Design of a Real-time Spindle Health Monitoring and Diagnosis System Based on Open Systems Architecture

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Abstract
Accurate identification of spindle health in real-time is an important feature of next generation smart machining systems that are capable of self-diagnosis. This paper presents a software design for an automated spindle health monitoring system based on open systems architecture. An analytic wavelet-based envelope spectrum algorithm is proposed and coded in software for effective and efficient spindle degradation identification, defect localization, and damage growth tracking. The software is functionally adaptive and contributes directly to the development of a new generation of smart machine tools.

Keywords:
Analytic Wavelet, Condition-Based Maintenance, Open Systems Architecture, Remaining Useful Life, Smart Machining Systems, Spindle Health Monitoring.

1. INTRODUCTION

Spindles are important components of machine tools in machining systems. Unexpected failure of a spindle can cause severe part damage and costly machine downtime, affecting overall production logistics and productivity. Any intelligent capability that can be added to a spindle for the purpose of monitoring the health of the spindle and predicting its impending failure based on the sensor measurement data will enhance the overall performance of machining systems. A spindle with such added capability is called a “smart spindle.” Smart spindles are key components of the next generation of smart machine tools that will be capable of self-diagnosis, leading to condition-based, “intelligent” maintenance. This paper addresses the subsequent need for accurate identification of spindle health in real-time by presenting the architectural design of a dynamic data-driven and knowledge-based integrated software package for condition monitoring and health diagnosis of spindles. The purpose of the developed system is to reduce machine maintenance costs by improving maintenance planning and logistics support. It will also help to achieve improved operational flexibility by accurate prognostics that will enable machine operators to make tactical, mission-specific decisions with full knowledge of the remaining useful life of machine tool spindle.

2. OPEN SYSTEMS ARCHITECTURE

The design of the real-time spindle condition monitoring and diagnosis system based on sensor input uses a modular approach by adopting the Open Systems Architecture for Condition Based Maintenance (OSA-CBM) [1,2], which is a standardized framework accepted by industry. The OSA-CBM architecture consists of seven layers including 1) Sensing and Data Acquisition, 2) Signal Processing, 3) Condition Monitoring, 4) Health Assessment, 5) Prognostics, 6) Decision Support, and 7) Human-Machine Interface. Data communication among the layers is enabled by the OSA-CBM interface standards. The layered architecture facilitates the integration and interchangeability among sensors, electronics, and software components, with each layer representing a functional decomposition of a condition-based monitoring application. Higher layers use the information produced by lower layers. For instance, a signal measured by the Data Acquisition layer is used by the Signal Processing layer to perform machine condition-related information extraction. Such information is in turn used by the Condition Monitoring layer to compare against expected values and output condition indicators. The Health Assessment layer then utilizes the input from the Condition Monitoring layer to derive the current state of the system, which is subsequently used by the Prognostics layer to predict the future performance of the system. The current state and predictions are fed into the Decision Support layer to provide recommended actions for system maintenance. In addition, the current state and predictions, together with all measured and computed data, are displayed by the Human-Machine Interface layer such that the users can have visual interaction with the system [3].

In actual modular design of the condition monitoring system, a module may implement functionality of one or more layers. Modules of the Human-Machine Interface layer usually do not implement any OSA-CBM layers, as it displays the information produced by other layers to users. In Figure 1, typical data flow among the first four layers, together with the Human-Machine Interface layer, is illustrated. Different types of sensor measurement data obtained in the Sensing and Data Acquisition layer are transferred to the Signal Processing layer and then processed to extract features that characterize the spindle dynamics. Several advanced signal processing algorithms are embedded in this layer, which includes an analytic wavelet-based algorithm, called Wavelet Envelope Spectrum [4], for spindle degradation identification, defect localization, and damage growth tracking. Characteristic frequencies extracted by the Signal Processing layer are fed into the Condition Monitoring layer, where the ratio of the magnitude of each characteristic frequency to the noise floor is compared against a predefined threshold. The result is an enumerated condition indicator, which describes the operational state of the spindle. Based on the trending information recorded in the system, the output of the Condition Monitoring layer is assessed in the Health Assessment layer to determine if the system health is degraded, and to specify the type and location of the identified degradation.

