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ORIGINAL RESEARCH

Mechanical vibration monitoring system for electrocardiogram machine based on Hilbert-Huang transformations

Zhu Yongbo[1] | **Xu Lijun**[1] | **Issah Abubakari Samori**[2]

[1]Hunan Mechanical and Electrical Polytechnic, Changsha, China

[2]School of Engineering Sciences, University of Ghana, Accra, Ghana

Correspondence
Issah Abubakari Samori, School of Engineering Sciences, University of Ghana, Accra, Ghana.
Email: iasamori@st.ug.edu.gh

Abstract
The monitoring of health and the technologies that are related to it are an exciting area of research. The paper proposes a mechanical manufacturing vibration monitoring system that is based on Hilbert-Huang transformation (HHT) feature extraction to monitor the running state of the spindle of a mechanical numerical control (NC) machine tool of an electrocardiogram (ECG) machine. Real-time monitoring of the time–frequency characteristic quantity of the spindle vibration signal for ECG signals has been made possible due to the online empirical mode decomposition (EMD) method, which is used to obtain the time–frequency characteristic quantity of the spindle vibration signal based on HHT. The experiment shows that the frequency doubling characteristic components in the time–frequency distribution are obvious in the time interval without copper rod contact, but they disappear in the time interval during which copper rods are in contact (0.3 1.1 s, 3 4s in the figure). It has been demonstrated that the system is capable of not only accurately monitoring the characteristic quantity in the frequency domain of the vibration signal produced by the NC machine tool spindle, but also of successfully implementing the monitoring of the time–frequency characteristic quantity in real time.

1 | INTRODUCTION

In the field of biomedical, electrocardiogram (ECG) machines stand out to be one of the important machines for analysis health of an individual. The analysis of ECG signals needs to be handled with utmost care. In this paper the mechanical vibrations of these machines are analyzed. Mechanical vibration is a common phenomenon in modern industrial production. Strong vibration will have an adverse impact on the normal operation of equipment, lead to component loss, greatly shorten the service life of mechanical equipment, and may have more serious accidents, and even endanger the life safety of workers [1]. Any structure or mechanical equipment will produce certain vibration under dynamic conditions. When the mechanical system is running, if the excitation load is close to the natural frequency component of the system, it will cause the resonance of the system. This large-scale vibration may affect the normal operation of the mechanical system, and even lead to system damage and major accidents [2]. Large bridges, buildings and other engineering structures will also produce vibration under the influence of various environmental excitation. Under the action of natural factors such as earthquake, climbing wind, and waves, as well as long-term fatigue and corrosion, its structure will produce varying degrees of damage and damage. The evaluation of the state of the structure is of great significance to ensure social economic security and personal safety. Through the modal analysis method, the vibration components of each mode in vibration are analyzed, and the modal parameters are identified accordingly, which can better identify the natural vibration characteristics of mechanical equipment and structure, so as to evaluate its structural characteristics and working state [3–6].

The ECG is a biomedical equipment that is used to analyze the heart signals and electrical activity. It makes use of sensors that are attached to various part of the human chest and then electrical signals are captured each time the heart beats. These electrical signals are then processed and analyzed through a graph in order to check the condition of the human heart. In this paper these signals are analyzed and features are extracted in order to reduce the faults that can arise.

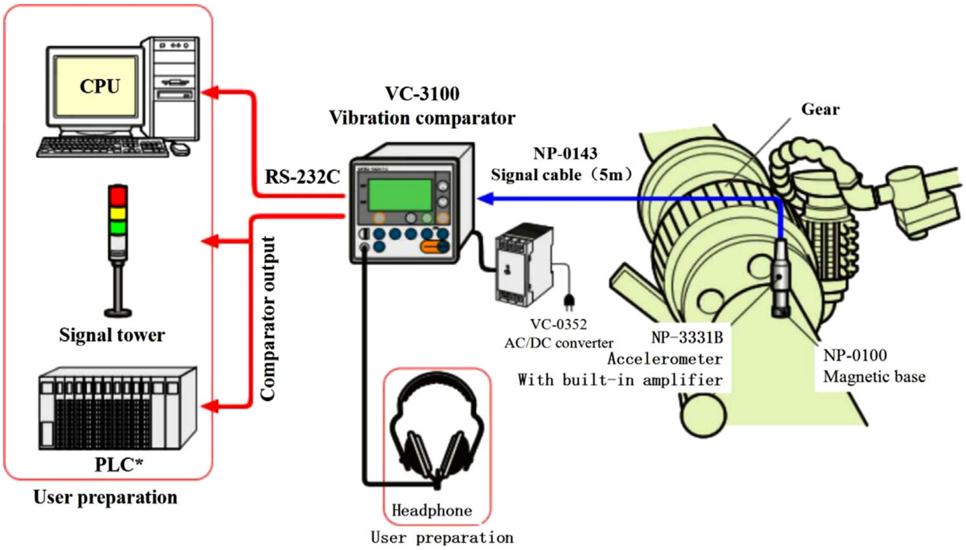

FIGURE 1 Schematic diagram of mechanical manufacturing vibration system detection

