Discrimination of Normal and Abnormal Knee Joint VAG Signals Using EMD

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Abstract. Knee is the most intricate joints in the body. This joint faces immense reaction forces during daily routine work that may vary around three to seven times of the body weight. These high reaction forces may convert small malfunctioning into severe conditions and can be avoided by early detection of knee health conditions. Vibroarthrography (VAG) is the most emerging tool to detect knee joint abnormalities. In this paper, an application of the empirical mode decomposition (EMD) is presented to discriminate between normal and abnormal knee joint VAG signals. EMD is employed to decompose VAG signals into several intrinsic mode functions (IMFs). Twelve different non-linear, entropy, and shape-based features are elecited from each IMF provided by EMD. Kruskal-Wallis (K-W) test is employed to identify the best suitable features to discriminate between normal and knee joint affected VAG signals. The simulation results with the publicly available VAG database are included to show the effectiveness of the presented work.

Keywords: Knee abnormalities · Vibroarthrography · Empirical mode decomposition · Kruskal-Wallis test.

1 INTRODUCTION

Knee joint is one of the most commonly injured and complex joints in the human body. It joins the thigh bone (known as Femur) and lower leg bone (known as Tibia). The knee joint is a sort of hinge joint, that allows bending and straightening movements. This joint has to face an enormous reaction force that is nearly equal to the weight of the human body [1]. The degradation of these joints is being common in elderly people [2]. Osteoarthritis is the most common knee joint complication caused by articular cartilage degeneration. According to WHO statics, symptomatic osteoarthritis affects 9.6% of males and 18.0% of women in the world [2]. In case of severe knee complications, the patient needs to go for a knee replacement, which is an invasive technique that includes the removal of dented and worn out surface of knee joint [2]. In the knee replacement technique, a surgeon has to remove and replace the damaged and worn-out part with components made up of plastic and metals. This procedure sounds expensive and complex too. Therefore, an easier and more economical approach is required for the timely detection of knee joint abnormalities. Various traditional techniques like computer tomography (CT), X-Ray imaging, and magnetic resonance imaging (MRI), are available for the screening of knee-related abnormalities, but these traditional techniques are unable to identify the minute changes that come in the early stage [3]. Computer aided diagnosis is the need of the hours [19, 20]. Vibroarthrography (VAG) is the most emerging tool to diagnose various knee-related disorders [3]. VAG signals are generated from the movements of the femur and tibia and can capture the knee joint abnormalities in a better way [4]. VAG signals are generated around the mid-patella region and measured using an accelerometer when the leg is moving. The nature of VAG signal is nonlinear and non-stationary, and can not be examined with the help of a naive signal processing technique. Some of the salient features of the VAG signal are listed below: [5].

1. VAG signals are non-stationary in nature because the quality of joint surfaces in contact may vary from one angular position (point in time) to a next during joint articulation.
2. Normal and aberrant VAG signals have varied amplitude and frequency-based properties.
3. The friction between the femoral condyle and the layer above the patella causes an aggregation of many vibrations as the leg moves, the potential of the VAG signal becoming a multi-component signal is also high.
4. The noise may be introduced to the signal during data recording, a priori assessment of the signal to noise ratio (SNR) of VAG signals is difficult.

In the literature, various researchers proposed different computer-aided discrimination systems to distinguish between normal and knee-joint affected VAG signals. For example, authors in [6] utilized the wavelet decomposition method to decompose VAG signals into several wavelet coefficients. For the categorization of normal and pathological VAG signals, Ranggayyan and Wu [7] derived several entropy-based characteristics. In another study, the same group [8] extracted fractal dimension-based features from the VAG signals. Time-frequency distribution (TFD) of input VAG signal has been scrutinized using double-density dual-tree complex wavelet transform (DTCWT) by Sharma *et al.* [2]. The short-time Fourier transform (STFT) approach has been employed to fetch statistical characteristic features from VAG signals by Mrunal *et al.* [9]. For reliable identification of knee joint pathologies with minimal time, a new approach is introduced in [10]. TQWT has been introduced to deconstruct the VAG signals into subband signals, and entropy information is retrieved from each subband by Mascarenhas *et al.* in [11]. Various other machine learning-based approaches are described in the literature. The selection of more appropriate features for a machine learning classifier is difficult and time-consuming. Therefore, this study presents automated discrimination of normal and knee joint affected VAG Signals by utilizing empirical mode decomposition (EMD) and Kruskal Wallis (KW) test. EMD is applied to disintegrate VAG signals into several intrinsic mode functions (IMFs). Twelve different non-linear, entropy, and shape-based features are elicited from the IMFs. Kruskal-Wallis (K-W) test is used to discriminate the best suitable features to identify normal and knee joint affected VAG signals. This remainder of this article is assemble as follows: Section II presents the information about the data set, decomposition technique, features extraction. Section III contains the findings of this study along with a brief discussion. Section IV depicts the conclusion of the work.

