pocket decomposition for the feature vector to describe part characteristics of the measured force signal.

To sum up, there are 72 heterogeneous feature subsets are extracted from the measured vibration and force signal by the above three signal processing methods. Part of these subsets are irrelated.
and redundant, so an effective feature selection method need to be developed to decrease the sets dimension.

**Feature Selection**

If several data sets are related to feature $J_i$ these data can be divided into $X_{ji}(j=1,2,...,N)$ stages to denote for different cluster. For example, if the tool wear condition is divided into three clusters, i.e. slight/intermedia/severe wear stage, then the data sets can be divided as $X_{1i}/X_{2i}/X_{3i}$ stages to be used for the feature $J_i$ extracting. The proposed method define $SJ_i$ as the selection factor of the feature subset $J_i$:

$$SJ_i = \frac{SB_i}{SW_i \cdot K_i}$$

(1)

$SW_i$ is the dispersion in clusters and defined as

$$SW_i = \sum_{j=1}^{N} \sum_{j=1}^{n_j} \left( x_{ji} - \bar{x}_j \right) \left( x_{ji} - \bar{x}_j \right)$$

(2)

Where $Var_{ji}$ is $j$th class data stage variance of the feature $i$, $n_j$ is the length of the data stage $x_{ji}$, $\bar{x}_j$ is the mean of cluster data stage $x_{ji}$.

$SB_i$ is the dispersion between clusters and defined as

$$SB_i = \sum_{j=1}^{N} \left( \bar{x}_j - m_i \right)^2$$

(3)

Where $m_i$ is the mean value of data sets related to feature $J_i$, $K_i$ is the sensitivity and defined as

$$K_i = \sum_{k=1}^{4} C_k$$

(4)

where $C_k$ describe the influence parameters come from maching enviroment, such as spindle speed, feed rate, cutting depth and power percent.

For the measured vibration signal, 8 and 16 heterogeneous feature subsets are extracted by time/frequency domain analysis (as shown in table1) and wavelet pocket decomposition respectively. The dispersion in/between class and sensitivity for each feature subset is calculated based on equation (2)-(4) and the final value of the selection factors are illustrated in Fig.4.

Based on the description of selection factor in equation(1), the larger is $SB_i$ and the smaller is $SW_i$, the larger is $SJ_i$ and the easier is the features to be clustered. With top 30% of the feature subsets are selected, VibAlpha, VibVF are selected from time/frequency domain features, and vibwp1, vibwp6, vibwp9, vibwp10, vibwp14 are selected from wavelet transform feature subsets. In conclusion, the initial 24 potentially heterogeneous discriminant features extracted from different signal processing technologies, are decreased to 7 selected features for describing the tool wear attribute based on the measured signal from the same vibration sensor.

![Figure 4. Feature selection based on vibration signal processing.](image)
The same process is deployed for the measured force signal. The three independent directions (x, y, z) of the grinding forces could be detected at the same time using the dynamometer. The force measurement of X/Y/Z direction show the tool condition of rotary ultrasonic machining process in different way. Here the same heterogeneous feature subsets are extracted by time/frequency domain analysis and wavelet pocket decomposition. As shown in table1, from the force measurement data of X/Y/Z direction, total 24 feature subsets are extracted by time/frequency domain analysis, and 24 feature subsets are extracted from the wavelet pocket decomposition. the final value of the selection factors are illustrated in Fig5. With top 30% of the feature subsets are selected, xfRMS, xfVar, yfVar, yfK, zfRMS, zfVar are selected from time/frequency domain features, and xfwp2, xfwp4, yfwp5, yfwp6, zfwp1, zfwp3 are selected from wavelet transform feature subsets.

![Figure 5. Feature selection based on force signal processing.](image)

In conclusion, the initial 48 potentially heterogeneous discriminant features extracted from different signal processing technologies, are decreased to 12 selected features for describing the tool wear attribute based on the measured signal from the same dynamometer.

**Diagnose Result**

In this part, artificial neural networks (ANNs) are employed to recognize the attributes corresponding to different stages of tool wear. The inputs of the network are from the above feature extraction and selection algorithms. Thus, if the number of features is n, then the number of input nodes is also n. The number of outputs, which is the tool condition stage, is three. There have already been several ANNs developed and applied to engineering problems. Each has its own advantages and disadvantages. After the performance testing and comparison, a feed forward network with an error back propagation learning algorithm is applied to the tool wear diagnose process.

With the tool wear condition ranging from the initial good stage, slight wear stage, intermediate wear stage, and severe wear stage, the tool experienced 30 grinding circles, and the corresponding raw data sets of vibration and force were recorded respectively. For each circle, the raw data set was divided into 5 parts, the first 3 parts forming the training sets, and the rest 2 parts forming the testing sets. For the features obtained from the above feature extraction and selection algorithm, the
architecture of BP networks consists of 19 input units and 3 output units (i.e. three stages of tool wear, slight/intermediate/severe wear stage).

For the features directly extracted from the time/frequency domain analysis and wavelet transform, the architecture of BP networks consists of 72 input units, which are connected to the hidden units related to three output units (three stages of tool wear). Regarding the number of hidden units, possibilities are tested for the optimal condition. The results showed that 143-hidden-unit can provide the smallest MSE value. Therefore, the network structure is 72 (input)-143 (hidden)-3(output).

For training of the proposed network, the training rate which influences the speed and quality of learning is set to 0.1, and the maximum iteration number is set to 500. After repeating the back-propagation algorithm for a sufficiently large number of training cycles, the network will converge to a state where the output error is much smaller than 0.01. After completing the training sessions, testing data sets randomly chosen from raw data set are applied to the trained network. For the proposed network with input nodes from the feature extraction, the diagnose result which is accordant with the testing data output is 95%. However, for the proposed network without feature extraction, the diagnose result is 81.67%. The accuracy of the tool wear condition evaluation is improved greatly.

Conclusion

In this paper, a feature selection and extraction method applied for processing heterogeneous multi sensory signal were addressed. The proposed method consists of signal preprocessing, feature extraction and selection, and building ANN based tool condition diagnose system. An accelerometer and a dynamometer were used in the experiments for monitoring the tool wear condition of a rotary ultrasonic machining operation. The feature elements were extracted from the detected signals and selected based on the proposed heterogeneous feature selection method, before they were used as the input data of neural networks. The analysis of results based on the experimental data show that the efficiency and performance releated to tool wear condition diagnose were greatly improved after the heterogeneous data feature selection processing.

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