Feature extraction is the core of fault diagnosis. The accuracy of signal processing and feature extraction will directly affect the reliability of fault diagnosis. Traditional fault feature extraction methods include wavelet transform, Fourier transform, short-time Fourier transform and other methods [7]. Hilbert-Huang transform (HHT) is an adaptive time–frequency analysis method, which overcomes the defects of traditional spectrum analysis methods. The HHT method is used to analyze the signal, which has good time–frequency aggregation, can obtain very high time–frequency resolution, and is very suitable for analyzing the non-stationary signals that may be included in the rotor vibration signal [8]. In this paper, taking the spindle of mechanical manufacturing numerical control (NC) machine tool as an example, the mechanical manufacturing vibration monitoring system based on HHT feature extraction is studied. Whether the spindle of NC machine tool operates normally or not directly affects the machining quality and production efficiency of the machine tool. The spindle vibration signal contains a large amount of information reflecting its working condition characteristics. The real-time monitoring of spindle vibration is of great significance to ensure the machining quality and production efficiency of machine tools. In recent years, the vibration monitoring method of NC machine tool spindle has been widely studied, and the corresponding monitoring system has been developed. When the working conditions of NC machine tool spindle change or faults occur, its vibration signal has obvious non-stationary characteristics [9]. Therefore, the strong non-stationary local characteristics in the spindle vibration signal can characterize the change of working conditions and the existence of some faults. Figure 1 is the schematic diagram of mechanical manufacturing vibration system detection. Accelerometers, velocity sensors, proximity probes, and laser displacement sensors are some examples of the various types of sensors that can be utilized in the process of measuring vibration. A built-in accelerometer can be seen in Figure 1; this accelerometer measures the changing acceleration with a level of accuracy that is satisfactory. The high-performance digital signal processors that make up the VC-3100 vibration comparator offer three fundamental capabilities: detection, measurement, and evaluation. The accelerometer sends signals to the comparator, and the comparator uses those signals to detect irregularities in the machine (detection), measure vibration levels (measurement), and judge vibration levels based on the measurements (judgement). It is possible to listen to the vibration sound by attaching a regular set of headphones to your device and doing so. An output of the vibration sound is provided for each band, which enables verification of specific vibration occurrences.

Recent developments in medical and biological technology have resulted in an explosion in the volume of data pertaining to biological and physiological processes. Examples of this include medical imaging, electroencephalography, genomic sequences, and protein sequences. Understanding human health and disease is made easier by the use of this data as a learning resource. As a result of developments in high-throughput technology, the past several decades have seen a meteoric rise in the amount of biomedical data, such as genomic sequences, protein structures, and medical pictures. This expansion has been observed across a wide range of disciplines. This flood of biomedical big data makes it necessary to develop computational tools that are both effective and efficient in order to store, analyze, and interpret the data. The paper focuses on vibration monitoring systems; however, in the previous researches there are three analysis techniques, namely, acoustic analysis, vibration signal analysis, and thermal imaging analysis. The acoustic and vibration signal analyses stand out as two of the most common options available among these studies. This is due to the fact that numerous issues can be found without the machine needing to be stopped or taken apart. The variations in these signals frequently serve as an early warning sign of the existence of a problem. In addition to its excellent recognition efficiency and non-destructive testing capabilities, acoustic analysis benefits from a relatively quick analysis time. However, it is extremely difficult to capture the acoustic signals in an accurate manner due to a number of elements including environmental conditions. Analysis of vibration signals comes with its own set of benefits as well as drawbacks. Vibration analysis is one method that can be utilized to accomplish real-time machine monitoring, and there are a variety of highly developed signal processing techniques that can be utilized. Noise contamination and the correct mounting position of the vibration sensors are two factors that prevent vibration analysis from being completely accurate. Lastly, the thermal imaging analysis method can be utilized for the purpose of monitoring and diagnosing mechanical systems. For the purpose of this investigation, an infrared camera is typically utilized to identify several electrical defects in the machine on the basis of the thermal irregularities. The thermal pictures that were obtained are helpful in detecting and localizing the flaws that are present in the equipment. However, this method is time-consuming and costly, and it takes significantly more effort to analyze thermal images than it does auditory or vibration data. It is generally agreed that vibration analysis is the most accurate way for determining the state of a machine. Based on the above-mentioned reasons the paper focuses on monitoring vibration signals for ECG machines using the HHT feature extraction method.