2 Material and Method

The layered diagram of the presented system is shown in Fig. 1.

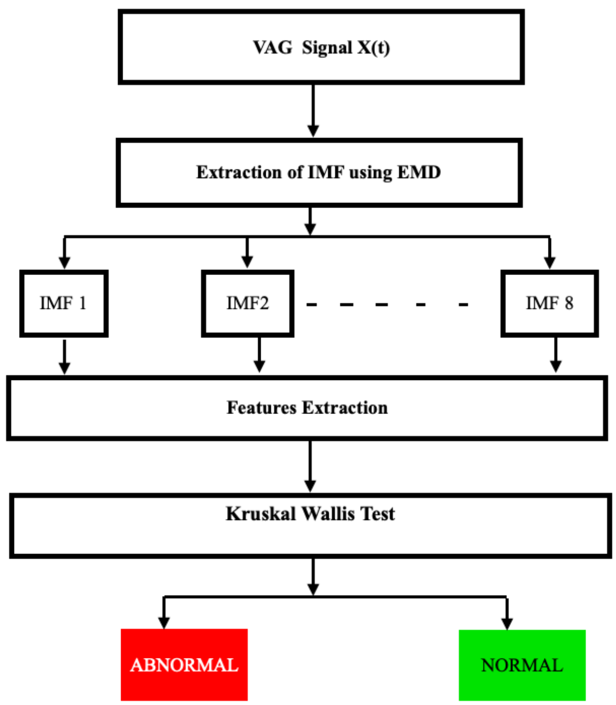

Fig. 1. Layered diagram of the presented system.

2.1 Dataset

A publicly available VAG data set is used to validate this study. The data set is obtained from 51 normal and 38 abnormal volunteers [12]. To record the VAG signal each volunteer was said to sit on a bench, and an accelerometer setup was utilized to acquire VAG signals. The volunteers were told to swing their leg from extension to flexion and back to an extension, which means from zero degrees to one hundred forty degrees and back to zero degrees again, such that the movement process completes in $4-sec$ [13]. The data set is recorded with a sampling frequency of 2KHz. Before digitizing the signal, it was filtered and amplified. This process had been done in the laboratory of the University of Calgary, Canada. The details of the data can be found in [12]. VAG signals of normal and unhealthy subjects are represented in Figure 2.

