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Saif Nalband
DY Patil International University


Valliappan Ca
Indian Institute of Science


A Amalin Prince
BITS Pilani, K K Birla Goa


Anita Agrawal
BITS Pilani, K K Birla Goa

Feature Extraction and Classification of Knee Joint Disorders Using Hilbert Huang Transform

Saif Nalband, C.A. Valliappan, Raag Gupta A. Amalin Prince* and Anita Agrawal
Department of Electrical and Electronics Engineering
Birla Institute of Technology and Science, Pilani
KK Birla Goa Campus, Goa-403726, India
Email: *amalinprince@gmail.com, Ph No:+91 832-2580155

***Abstract*—Non-invasive investigation methods along with computer based exploration of vibroarthrography (VAG) signals can contribute compiling indication of human knee-joint deformity. The VAG signals are characterized as non-stationary and aperiodic in nature. As a result, feature extraction technique is challenging for researchers. This paper proposes analysis of VAG signal using Hilbert-Huang transform (HHT). The ensemble empirical mode decomposition (EEMD) decomposes raw VAG signal individual characteristic scales known as intrinsic mode function (IMF). The analytical signal representation of IMFs is attained by implementing Hilbert transform on IMFs. In the *z-plane*, the fundamental analytic IMFs are plotted which are circular in geometry. Area of these circular curves in the *z-plane* are computed using the central tendency measure (CTM) and chosen as feature in differentiating between healthy and unhealthy VAG signals. A pattern analysis is carried out using least square support vector machine (LS-SVM) which gives a classification accuracy of 83.12% and area under receiver operating characteristic of 0.6708 were obtained.**

Keywords - Vibroarthrography, Hilbert-Huang transform, Ensemble Empirical Mode Decomposition, Central Tendency Measure, Least square support vector machine.

I. Introduction

Non-invasive methods in the form of vibroarthographic (VAG) signals provide an effective mode of diagnosing knee-joint disorders [1]. Though other methods in form CT scans, MRI are available but they are quite expensive and are not suitable for routine check up. But importantly, they lack in providing dynamics details of knee joint disorders [1]. Hence, VAG signals provides an effective and low cost alternative solution in diagnosing knee-joint disorders. VAG signals are the acoustic sound emitted from the mid patella of a human leg. The VAG signals signify the pathological conditions of knee-joint disorders. These conditions could be a decrease in muscles strength, degeneration of the cartilages, loss of elasticity, capsular fibrosis and chondromalacia of the patella etc.

VAG signals are non-stationary and non-linear in nature. As a result, traditional signal processing techniques are inadequate in providing effective inference about the diagnosis of knee-joint disorders [2]. Hence, various studies have been carried out by using advance signal processing. Most of the research studied are carried out in distinguishing healthy and unhealthy VAG signals. Nalband *et al.* had used wavelet decomposition based feature extraction technique [3]. Recently, empirical mode decomposition (EMD) which was proposed by Huang, has widely used for analysis of non-stationary and non-linear signals especially biomedical signals [4]. But considering the drawback of mode mixing observed in EMD, Huang *et al.* proposed ensemble empirical mode decomposition (EEMD) where a Gaussian noise is added [5]. Wu *et al.* applied on VAG signal as an essential preprocessing technique for removing noise and artifacts [6]. Our primary objective would be diagnosing knee joint disorder in terms of healthy and unhealthy conditions of subjects.

The HHT consists of two parts. First, obtaining the intrinsic mode functions (IMFs) by applying EEMD and second, taking Hilbert transform for respective IMFs [4]. The analytical representation of individual IMFs are plotted in *z-plane* which are circular in shape. Each analytical representation of the IMF has its own and unique center. Feature extraction is been carried out by computing the area of the circle in the *z-plane* using central tendency measurement (CTM) for each IMF. The extracted feature would be used in order to differentiate unhealthy VAG signals from the healthy VAG signals. Finally, extracted feature obtained from different IMFs are used as the input vector for the classifier. In the proposed work, LS-SVM with radial basis function (RBF) as kernel function is used to classify healthy and unhealthy VAG signals since, LS-SVM has been widely accessed for various biomedical signal [7].

The present study has been tabulated in categorical sections. Details regarding the proposed methodology have been explained in section 2. Section 3 covers the results and discussion related to methodology and conclusion is presented in the section 4.

II. Methodology

A. Hilbert-Huang Transform

N.E Huang *et al.* has proposed HHT method for effectively analyzing the non-stationary and aperiodic signals [4]. It consist of two part: Obtaining IMFs using EEMD and then computing time-frequency distribution by applying Hilbert transform on IMFs. The most important part of HHT is decomposing the signal into finite number of distinct oscillations called IMFs.