3. SOFTWARE IMPLEMENTATION

Based on open systems architecture standards, the software design was realized using the graphical programming language of LabVIEW **. At this stage, the Data Acquisition, the Signal Processing, the Condition

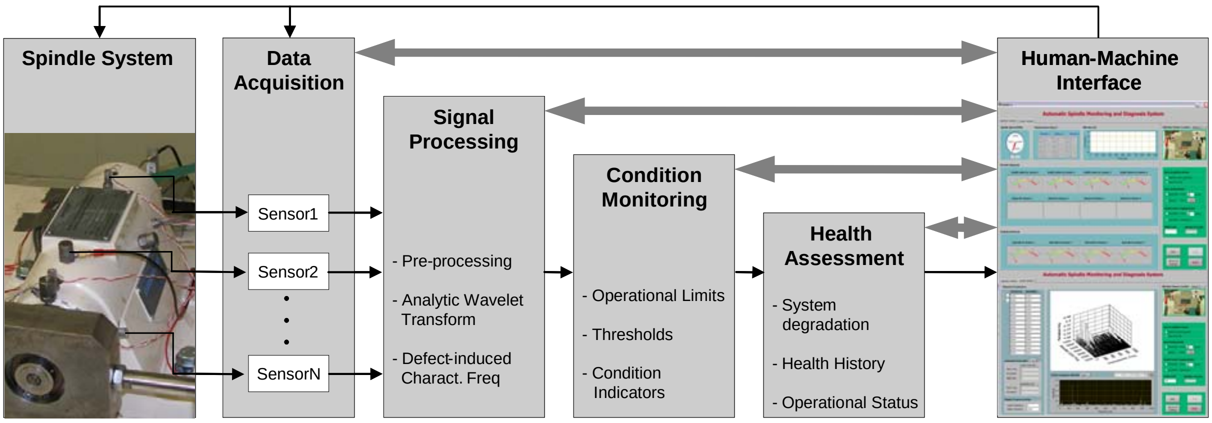

Figure 1. Data flow and functional diagram of the software system

Monitoring, the Human-Machine Interface, and preliminary Health Assessment layers have been implemented. The modular design approach of the OSA-CBM standards was adopted in coding the software, resulting in functional modules that are transferable to other CBM software implementations. In the Human-Machine Interface layer, machine health states are presented in two windows: a simplified spindle condition display and warning window for standard machine operators (operator window) and an advanced parameter-setup and sophisticated diagnosis window for machine experts (expert window).

The operator window allows efficient communication with machine operators regarding current status of the machine without the distraction of behind-the-window calculations. It displays the speed, temperature, statistics, and health index of the machine in real-time and sets off alarms when defects are detected. The expert windows allow the expert to interactively adjust data analysis algorithms (specifically the Wavelet Envelope Spectrum method), and to conduct a complete investigation of the machine status, thus enhancing on-line defect detection capability.

3.1 Signal Processing Algorithm

The developed analytic wavelet-based envelope spectrum algorithm for spindle defect-related feature extraction is the core function of the Signal Processing layer of the system. The extracted features, i.e., the magnitude and location of the defect-induced characteristic frequency, are used as the inputs to monitor the condition and assess the health status of the spindle system.

Combining the advantages of enveloping and the wavelet transform, the algorithm extracts defect-induced impulses from the spindle vibrations and constructs their envelopes in a single step. This eliminates the need for intermediate operations such as a convolution and a Hilbert transform, thus improving the computational efficiency [5]. In addition, the analytic wavelet uses flexible windows, and is therefore adaptive to the signal under investigation.

An analytic wavelet $\psi(t)$ is defined as a complex wavelet whose imaginary part is the Hilbert transform of its real part:

$$\psi(t) = w(t) + j\tilde{w}(t) \tag{1}$$

where $w(t)$ denotes the real part of the complex wavelet. The imaginary part $\tilde{w}(t)$ is the Hilbert transform of the real part $w(t)$. According to the linearity property of the Fourier transform, the analytic wavelet $\psi(t)$ can be expressed in the frequency domain as:

$$\hat{\psi}(f) = \hat{W}(f) + j\hat{\tilde{W}}(f) \tag{2}$$

where $\hat{W}(f)$ and $\hat{\tilde{W}}(f)$ are the Fourier transforms of $w(t)$ and its Hilbert transform $\tilde{w}(t)$, respectively, and their relationship can be expressed as:

$$\hat{\tilde{W}}(f) = (-j\operatorname{sgn} f)\hat{W}(f) = \begin{cases} -j\hat{W}(f) & \text{for } f > 0 \\ j\hat{W}(f) & \text{for } f < 0 \end{cases} \tag{3}$$