Main contributions of the paper are:

1. The proposed model aims to monitor the running state of spindle of mechanical NC machine tool of ECG machine that is a vibration monitoring system based on HHT.
2. The method that includes the design of spindle vibration monitoring system of mechanical NC machine tool.
3. The experiment uses characteristic quantity in frequency domain of vibration signal produced by NC machine tool spindle and monitoring of time–frequency characteristic quantity in real time.
4. The experimental results prove the disappearance and recurrence time points of frequency doubling characteristics components in the time–frequency energy distribution are consistent with the generation and termination time points of external excitation.

The organization of this paper is as follows: Section 2 discusses the associated literature; Section 3 illustrates the research methods by categorizing it into four parts: First part explain the basic details of HHT method, second part explains the overall design of spindle vibration monitoring system of mechanical NC biomedical machine tool, third part introduces the hardware development of the monitoring system, and the last part discusses the software design of monitoring system including the time–frequency feature extraction method; Section 4 discusses and analyzes the results obtained; Section 5 presents the conclusion and scope for future work.

2 | LITERATURE REVIEW

In recent years, the vibration monitoring method of NC machine tool spindle has been widely studied, and the corresponding monitoring system has been developed. Teng et al. analyzed the machine tool spindle signal based on the weak feature extraction method of cascaded bistable stochastic resonance system, and developed the condition monitoring system [10–12]. Zhao et al. designed an optical fibre monitoring system for collecting vibration signals during mechanical operation to monitor the mechanical operation status in real time [13]. Huang et al. developed the spindle vibration monitoring system of NC machine tool based on spectrum analysis on the basis of analyzing the spectrum characteristics of vibration signal [14, 15]. Abdeljaber et al. described the vibration signal monitoring system of medical equipment products based on servers, nodes, and sensors [16]. Zafarani et al. designed the working condition monitoring system of vibrating screen based on wireless communication, and used the method of vibration signal analysis to judge the working state of machinery [17, 18]. Wszoek et al. applied the wavelet method to spindle vibration monitoring and developed a spindle vibration monitoring system with strong anti-interference ability [19]. Casamenti et al. studied the influence of load, position, and instantaneous acceleration on the measured signal, and proposed a machine tool condition monitoring system that can trace the fault source [20, 21]. Yang et al. developed the vibration monitoring system of spindle bearing of NC machine tool with virtual instrument technology based on LabVIEW [22]. Nazolin et al. used wavelet transform to analyze the time–frequency characteristics of machine tool spindle vibration signal, but the essence of wavelet transform is Fourier transform with adjustable window. Once the local feature scale of the signal is smaller than the feature scale of the selected base wavelet, it is difficult to accurately describe the local features with strong non-stationary in the spindle vibration signal of NC machine tool due to working condition change or fault [23, 24]. The authors of [41] are concerned with the construction of a new fractional-order controller for the autonomous rudder of underactuated surface vessels. This controller is to be developed with the required gain and phase margin. They offered two different models for USV course control and discovered that the performance of their controllers was superior to that of the other controllers that were already in use. Reference [42] is an attempt to solve the issue of poor diagnosis effect, which is brought on by the mutual interference of many fault responses. They proposed a unique new method for the diagnosis of compound faults that they called MDSRCFD. This method is based on optimal maximum correlation kurtosis deconvolution (MCKD), and it uses sparse representation. The findings of both the simulation and the actual application demonstrate that the proposed MDSRCFD is able to efficiently separate and extract the compound fault characteristics of rolling bearings, which allows for the accurate diagnosis of compound faults. Reference [43] investigated the clinical outcomes of individuals with a high-risk diabetic foot who had been provided with custom-moulded offloading footwear and who had been subjected to varying levels of adherence to their treatment regimens. The suggested [44] approach has the ability to successfully boost PS convergence and distribution while also improving PF variety and distribution. An adaptive crossover approach is intended to assure the development of a high-quality offspring population while also weighing the impact of two distinct techniques on the variety of decision and object space. This is done by examining how two distinct crossover procedures optimize their application to two distinct environments. In [45], the authors suggest a novel defect diagnostic approach for rolling elements of rolling bearings based on variational mode decomposition (VMD) and MCKD. This method is called VMD-MCKD-FD. The goal of this method is to improve the diagnosis accuracy and solve the problem of a weak fault signal caused by the long transmission path of the rolling element of the rolling bearing. The findings of the experiments indicate that the VMD-MCKD-FD approach is capable of accurately diagnosing rolling element faults in rolling bearings and achieving higher levels of fault precision. The authors of the paper [46] build hybrid machine learning (ML) classifiers for biomedical data using a meta-heuristic feature selection technique. The model is validated with data derived from biomedical studies of cardiac disease. In conjunction with the E-GWO feature selection technique, seven different types of hybrid classifiers were applied, including NBBT, RFBT, DTBT, KNNBT, NNBT, ABBT, and GBBT. The K-fold cross-validation technique was utilized in order to verify the accuracy of the produced models. The innovative E-GWO feature selection algorithm chooses important features from among all of the available ones. The purpose of [47] is to analyze data using ML classification algorithms so that heart disease can be predicted. It has been suggested that cloud-based IoMT diagnostics could be used for cardiac disease. A rapid analysis of patient data using ML classification methods can be performed with the help of the fog layer. The performance of the healthcare model is evaluated using a variety of simulations, which represents a significant improvement in comparison to earlier models. The proposed algorithm [48] classifies healthcare data, selects appropriate gateways for data transfer, and improves transmission quality by considering throughput, end-to-end delay, and jitter. Proposed algorithms classify healthcare data and deliver high-risk data to end-user using best gateway. The goal of [49] is to apply a variety of ML approaches to the data that was created. For the purpose of early diagnosis of cardiac disease through the Internet of Things, a ML framework has been developed.