1) Ensemble Empirical Mode Decomposition (EEMD): N.E Huang proposed EEMD which is an upgraded version of empirical mode decomposition (EMD) [4]. The major drawback of the EMD are the frequently occurring of mode mixing [5]. IMF either consist of extensively disparate scales or a signal of alike scale residing in different IMF components. In this method, white noise is added to the input signal. IMFs are obtained by computing EMD to the designated number of ensembles. The mean of these ensembles IMFs are used to compute the required IMFs. The configuration of the ensemble number and the amplitude of added Gaussian white noise determines the efficiency of EEMD.

2) Hilbert Spectral Analysis: Inorder to obtain the analytical representation of the signal, instantaneous phase and amplitudes is computed by applying Hilbert transform to each IMF obtained from EEMD. For an arbitrary time series data *u(t)*, its Hilbert transform *v(t)* as

$$v(t) = \frac{1}{\pi} C.V \int_{\infty}^{\infty} \frac{v(\tau)}{(t-\tau)} d\tau \tag{1}$$

Where $C.V$ shows the principal of Cauchy value. The analytic signal of *w(t)* is defined as follows:

$$w(t) = u(t) + jv(t) = B(t)e^{j\phi(t)} \tag{2}$$

The amplitude *B(t)* and instantaneous phase $\phi(t)$ are defined as

$$B(t) = \sqrt{x(t)^2 + y(t)^2} \tag{3}$$

$$\phi(t) = arctan\frac{v(t)}{u(t)} \tag{4}$$

The instantaneous frequency $\omega(t)$ is obtained by differentiation:

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

B. Feature Extraction

1) Central Tendency Measurement (CTM): CTM is a method used to sum up the observable data in the plots [8]. CTM is used to quantify the variability of the signal. CTM is computed by initially finding the circular region of particular radius *'r'*. Then, dividing the number of data points existing within that circular region by the total number of data points. In the analytical representation of IMFs, the real part of the signal is plotted against the imaginary part of the signal in *z-plane*. CTM is exploited to compute the circular region, which is the area of the analytic representation of IMF in the *z-plane*. For computing CTM, let *r* the radius of the central area and *N* be the total number of points. Then, the CTM for analytic signal *w[t]* is given as

$$CTM = \frac{\sum_{n=1}^{N} \triangle(d_i)}{N} \tag{6}$$

$$\triangle(d_i) = \begin{cases} 1 & if \sqrt{real\ (w[t])^2 + imag\ (w[t])^2}\ < \ r \\ 0 & otherwise \end{cases} \tag{7}$$

C. Classification

1) LS-SVM: Support vector machine(SVM) is supervised machine learning algorithm which has been broadly used in non-linear estimation and pattern analysis [9]. It is based on principles of structural risk minimization and learning theory. SVM requires large computation and constrained optimization programming and therefore it creates unequal constraint. LS-SVM overcomes these drawbacks by obtaining well defined solution by solving linear equations and having equal constraints. It is a class of kernel-based learning methods [9]. In this study we have used radial basis function (RBF) kernel for classification.

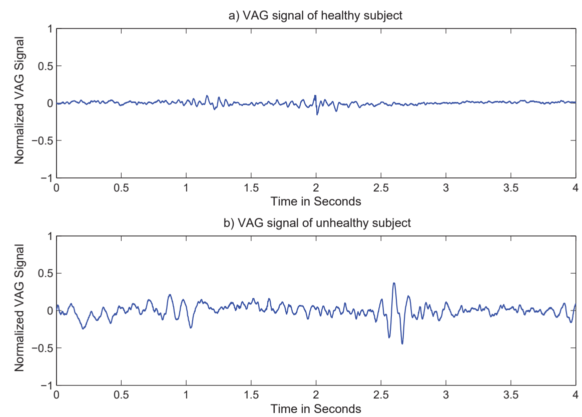

Fig. 1: Sample VAG signal of (a) healthy subject (b) unhealthy subject

III. Results and Discussion

A. Dataset

In the present study, the proposed methodology was implemented on the dataset acquired by the team of Rangayyan, University of Calgary, Calgary, AB, Canada [10] . The dataset consisted of 51 healthy and 38 unhealthy subjects, a total of 89 VAG knee joint signals were acquired. The 38 unhealthy subjects were arthroscopically identified. The unhealthy subjects consisted of having deformities in chondromalacia of distinct category at anterior cruciate ligament, patella, meniscal tear and tibial chondromalacia injuries. An example of VAG signal consisting of a healthy and unhealthy subject is observed in figure 1 (a) and figure 1 (b) respectively. The figure illustrates that subjects suffering from deformities exhibit larger variation in the time domain as compared to healthy one.

