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EXTRACTION AND SCREENING OF KNEE JOINT VIBROARTHROGRAPHIC SIGNALS USING THE EMPIRICAL MODE DECOMPOSITION METHOD

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Abstract. *This study presents a method for the extraction and screening of knee joint vibroarthrographic (VAG) signals using an Empirical Mode Decomposition (EMD) technique. The proposed analysis method is based on the Hilbert Huang transform, which is a powerful tool for the analysis of non-stationary and non-linear time series and basically consists of an empirical mode decomposition method and Hilbert spectral analysis. A technique for time-frequency analysis of the extracted vibration signals is proposed with the goal of diagnosing knee joint diseases. The performance of the EMD technique is verified experimentally. The screening accuracy of the statistical pattern classification is 85.3% in Vibroarthrographic signals. The results confirm that the proposed approach is indeed feasible for the noninvasive diagnosis and monitoring of articular cartilage pathology.*

Keywords: Vibroarthrographic, Empirical mode decomposition

1. **Introduction.** The knee joint is the most commonly injured or diseased joint in the human body. Arthritic degeneration of an injured knee is a well-known phenomenon. Vibroarthrography, the recording of vibrations or acoustic signals from the human knee joint during active movement of the leg, can be used as a noninvasive diagnostic tool to detect articular cartilage degeneration. Conventional imaging techniques and x-ray diagnostic tests are not feasible for an accurate diagnosis of knee joint pathology, for they are not able to show objective signs of degenerative joint disease, especially in the early stages of deterioration. Even after gross cartilage degeneration or injury has occurred, in many cases changes cannot be detected without invasive tests such as arthroscopy [1-3]. Arthroscopy is one of the best-known diagnostic procedures for screening knee joint disorders. It is a semi-invasive procedure where a fiber optic cable is inserted into the knee

joint to allow the physician to look at the joint through an arthroscope. Due to its semi-invasive nature, arthroscopy is not suitable for repeated assessment, follow-up studies or for monitoring purposes. On the other hand, noninvasive imaging techniques such as x-rays and computed tomography (CT) scans cannot detect knee joint disorders until they are in the advanced stages. Compared with the other imaging techniques, magnetic resonance imaging (MRI) is much more sensitive for the detection of knee joint disorders, but it is still evolving. In addition, MRI scanners are expensive and not commonly available, which make them an uneconomical choice, in terms of both money and time, for screening purposes and particularly for follow-up studies [4-14].

The vibration signals emitted from knee joints during their flexion or extension provide valuable clues regarding their pathological condition or physiological state. As a result, vibroarthrography (VAG), specifically the recording of human knee joint vibrations or acoustic signals during active movement of the leg, provides an invaluable noninvasive diagnostic tool for the early detection of articular cartilage degeneration. However, the detected joint signals can be contaminated with noise from a variety of sources, including the transducer used to detect the signal, the measurement apparatus, manual intervention during the test procedure, and so forth. Moreover, the resulting signal interference is not stable, but varies over time, from swing to swing, and from one individual to another. Therefore, effective interference cancellation techniques are required to reduce the variability of the vibration signal so that more reliable diagnostic results can be obtained.

Early medical researchers had no choice but to use simple electric-stethoscopes or microphones for knee joint signal detection purposes. However, the signals detected using such instrumentation were inevitably affected by high levels of extraneous interference arising from hand tremors, skin friction, background noise, and so forth. In 1976, Chu et al. [15] developed a double microphone differential amplifier setup to address this problem. However, while the proposed setup successfully suppressed extraneous background noise, it did not resolve the characteristic problem of all acoustic systems, namely the poor response to low-frequency signals (such as those generated in a knee joint) [16]. Modern VAG methods, in which the vibration signals are detected directly via accelerometers attached to the subject, are capable of measuring these lower frequency joint signals. However, the contact sensors used to detect the vibration signals are highly sensitive to low frequency inputs, and hence the VAG signal is severely contaminated by low-frequency artifacts caused by the muscle contraction required to move the knee for measurement purposes. This artifact, conventionally referred to as muscle contraction interference, encompasses all the signals induced by muscle contraction, including muscle activity, muscle sounds and tremors, vibromyographic signals, and so on [17]. Muscle contraction interference is inevitable in VAG applications, since the muscles involved with knee movement cannot be maintained in a totally relaxed state at all times during the measurement procedure, and the muscle contraction required to execute knee movement cannot be kept constant as the leg is swung backward and forward due to the inherent inertia of the movement.