Equation (3) indicates that when the frequencies are negative, the spectra of the real part of the analytic wavelet $\hat{W}(f)$ and its Hilbert transform $\hat{\tilde{W}}(f)$ cancel each other out, thus resulting in an analytic wavelet with a one-sided spectrum. Therefore, the wavelet transform of a signal $x(t)$ using an analytic wavelet results in the corresponding wavelet coefficients being an analytic function. Since the continuous wavelet transform is by nature the convolution between the signal and the wavelet function in the time domain, it can be computed in the frequency domain by direct multiplication of the Fourier transform of the signal $\hat{x}(f)$ with the Fourier transform of the wavelet function $\hat{\psi}(f)$ [6]. The wavelet coefficient is then the inverse Fourier transform of the product of $\hat{x}(f)$ and $\hat{\psi}(f)$ (as illustrated in Figure 2):

$$CWT(s,\tau) = \frac{|s|^{1/2}}{2\pi}\int_{-\infty}^{\infty} \hat{x}(f)\hat{\psi}^*(sf)e^{j2\pi ft}df \tag{4}$$

Equation (4) indicates that the wavelet transform of a signal $x(t)$ at scale *s* can be viewed as the signal passing through a band-pass filter, which is a contracted (by a frequency factor of *s*) and amplified (by a factor of $|s|^{1/2}$) version of the wavelet function. Furthermore, the advantage of the analytic wavelet coefficients is that their envelopes can be readily calculated from their modulus as:

$$A(s,\tau) = \|CWT(s,\tau)\| \tag{5}$$

Subsequently, the Fourier transform is performed repetitively on the envelope signal at each scale *s*, resulting in an "envelop spectrum" of the original signal at the various scales. The implementation of the algorithm using LabVIEW is given in Figure 3.

To obtain effective characteristic frequency feature extraction for defect detection of the spindle, an appropriate wavelet function should be chosen before applying the developed algorithm to the sensor measurement data. In accordance with the essence of the

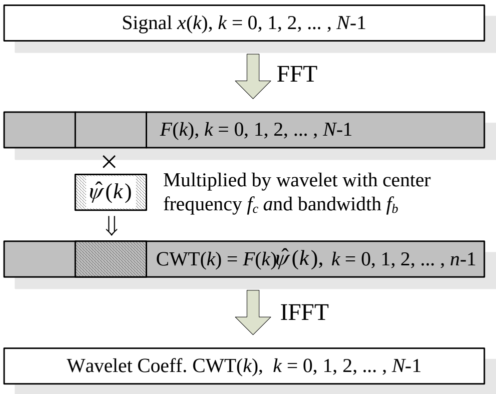

Figure 2. Algorithm for performing analytic wavelet transform.

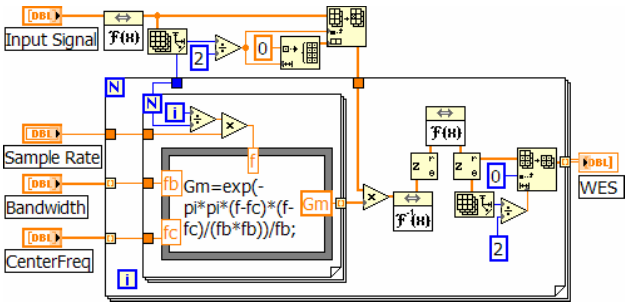

Figure 3. Coded algorithm for performing the wavelet envelop spectrum

wavelet transform, i.e., to measure “similarity” between the measured data and the wavelet function at various scales, correlation analysis (measuring the relationship between two signals using correlation coefficient) can be naturally used to evaluate the performance of different wavelet functions when analyzing the measured data. Considering that an appropriate wavelet function should be capable of effectively extracting the characteristic frequency features, the corresponding wavelet coefficients will show relatively high similarities to the signal. This leads to a higher correlation coefficient than those obtained by other wavelet functions. Accordingly, the complex Morlet wavelet is chosen as the wavelet function for the developed algorithm, as it has the maximum correlation coefficient among various types of analytic wavelet functions (e.g., complex Gaussian wavelet, Harmonic wavelet, Shannon wavelet, etc.).