B. Results

This work has been implemented in MATLAB 2014a, which includes feature extraction and classification technique. The parameters for EEMD has been carried out as suggested by Wu [6]. The ensemble number was set as N = 100. This was the mean of IMFs obtained from 100 trials of EEMD and 0.2 times the standard deviation (SD) of raw VAG signal was fixed as added noise. EEMD method decomposes the raw VAG

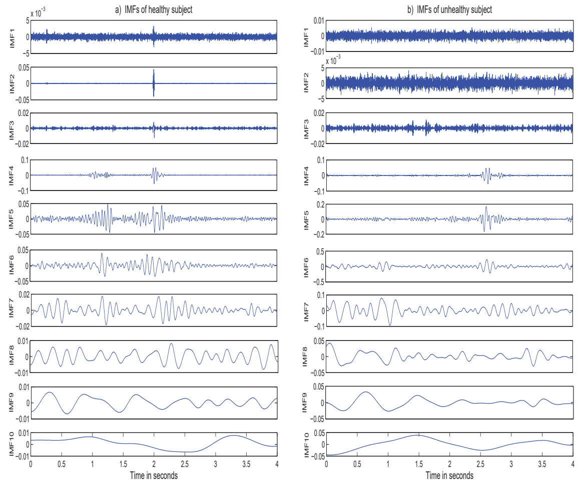

Fig. 2: IMFs of (a) healthy subject (b) unhealthy subject

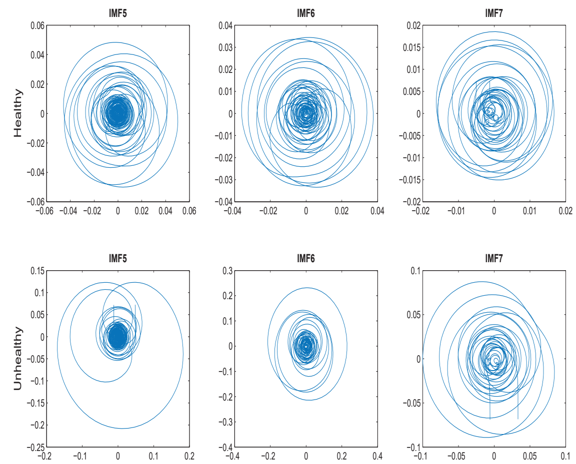

Fig. 4: Analytical representation of IMF5, IMF6 & IMF7 for healthy and unhealthy subject

signals into distinct IMFs, as shown in figure 2. Figure 2 (a) and (b) shows the IMFs obtained from healthy and unhealthy subject respectively. The high-frequency oscillation can be observed in IMF1 - IMF3 while the low-frequency oscillations are observed in IMF4 - IMF12s. The flat envelopes observed in IMF1 and IMF3 are high-frequency components and thereby don't contribute in the pathological conditions of knee-joint disorders [6]. The selection of the fundamental IMFs were carried out using detrended fluctuation analysis (DFA) as per work carried out by Wu. Work concluded by Nalband *et al.* suggested that IMF5, IMF6 & IMF7 are considered as fundamental IMFs of VAG signals [11]. Hilbert transform

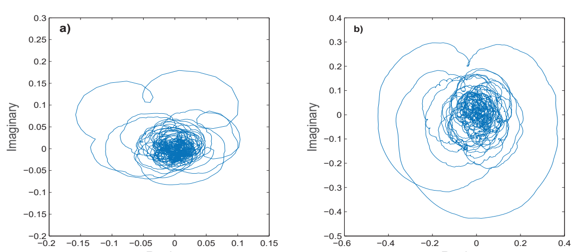

Fig. 3: Analytical representation of raw VAG signal (a) healthy subject (b) unhealthy subject

is applied to the raw VAG signal and its IMFs in order to represent it in analytical form. It is obtained by plotting the imaginary part of the signal against the real part of the signal in a *z-plane*. Figure 3 and 4 shows the analytical representation of raw VAG and its IMFs respectively. From figure 3 it can be observed that analytical representation of healthy and unhealthy VAG signal do not possess any geometrical shape. As a result it is quite difficult to analyze the raw VAG signal. Whereas in figure 4, prominent circular curves are observed for IMFs. These circular curves possess proper individual center for a particular circular curve. It can be also observed that there are many circular curves having respective centers. This might indicate the presence of distinct frequency components in the VAG signal. Considering these observed discrimination, we explore to extract the uniqueness described in analytical representation of IMFs among healthy and unhealthy subjects.

