Health Assessment for Tools in Milling Machine Using the Mahalanobis–Taguchi System Based on WPT-AR

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Abstract. A real-time tool health assessment has a profound significance on reliable machining operations. This paper proposes a health assessment method for tools in milling machine using the Mahalanobis–Taguchi system (MTS) based on Wavelet Packet Transformation and Autoregression (WPT-AR). In this method, the nonlinear and non-stationary vibration signal from milling process is first decomposed by wavelet packet transforms. Second, an AR model is constructed for each coefficient of the reconstructed signal, and the parameters and the variance of the remnant of each AR model are employed to form the initial feature matrix. Singular values of this feature matrix are obtained by Singular Value Decomposition, at which point MTS is employed. In this study, MTS provides: (1) a computational scheme based on the Mahalanobis distance (MD) for obtaining the health index of a tool; and (2) Taguchi methods to extract the key features and reduce the redundant ones. Finally, the performance and effectiveness of the proposed method was validated by vibration signals acquired from milling machining process.

1. Introduction

In a modern machining system, tool health assessment systems are needed to get higher quality production and to prevent the downtime of machine tools due to catastrophic tool failures [1]. Tool health status directly affects the surface finish and dimensional accuracy of the product. Therefore, tool health assessment has a profound significance on the economics of machining operations [2].

Realizing effective tool health assessment, one challenge is selecting a proper feature space that can reflect comprehensive performance [3]. Traditional time-domain and frequency-domain analysis are based on the assumption that the processing signals are stationary and linear. However, the vibration signal of worn tool is a nonlinear and non-stationary signal. Wavelet packet transform (WPT) has particular advantages for extracting features that combine nonlinear and non-stationary characteristics [4]. Thus, WPT is employed for feature extraction in this method.

Since the autoregression parameters of AR model are very sensitive to condition changes, however, the estimation of the AR parameters may not be available for nonlinear and non-stationary signal. Thus, the integration of the WPT and AR model is employed to provide better efficacy in the fault feature extraction. After that, SVD method is used to decompose the feature vector matrices and obtain singular values [5].

After extracting feature vectors, another challenge of realizing effective tool health assessment is how to build an intelligent assessment model. Mahalanobis-Taguchi System (MTS) is a pattern information technology introduced by G. Taguchi. In MTS approach, Mahalanobis distance (MD) is used to measure the degree of abnormality of patterns whereas the Taguchi methods are used to optimize the system [6]. In this study, MTS is employed to provide a computational scheme based on the MD and extract the key features based on Taguchi methods.

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2. Methodology

2.1. WPT-AR based feature extraction

The tool vibration signal can be decomposed to 2^n sub-bands with different frequency by n-level WPT. Coefficients of the reconstructed signal can be defined as $c_1(t), c_2(t), ..., c_j(t)$ ($j = 2^n$). The AR model for each coefficient $c_i(t)$ is constructed as:

$$c_i(t) = \varphi_{i1}c_i(t-1) + \varphi_{i2}c_i(t-2) + \ldots \varphi_{ip}c_i(t-p) + e_i(t) = \sum_{k=1}^{p} \varphi_{ik}c_i(t-k) + e_i(t) \quad (1)$$

where φ_{ik} (k=1,2,…,p) and p respectively are the kth model parameters and model order of the AR model of the ith coefficient; $e_i(t)$ is the remnant of the model, a white noise sequence with zero mean value and variance σ_i^2 [7]. Feature matrix $A_i = [\varphi_{i1}, \varphi_{i2}, ..., \varphi_{ip}, \sigma_i^2]$ can be chosen to identify the tool condition in milling machine.

2.2. Mahalanobis–Taguchi System

2.2.1. Mahalanobis distance (MD). The MD is measured in terms of the standard deviations from the mean of the benchmark samples. It is calculated as follows [6]:

$$MD_j = \frac{1}{k} Z_{ij}^T C^{-1} Z_{ij} \quad (2)$$

where C^{-1} is the inverse of the correlation matrix C, which contains correlation coefficients between the variables, Z_{ij} is the column vector of standardized variables, MD_j is the Mahalanobis distance for the jth observation, and k is the number of characteristics.

