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Open Architecture Software Design for Online Spindle Health Monitoring

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Abstract –*This paper presents an open systems architecture-based software design for an online spindle health monitoring system. The software is implemented using the graphical programming language of LabVIEW, and presents the spindle health status in two types of windows: simplified spindle condition display and warning window for standard machine operators (operator window) and advanced diagnosis window for machine experts (expert window). The capability of effective and efficient spindle defect detection and localization has been realized using the analytic wavelet-based envelope spectrum algorithm. The software provides a user-friendly human-machine interface and contributes directly to the development of a new generation of smart machine tools.*

Keywords – *Software Design, Open Systems Architecture, Spindle Health Monitoring, Analytic Wavelet, Smart Machining Systems*

I. INTRODUCTION

Unexpected failure of machine tools can cause severe part damage and costly machine down time, affecting the overall productivity as well as maintenance cost. Since spindles are essential elements in virtually all machine tools and their working condition directly reflects upon machine tool performance, effective and reliable spindle health monitoring is highly desired to capture any potential failure at its early stage based on the sensor measurement data, which will enhance the overall performance of the machine tool system. A spindle with such added capability would represent one of the key components in the next generation of smart machine tools with self-monitoring and diagnosis functionality. A dynamic data-driven integrated software package is needed to help realize accurate identification of spindle health condition in real-time.

Efficient software design and implementation requires a modular and interchangeable architecture. A related effort is the Open System Architecture for Condition Based Maintenance (OSA-CBM) program set up by the Machinery Information Management Open Systems Alliance (MIMOSA) [1]. The objective of the OSA-CBM program is to develop an open architecture and standards for distributed CBM software components. Such an architecture has been defined in terms of functional layers (Figure 1), which include: 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.

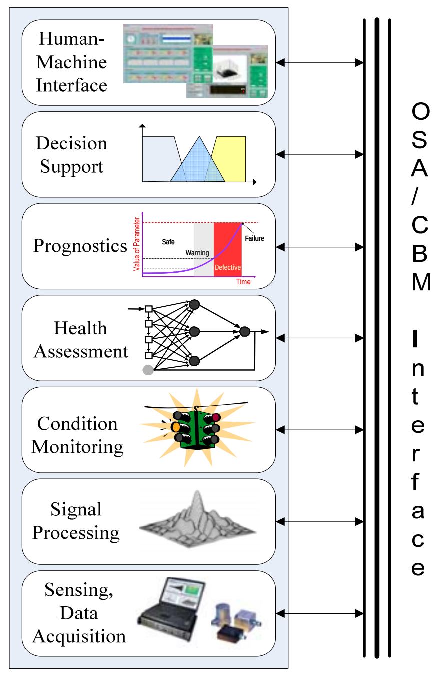


Fig. 1. Functional Layers of the OSA-CBM

These layers represent a logic flow of information from the physical sensor to the decision support in the upper layer. The Human-Machine Interface layer can communicate with all other layers. For instance, a signal measured by the Data Acquisition layer is used by the Signal Processing layer to perform machine condition 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.

The layered architecture shown in Figure 1 facilitates the integration and interchangeability among sensors, electronics, and software components [2, 3], which allows flexibility for upgrading or expanding the system by incorporating new functions into corresponding layers. By taking advantage of the open systems architecture, this paper presents the software design of an online spindle health monitoring system. After introducing the system configuration in section II, Section III discusses various modules embedded in the software in detail. Then, the graphical user interface of the software is designed and implemented in Section IV. After that, the designed software is experimentally evaluated by monitoring a custom-designed test-bed spindle in section V. Finally, section VI draws some conclusions.