In order to extract the feature from the analytical representation of IMFs, the radius of the circular curve of the IMFs in the *z-plane* has been identified. Then, the area of the IMFs in the *z-plane* is computed with 95% CTM utilization of data points. That is, the number of data points enclosed within the area of the circle is computed. This provides a significant difference in surface area between unhealthy and healthy VAG signals. The area parameter as a feature has been computed for 89 VAG signals. The computed area for healthy subjects were found to be smaller in comparison with the area computed for unhealthy subjects. The larger area could signify the presence of high amplitude for unhealthy subjects. Computed area is quite high for IMF5, IMF6 and IMF7 of unhealthy subjects as compared to healthy subjects.

The extracted features are given as input to LS-SVM classifier. The estimated area of IMFs (IMF5, IMF6 and IMF7) from the two groups area used as feature. The individual feature extracted from IMFs and combined features from IMFs as a vector are given as input to LS-SVM. Trail and error approach has been applied in order to select the effective kernel specification of LS-SVM. RBF was used as kernel function for LS-SVM. Moreover, to avoid over-fitting, regularization constant was chosen appropriately. The parameters used to evaluate the performance of the classifier are sensitivity, accuracy, specificity and area under the receiver operating curve classifier (AUC). VAG signals of healthy subjects were marked as '0' while VAG signals of unhealthy subjects were marked as '1' in the target set. 10 fold cross-validation was carried out in order to build an effective classifier model. Table 1 gives

TABLE I: Classification Results

Parameters	IMF5	IMF6	IMF7	IMF5 IMF6 IMF7
Sensitivity	0.8909	0.9259	0.9272	0.9807
Specificity	0.6471	0.6571	0.4411	0.6216
Accuracy	0.7977	0.8202	0.7415	0.8314
AUC	0.6455	0.6205	0.6692	0.6708
MCC	0.5629	0.6195	0.4368	0.6689

the complete description about the performance of LS-SVM classifier. From table 1 it can be observed that the accuracy of combined vector consisting of IMF5, IMF6 & IMF7 is highest (83.14%) in comparison with other individual IMF5, IMF6 & IMF7. Other parameters such as sensitivity and Matthews correlation coefficient (MCC) are quite high for combined vector of IMF5, IMF6 & IMF7 as compared to other individual IMFs.

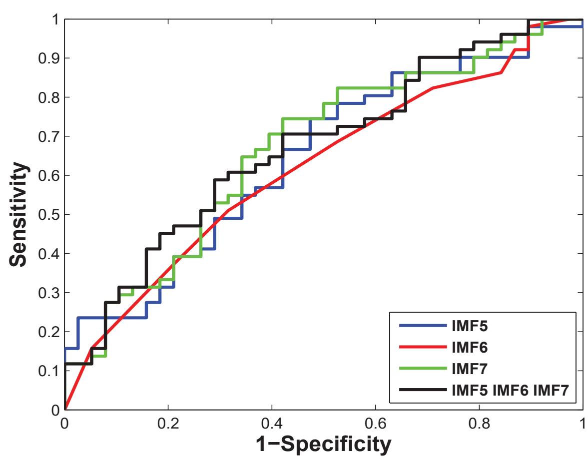

Fig. 5: Receiver operating curve plot for different IMFs

AUC is an efficient method of correlating the performance of classifier. It measures the effectiveness of classifier model based on how substantially the model is able to discriminate among the diagnostic class. A good classification performance is characterized by larger AUC. Any random discrimination would yield the points along the diagonal line from the left bottom to the top right corners and would generate an area of 0.5 under the curve. An ideal performance of classification model would yield points in the upper left corner of the ROC space and generate unity area curve. Figure 5 depicts the AUC of combined vector IMFs, IMF5, IMF6 & IMF7. From figure, it can be observed that AUC for combined IMFs (0.6708) was highest among other IMFs and thus indicate better classification model. Hence using area parameter of combined vector of IMF5, IMF6 and IMF7, LS-SVM was able to distinguish among between unhealthy and healthy VAG signals more accurately.

IV. Conclusion

In this paper, we inspect the analysis of VAG signal using HHT in diagnosing knee joint disorder. EEMD was applied on raw VAG signal to decompose into intrinsic mode functions (IMFs) and fundamental IMFs inferring information regarding knee-joint disorder were considered for further analysis. Hilbert transform was applied and real part of signal were plotted against imaginary part in complex domain to represent the analytical signal. CTM was implemented to measure the area bounded in *z-plane* as feature extraction. Prominent discriminate variations among fundamental IMFs were observed between healthy and unhealthy subjects. Pattern analysis was accomplished using LS-SVM and their performance was evaluated. Results inferred that combined vector of IMF5, IMF6 and IMF7 gave the highest accuracy of 83.14% and area under the ROC was 0.6708. Further analysis can be carried out in establishing the extent of pathological conditions of knee joint deformities.

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