Accordingly, in the current study, we have developed an enhanced VAG detection and diagnosis method based on Empirical Mode Decomposition and time-frequency analysis. EMD is a data analysis technique similar to wavelet analysis and singular spectrum analysis (SST); it is particularly suitable for nonlinear and non-stationary time series analysis. However, EMD does not assume an a priori basis. Unlike wavelet analysis and SST [18,19], EMD is suitable for describing nonlinear phenomena. In 1998, Huang [20-26] proposed an EMD method for analyzing nonlinear and non-stationary data. This decomposition method is adaptive and highly efficient. In this study, the degree of injury to the knee can be diagnosed by EMD.

Traditional VAG systems often receive mixed signals, arising from the VAG signal and other noise, causing difficulty in monitoring knee health. The use of EMD can improve the quality of VAG signals and ensure accurate understanding of the knee's condition. Other means of improving VAG quality have been tested in previous studies [4-14]; however, none of these approaches is as simple and effective as EMD.

2. **Data Acquisition.** During the experiments, the VAG signal was amplified before being digitized at a sampling rate of 5 kHz; see Figure 1. Miniature accelerometers (Model 353-B33, PCB Piezotronics Inc., USA) were attached to the subject's skin using double-sided adhesive tape in the region of the knee corresponding to the lateral condyle of the tibia (LCT). The accelerometers were positioned such that the majority of the sensors detected the VAG signal, while the remainder monitored variations in the signal along the leg, providing information with which to discriminate the noise signals from the VAG signals. The resulting signals were amplified by a pre-amplifier (Model 482A20, PCB Piezotronics Inc., USA) and then output to an oscilloscope for observation purposes and a computer for data processing. The recorded signals were digitized using a signal data acquisition board (Model USB 9233, National Instruments Inc., USA) and processed using Labview software (National Instruments Inc., USA).

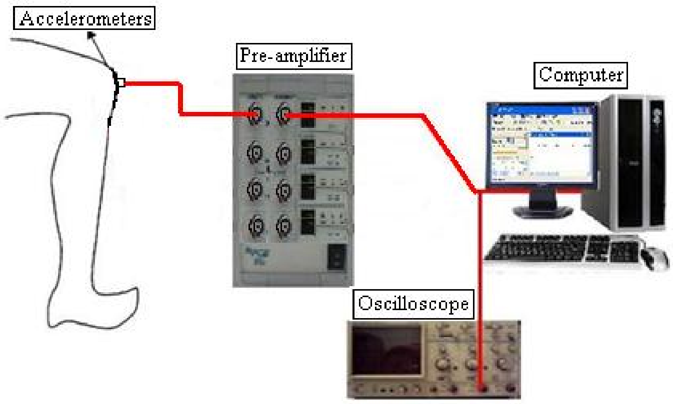

Figure 1. Schematic illustration of the experimental setup

3. **VAG Signal Monitoring and Diagnosis Using EMD.** In the VAG scheme described in this study, the signals obtained by the four accelerometers are processed using EMD to identify individual contributions of the VAG and noise signals. A time-frequency technique is then applied for further signal processing and to facilitate obtaining a reliable diagnostic result. Figure 2 presents a block diagram of the overall VAG detection and diagnostic approach.

3.1. **Hilbert Huang transform (HHT) theory.** Once the underlying source is determined, EMD can be used to decompose the original sources into their constituent components, known as the intrinsic mode functions (IMFs). EMD decomposes the variance of the set into a finite number of intrinsic mode functions (IMFs) based on an adaptive basis derived from each data set. The instantaneous frequency can then be computed through the Hilbert transform. An IMF is a function that satisfies two conditions [20]: (1) the number of extremes and the number of zero crossings in the whole data set must either be equal or differ at most by one; (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. To