II. SYSTEM CONFIGURATION

The effectiveness and efficiency of a software design is dependent on how the programming process is executed. As compared to a text-based programming language, such as C and C++, the programming language of LabVIEW is graphic-based, and uses graphic icons to replace the text command. These graphic icons are wired together through drag-and-drop operations to realize various functions, such as data acquisition, signal analysis, etc., which simplifies the software development. Therefore, the graphical programming language of LabVIEW has been chosen to design and implement the spindle health monitoring system. As schematically shown in Figure 2, signals from various sensors are acquired through a data acquisition (DAQ) board and displayed on the computer through the graphical user interface (GUI) of the software. The software takes a modular approach to integrate various measurement functions into one entity and allows for evaluation of the spindle health status. Each module is programmed independently, and whenever certain function needs to be modified, only the module related to that function will be reprogrammed. New functions can be added into the software as independent modules. According to the OSA-CBM, each of the modules represents the functionality of either one or more layers. The data flow of the software that is related to the OSA-CBM layers is illustrated in Figure 3. 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 for spindle defect detection are embedded in this layer with each being implemented as a module. For example, 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. In the Health Assessment layer, the output of the Condition Monitoring layer is assessed, based on the trending information recorded in the system, to determine if the system health is degraded and specifies the type and location of the identified degradation.

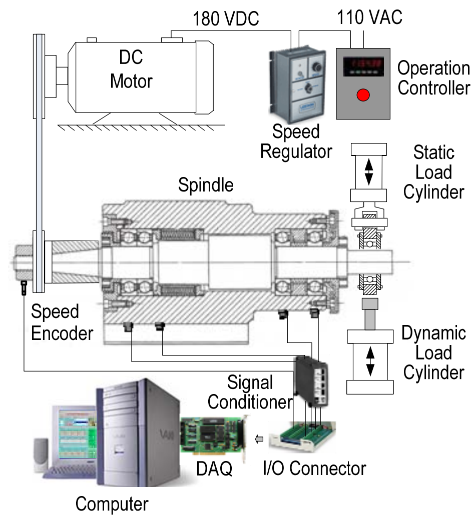


Fig. 2. Schematic view of the spindle test system

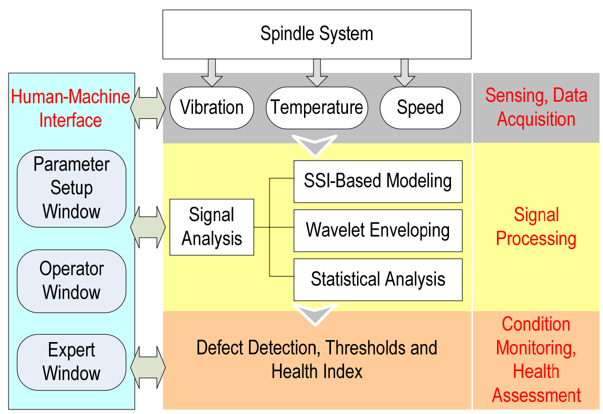


Fig. 3. Data flow and functional diagram of the designed software

The core functions of the software, which include data acquisition, wavelet envelope spectrum analysis [4], Stochastic Subspace Identification (SSI), spindle health index indication, and data storage and logging, are designed as individual modules. Each module features a hierarchical structure in that it can call its second-level sub-module, and each sub-module can further call its next lower level sub-modules. In the following sections, all of the modules are discussed in detail except for the data acquisition module, as it can be easily implemented using standard modules embedded in the software development environment.

III. SOFTWARE MODULE DESIGN

A. Wavelet Envelope Spectrum Module

Envelope spectrum analysis using band-pass filtering has been widely employed for detection and identification of structural defects [5-6]. While envelope extraction has been traditionally implemented by rectifying and low-pass filtering the band-pass filtered vibration signals, the Hilbert transform has shown to present a good alternative to forming a signal's envelope [7]. Performing a Hilbert transform on a signal leads to the formulation of a corresponding *analytic* signal, with its real and imaginary parts being the original signal itself and the Hilbert transform of the signal, respectively. The modulus of the *analytic* signal represents the signal's envelope. However, the frequency coverage of the band-pass filter needs to be known *a priori*. Furthermore, the effectiveness of the traditional envelope spectrum analysis suffers from a low signal-to-noise ratio, especially when the defect-related vibration is weak and overwhelmed by strong structural-borne noise. The development of a wavelet transform provides an effective tool for extracting a weak signal component out of a strong noise environment through time-scale analysis [8]. Wavelet transform essentially measures the "*similarity*" between the signal to be analyzed and the scaled wavelet function. Thus it can be viewed as a band-pass filter that extracts specific information from a time series, e.g., defect-induced vibrations. Since the imaginary part of a complex wavelet is inherently the Hilbert transform of its real part, the wavelet coefficients of a transformed signal, in which the complex wavelet is used as the base wavelet, are analytic in nature, and their corresponding modulus forms the signal's envelope. Therefore, a complex wavelet-based signal transformation combines the ability of band-pass filtering with enveloping into one single step, thus eliminating the need for additional operations such as the Hilbert transform, or low-pass filtering to extract signal envelope.