The authors of [52] compared their suggested model to other algorithms already in use for TSP in order to determine which provided superior results in terms of solution quality, robustness, and space distribution. The model serves as a reference for resolving the large-scale TSP in order to get more desirable path lengths. The problem of low reliability in the detection of features and tracking boxes in visual object tracking is addressed by [53]. The authors have provided evidence to demonstrate that their proposed model may be incorporated into any tracking model by making use of a variety of attributes. The authors of [54] present a method for calculating the amount of time needed for travel by road for a variety of time periods. Taking into account time-varying vehicle speeds, fuel consumption, carbon emissions, and customers' time windows led to the utilization of a satisfaction measure function based on a time window as well as a measure function of the economic cost. In conclusion, the results of the experiments demonstrate that the recommended strategies are highly effective in lowering total distribution costs, fostering energy saving, and improving customer satisfaction. The proposed model in [55] would increase the time–frequency energy aggregation of non-stationary signals as well as the immunity to cross-term interference. The goal is to obtain a time–frequency representation of the signal while also aggregating a significant amount of energy. The findings of the experiment demonstrate that the proposed model is able to process non-stationary signals successfully, despite the fact that the simulated signal and genuine fault signals have changing instantaneous frequencies (Table 1).

This paper analyzes the advantages of non-stationary data combined with the HHT method. Based on the on-line EMD method, a feature extraction method of NC machine tool spindle vibration signal based on HHT is proposed and applied to the developed NC machine tool spindle vibration monitoring system to monitor the time–frequency characteristics of spindle vibration signal on-line.

3 | RESEARCH METHODS

3.1 | Basic theory of HHT

In the traditional spectrum analysis, the global spectrum and energy distribution of the signal are generally obtained. This method is effective for processing stationary signals, but when processing non-stationary signals, the information that the frequency of the signal changes with time will be lost, so it needs time–frequency analysis to process it. The frequency of non-stationary ECG signal changes with time, which can be regarded as a function of time. Therefore, in order to obtain the frequency information of signal at a certain time, it is necessary to define its instantaneous frequency. In the HHT method, the Hilbert transform (HT) of the signal is generally used to obtain the instantaneous frequency information [25, 26]. For any time-series $X(t)$, the definition of HT $Y(t)$ is shown in formula (1):

$$Y(t) = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{X(\tau)}{t-\tau} d\tau \tag{1}$$

where P is the Cauchy principal value. HT exists for all plant level functions. Different from Fourier transform, HT is a transformation from time domain to time domain. As can be seen from Equation (1), HT of a signal represents the convolution of $X(\mathrm{T})$ and $1/t$, emphasizing the locality of $X(t)$.

An analytical signal can be constructed from the original time series $X(t)$ and its HT $Y(r)$, as shown in formula (2)

$$Z(t) = X(t) + iY(t) = a(t)\, e^{j\theta(t)} \tag{2}$$

TABLE 1 Qualitative comparison with current state-of-the-art techniques

Related work	Objective	Model	Advantages
Our paper	To design and implement the mechanical manufacturing vibration monitoring system for ECG signal monitoring based on HHT feature extraction	Proposed model	Efficiently monitor the time–frequency characteristics of spindle vibration signal on-line
[50]	To develop local frequency to extract the limitation of traditional frequency	Hybrid adaptive waveform decomposition and normalized Lempel-Ziv complexity method	Accurately distinguish the different fault states of rolling bearings
[51]	To facilitate an appropriate distribution selection in a specific application	Multidimensional form	Could be used to generalize the existing approaches defined in either the Fourier or the DCT domain