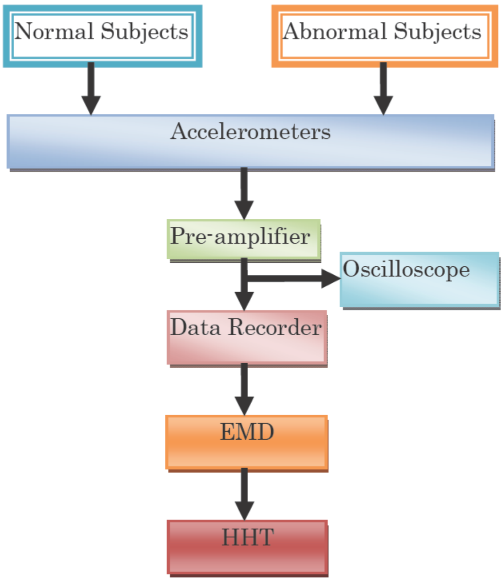

FIGURE 2. Block diagram of the proposed detection and diagnosis technique

obtain an IMF from the original signal, Huang [20] suggests the sifting process described below. The sifting process begins with the identification of the local minima and maxima of a time series, $X(t)$. First, identify all the local maxima, and then connect them with a cubic spline line to form the upper envelope, $e_u(t)$. Repeat the procedure for the local minima to produce the lower envelope, $e_l(t)$.

The local mean can be calculated as shown:

$$m_1(t) = \frac{e_u(t) + e_l(t)}{2}. \tag{1}$$

The mean is designated in Equation (1), and the difference between the data and $m_1(t)$ is the first component, $h_1(t)$, as obtained in the following equation:

$$h_1(t) = x(t) - m_1(t). \tag{2}$$

In the subsequent sifting process, $h_{1k}(t)$ is considered the data:

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t). \tag{3}$$

In EMD this sifting procedure is repeated k times, until h_{1k} is an IMF. Now

$$c_1 = h_{1k}, \tag{4}$$

which is the first IMF component derived from the data. The standard deviation determines a criterion for stopping the sifting process. This can be accomplished by limiting the size of the SD, computed from the two consecutive sifting results as follows:

$$SD = \sum_{t=0}^{T} \left[\frac{|(h_{1(k-1)}(t) - h_{1k}(t))|^2}{h_{1(k-1)}^2(t)} \right]. \tag{5}$$

When the SD can be set between 0.2 and 0.3, the first IMF c_1 is obtained, which can be written as

$$X(t) - c_1 = r_1. \tag{6}$$

Note that the residue r_1 still contains some useful information. We can therefore treat the residue as new data and apply the above procedure to obtaining

$$\begin{aligned} &r_1 - c_1 = r_2 \\ &\vdots \\ &r_{n-1} - c_n = r_n \end{aligned} \tag{7}$$

This procedure should be repeated until the final series r_n no longer carries any oscillation data. The remaining series is the trend of this non-stationary data $X(t)$. Combining Equation (6) and Equation (7) yields the EMD of the original signal:

$$X(t) = \sum_{j=1}^{n} c_j + r_n. \tag{8}$$

Thus, one can achieve a decomposition of the data into n-empirical modes, and a residue r_n, which can be either the mean trend or a constant. The IMFs $c_1, c_2, \cdots c_n$ include different frequency bands ranging from high to low.

The Hilbert transform is used in the second stage of the proposed signal processing technique. The Hilbert transform $y(t)$ for an arbitrary signal $x(t)$ can be defined by [20]

$$y(t) = \frac{1}{\pi} p \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{9}$$

where p is the Cauchy principal value. In Equation (9), the Hilbert transform is defined as the convolution of the signal $x(t)$ with $1/t$. Therefore, the Hilbert transform is capable of identifying the local properties of $x(t)$. Coupling $x(t)$ and $y(t)$, we can obtain the analytic signal $z(t)$ of $x(t)$

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)} \tag{10}$$

where

$$a(t) = \sqrt{x^2(t) + y^2(t)}, \quad \theta(t) = \tan^{-1}\left(\frac{y(t)}{x(t)}\right) \tag{11}$$

$a(t)$ is the instantaneous amplitude of $z(t)$, which can reflect how the energy of $x(t)$ varies with time, and $\theta(t)$ is the instantaneous phase of $z(t)$. The instantaneous frequency $\omega(t)$ is defined as the time derivative of the instantaneous phase $\theta(t)$, as follows:

$$\omega(t) = \frac{d\theta(t)}{dt}. \tag{12}$$

In the above process, both the amplitude and the instantaneous frequency are a function of time. This frequency-time distribution of the amplitude is designated as the Hilbert spectrum $H(\omega, t)$. After performing the Hilbert transform for the signal component, the original signal can be expressed as the real part, in the following form:

$$H(\omega, t) = \mathrm{Re} \sum_{i=1}^{n} a_i(t) e^{j\int \omega_i(t)dt}. \tag{13}$$

The Hilbert Huang spectrum analysis technique is particularly suitable for characterizing signals at different localization levels over time and in different frequency domains. Results presented in this paper have demonstrated that the extracted energy characteristics reflect the energy shift with the variation in pattern.