Figure 4 illustrates the design and implementation of the wavelet envelope spectrum module. As an analytic wavelet, the complex Morlet wavelet chosen in this module has been identified as an appropriate base wavelet for defect detection [4]. Another advantage of the complex Morlet wavelet is that it has explicit expression in the frequency domain as:

$$\hat{\psi}_m(f) = \frac{1}{f_b} e^{-\frac{\pi^2 (f-f_c)^2}{f_b^2}} \tag{1}$$

with symbols f_b and f_c being the bandwidth and wavelet center frequency parameters, respectively. Equation (1) is designed and implemented in the module as a formula node, which is used to evaluate the mathematical expressions. As shown in Figure 4, with the inputs from sampling rate f, a pair of bandwidth f_b and center frequency f_c, the output G_m of the complex Morelet wavelet in the frequency domain is obtained. By multiplying G_m with coefficients that are resulted from Fourier transform of the input signal, and then applying the inverse Fourier transform, the wavelet transformation of the input signal is realized. Further operation is taken by performing the Fourier transform on the modulus of the wavelet coefficients to obtain the wavelet envelope spectrum (denoted as WES).

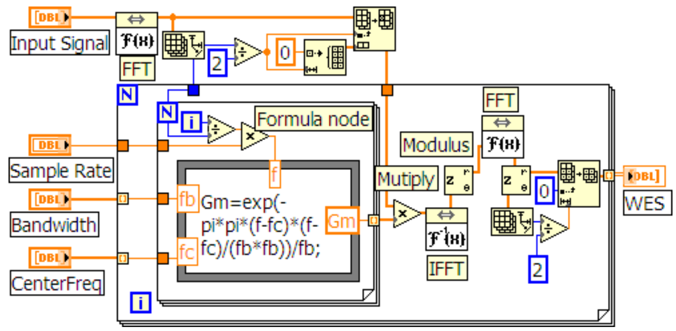


Fig. 4. Coded algorithm for performing the wavelet envelope spectrum

B. Stochastic Subspace Identification Module

To ensure complete frequency coverage of the vibration signal when applying the wavelet envelope spectrum algorithm, a data-driven scheme for wavelet center frequency f_c selection is designed. The appropriate wavelet center frequency can be dynamically modified by the program, based on the output of model parameters identified using the SSI technique [9, 10]. Instead of fitting an empirical model to the Frequency Response Function (FRF) from artificial excitations (e.g., hammer strikes) as the traditional approach does, the SSI technique accounts for dynamic changes caused by the rotations of the spindle without the need for artificial excitations, and extracts the modal parameters from its measured output only, thus satisfying the requirement of online operation. Mathematically, the SSI technique is formulated and solved using a discrete time-state space model of a linear, time-invariant system (e.g., the spindle) without known external inputs according to the following equation:

$$\begin{cases} x_{k+1} = Ax_k + w_k \\ y_k = Cx_k + v_k \end{cases} \tag{2}$$

where $x_k = x(k\Delta t)$ is the discrete-time state vector, y_k is the system response vector, A is the state matrix, and C is the output matrix. The two components, w_k and v_k, represent the disturbance noise to the spindle and measurement noise due to sensor inaccuracy, respectively, and are stochastic in nature. Equation (2) indicates that the new state of the spindle physical system, x_{k+1}, can be obtained by the sum of the state matrix A multiplied with the old state vector x_k and the disturbance noise vector w_k. As a result, the dynamic behavior of the spindle is completely characterized by the state matrix A. Generally, a Kalman filter is used for the optimal prediction of the state vector x_{k+1}. Numerical techniques, such as singular value decomposition, are then applied to estimate the state matrix A and output matrix C.