The amplitude function is shown in formula (3):

$$a(t) = \left[X^2(t) + Y^2(t)\right]^{1/2} \tag{3}$$

The phase function is shown in formula (4):

$$\theta(t) = \arctan\left(\frac{Y(t)}{X(t)}\right) \tag{4}$$

The instantaneous frequency can be defined as the derivative of the phase function of $z(t)$, as shown in formulas (5) and (6):

$$\omega(t) = \frac{d\theta(t)}{dt} \tag{5}$$

$$f(t) = \frac{1}{2\pi}\frac{d\theta(t)}{dt} \tag{6}$$

It can be seen from Equations (5) and (6) that the instantaneous frequency of the signal obtained by HT is a single value function of time, so it can only reflect the frequency value of one component of the signal. To use the instantaneous frequency to analyze the signal, it is required that the signal is a single component. Therefore, Cohen introduced the concept of 'single component' function to make the instantaneous frequency have physical meaning. However, there is still no clear definition of 'single component' function. Narrow band condition and symmetry condition are usually used to judge 'single component' function. The preceding investigation demonstrates that the HT cannot directly supply the entire frequency information of a complex signal. As a result, Huang established the concept of intrinsic mode function. The intrinsic mode function he invented fulfils two conditions: the whole data set has the same number of extreme points and zero crossings. The envelopes created by the local maximum and local minimum are locally symmetrical along the time axis, which means that the upper and lower envelopes have the same mean value. These two limitations ensure that the immediate frequency of the natural mode function is meaningful [27, 28].

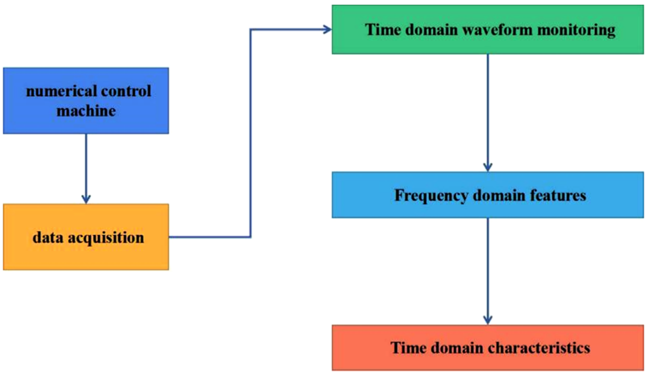

FIGURE 2 Structural block diagram of spindle vibration monitoring system of mechanical NC machine tool

3.2 | Overall design of spindle vibration monitoring system of mechanical NC biomedical machine tool

Combined with the characteristics of spindle vibration signal of mechanical NC machine tools, and based on the study of a large number of rotating machinery condition monitoring systems, this paper designs the spindle vibration monitoring system of NC biomedical machine tools. The structural block diagram is shown in Figure 2. During the working process of NC machine tool, the spindle vibration acceleration signal is transmitted to the upper computer through the data acquisition module. The upper computer software system includes two modules: time domain waveform monitoring and characteristic data monitoring. The characteristic data monitoring module has the function of monitoring frequency domain characteristic quantity and time–frequency characteristic quantity. The power spectral density of vibration signal is selected as the frequency domain characteristic of vibration response of machine tool spindle [28, 29]. The time–frequency distribution based on HHT is selected as the monitored time–frequency characteristic quantity, which describes the time and frequency domain information of the vibration response of the machine tool spindle at the same time, and can effectively reflect the variation law of the characteristic frequency with time.

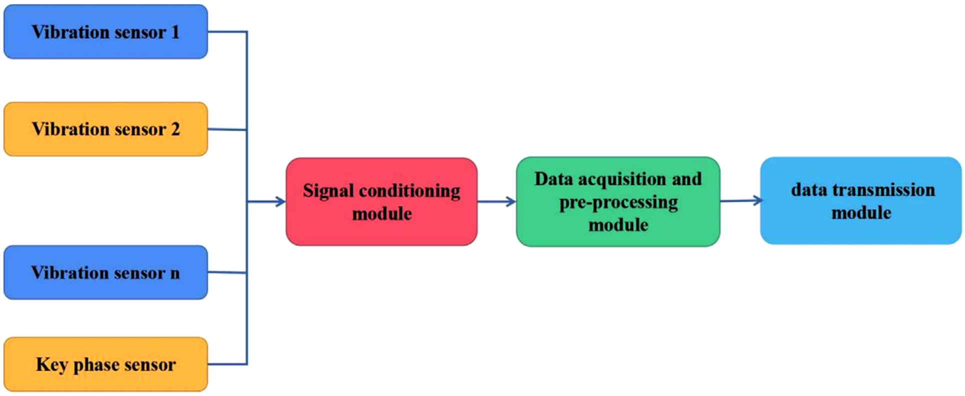

FIGURE 3 Hardware structure block diagram of spindle vibration monitoring system of NC machine tool