4. **Experimental Study and Results.** The observed differences between normal and abnormal VAG signals are characterized using EMD and HHT. The VAG signals measured in the 10-second period for a subject with no knee disability are shown in Figure 3. There are mixed VAG and noise signals. The signals correspond to the gradual movement of the subject from a standing position to a squatting position and then returning to an upright position over the 10-second interval. Figure 4 shows mixed VAG and noise signals. The signals correspond to the gradual movement of the subject from a standing position to a squatting position and then back to an upright position over the 10-second interval. However, in the present form, these signals provide no insight into the pathological condition of the knee joint. Figure 5 shows the resulting EMD components obtained from the knee joint. All IMFs (C1 to C11) and the Hilbert Huang spectrum obtained utilizing the HHT to analyze the knee joint signal are displayed in Figure 4. The temporal waveform of the VAG signal, which is a linear frequency modulation signal, and its instantaneous frequency, as calculated by Equations (11) and (12), are shown in this figure. The horizontal axis indicates the elapsed time, the vertical axis, the frequency domain, and the color spectrum the signal volume in dB. Low frequency signals that possess higher energy are presented in red, while high frequency signals are depicted in blue or green. In this study, Figure 6 shows IMFs (C2 to C4) and the Hilbert-Huang spectrum obtained utilizing the HHT to analyze the knee joint signals. The changes in the signals over time are clearly observable in the sub-figures. We can see the normal components and the high frequency signal of the small area, but the abnormal knee components, such as the impact and highest frequencies of the large area, cannot be observed in a healthy subject. The process of EMD reduces the time series under analysis into components, such as intrinsic mode functions (IMFs), thereby "sifting" or separating out the different frequency scales of the data. The sifting is done adaptively, without an a priori structure imposed on the data. This approach has the advantage that it can be easily constrained to yield the real distributions, which can be interpreted as a two-dimensional decomposition of a signal's energy.

Figure 7 shows VAG signals from a subject with degenerative knee joint pathology. Since the VAG and muscle contraction motion signals are both in the low frequency range, it is impossible to separate them using a classical filter. Furthermore, although the muscle contraction interference signals can be canceled using an adaptive filter, the noise