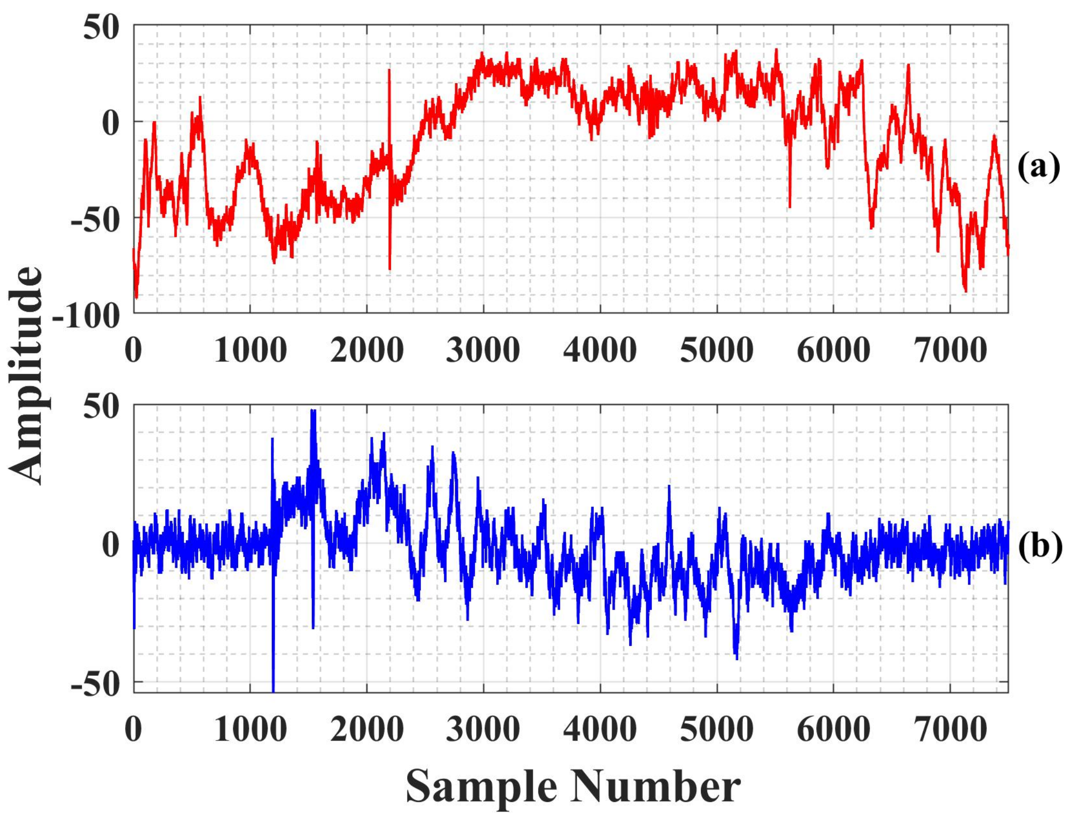

Fig. 2. Typical VAG signals of (a) abnormal (b) Normal subject

2.2 Emperical Mode Decomposition (EMD)

EMD is a data-dependable and adaptable approach. The EMD method does not involve any prerequisites about the signal's stationarity or linearity. The essence of the EMD is to decompose non linear and non stationary VAG signals $z(t)$ into various intrinsic mode functions (IMFs) [14, 15]. Each IMFs must have to satisfy the following criteria: 1) the total of maxima (max) or minima (min) and the number of zero crossings should be the same or differ by no more than one. 2) the average scores of the envelope formed by the local maxima and the envelope provided by the local minima is zero at any moment in time.

The EMD procedure for an input VAG signal $z(t)$ can be summed up as follows [14]:

1. Identify max and min of the input VAG signal $z(t)$.
2. With the help of cubic line interpolation connect the local max and local min to obtain upper and lower envelope $V_u(t)$ and $V_l(t)$ respectively.
3. Estimate the local mean as $m_e(t)$

$$[m_e(t) = [V_u(t) + V_l(t)]/2] \tag{1}$$

4. Extracts the details.

$$h_1(t) = z(t) - m_e(t) \tag{2}$$

5. Decide whether $h_1(t)$ belongs to IMF, with the help of previously discussed two conditions.
6. Repeat the process from 1 to 4 until the first IMF is obtained.

As first IMF is extracted, interpret $p_1(t) = h_1(t)$, is the lower temporal scale in $z(t)$. To obtain the remaining IMFs, produce residue $r_1(t) = z(t) - p_1(t)$, which is processed as a new signal. Repeat all the steps over the new signal until the final residue is obtained in the form of nearly constant or from which no more IMFs can be evoked. The input VAG signal $z(t)$ can be symbolize as at the end of the decomposition.

$$z(t) = \sum_{n=1}^{N} p_n(t) + res_N(t) \tag{3}$$

where, N represents the total generated IMFs, $p_n(t)$ represents the n^{th} IMF, and $res_N(t)$ denotes the residue term. Each IMF obtained from Eq. 3 is posses of consequential local frequency, different IMFs never possess the same frequency at the same time. The IMFs obtained from decomposition of normal and problematic VAG signals are shown in Fig. 3.