Subsequently, the modal parameters can be extracted from the state matrix *A*. Based on the SSI technique, Figure 5 illustrates how the model parameters of the spindle system are identified in the designed module. As shown in Figure 5, a Hankel matrix is first constructed based on the input signals. Then a sub-module is called to estimate the state matrix *A* and output matrix *C* using the singular value decomposition method. After that, the eigenvalues of the state matrix *A* are extracted to estimate the resonance frequencies and their corresponding damping ratios.

Since a structural defect may excite the spindle system at any of the identified resonance frequencies, the equally spaced wavelet center frequencies, which cover the range of these natural frequency components, are chosen for implementing the wavelet envelope spectrum algorithm.

C. Spindle Health Index Module

To characterize the defect severity level of the spindle (e.g., healthy, small defect, medium defect, and severe defect), and to present a first step towards a generic data model for quantifying the working condition of various types of spindles and machine tools, trending information on the magnitude of the wavelet envelope spectrum is recorded to construct a database, which is used subsequently for setting up a spindle health index. As illustrated in Figure 6, the magnitude information within a series of frequency intervals that covers possible defect-related frequency components (e.g., Ball Pass Frequency of the Inner raceway, denoted as BPFI) is extracted from the wavelet envelope spectrum first. The signal-to-noise ratio (SNR), defined as the ratio of magnitudes of the defect-characteristic frequency to the other frequency components, is then calculated and compared with the predefined thresholds at different levels. If the SNR is within a certain threshold interval, a corresponding health index is derived.

D. Data Logging Module

The software logs the machine conditions (e.g., health status and health index) in a unified format automatically or based upon user command. Presently, the eXtensible Markup Language (XML)-based data format is adopted in the software, which can be used with any networking technology (e.g., Time Control Protocol/Internet Protocol TCP/IP) for data transfer [11]. Figure 7 gives an example for how the health status and the health index are logged with XML. During each data sampling cycle, the vibration signals are acquired and then processed to output spindle health status and index values. These values, together with a time stamp, are converted to XML format. Based on the predefined XML schema, which is embedded in the software development environment, the time information, spindle health status, and health index are logged into an XML file. Figure 8 shows a piece of the XML-based data format, where the health index and status of the spindle bearing are logged during one sampling cycle. All of the information stored with such a format can be retrieved through web-based applications.