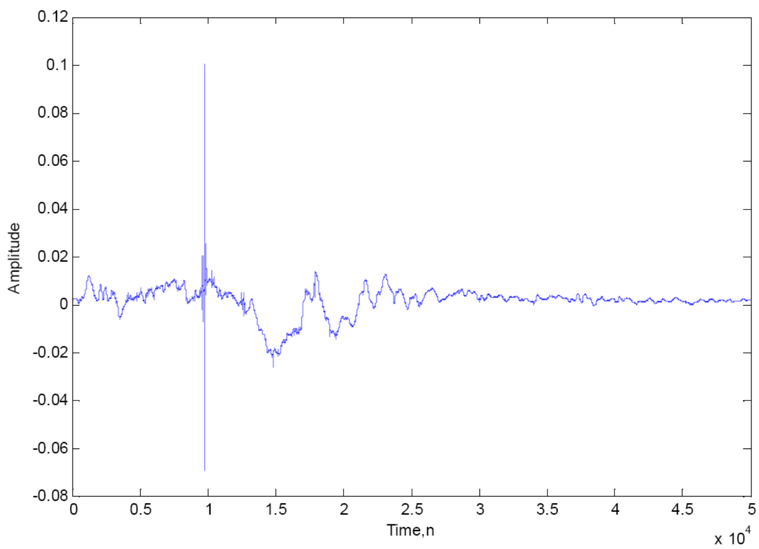

FIGURE 3. VAG signals acquired from a healthy subject

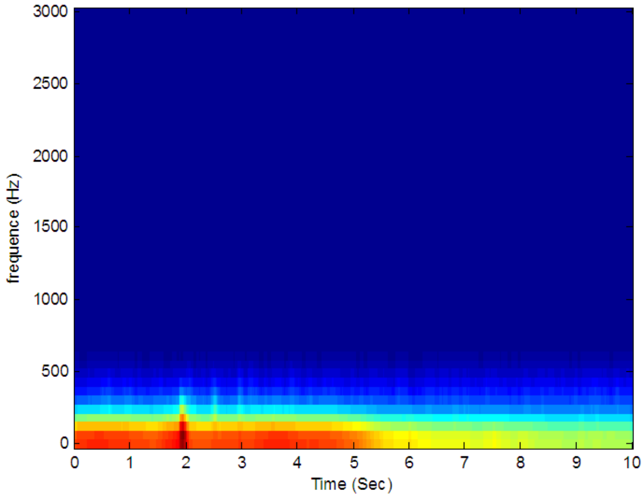

FIGURE 4. Time-frequency analysis of VAG signals acquired from a healthy subject without using EMD