2.3 Features extraction

To analyze the graphical variation of each IMF, and to discriminate between normal and abnormal VAG signals. We have extracted twelve different features, defined as follows [16, 17]:

- **Mean (M):-** The mean is the average value of dataset. Computed as

$$mean = \frac{1}{n} \sum_{i=1}^{(N-1)} x_i \tag{4}$$

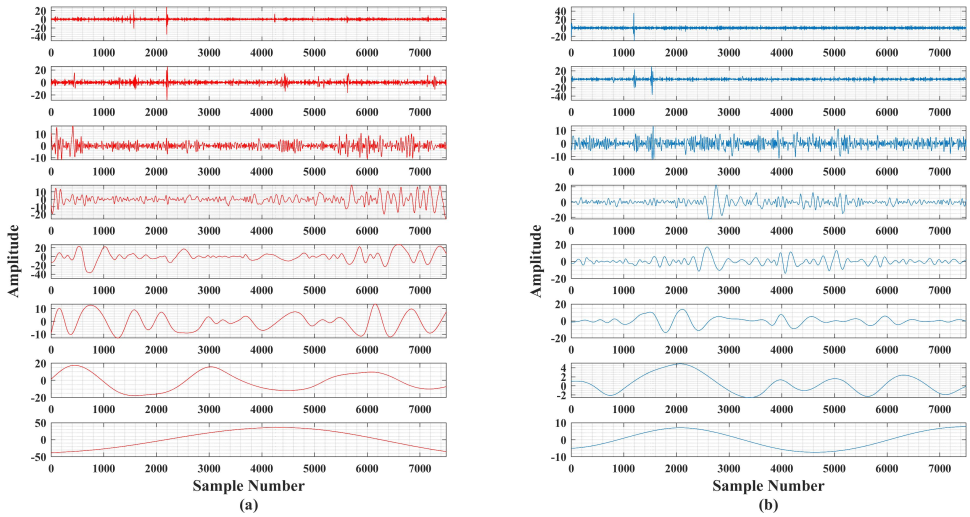

Fig. 3. Imfs of (a) Abnormal (b) Normal knee joint VAG signal

- **Root Mean Square (RMS):-** It is also known as quadratic mean and is termed as the square root of the mean square. It is expressed as,

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {x_i}^2} \tag{5}$$

- **Standard Deviation (σ) :-** It is the estimation of variations of a set values. Higher the value of σ indicates values spread over a wider range and value close to mean for lower value of σ. This is expressed as,

$$\sigma = \sqrt{\frac{1}{(n-1)} \times \sum_{i=1}^{n} (x_i - x_m)^2} \tag{6}$$

- **Shanon Entropy (ShanEn) :-** It is the average amount of information in x. It is given as

$$H_{ShanEn}(x) = -\sum_{i=0}^{(N-1)} (s_i(x))^2 (log_2(s_i(x)))^2 \tag{7}$$

- **Log Energy Entropy (LogEn) :-** The expression of LogEn is given as,

$$H_{LogEn}(x) = -\sum_{i=0}^{(N-1)} (log_2(p_i(x)))^2 \tag{8}$$

The more regularity in the VAG signal will result in a lesser value of entropy.

– **Threshold Entropy (TE) :-** Entropy thresholding is a method of selecting an optimal threshold value for a signal by selecting the data intensity from a signal histogram that has the highest entropy of the total signal.
– **Sure Entropy (SE) :-** SE is depends on the Stein's unbiased risk estimator. It's a technique for measuring aspects of information in order to accurately describe a signal.
– **Norm Entropy (NE) :-** It is evaluated as

$$\frac{\sum_{i,j=1}^{N} |t(i,j)|^p}{N} \tag{9}$$

where p indicates the power and it must reside in the range of 1 to 2.
– **Permutation Entropy (PE) :-** Permutation entropy is an adaptable time-series technique that gives a quantifiable quantification of the complexity of a dynamic system.
– **Skewness (Sk) :-** The skewness deals with the symmetry of distribution heaviness of the distribution of the tail. Expression for the evaluation of Sk is given by

$$S_k = (Mean - Mode)/StandardDeviation \tag{10}$$

– **Kurtosis (K) :-** Kurtosis gives facts about the flatness of the curve. The expression of kurtosis is given as

$$\beta_2 = \mu_4/\mu_2^2 \tag{11}$$

where, β_2 belongs to Kurtosis, μ_4 belongs to the fourth central moment, μ_2 belongs to the second central moment of distribution.
– **Simple squared integral (SSI) :-** It expresses the energy contain of VAG signals. It is given as,

