Health Condition Evaluation of Servo Turret Based on Time Sequence Signal Feature Map

W Z Chen1,2, F Chen1,2, T Ma1,2 and B B Xu1,2
1 Key Laboratory of CNC Equipment Reliability, Ministry of Education, P.R.China
2 School of Mechanical and Aerospace Engineering, Jilin University, Changchun, P.R.China

Corresponding author: chenfeicn@jlu.edu.cn

Abstract. The health condition of servo turret depends machining quality of CNC lathe. Performance tests of servo turret are taken to evaluate the health condition and overall status during its service life. This paper selects the core signals during one tool change-cutting cycle from multichannel physical signals and describes the performance of tool change-cutting cycle by defining a series of feature matrixes. In order to clearly and visually express the health condition of different working stages and tool position, a multidimensional features map is designed according to the combination of different time sequence feature matrixes. The above method is applied on a servo turret test platform which is equipped to acquire abundant signals. The result shows that the feature map clearly defines the health condition with one easily interpreted picture instead of unarranged signals. The proposed method provides a new idea of feature selection and visual expression, which can be an instructive tool for health evaluation and fault isolation.

1. Introduction
As core components in CNC lathe, the performance of servo turret determines the machining accuracy of the workpiece. With the development of manufacturing technology, higher performance and reliability of servo turret are required. Regular health assessment of the servo turret is meaningful for engineers to assess the performance and arrange maintenance policy quickly. This, in turn, decreases the production downtime while minimizing the impact of failures due to malfunctioning [1-2].

Abundant information appears during the working period of servo turret, including tool position, load, vibration, current, precision, deformation. There is an ever-increasing interest in multi-disciplinary research on multi-sensor data fusion technology, driven by its versatility and diverse areas of application. Therefore, it is a real need for an analytical review of recent developments in the data fusion domain [3]. Ming Dong and David proposed a multi-sensor integration platform based on the semi-hidden Markova model, which realized multi-information fusion by adjusting the importance assigned to each sensor through discriminant function analysis [4]. Using Dempster-Shafer evidence theory, Otman Basir established a fusion model including engine vibration, temperature, sound, pressure, and other sensor signals, and effectively diagnosed engine faults [5]. H.O.A. Ahmed et al. proposed a method based on sparse feature coding to monitor the health status of the bearing, equipping the system with the ability to process data and feature during collecting data [6].

The health assessment system of servo turret has not been fully automated, and the applying of visualization result to engineers can help them make decisions more efficiently and accurately. In Lee J’s review of visual assessment methods for PHM, degradation charts, performance radar charts, failure charts, and risk radar charts are described [7]. However, the visual information interaction for
different fault modes, positions, and fault effects is still one of the issues in the field of fault diagnosis of complex electromechanical products. When the information is transmitted to the receiver in a pattern with visual laws, the human brain can more efficiently understand [8] and make further decisions. Yujie Xu et al. obtained the transfer rule of characteristic caused by performance recession through the engine air path map. Based on the analysis of the structure of the characteristic space in different environments and working conditions, fault type, and position of the engine can be identified quickly [9]. Therefore, it is of great practical value to establish the correlation of feature of servo turret in different working stages, and design a visualized health analysis tool for the health evaluation.

In order to analyze, extract and visualize the expression of features in different stages of servo turret, this paper classifies signals into different stages after which a signal state map that could quickly identify unnatural links and abnormal positions of the servo turret was designed. This map provides a new idea for the abnormal isolation and fault diagnosis of the work cycle. On the other hand, the proposed method optimizes the relationship of multi-dimensional signals of mechanical equipment, facilitates the management of data, and brings a new idea for mining the information of mechanical equipment.