2.2.2. Taguchi Methods. Taguchi methods are employed to extract the key features. An Orthogonal Array (OA) is a table that lists the combination of characteristics, enabling the effects of the presence or absence of a characteristic to be tested. In MTS, characteristics in the OA have two levels. Level 1 represents the presence of a characteristic, whereas Level 2 represents the absence of a characteristic. For the abnormal cases, MD values are calculated using the combination of characteristics dictated by the OA and the larger-the-better signal-to-noise ratio is calculated as follows [6]:

$$\eta_q = -10\log\left[\frac{1}{n}\sum_{j=1}^{n}\frac{1}{MD_j}\right] \quad (3)$$

where η_q is the signal-to-noise ratio for the qth row of the OA, and n is the number of observations under consideration. Then, an average signal-to-noise ratio at Level-1 (t_1) and Level-2(t_2) of each characteristic is obtained. If $t_1 - t_2 > 0$, this characteristic is useful; otherwise, it is useless for diagnosis.

2.2.3. Health assessment. This method adopts CV (Confidence Value), proposed by Qiu [8], as an index for evaluating the degree of health condition. A normalized function based on sigmoid function is proposed, as follows, in order to convert the MD obtained by MTS to CV.

$$CV = \exp\left(-\frac{\sqrt{MD}}{c_0}\right) \quad (4)$$

In this equation, c_0 is the scale parameter determined by the MD and the CV value under normal state. CV value under normal condition, defined as CV_{pre}, can be denoted as:

$$CV_{pre} = \exp\left(-\frac{\sqrt{mean(MD_{normal})}}{c_0} \right) \tag{5}$$

where $mean(MD_{normal})$ is the average of MDs under normal condition. By converting the aforementioned equation, c_0 is denoted as follows.

$$c_0 = -\frac{\sqrt{mean(MD_{normal})}}{\ln(CV_{pre})} \tag{6}$$

2.2.4. Health assessment method based on WPT-AR and MTS. As aforementioned, the scheme of the proposed health assessment method can be summarized as figure 1.

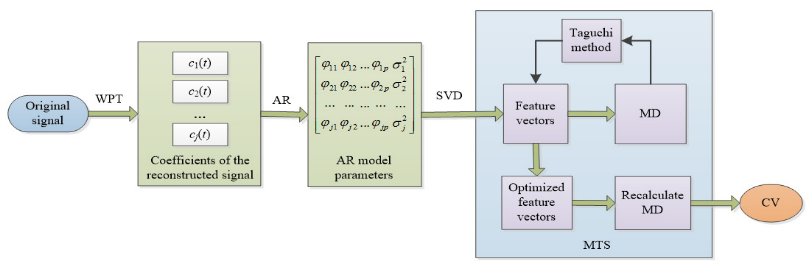

Figure 1. Scheme of the proposed health assessment method.

The original vibration signal is first decomposed into 2^n different sub-bands by n-level WPT. Second, the AR model is constructed for each coefficient $c_1(t), c_2(t), ..., c_j(t)$ ($j = 2^n$), and the parameters φ_{ik} and the variance of the remnant σ_i^2 of each AR model are chosen to form the initial feature matrix. Third, SVD is employed to obtain an n-dimensional feature vector of singular values. After the feature extraction, the Taguchi method is employed to optimize the n-dimensional feature vector. With the identified key features, the MDs are recalculated for health assessment and finally converted into CVs, thereby achieving the health condition assessment.

3. Case study

The data in this study is sampled by vibration sensor from runs on a milling machine. Figure 2 shows the mounting position of the vibration sensor. Tool wear comes in different forms. In our experiments, we measured the flank wear VB as a generally accepted parameter for evaluating tool wear, as shown in figure 3.

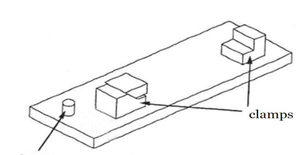

Figure 2. Mounting position of the vibration sensor.

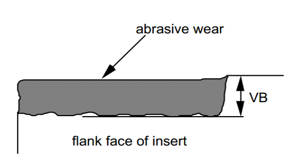

Figure 3. Measure of flank wear VB.

3.1. Feature extraction

40 samples are acquired under normal condition. Among them, the first 30 normal samples are used to construct the normal space, while the others for testing. 10 samples with VB of 0.18mm are also

acquired for testing process. Figure 4 shows a sample of WPT results of the normal vibration signal.