3.3 | Hardware development of monitoring system

The real-time and accuracy of the data collected by the system hardware and the speed of data transmission are the primary premise to realize the spindle vibration monitoring of NC biomedical machine tools. Based on the above requirements, this paper divides the hardware of CNC machine tool spindle monitoring system into sensor, signal conditioning module, data acquisition module, and data communication module. The system hardware structure block diagram is shown in Figure 3. Among them, the sensor converts the spindle vibration displacement and speed into electrical signals, the signal conditioning module regulates the sensor electrical signals to meet the data acquisition requirements, the data acquisition module converts the electrical signals into A/D, and the data communication module uploads the real-time data to the upper computer [30].

3.4 | Software design of monitoring system

The spindle vibration monitoring system of NC biomedical machine tool generally adopts the classical signal processing method based on stationary process, which is difficult to accurately describe the local characteristics with strong non-stationarity caused by working condition changes or faults. Therefore, the spindle vibration monitoring system of NC biomedical machine tool needs to be able to monitor not only the time domain waveform and frequency domain characteristic quantity of vibration signal, but also the time–frequency characteristic quantity that can reflect the local characteristics of vibration signal [31, 32].

3.4.1 | Time–frequency feature extraction method

The HHT approach is used to extract time–frequency information from the non-stationary properties of an NC machine tool's spindle vibration signal. The HHT method is a non-stationary signal analysis method based on empirical mode decomposition (EMD), in which the frequency domain signal is decomposed into several IMF frequency components ranging from high to low frequency, and then HT is applied to each IMF component to describe the time–frequency characteristics of non-stationary signals. HHT incorporates both EMD and HT. EMD decomposition of signal $x(t)$.

The basic idea of the proposed algorithm is as follows:

Step 1: All the maximum and minimum points of $x(t)$ are interpolated by cubic spline curve to obtain the upper and lower envelopes of $x(t)$.

Step 2: Calculate the mean $m(t)$ of the upper and lower envelopes.

Step 3: Remove the mean $m(T)$ in the signal and extract the detailed components of the signal$d(t) = x(t) - m(t)$, and use it to extract the first-order IMF.

Step 4: Remove the first-order IMF from $x(t)$, repeat steps 1 to 4 as a new signal, and extract each order IMF successively. During extraction, $d(t)$ screening operation in step 3 is required [33]. When $d(t)$ satisfies the IMF definition and iteration termination conditions at the same time, the screening operation is terminated. After EMD decomposition, $x(t)$ can be expressed as the sum of each order of IMF and trend term [34–36], as shown in formula (7)

$$x(t) = \sum_{k=1}^{k} d_k(t) \tag{7}$$

where K is the number of IMF components; $d_k(t)(k = 1 \sim (k-1))$ is the kth order IMF component and is recorded as the kth order IMF [37, 38].

HT is performed for each order of IMF, as shown in formula (8):

$$D_k(t) = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{d_k(\tau)}{t-\tau} d\tau \tag{8}$$

where PV is Cauchy Principal component. Form $d_k(t)$ and $D_k(t)$ into the analytical form of the kth order IMF [39, 40], as shown in formula (9):

$$Z_k(t) = a_k(t)\exp\left[i\theta_k(t)\right] \tag{9}$$

Among them

$$a_k(t) = \sqrt{d_k^2(t) + D_k^2(t)} \tag{10}$$

$$\theta_k(t) = \arctan\left[\frac{D_k(t)}{d_k(t)}\right] \tag{11}$$

where $a_k(t)$ is signal amplitude; $\theta_k(t)$ is the signal phase.

The instantaneous frequency of the signal is defined as the derivative of D, as shown in formula (12):

$$\omega_k(t) = \frac{1}{2\pi}\frac{d\theta_k(t)}{dt} \tag{12}$$

The original signal $x(t)$ is expressed as shown in formula (13):

$$x(t) = (reat)\sum_{k=1}^{k-1} a_k(t)\exp\left(i\int \omega_k(t)\,dt\right) \tag{13}$$

As a function of time t, the frequency components of non-linear and non-stationary signals at each time can be accurately described by the signal $x(t)$, amplitude $a_k(t)$, and instantaneous frequency $\omega_k(t)$ of Equation (13).