2. Signals in the different working stage
Servo turret is responsible for replacing cutters so that the CNC lathe can perform different cutting types. During a work cycle, there is a conversion between the electric energy and the tools’ kinetic energy, resulting in vibration and current signal, as shown in Figure 1. During the tool change process, the vibration and current signals are used to characterize the performance of the servo turret. The repeated positioning accuracy after the tool change is completed to characterize the precision performance of the servo turret, and the vibration and deformation generated by cutting force under the process of cutting can fully reflect the affordable loading ability of the servo turret. The increasing of motor current and vibration signal of the A period in Figure 1 reflects the abnormal condition of the motor and the transmission system of servo turret. The main reason for the increasing of locking vibration and the poor repeatability of the B period in Figure 1 is a sign that the meshing-toothed discs are degrading. Large deformation and severe vibration in the C period indicates that the rigidity and dynamic performance of the servo turret are defective. Multi-sensor information fusion technology based on a variety of sensing signals that can accurately and completely reflect the working state of the CNC lathe and has a positive impact on the aspects of subsequent maintenance and fault diagnosis.

Figure 1. Signals during tool change and cutting cycle.
3. Feature defining of different working stages

3.1. Feature selection at the transposition stage

The process of transposition stage can be evaluated by the effective value of current \( I \), starting vibration \( V_a \) and tool change vibration \( V_b \). Let the performance index characteristic matrix from \( x \) position to \( y \) position be \( T_{(x,y)} \), the feature quantity matrix in the tool transposition process can be expressed as:

\[
T_{(x,y)} = [I \ V_a \ V_b]
\]  

Suppose that the servo turret has \( N \) positions, the tool transposition state matrix \( HI_1 \) switched between different tools position can be described as:

\[
HI_1 = \begin{bmatrix}
T_{(1,2)} & \cdots & T_{(1,N)} \\
\vdots & \ddots & \vdots \\
T_{(N,1)} & \cdots & T_{(N,N-1)}
\end{bmatrix}
\]  

3.2. Feature selection at locking stage

After the tool rotates to the target position, the double-toothed fluted disc mesh with the movable fluted disc connected to the cutter head and the located fluted disc fixed to the servo turret enclosure, which further ensures the location accuracy and strengthens the rigidity of servo turret. The locking vibration of the fluted disc is related to the locking force generated by hydraulic pressure and the contact quality among fluted discs. Since the oil pressure value that controls the locking force is adjustable, this paper selects the RMS of locking vibration \( V_{c(x,y)} \) under the recommended oil pressure for evaluation:

\[
HI_2 = \begin{bmatrix}
V_{(1,2)} & \cdots & V_{(1,N)} \\
\vdots & \ddots & \vdots \\
V_{(N,1)} & \cdots & V_{(N,N-1)}
\end{bmatrix}
\]  

Repeated positioning accuracy is used as the accuracy evaluation index for repositioning the machining point after the tool change, which directly affects the machining error. Therefore, the performance index needs to be tested regularly and defined as \( HI_3 \):

\[
HI_3 = [P_1, P_2, \ldots, P_N]'
\]  

3.3. Feature selection at cutting stage

The rigidity of the servo turret system directly affects the cutting vibration and then affects the roughness and precision of the workpiece. The failure of the servo turret system often causes abnormal vibration. Therefore the cutting vibration under specific loading force is used to evaluate the performance of the servo turret during cutting indirectly. In order to simplify the test, the cutting vibration under a typical working condition can be monitored according to the cutting load spectrum. According to the vibration test standard, vibration is evaluated using the root mean square value.

\[
x_{rms} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} x_i^2, i = 1, 2, \ldots, N
\]  

According to the relationship between the loading force and the deformation of the cutting tool, the least square fitting is performed to solve the rigidity \( k \) value of the servo turret.

Hence, the characteristic matrix for the cutting vibration of different tool positions can be expressed as:

\[
HI_4 = [x_1 \ k_1, x_2 \ k_2, \ldots, x_N \ k_N]'
\]  

4. Health feature map

For those feature index that already has the industry standard, the degree of the deviation from the factory standard can be directly used for condition monitoring, such as repeated positioning accuracy, cutting vibration and servo turret rigidity. Others need to be artificially defined, combining with the
health status data. In order to comprehensively consider features in different working stages of the servo turret and locate the weak link of servo turret, a visual map is established in this part.