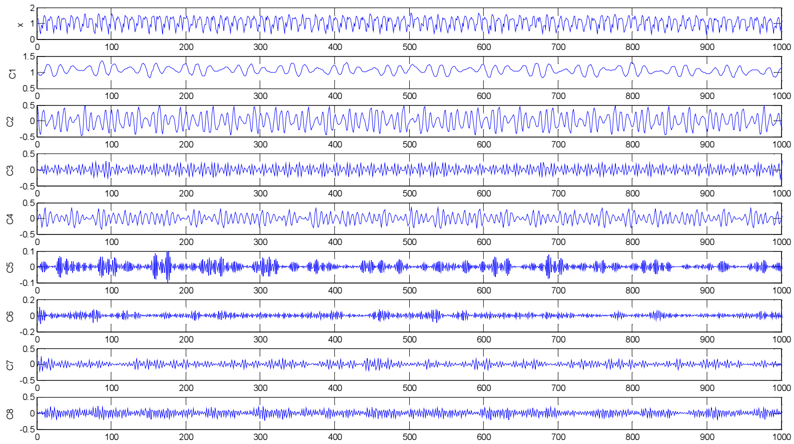

Figure 4. A sample of WPT results of the normal tool signal.

The AR model is constructed for each coefficient of the reconstructed signal $c_1(t), c_2(t), ..., c_8(t)$. In this case, the order, *m*, was determined 7, so the AR parameters $\varphi_{ik}(k=1,2,...,7)$ and σ_i^2 are chosen to form the initial feature matrix. Then, SVD is employed to obtain an 8-dimensional feature vector of singular values. A part of the extracted singular values are listed in table 1 and table 2.

Table 1. Extracted singular values for model training.

Num	State	1	2	3	4	5	6	7	8
1	Normal condition	12.6596	11.6476	2.0088	1.4113	0.8029	0.2152	0.1703	0.1328
2		12.6885	11.6316	1.9789	1.3542	0.7955	0.2255	0.1741	0.1356
3		12.6753	11.6344	1.9908	1.3871	0.8048	0.2168	0.1707	0.1353
4		12.6696	11.6170	1.9811	1.3794	0.8038	0.2169	0.1782	0.1333
5		12.6602	11.6247	1.9926	1.3935	0.8071	0.2120	0.1749	0.1238
6		12.7062	11.6544	1.9851	1.3911	0.7982	0.2188	0.1701	0.1367
7		12.6904	11.6415	1.9842	1.3958	0.8019	0.2133	0.1681	0.1425
8		12.7053	11.6178	1.9692	1.3776	0.8057	0.2307	0.1792	0.1370

Table 2. Extracted Characteristic vectors for testing.

Num	State	1	2	3	4	5	6	7	8
1	Normal condition	12.7162	11.6418	1.9826	1.3946	0.8055	0.2281	0.1677	0.1303
2		12.7171	11.6276	1.9775	1.3630	0.8071	0.2273	0.1749	0.1199
3		12.7272	11.6938	1.9952	1.3934	0.8066	0.2262	0.1592	0.1271
4		12.7631	11.6370	1.9657	1.3776	0.8092	0.2355	0.1642	0.1317
1	Worn condition	12.6851	11.7671	1.8333	1.3133	0.7581	0.4003	0.1844	0.1161
2		12.6662	11.7570	1.8504	1.3368	0.7604	0.4170	0.1797	0.1168
3		12.6434	11.7149	1.8185	1.3063	0.7584	0.3785	0.1872	0.1193
4		12.6591	11.7237	1.8676	1.3518	0.7586	0.3786	0.1816	0.1210

3.2. Health assessment based on Mahalanobis–Taguchi system (MTS)

3.2.1. Mahalanobis Distance (MD) calculation. After feature extraction, the MD values of the testing samples in normal condition and worn condition are calculated. Table 3 lists the experimental results. These results verified that the MD method is very notable for fault diagnosis.

Table 3. Mean, minimum and maximum of MDs.

	Normal condition	Worn condition
Mean	2.6454	337.1591
Min-max	1.0153—5.3637	252.4657—408.8422

3.2.2. Optimization based on Taguchi method. The extracted feature vector is constructed by 8-dimitional singular values. Therefore, the $L_9(2^8)$ orthogonal array is utilized to identify the useless characteristics. 30 samples of normal condition (VB=0mm) and 10 samples of worn condition (VB=0.18mm) are sent to Taguchi experiment. The result is shown as table 4.

