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Analysis of Knee Joint Vibration Signals using Ensemble Empirical Mode Decomposition

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Abstract

Knee joint vibroarthrographic (VAG) signals acquired from extensive movements of the knee joints provide insight about the current pathological condition of the knee. VAG signals are non-stationary, aperiodic and non-linear in nature. This investigation has focussed on analyzing VAG signals using Ensemble Empirical Mode Decomposition (EEMD) and modeling a reconstructed signal using Detrended Fluctuation Analysis (DFA). In the proposed methodology, we have used the reconstructed signal and extracted entropy based measures as features for training semi-supervised learning classifier models. Features such as Tsallis entropy, Permutation entropy and Spectral entropy were extracted as a quantified measure of the complexity of the signals. These features were converted into training vectors for classification using Random Forest. This study has yielded an accuracy of 86.52% while classifying signals. The proposed work can be used in non-invasive pre-screening of knee related issues such as articular damages and chondromalacia patallae as this work could prove to be useful in classification of VAG signals into abnormal and normal sets.

Keywords: Ensemble Empirical Mode Decomposition; Knee Joint Vibration Signals; Permutation Entropy; Spectral Entropy; Random Forest Classifier; Tsallis Entropy.

1. Introduction

Articular cartilage damage is one of the most commonly occurring knee joint disorders, yet it is difficult to detect them as they are not usually accompanied by pain or swelling. Arthroscopy, an invasive diagnosis method, is used for detection of damage to the articular cartilage. Some non-invasive methods such as Magnetic Resonance Imaging (MRI) scans are used but they are both expensive and time consuming. X-rays help in detecting injuries to the bone and are certainly not used in diagnosing articular cartilages. These techniques are infeasible for regular use in outpatient clinics. A non-invasive and feasible diagnosis technique is required for detection of knee joint disorders in its early stages. Vibration signals obtained from the knee can be used for detection of articular cartilage damage. Knee joint vibration signals are obtained using an accelerometer placed at the mid platella position of the knee. These signals are also referred to as VibroArthrographic (VAG) signals. These signals can be used to design a computer-aided diagnosis system for non-invasive detection of knee joint disorders.

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VAG signal is a non-stationary, aperiodic and non-linear signal, just like other naturally occurring signals[1]. Tavathia *et al.* have used linear prediction methods[2] whereas Maussavi *et al.* have adaptively segmented the signal using auto regression for analysis of the signal[3]. Rangayyan *et al.* have used recursive least squares lattice algorithm for parametric representation and classification of VAG signals[1]. Correlations in time series of VAG signals have been computed using the power spectrum, which actually measures the frequency components present in the signal. Rangayyan *et al.* have used fractal analysis using power spectral analysis for analysis of VAG signal[4]. Nalband *et al.* have used Wavelet analysis for classification of VAG signals[5]. Wavelet analysis doesn't remove noise from the sub-bands of the decomposed signal. This could hamper the results obtained during feature extraction and classification of VAG signals.

Huang *et al.* proposed Empirical Mode Decomposition (EMD) for analysis of non-stationary and non-linear signals. Wu *et al.* have used EMD for detection of chrondomalacia patellae[6]. One of disadvantages of EMD is mode-mixing. Zhaohua Wu and Huang have used gaussian white noise to tackle the problem of mode-mixing and proposed EEMD[7]. In our investigations on VAG signals, we have used EEMD for decomposition of signals as it neither needs an apriori nor does it assume that the signals are stationary or linear. Golińska has used DFA to extract features for classification of ECG, EEG and EMG signals[8]. Wu's study models a reconstructed signal which is devoid of random noise and baseline wander[9]. This study uses the modeled reconstructed signal for extraction of features and screening of VAG signals. In this work, the reconstructed signal has been used to conduct a study using entropy based measures. Entropy based measures have been extracted for classification of other bio-medical signals[10,11]. In our exploration, we have extracted Tsallis entropy (TEn), Permutation entropy (PEn) and Spectral entropy (SpEn) measures for classification of VAG signals into two sets namely normal and abnormal. Nalband *et al.* have used Support Vector Machines (SVM) to classify VAG signals[5]. Mu *et al.* have used strict-2-surface proximal classifiers to screen VAG signals[12]. Our work has concentrated on using random forest classifier for classification of signals into normal set or abnormal set.

Section 2 describes the dataset from where signals were acquired for conducting simulations and it also describes the methods involved in the proposed methodology. Section 3 produces the results obtained from our work. Section 4 discusses the results obtained using our proposed methodology. Section 5 concludes the work by providing future aspects of this work.