As is shown in Figure 2, signals in one tool change cycle of servo turret are selected first while some coral features are extracted. In order to explore the condition of different position, features are classified into start position matrix, arrived position matrix, and unrelated position features. These features are arranged by time sequence and are designing several noteworthy dimension of equipment. Health condition map is designed to vividly exam and evaluate the health condition of servo turret. When an abnormal situation happens, related operation data can be used to assist health evaluation and abnormal diagnosis.

Figure 2. The framework of the proposed method.

The feature maps established in this paper include tool position, working stage, features, and health level. The dimensions of the working stage and features are based on the characteristic signals generated by different stages and different parts of the full-cycle servo turret. The health level is scored according to the degree of deviation between the characteristic value and the set value and is converted into RGB values according to the score value, which has three levels of excellent (green), good (orange) and poor (red). The feature map has two modes: relative reference and absolute reference. In the relative reference, the map health level describes the deviation of each feature quantity from the initial value of servo turret itself. The value of the feature value directly describes the absolute reference without comparison.

The health matrix is arranged in the way of working stage of servo turret, and is graphically converted into a full-cycle performance mapping framework as shown in Figure 3:

$$CHI = \begin{bmatrix}
T_{(1,2)} & \cdots & T_{(1,N)} \\
\vdots & \ddots & \vdots \\
T_{(K,1)} & \cdots & T_{(K,N-1)} \\
V_{(1,2)} & \cdots & V_{(1,N-1)} \\
\vdots & \ddots & \vdots \\
V_{(K,1)} & \cdots & V_{(K,N-1)} \\
F_{1} & \cdots & F_{K} \\
\vdots & \ddots & \vdots \\
F_{1} & \cdots & F_{K}
\end{bmatrix} \begin{bmatrix}
x_{1} \\
\vdots \\
x_{K}
\end{bmatrix}$$

(7)

Figure 3. Designed feature map.
5. Experiment and application

In order to verify the proposed method, an experiment in servo tool test system is performed, and health performance is evaluated by using the feature map. Servo turret controlled by PLC can change tool automatically while the cutting force is loaded by electro-hydraulic servo loading device. In the test system, vibration sensors are arranged on the shell, current sensors are connected to the three-phase servo motor, the force sensor is installed on the end of the force loading mechanism, and laser displacement sensor is used to detect the repetitive positioning and deformation after loading. All detected signals are captured by a data acquisition device which provides a basis for health assessment.

![Figure 4. Test platform of servo turret and vibration data of different stages.](image)

The average value of RMS of current turning to the same target position varies from 1.39A to 1.42A with maximum variance for the difference between different interval transpositions is also only 0.06. Therefore, it can be considered that the current is an inherent characteristic of the servo motor, which is independent of tool position. The relationship between starting vibration, tool change vibration, and locking vibration of different tool positions are shown in Figure 4. It can be found that the difference in starting vibration of different tool positions is noticeable, and the maximum value is six times the minimum value. The average value of the tool change vibration is similar with small variance. So the relationship between the tool change vibration and the tool position can be ignored. The locking vibrations under different target positions are different, with the maximum value is 2.5 times as the minimum value.

The test results of the repeated positioning accuracy $P_n$ and the loading vibration $X_n$ of different tool positions are shown in Table 1. The repeating positioning accuracy is the average value of the test results with each position rotating forward and backward 3 times. The loading vibration is measured under a typical load spectrum condition, where the cutting force is 300N and the frequency is 28Hz.