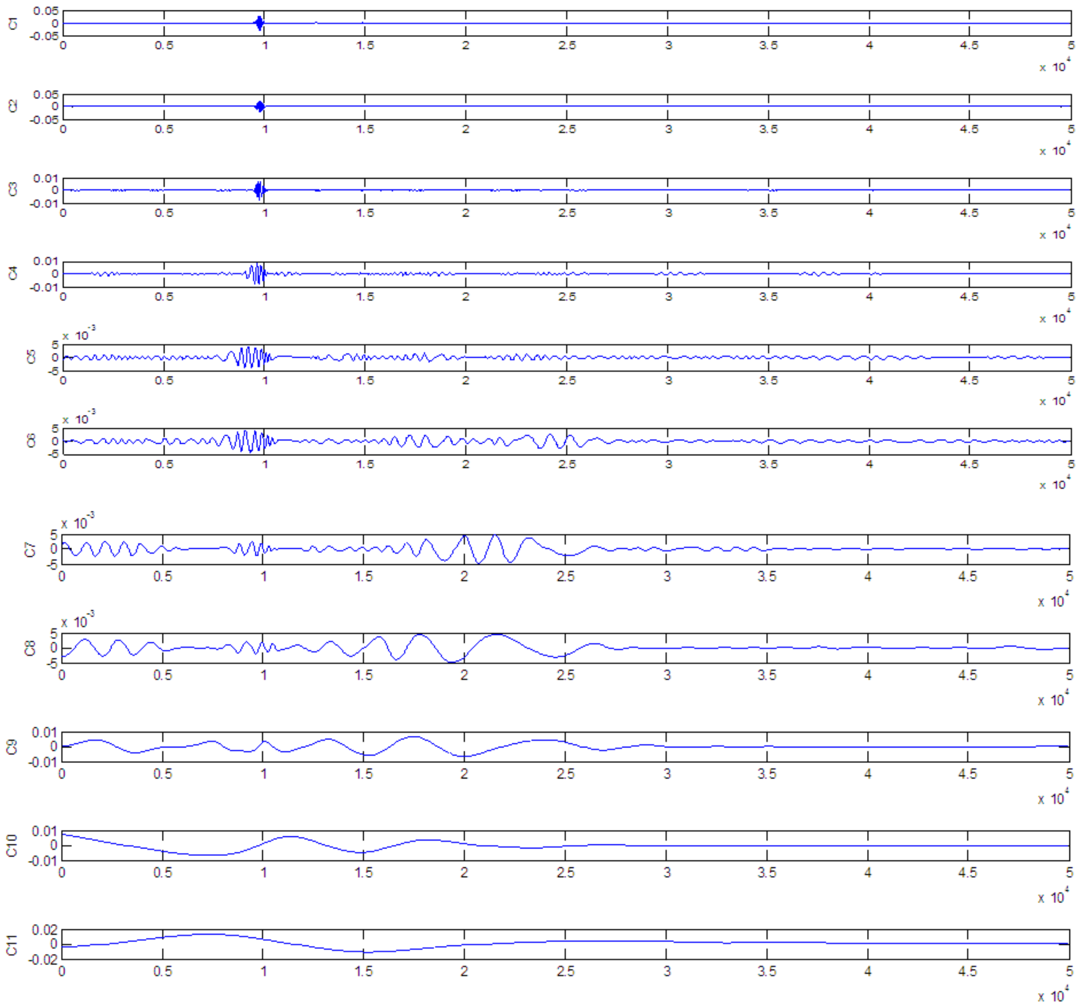

FIGURE 5. VAG signals from a healthy subject after being processed by EMD

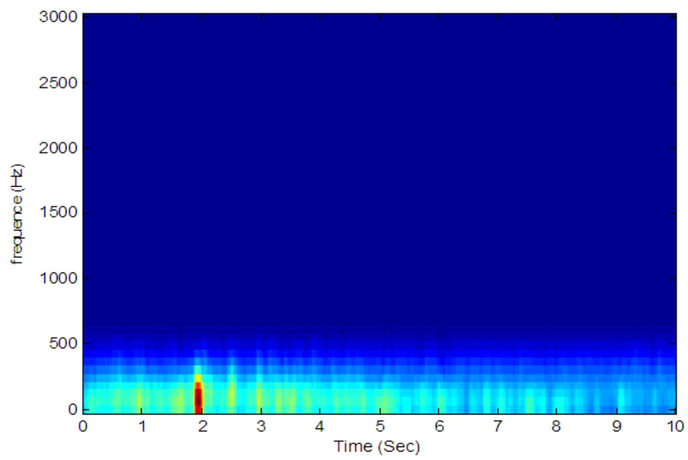

Figure 6. Time-frequency analysis of VAG signals acquired from a healthy subject using EMD

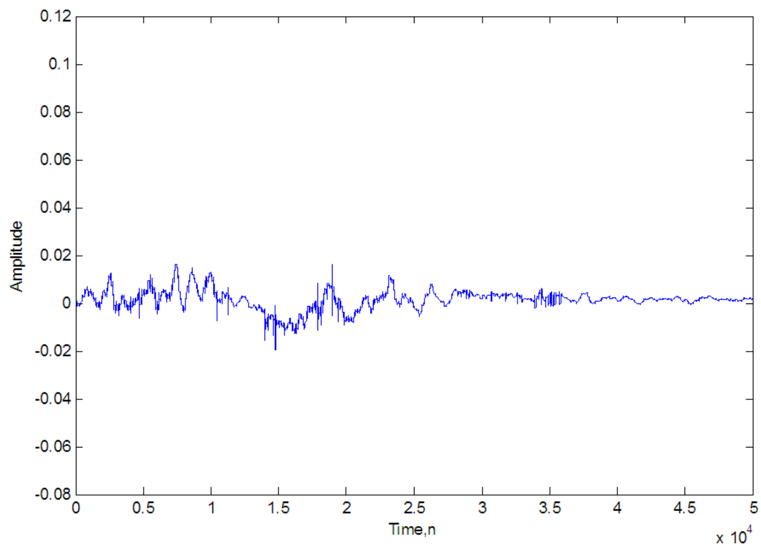

Figure 7. VAG signals from a subject with degenerative knee joint pathology

signal continues to interfere with the VAG signal. However, with the signal processing scheme developed in this study, the EMD will decompose the acquired signal into a collection of intrinsic mode functions (IMF). The IMF is a kind of complete, adaptive and almost orthogonal representation of the analyzed signal. Since the IMF is almost a mono-component, it can determine all the instantaneous frequencies from the nonlinear or non-stationary signal; see Figure 8. The sifting process first identifies and removes the components with the highest frequencies, then does the same for lower frequencies down to the lowest trends, as shown in Figures 8 (C1) to (C11). However, in the present form, these signals provide insight into the pathological condition of the knee joint. Thus, they are transformed into a time-frequency figure by the Hilbert transform technique. When a joint moves, the tendon's position changes and moves slightly out of place. We may hear a snapping sound as the tendon returns to its original position. In addition, ligaments may tighten as we move our joints. This commonly occurs in our knee or ankle, and can make a cracking sound or vibration, with the vibration at about 2 seconds, as shown in Figure