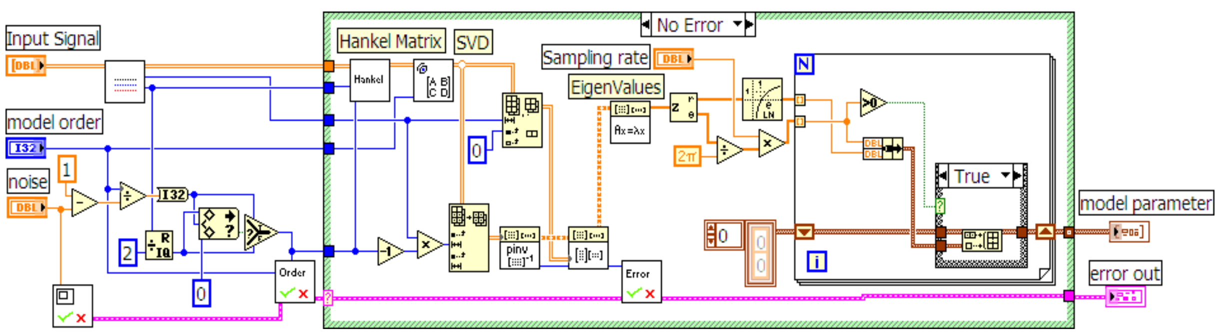


Fig. 5. Code for SSI-based modal parameter identification

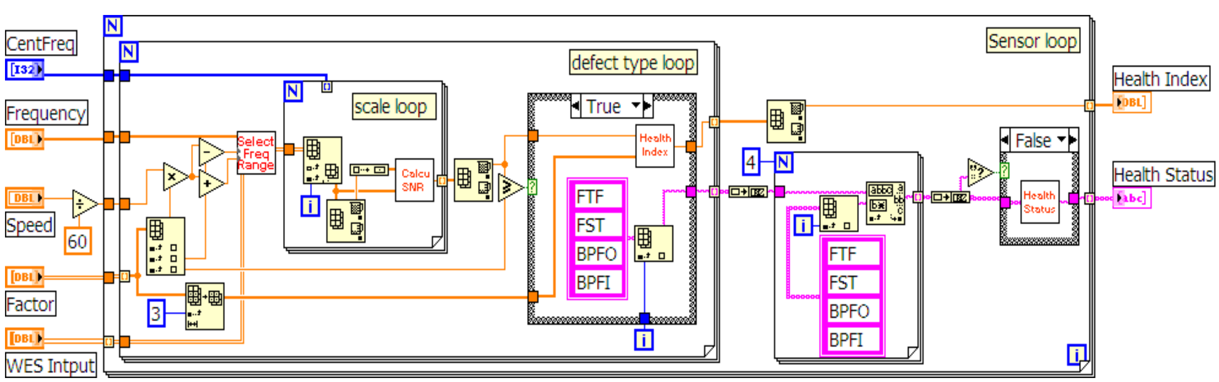


Fig. 6. Code for spindle status and health index indication

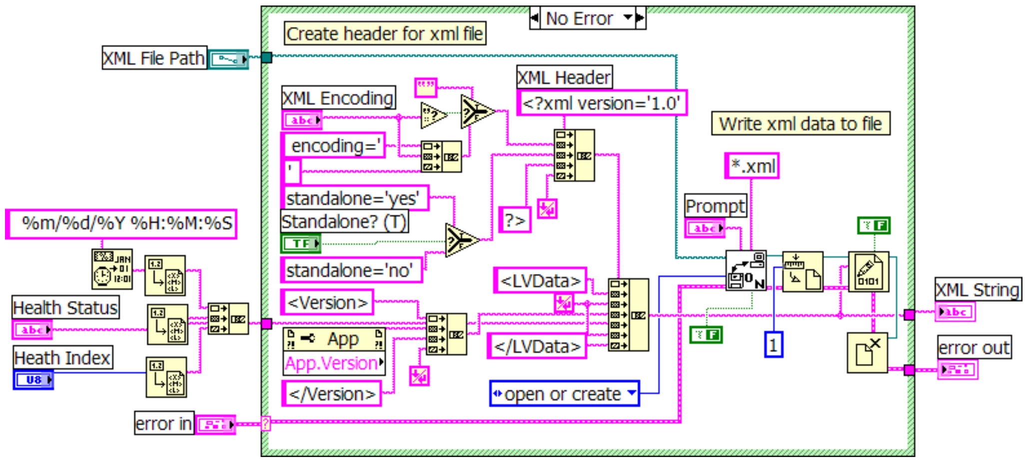


Fig. 7. Code for data logging module


```
<?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>
```


Fig. 8. Representation of health index and status of the spindle using XML-based data format

IV. GRAPHICAL USER INTERFACE DESIGN

According to the open systems architecture, the software is designed and implemented with a user-friendly human-machine interface, which needs to consider the visual appearance, ease of operation, and accommodation of the needs for different users, etc. Figure 9 illustrates the designed user interface for online spindle health monitoring. The right side of the user interface shows general parameter setup options, such as data archiving mode and spindle health index logging mode. The left side of the user interface has integrated previously designed modules and presents the machine health conditions in two types of windows: simplified spindle condition display and warning window for standard machine operators (operator window) and advanced parameter-setup and diagnosis window for machine experts (expert window).

The operator window (as shown in Figure 9a) allows interactive communication between machine operators and the software regarding the current status of the machine without the distraction of behind-window calculations. It displays the speed, temperature, and vibration signals in real-time. Furthermore, the health status and health index of the spindle are updated online based on the results from the embedded modules, and an alarm will be set off when defects are detected. A statistical parameter, Kurtosis, is also implemented in this operator window to track the status of the spindle. The expert window shown in Figure 9b allows the experts to interactively adjust input parameters for the wavelet envelope spectrum module, such as the wavelet center frequency and bandwidth, to conduct a complete investigation of machine status, thus enhancing on-line defect detection capability. Furthermore, quantitative evaluation of the spectrum resulting from each pair of wavelet center frequency and bandwidth is conducted on the bottom of the expert window, which provides detailed frequency information of the vibration signal.