3.2 Data-Driven Scheme

To achieve accurate spindle health assessment in the Health Assessment layer, appropriate selection of the extracted features is performed in the Condition Monitoring layer. The spectrum contained in each wavelet scale needs to be compared and evaluated. The scales containing the most defect-induced characteristic frequencies need to be chosen. To achieve efficient and fast feature selection, a data-driven scheme is implemented in the Condition Monitoring layer. As illustrated in Figure 4, with dynamic data feedback from the Condition Monitoring layer to the Signal Processing layer, the appropriate scales of the wavelet envelope spectrum algorithm can be dynamically modified by the program, based on the energy contained in each scale of the wavelet envelope. As a result, scales that do not contain significant energy content will be automatically removed to improve the algorithm efficiency. Trending information on the rate of magnitude increase of the defect-related characteristic frequencies is recorded to construct a database, which is used subsequently for setting up a spindle health index, as illustrated in Figure 5.

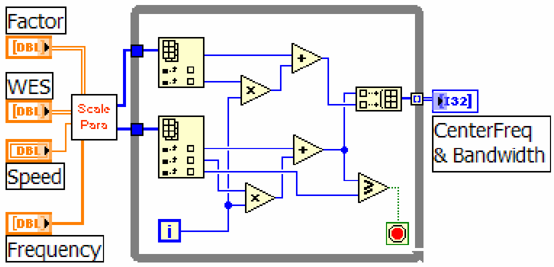

Figure 4. Code for wavelet scale selection

3.3 XML-Based Data Format

In addition, the software archives the raw data and logs the machine condition data in a unified format automatically or upon user command. Presently, the eXtensible Markup Language (XML)-based data format is adopted in the developed software, which can be used with any networking technology for data transfer [7]. All of the information stored with such a format can be retrieved through web-based applications. Figure 6 illustrates an example of the XML-based data format, where the health index and status of the spindle bearing are logged during one sampling period.

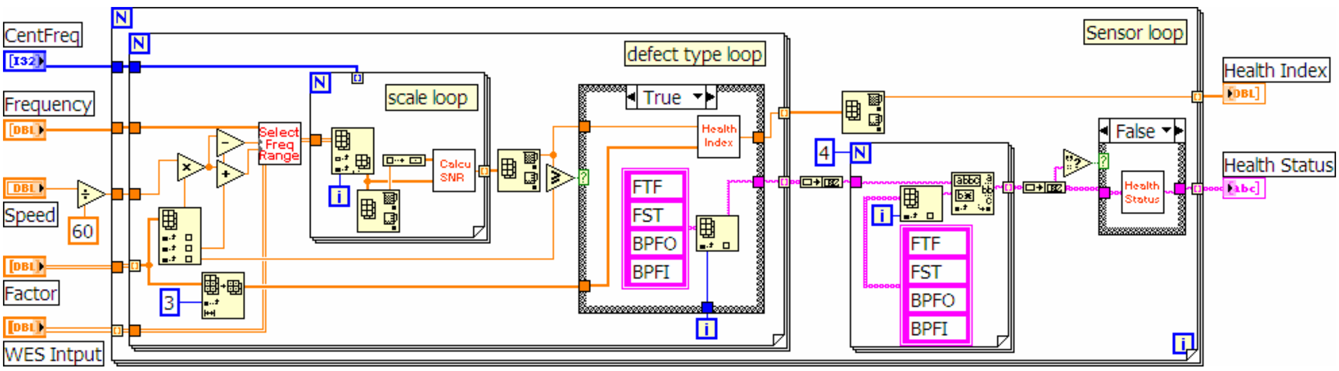

Figure 5. Code for spindle status and health index indication

4. CASE STUDY

The developed system has been evaluated on a spindle test bed consisting of four support ball bearings, as shown in Figure 7. Based on the bearing pitch diameter D, rolling element diameter d, and number of rolling elements n, defect-related characteristic frequencies of the spindle bearings can be analytically determined as a ratio to the shaft rotational speed. In Table 1, formulae used to calculate four major defect types are shown.

```
<?xml version="1.0" standalone="yes" ?>
- <LVData>
    <Version>8.0</Version>
  - <String>
      <Name>Sampling Time</Name>
      <Val>11/22/2006 10:58:56</Val>
    </String>
  - <String>
      <Name>Health Status</Name>
      <Val>Inner raceway defect</Val>
    </String>
  - <U8>
      <Name>Heath Index</Name>
      <Val>3</Val>
    </U8>
    ...
  </LVData>
```