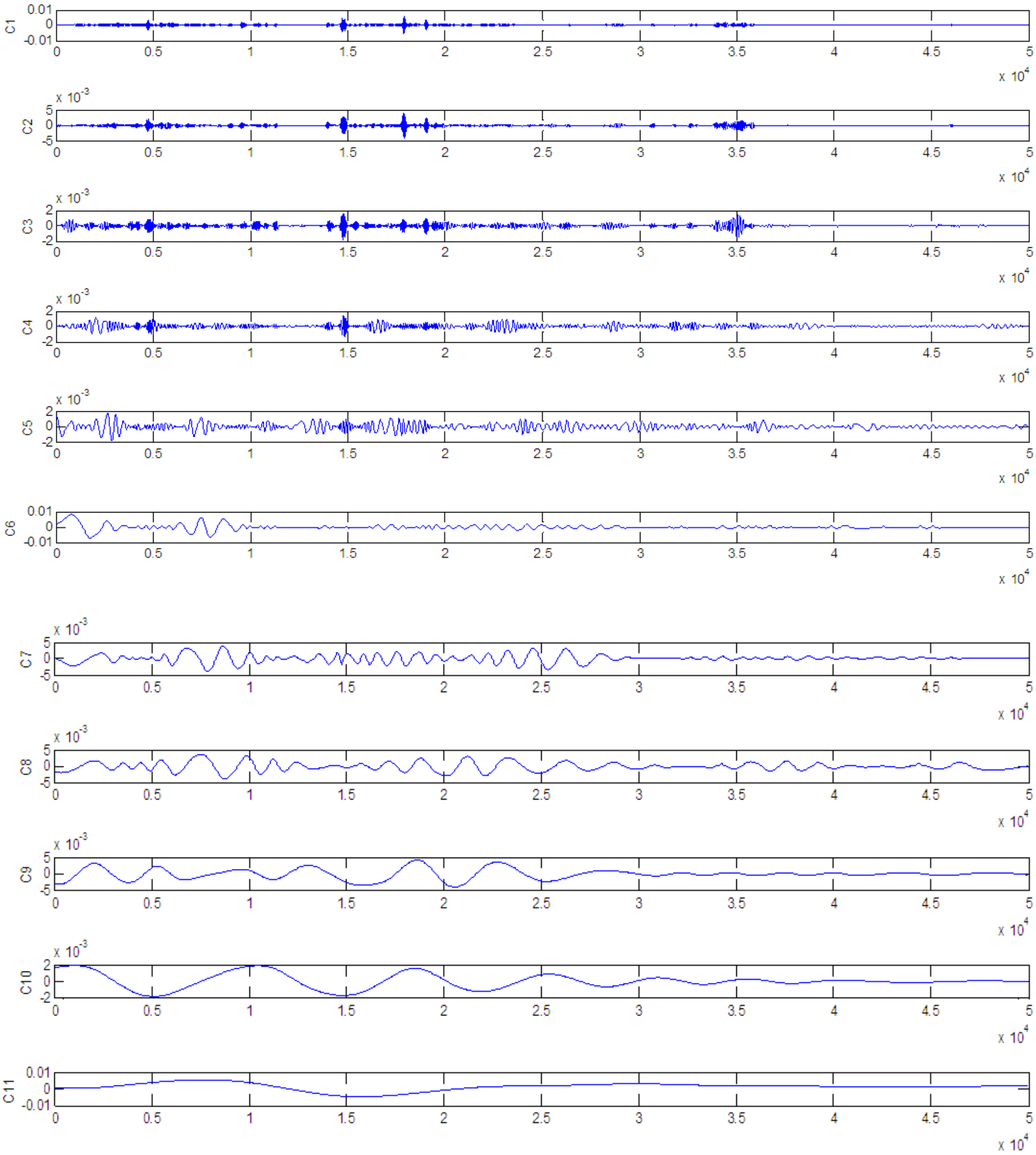

FIGURE 8. VAG signals from a subject with degenerative knee joint pathology

3. C1 indicates the noise signal (cracking vibration), (C5) to (C11) encompass all signals induced by muscle contraction, including muscle activity and muscle tremors, while (C2) to (C4) indicate the VAG signals. The VAG signal lasts approximately 1-7 seconds. The VAG and noise signals can now be clearly identified. The results show the high frequency signals processed by EMD at C1. The signals (C2) to (C4) are transformed into time-frequency by HHT as shown in Figure 9. High-energy VAG signals of 0.5-7 seconds are indicative of degenerative knee joint pathology. Observations are made during movement from a standing to squatting position within a 10-second period. The VAG friction signals from the movement of the joint are shown. The degenerative knee joint pathology can be confirmed from the high energy of the observed signal.