$$SSI = \sum_{i=1}^{n} (|x_i^2|) \tag{12}$$

2.4 Kruskal-Walis (K-W) Test

The K-W test is a more generalized form of the two-class Wilcoxon rank test and one-way analysis of variance (ANOVA) test. ANOVA is a parametric test that can be applied to a normally distributed continuous variable. Whereas, K-W is a non-parametric statistical test, that compares the contretemps between two or more distinguishable sampled classes on a single, infrequently dispersed continuous variable. K-W test is commonly used to determine when two or more classes vary on a single variable that fails to meet the uniformity constraints of ANOVA test [18, 17].

3 Results And Discussion

The selection of most suitable feature to discriminate between normal and abnormal VAG signals is a time-consuming task. Therefore, in this work input VAG signal is disintegrated into several IMFs by applying EMD algorithm. Twelve different entropy-based and statistical features are evaluated from each IMF. K-W test is used to discriminate the most suitable feature. The probabilistic values for entropy-based features are depicted in Table 1. It is obvious from the Table 1,

Table 1. Probabilistic values for entropy-based features

Imf No.	ShanEn	LogEn	NE	TE	PE	SrE
Imf-1	0.0065	2×10^{-5}	0.0002	0.0002	0.0449	1.28×10^{-5}
Imf-2	0.0573	0.0472	0.0377	0.0001	0.7553	0.0407
Imf-3	0.868	0.2531	0.7084	0.0039	0.4001	0.2531
Imf-4	0.4298	0.5061	0.3136	0.4703	0.0018	0.3943
Imf-5	0.4671	0.2707	0.3237	0.0428	0.0016	0.1735
Imf-6	0.9255	0.8926	0.9503	0.3448	0.2619	0.9255
Imf-7	0.7711	0.868	0.9669	0.8762	0.7474	0.9388
Imf-8	0.9751	0.5962	0.8031	0.589	0.7632	0.8926

all entropy-based features are suitable for IMF-1. NE, TE, and SrE are suitable for IMF-2. Only TE is suitable for IMF-3. Only PE is suitable for IMF-4. PE and TE are suitable for IMF-5. No any entropy-based features are appropriate for the rest of the IMFs.
The probabilistic values for statistical-based features are mentioned in Table 2. It can be noted from Table 2, RMS, STD, SSI, and IVAG are suitable for IMF-1.

Table 2. Probabilistic values for statistical-based features

Imf No.	M	RMS	STD	Sk	K	SSI
Imf-1	0.28	0.0034	0.0034	0.4735	0.1941	0.004
Imf-2	0.5962	0.0496	0.0496	0.6327	0.3829	0.0521
Imf-3	0.1096	0.0981	0.0891	0.693	0.2619	0.9917
Imf-4	0.4059	0.4059	0.4059	0.5061	0.1836	0.3885
Imf-5	0.1941	0.4545	0.4482	0.0097	0.0865	0.442
Imf-6	0.6551	0.9586	0.9669	0.4735	0.6035	0.9751
Imf-7	0.3186	0.8598	0.8762	0.7791	0.6254	0.8031
Imf-8	0.0276	0.8597	0.8598	0.884	0.1487	0.868

RMS, STD, and IVAG are suitable for IMF-2. Mean is suitable for IMF-8. No any statistical-based features are suitable for the rest of the IMFs. This work has been simulated on the system having intel processor, 16GB RAM, 1TB hard drive, with the help of MATLAB software.

4 Conclusion

In this study, an application of EMD is explored to disintegrate between knee-joint affected and healthy control VAG signals. EMD is a non stationary signal processing technique that has been used for decomposing VAG signals into multiple IMFs. Twelve different features are elicited from each IMF. In order to find the most relevant features, a non-parametric K-W test is applied. It is concluded from this work entropy -based features are most suitable to distinguish between normal and knee joint affected VAG signals. The results suggested EMD and K-W test-based algorithm can be utilised to design a automated screening system for identifying knee joint diseases in a clinic. In the future, a suitable machine learning algorithm will be employed for automated classification of VAG signals.

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