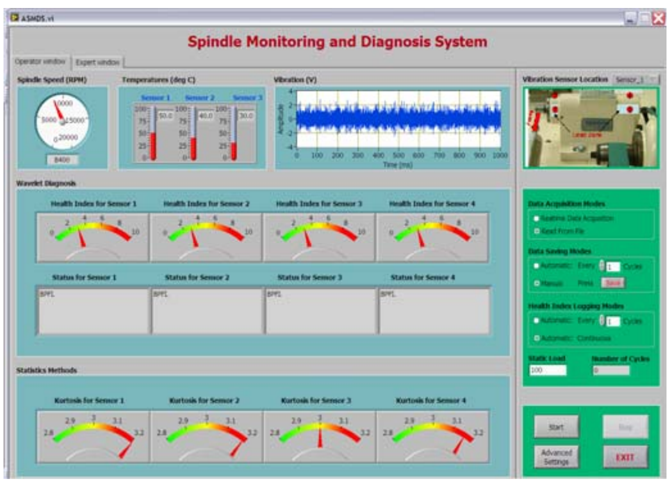
V. EXPERIMENTAL EVALUATION

To experimentally verify the designed software, a custom-designed spindle system was constructed as shown in Figure 2. Since the bearings are the most critical and vulnerable component in a machine tool spindle, four accelerometers were placed at the front and rear ends of the spindle, within the loading and unloading zones of the bearings, to measure their vibrations. Based on the geometry parameters (i.e., pitch diameter, ball diameter, contact angle, and number of balls) of the bearing, its defect-rated characteristic frequencies can be determined as a ratio to the spindle rotating speed, as listed in Table 1.

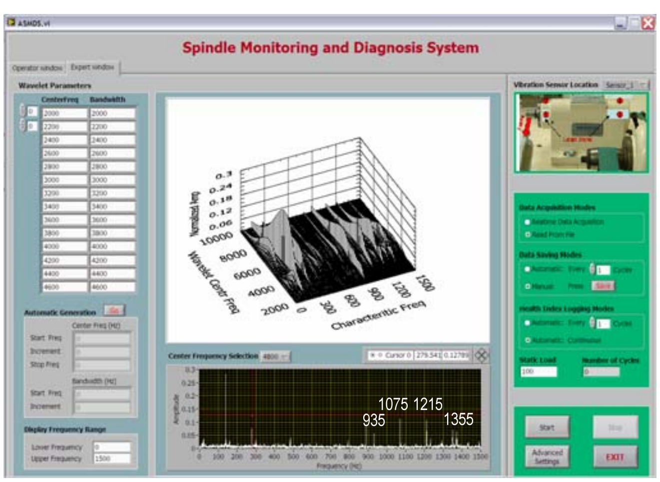
Table 1. Defect-related characteristic frequencies of the bearing

Defect Type	Characteristic Frequency
Unbalance	$f_r \approx rpm/60$
Rolling Element	$f_{BSF} \approx 2.346 f_r$
Outer Raceway	$f_{BPFO} \approx 4.414 f_r$
Inner Raceway	$f_{BPFI} \approx 6.586 f_r$

The spindle was continuously monitored by the designed software system. Figure 9a displays the measured signals, where the spindle was operated at 8 400 rad/s, and its corresponding analysis results after 700 impacts with a force of 13 300 N were consecutively applied to the rotating spindle. The software system diagnosed that a localized defect on its inner raceway had developed. This can be verified by observing the wavelet envelope spectrum in Figure 9b. Based on the equations in Table 1, the frequency peak at 935 Hz shown in Figure 9b can be identified as the BPFI. Theoretically, the BPFI frequency at 8 400 rad/s 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 mathematically specified as $BPFI + k \cdot (rpm), \text{ with } k = 1,2,...n$, and reflect upon combined effect of spindle unbalance and inner raceway defect.



(a) Operator window



(b) Expert window

Fig. 9. A graphical user interface for the software

VI. CONCLUSION

An open systems architecture-based software package for online spindle health monitoring has been designed and implemented. For experimental evaluation conducted on a custom-designed spindle test system, the designed software was able to detect the bearing defect due to the accumulated impacts. The software package is functionally adaptive and presents a new tool that enables more effective and efficient monitoring and diagnosis of machine spindles, and 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.

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