The results confirm that the HHT scheme can successfully distinguish knee signals, thereby enabling medical staff to better monitor degenerative knee joint pathology.

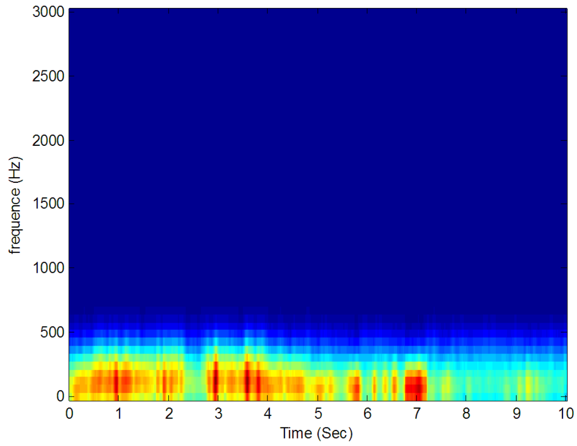

Figure 9. Time-frequency analysis of VAG signals from a subject with degenerative knee joint pathology (C2 to C4)

5. **Conclusion and Discussion.** This novel approach can separate noise from VAG signals to enhance feature extraction and identify problems. Since VAG applications require the use of algorithms with a rapid convergence speed, EMD is the most suitable for processing VAG signals. The EMD and time-frequency analysis scheme presented in this study makes a significant contribution to the detection and diagnosis of VAG signals and are intended to pave the way toward the development of an enhanced non-invasive technique for monitoring knee joint health. We improve the ability of the physician to detect pathology in the knee joint. The primary analytical methods are EMD and the Hilbert spectrum.

In comparison with the results reported in previous studies [2,28-30] on the analysis of VAG signals, the results obtained in the present study are important. The proposed method, derived from the VAG signals with no segmentation and no additional clinical information, have provided screening accuracies comparable with or better than those obtained with more sophisticated methods [2,28-30]. Krishnan et al. [2] used the matching pursuit time-frequency distribution (TFD), a non-stationary signal analysis tool, to avoid segmentation and joint angle estimation. The best normal versus abnormal classification accuracy achieved was 68.9%, as evaluated by TFD. Rangayyan et al. [28] derived dominant poles and cepstral coefficients using logistic regression analysis from CC-LRA models of adaptively segmented VAG signals using the same database as above. The cepstral coefficients appeared to be the best discriminant features, providing a classification accuracy of 75.6%, as evaluated by CC-LRA. Krishnan et al. [29] derived autoregressive (AR) coefficients from VAG signal segments and tested the methods with a database of VAG signals of 90 subjects (51 normal subjects and 39 abnormal subjects); the methods provided a classification accuracy of 68.9% using logistic regression analysis (AR-LRA). Recently, Umapathy and Krishnan [30] applied wavelet packet decomposition and a modified local discriminant based algorithm (WD-LDA) to the 89 VAG signals, as in the present work (51 normal subjects and 38 abnormal subjects), and achieved a classification accuracy of 76.4% using linear discriminant analysis (WD-LDA). Table 1 shows the comparison results of the classification accuracy for different feature extraction and pattern classification methods. The proposed approach provides a classification accuracy of 85%. The results confirm that the proposed scheme can successfully extract target signals from mixed signals, thereby enabling medical staff to better monitor degenerative knee joints.

TABLE 1. Comparison of the classification accuracies using different feature extractions and pattern classification methods [27]

Method	Subject number	Diagnosed results		Average accuracy (%)
		Normal	Abnormal	
TFD [2]	Normal (51)	40	11	68.9
	Abnormal (39)	17	22	
CC-LRA [28]	Normal (51)	N/A	N/A	75.6
	Abnormal (39)	N/A	N/A	
AR-LRA [29]	Normal (51)	N/A	N/A	68.9
	Abnormal (39)	N/A	N/A	
WD-LDA [30]	Normal (51)	38	13	76.4
	Abnormal (38)	8	30	
The proposed EMD	Normal (12)	10	2	85.3
	Abnormal (23)	2	21	

Further detailed studies of knee joint disorder monitoring must be carried out with a large number of patients. We are also conducting further investigations of more advanced methods for feature selection, nonlinear pattern classification, and the optimization of the parameters of the classifier.

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