4 | RESULT DISCUSSION

In order to verify the effectiveness of the spindle vibration monitoring system of CNC biomedical machine tools, the spindle vibration of Takumi vertical machining centre is monitored by the system [25]. In the test, the sampling frequency of the system is 1280 Hz, and the time-domain waveform displayed by the original data monitoring module is set to 0.2 s. Adjust the spindle speed of the NC machine tool to 3840 r/min. after the spindle runs stably for a period of time, contact the spindle with a copper rod to make the speed fluctuate. The system monitors the time domain waveform of spindle vibration signal when there is no copper rod contact, as shown in Figure 4. The time domain waveform of the spindle vibration signal monitored by the system when the copper bar contacts is shown in Figure 5. Comparing Figures 4 and 5, it is difficult to see the difference between them from the time domain waveform. The power spectral density reflects the average energy distribution characteristics of the frequency components of the energy signal in a certain time interval, and can be used as the frequency domain characteristic analysis of the monitored signal. The stationary characteristic quantity (power spectrum) monitored by the system is shown in Figure 6. The frequency conversion (64 Hz) characteristic quantity and frequency doubling (128 Hz)

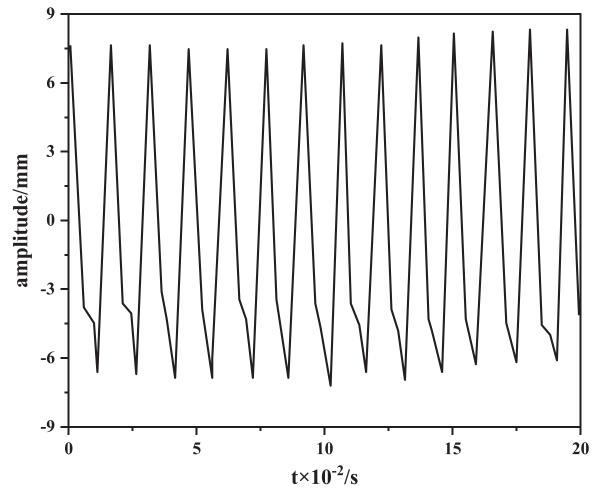

FIGURE 4 Time domain waveform of spindle vibration of NC machine tool without copper bar contact

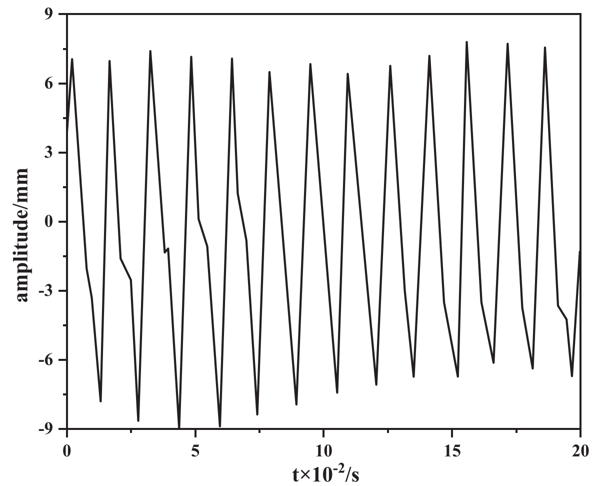

FIGURE 5 Time domain waveform of spindle vibration of NC machine tool when copper bar contacts

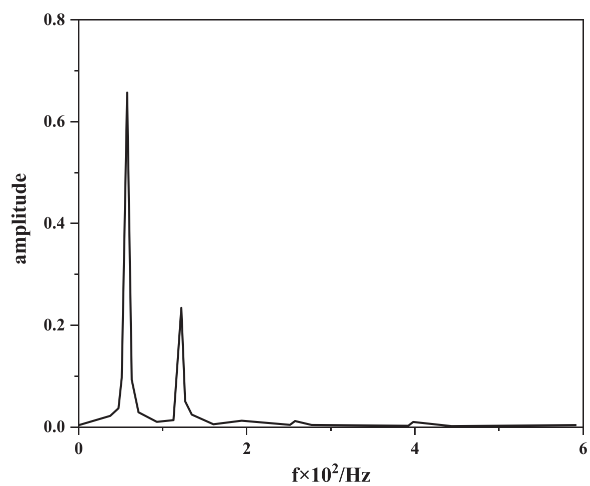

FIGURE 6 Frequency domain distribution of system monitoring

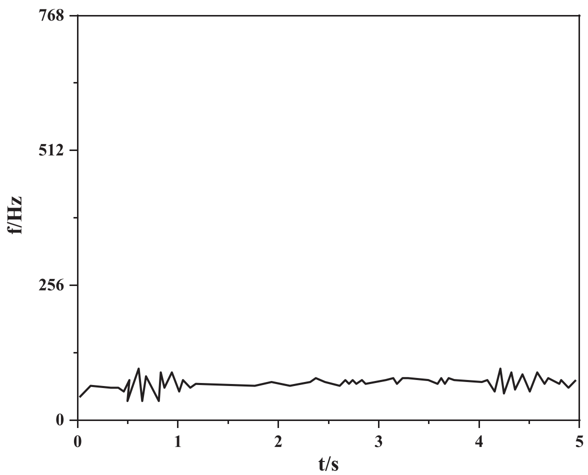

FIGURE 7 Time–frequency distribution of system monitoring

characteristic quantity are obvious, and the high-order frequency doubling characteristic quantity is small. However, the occurrence time and duration of external excitation (copper rod contact) of rotor system cannot be judged from the monitored stationary characteristic quantity.