2. Methods

2.1 Ensemble empirical mode decomposition

EEMD is a noise aided data analysis technique as it adds sequences of white Gaussian noise into the signal in many trials. Added noise helps in decomposing the original signal into similarly scaled and distributed signals. In every trial, different noises are added so that the generated IMFs are not correlated with the IMFs corresponding to the ones obtained from previous trials[9]. The true IMF obtained from this procedure is the mean of the ensemble of trials. With this approach of having many trials, the scale separation problem can be solved without any apriori criterion selection. The process of EEMD is described as follows:

1. In the l^{th} trial, white noise sequence $u_l(n)$ is added to a signal $x(n)$, in order to obtain a new time sequence $y_l(n) = x(n) + u_l(n)$, for $l = 1, 2, \ldots, L$, where L denotes the ensemble number.
2. The IMFs of the noisy signal is obtained using the traditional EMD method and the mathematical representation of the process is expressed in (1).

$$y_l(n) = \sum_{j=1}^{i} c_j^l + r_i^l \tag{1}$$

   where i denotes the total number of IMFs of each decomposition, c_j^l is the jth IMF, and r_i^l represents the remainder of $y_l(n)$ in the l^{th} trial.
3. Similar to the algorithm of EMD, the above mentioned steps are repeated L times, with different additive white noise components added in every trial.

4. The j^{th} IMF is calculated as the mean of the ensemble IMFs obtained in each of the L trials, that is

$$c_j^{\text{ave}} = 1/L \sum_{l=1}^{L} c_j^l \tag{2}$$

where c_j^{ave} is the final IMF of EEMD.

EEMD's efficiency in decomposition of signals depends on the configuration of the ensemble number and the amplitude of added noise. The amplitude of added noise sequence and the ensemble number are selected based on the criterion specified in (3)

$$\epsilon = A/\sqrt{L} \tag{3}$$

where ϵ denotes the error's standard deviation and it acts as an indicator for the dissimilarity between the original signal and the signal obtained from reconstruction of IMFs obtained through EEMD.

2.2 Detrended fluctuation analysis

DFA is a method used to determine the self-similarity of a signal. Wu has used DFA to remove the anti-correlated IMFs (IMFs 1 - 4) and the IMFs which contribute to baseline wander (IMFs 8 - 12)[9]. The scaling exponent α quantifies the auto-correlation parameter of the signal. The IMFs computed from EEMD were used to compute the scaling exponent. The IMFs whose scaling exponents lie between $0.5 < \alpha < 1.5$ were used for feature extraction purposes. IMFs 5, 6 and 7 were used for this purpose to extract features from the signals. IMFs 5, 6 and 7 were used to reconstruct the signal. This signal was used for computation of features. The following points elaborate the physical significance of the values of the scaling exponent.

2.3 Feature extraction

In Thermodynamics, entropy has been used as a quantitative analysis tool for finding the degree of randomness or disorder in a system. Shannon adopted the idea from Boltzmann –Gibbs statistical mechanics to postulate Shannon Entropy (ShEn)[13]. ShEn provides information about the energy present in the different frequency bands of the non-stationary time series. VAG signals are non-stationary and depict long-range interactions. As ShEn gives a good measure only when the signals don't have long-ranged interactions, this work has concentrated on quantifying the complexity of time series by computing entropy measures such as Tsallis entropy, Spectral entropy and Permutation entropy.

2.3.1 Spectral entropy

Spectral Entropy (SpEn) can be interpreted as the uncertainty about the event based on the spectral coefficients occurring at frequency f. It quantifies the randomness in the spectral components of the non-stationary time series. It is used as a quantitative tool for measuring the spectral complexity of the non-stationary time series. The power spectral density is obtained using the Fourier Transform of the sequence. Normalization of the $\hat{P}(f)$ gives us p_f. SpEn has been described in (4).

$$\text{SpEn} = -\sum_{f} p_f * \log(p_f) \tag{4}$$

2.3.2 Tsallis entropy

ShEn can be perceived as a logarithm moment of the meaured quantity. ShEn is an effective tool for measuring complexity if the states within a system don't exhibit long range interactions[14]. Tellenbach *et al.* prove that Tsallis Entropy (TEn) is useful for characterizing measures with non-Gaussian trends. As VAG signals depict long-ranged interactions, memory effects and non-Gaussian trends, Tsallis Entropy can be used to extract the complexity of the

VAG signal. Tsallis Entropy characterizes the behavior emulated by VAG signals in spikes and bursts. The advantage of Tsallis Entropy is that it helps us model the uncertainties using the empirical value q. The value of q was set to 2 for conducting simulations. Tsallis Entropy (TEn) is represented as

$$\text{TEn} = \frac{1 - \sum_{i=1}^{W} p_i^q}{q-1} \tag{5}$$

2.3.3 Permutation entropy

Permutation Entropy (PEn) was proposed by Bandt and Pompe to measure the complexity and irregularity of the non-stationary time series[15]. This method works by comparing the neighboring values to depict the features of the non-stationary signal. It also has the advantage of being robust and computationally simple. For a non-stationary time series of length L, the permutation entropy can be calculated as

$$\text{PEn} = \frac{\sum_{i=1}^{l} p_i * \log(p_i)}{ln(l)} \tag{6}$$

PEn gives a quantitative measure of the complexity of the time-series. The value os PEn acts as an indicator of the regularity of the time-series. The smaller the value of PEn, the time series is more regular. The calculation of PEn depends on the selection of two parameters namely, the embedding dimension m and the time delay N. Algorithm used to compute PEn follows the sequence. Here x denotes the time-series to be analyzed. The time series is constructed using the following equation and is represented as X

$$X_i = [x(i), x(i+N), \ldots, x(i+(m-1)N)], \forall i = 1, 2, 3, \ldots, L-(m-1)N. \tag{7}$$