Figure 6. Representation of health index and status of the spindle using XML-based data format

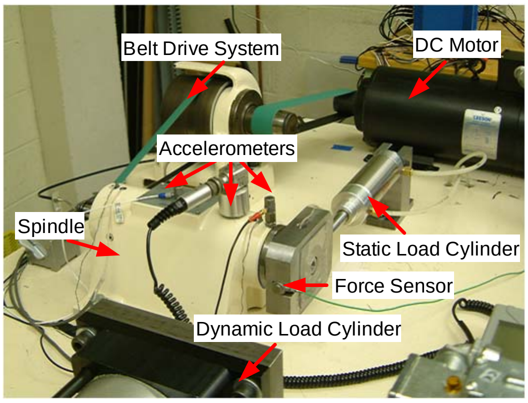

Figure 7. The spindle test bed used for the experimental verification of the designed software

Table 1. Defect related characteristic frequencies of the spindle bearings

Defect Type	Characteristic Frequency	Test Bearing
Unbalance	$rpm/60$	$f_r \approx rpm/60$
Rolling Element	$f_r D\left[1-(d/D)^2\right]/(2d)$	$f_{BSF} \approx 2.346 f_r$
Outer Raceway	$nf_r\left[1-d/D\right]/2$	$f_{BPFO} \approx 4.414 f_r$
Inner Raceway	$nf_r\left[1+d/D\right]/2$	$f_{BPFI} \approx 6.586 f_r$

Dynamic impact in the form of a 13,300 N impulse lasting about 25 ms was consecutively applied to the spindle system under a constant rotational speed of 3,600 rpm, for a total of 1,100 times. The spindle was constantly monitored by the designed system and an inner raceway defect on one of the front bearings was detected by the system. Figure 8 illustrates an example of the results. As shown in Figure 8, three frequency peaks have been found in the <500 Hz range, which are associated with the spindle shaft rotating frequency f_r = *rpm*/60 and its two harmonics 2f_r and 3f_r. Under the shaft rotational speed of 8,400 rpm, these peaks are located at 140 Hz, 280 Hz, and 420 Hz, respectively. The increase of these frequency components can be related to the increase of impact-induced spindle unbalance, which is the offset between the center of mass of the rotating spindle and its center of rotation. Structural unbalance can be represented in effect as a radial force that excites a rotating shaft at the frequency f_r. Based on the equations shown in Table 1, the frequency peak at 935 Hz can be identified as the Ball Pass Frequency of the Inner raceway (BPFI). The existence of such a frequency component in the spectrum indicates that one of the spindle front bearings has developed a localized defect on its inner raceway, as the result of dynamic impact. Theoretically, the BPFI frequency at 8,400 rpm is calculated as 922 Hz. The 1.4% difference between the theoretical and experimental values can be traced back to the combined effect of rolling element slippage and the slight drift of spindle speed from the nominal input values to the spindle drive controller. The spectrum also displayed several other frequency peaks at 1,075 Hz, 1,215 Hz, and 1,355 Hz, respectively, which can be specified as $BPFI + k \cdot (rpm), \text{ with } k = 1,2,\ldots n$, and reflect upon combined effect of spindle unbalance and inner raceway defect.

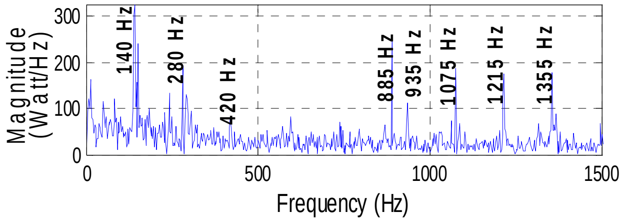

Figure 8. An example result of the automated spindle health monitoring system

5. CONCLUSION

In conclusion, the software design is functionally adaptive and presents a new tool that enables more effective and efficient monitoring and diagnosis of machine spindles. It also contributes directly to the development of a new generation of smart machine tools. In addition to spindles, the software can be applied to the health diagnosis of other types of machines.

6. REFERENCES

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