The time–frequency distribution obtained by the HHT method can reflect the variation law of characteristic frequency with time. The time–frequency distribution of vibration signal HHT is shown in Figure 7. To describe the time–frequency properties of non-stationary signals, the frequency domain signal is first decomposed into several IMF frequency components, going from high frequency to low frequency, and then the HT is performed for each of those IMF frequency components. The components with a frequency doubling feature can be found in the time–frequency distribution. A frequency multiplier is a non-linear circuit that, when it receives an input signal, distorts that signal and, as a result, generates harmonics that are related to the original signal. After that, a bandpass filter picks the harmonic frequency that is needed and eliminates the undesirable fundamental as well as any other harmonics that are present in the output.

It can be seen from Figure 7 that the frequency doubling characteristic components in the time–frequency distribution are obvious in the time interval without copper rod contact and disappear in the copper rod contact time interval (0.3–1.1 s, 3—4 s in the Figure). The disappearance and reappearance time points of frequency doubling characteristic components in time–frequency energy distribution are consistent with the occurrence and termination time points of external excitation. According to the subharmonic resonance theory, when the spindle frequency is close to 1/2 of the radial first-order natural frequency of the spindle system, the double frequency component of the frequency conversion will be excited. There are obvious frequency conversion (64 Hz) and double frequency (128 Hz) components in the time interval of 0 to 0.3 s. It is inferred that the machine tool spindle has subharmonic resonance due to misalignment. In the time interval of 0.3 to 1.1 s, due to the friction between the copper bar and the spindle, the machine tool speed fluctuates slightly, so that the frequency doubling frequency is far away from the radial first-order natural frequency of the spindle system, and the subharmonic resonance phenomenon disappears. In the time interval of 1.1 to 3 s, because the copper rod leaves the spindle, the spindle rotation frequency is stabilized at 1/2 radial first-order natural frequency again, and the subharmonic resonance phenomenon reappears. In the same way, it can be explained that the frequency composition of vibration signal when copper rod touches the main shaft within 3 to 4 s interval. Therefore, the time–frequency characteristic monitoring sub-module of CNC machine tool spindle vibration monitoring system based on HHT can not only describe the frequency domain information of CNC machine tool spindle vibration signal, but also track the change of frequency component with time, which can provide a basis for analyzing the causes of no stationarity of CNC machine tool spindle vibration signal.

5 | CONCLUSION

HHT is a very suitable analysis method for analyzing non-linear and non-stationary signals. In this paper, the mechanical manufacturing vibration monitoring system for ECG signal monitoring based on HHT feature extraction is designed and implemented. The combination of main control module and PC104 bus can ensure the real-time performance of data acquisition and the accuracy of data transmission. The test results of spindle vibration signal of mechanical NC machine tool show that while monitoring the time-domain waveform and spectrum distribution of signal, the system can use the instantaneous frequency description characteristics of HHT to realize the real-time monitoring of time–frequency distribution of spindle vibration signal of NC machine tool. The goal is to develop and implement a system for monitoring ECG signals based on HHT feature extraction, and this system will be utilized in mechanical production vibration monitoring. The system will be used in mechanical production vibration monitoring. As can be seen from the results of the experiments that were carried out, the suggested model has the capacity to monitor the time–frequency characteristics of the spindle vibration signal in an efficient and effective manner while it is being transmitted online. The proposed work is limited in that it cannot be applied to further biomedical tools that include signal analysis and processes like MRI machines. This is one of the limitations of the study.

AUTHOR CONTRIBUTIONS

Zhu Yongbo: Conceptualization; Formal analysis; Investigation; Methodology. Xu Lijun: Investigation; Methodology; Validation; Writing – original draft. Issah Samori: Resources; Validation; Writing review – editing.

CONFLICT OF INTEREST

The authors declare no conflict of Interest.

FUNDING INFORMATION

None.

DATA AVAILABILITY STATEMENT

The data shall be available on request from the corresponding author.

ORCID

Issah Abubakari Samori https://orcid.org/0000-0001-9990-5552

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