Table 4. Results of Taguchi method.

	1	2	3	4	5	6	7	8	SNR
1	1	1	1	1	1	1	1	1	21.24
2	1	1	1	1	1	2	2	2	20.84
3	1	1	2	2	2	1	1	1	15.75
4	1	2	1	2	2	1	2	2	21.86
5	1	2	2	1	2	2	1	2	15.94
6	1	2	2	2	1	2	2	1	17.92
7	2	1	2	2	1	1	2	2	19.23
8	2	1	2	1	2	2	2	1	13.14
9	2	1	1	2	2	2	1	2	13.98
t_1	18.93	17.36	19.48	17.79	19.81	19.52	16.73	17.01	
t_2	15.45	18.57	16.40	17.75	16.13	16.36	18.60	18.37	
$t_1 - t_2$	3.48	-1.21	3.08	0.05	3.68	3.15	-1.87	-1.35	
Useful	Y	N	Y	Y	Y	Y	N	N	

According to the rules of Taguchi method, the 2nd, 7th and 8th singular value should be excluded as redundant factors. With the identified key features, the MD values for all of the testing datasets were recalculated. Table 5 shows the comparison between the initial and optimized MDs for each dataset. The result verifies that the Taguchi methods are very effective in characteristic optimization.

Table 5. Comparison between the initial and optimized MDs.

	Normal condition	
	Initial	Optimized
Mean	2.6454	2.0733
Min-max	1.0153—5.3637	0.8284—3.5922
	Worn condition	
	Initial	Optimized
Mean	337.1591	130.8750
Min-max	252.4657—408.8422	112.5295—155.6077

3.2.3. Health assessment. 80 samples from the beginning to the end of the life testing of the tool are chosen to verify the effectiveness of the proposed method. Every ten samples are in the same VB. MD values and CVs of each group are calculated, as shown in figure 5.

Blue curves in figure 5 shows the health degradation of the tool. The first twenty samples with CVs above 0.9 can be considered at 'normal stage', indicating the tool is in good health condition. After that, the MDs increase while the CVs fall at the same time, considered as 'danger stage'. Given threshold 0.7, once the CV drops below 0.7, the tool is considered at 'failure stage'.

Thus, the health condition of the tool can be coincidently represents by CV. The experiment results demonstrate that the proposed health assessment method based on WPT-AR and MTS performs well.

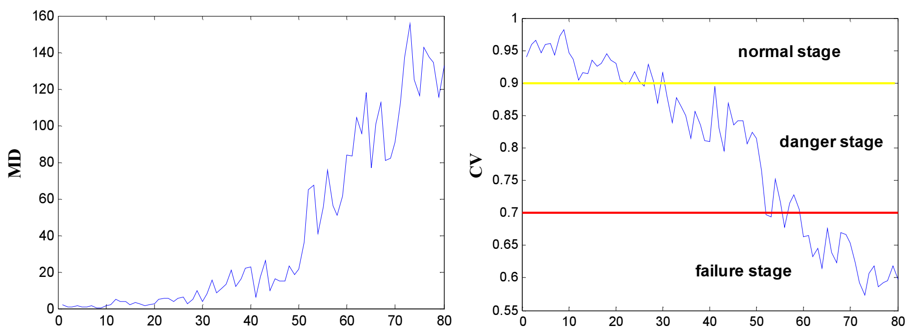

Figure 5. MDs and CVs from the beginning to the end of the life testing of the tool.

4. Conclusions

This paper presents a health assessment method for tools in milling machine using the Mahalanobis–Taguchi system (MTS) based on Wavelet Packet Transformation and Autoregression (WPT-AR). Targeting nonlinear and non-stationary signal from milling process, WPT-AR method is employed for feature extraction and form the initial feature matrix. Singular values of this feature matrix are obtained by Singular Value Decomposition (SVD). Then, MTS is employed for health assessment, which has been verified by vibration signals acquired from milling machining process. Generally speaking, the proposed approach has two benefits: (1) It extracts the suitable features that evidently reflect the health state of tools, since the combination of WPT and AR avoid some drawback in processing nonlinear and non-stationary signal. (2) It is a reliable real-time multivariate analysis and offers a systematic way to determine the principal characteristics by the employment of the MTS.

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