![Figure 4. Test platform of servo turret and vibration data of different stages.](image)

| NO. | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| $P_n$ | 2.3  | 5.9  | 3.5  | 2.5  | 3.4  | 4.5  | 1.1  | 4.0  |
| $X_n$ | 0.0032 | 0.0018 | 0.0029 | 0.0014 | 0.0015 | 0.0028 | 0.0028 | 0.0028 |
| $k_n$ | 15.6 | 13.3 | 14.5 | 14.4 | 13.6 | 14.1 | 17.5 | 15.6 |

The deviation area of the alarm can be defined according to actual demand and severity. The default setting is 50% off average data for exceptions. For different stages, the threshold of excellent, functional, and bad can be customized or be in a ratio of 3:4:3. Combined with the test data and analysis results, the main characteristic indicators, including the starting current, starting vibration, processing vibration, locking vibration, repeat positioning accuracy, loading vibration, and stiffness are adjusted. Among the indicators, current characteristics, turning vibration, repeated positioning accuracy and loading vibration are independent of the tool position, starting vibration can identify the initial tool position and locking vibration identifies the target tool position. Then the CHI' matrix can be constructed as follows:

$$ CHI' = [C_{b1} \ V_{a(x,y)} \ V_{b} \ V_{c(x,y)} \ P_{n} \ X_{n} \ K_{n}] $$

(8)
The health matrix is established in combination with the test data of the above full cycle and converted into a feature map by the relative reference, as shown in Figure 5. It can be seen from the figure that the first and position 2 have a large starting vibration, but the vibration is small when the tool is locked. The locking vibration of the third and fourth position is severe and should be concerned. The repeat positioning accuracy of the second and sixth position is the worst, and the first and the third tool positions vibrate significantly in the actual cutting. The seventh and eighth position has the worst stiffness.

Figure 5. Health condition evaluation result of tested servo turret.

6. Conclusion
Feature extraction is performed in this paper to quantify describe sensitive information of servo turret. A four-dimensional feature map is designed so that the health condition of servo turret can be visually and fully explained. Since experts focus on different aspects like reliability, overall performance, precision, and fault diagnosis, the proposed feature map is unable to express every useful information for users fully. However, the method classified the typical signals and its features and further rearrange them into a physical and time-related map, which provides a useful guide for health evaluation and even maintenance policy. The method describes in this paper has application wildly in the intelligent health evaluation and condition motoring of complicated mechanical equipment.

Acknowledgments
This paper is supported by the National Science and Technology Major Project (2018ZX04006039) and Program for JLU Science and Technology Innovative Research Team (2017TD23).

7. References
[1] Alaswad S Z and Xiang Y S, 2017 A review on condition-based maintenance optimization models for stochastically deteriorating system, Reliability Engineering and System Safety 157 54–63.
[2] Yin S, Ding S X, Xie X C and Luo H, 2014 A review on basic data-driven approaches for industrial process monitoring IEEE TRANSACTIONS Transactions on industrial electronic 61 6418-28.
[3] Khaleghi B, Khamis A, Karray F O and Razavi S N 2013 Multi-sensor data fusion: A review of the state-of-the-art Information Fusion 14 28–44.
[4] Dong M and He D 2007 Hidden semi-Markov model-based methodology for multi-sensor equipment health diagnosis and prognosis European Journal of Operational Research 178 858-78.
[5] Basir O and Yuan X H 2007 Engine fault diagnosis based on multi-sensor information fusion using Dempster-Shafer evidence theory Information Fusion 8 379-86.
[6] Ahmed H O A, Wong M L D and Nandi A K 2018 Intelligent condition monitoring method for bearing faults from highly compressed measurements using sparse over-complete features Mechanical Systems and Signal Processing 99 459-77.
[7] Lee J, Wu F J, Zhao W Y, Ghaffari M, Liao L X and Siegel D 2014 Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications Mechanical Systems & Signal Processing 42 314-34.
[8] Phil Simom 2014 *The Visual Organization: Data Visualization, Big Data, and the Quest for Better Decisions* (New Jersey: John Wiley & Sons Ltd)

[9] Hou X, Li W W and Zheng N 2018 Aero-Engine Gas-path Fault Diagnosis Based on Spatial Structural Characteristics of QAR Data 2018 *Annual Reliability and Maintainability Symposium (RAMS)* Reno 2018 1-7.