Then x is arranged in an ascending order:

$$[x(i+(j_1-1)N) \le x(i+(j_2-1)N) \le x(i+(j_3-1)N) \le \cdots \le x(i+(j_m-1)N)] \tag{8}$$

The total number of patterns in the group would be m!. Similar patterns are soted as sets and the probability of the ith permutation p_i. The PEn is then defined as

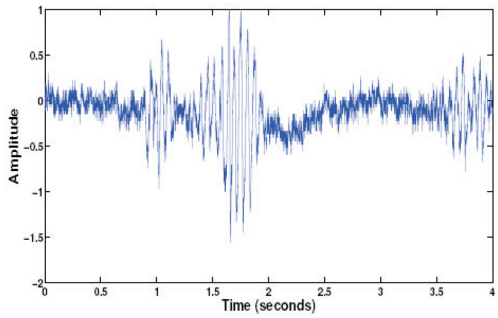
$$\text{PEn} = -\sum_{i=1}^{m!} p_i * \log(p_i) \tag{9}$$

The normalized entropy is calculated as

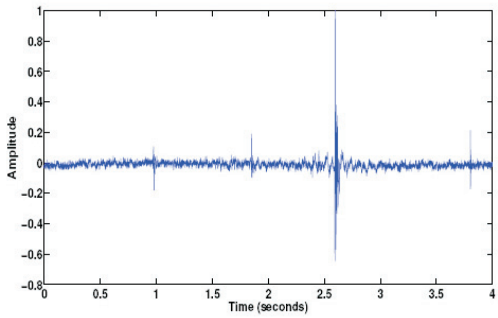
$$\text{PEn} = -\frac{\sum_{i=1}^{m!} p_i * \log(p_i)}{ln(m!)} \tag{10}$$

2.4 Random forest classifier

Random Forest (RF), a technique developed by Leo Brieman in 2001 works on the principle of ensemble learning wherein a group of decision trees are used to train the data[16]. The output class is obtained as the mode of the output classes obtained from each of the decision tree. This technique is a combination of bagging and random selection of features for training the dataset. This classifier overcomes the problem of overfitting of training set, a very common problem observed with decision trees.



(a) Signal of a Subject with Knee Joint Pathology



(b) Signal of a Healthy Subject

Fig. 1. Normalized VAG Signals.

3. Experiments

3.1 Dataset

The signals used for analysis in this work is the same as the ones used in previous works[1],[17] and[18]. The setup for acquisition of VAG signals was conducted at the University of Calgary, Canada. A small accelerometer was placed on the middle of the kneecap (patella) of the subjects. During the signal acquisition procedure, the patients voluntarily flexed and stretched the leg over a period of 4 s. The signals acquired from the patients were processed using National Instruments Data acquisition (DAQ) board and Labview software. The VAG signals were pre-filtered using a bandpass filter in the range 10 Hz to 1 kHz and amplified. The sampling frequency of the VAG signal was 2 kHz and digitized using a resolution of 12 bits. 89 signals were acquired from patients using this method and they were divided into two sets namely abnormal signals and normal signals, wherein the former and latter set consist of 38 and 51 signals respectively. Figure 1(a) and 1(b) depict the normalized versions of VAG signals acquired from an unhealthy subject and healthy subject respectively.

3.2 Results and discussion

The experiments were conducted using MATLAB R2014a. The stopping criterion for EEMD was set using the criterion presented in equation (3). In this investigation, we have used the values set by Wu in his book[9]. The value of ϵ was set as 20% of the standard deviation (SD) of the acquired VAG data. The value of L was set as 100 for computation of IMFs.

VAG signals are non-linear, non-stationary and aperiodic by nature, just like any other biologically occurring signal. Traditional signal processing techniques are not fit for analyzing VAG signals. The main purpose of this work is to provide a unique method to solve the problem of screening of VAG signals i.e classifying them into normal and abnormal sets. The presence of fast fluctuations in the abnormal VAG signals differentiate them from the set of normal VAG signals. The proposed methodology uses EEMD for decomposition of VAG signals into IMFs. Figure 2 and 3 depict the IMFs of signals acquired from a patient with knee joint pathology and a normal patient respectively. These IMFs are used along with DFA to distinguish between the significant IMFs and the artifact containing IMFs. In this work, we model a signal using DFA known as the reconstructed signal for further analysis. The reconstructed signal is an added sum of the time series of IMFs 5, 6 and 7. Figure 4(a) and (b) depict the normalized reconstructed signal obtained using EEMD and DFA. IMFs less than 4 don't contribute much to the signal, whereas IMFs 8–12 mostly contribute to baseline wander and other less significant effects of the signal.

The reconstructed signals were then used to extract features such as SpEn, TEn and PEn. The entropy measures were extracted as a measure to quantify the disorder in the VAG signals and to model the non-linear characteristics of the VAG signals. Extracted features were then passed on to a random forest classifier and results were obtained. To quantitatively measure the efficacy of the proposed methodology, parameters such as Accuracy (ACC),

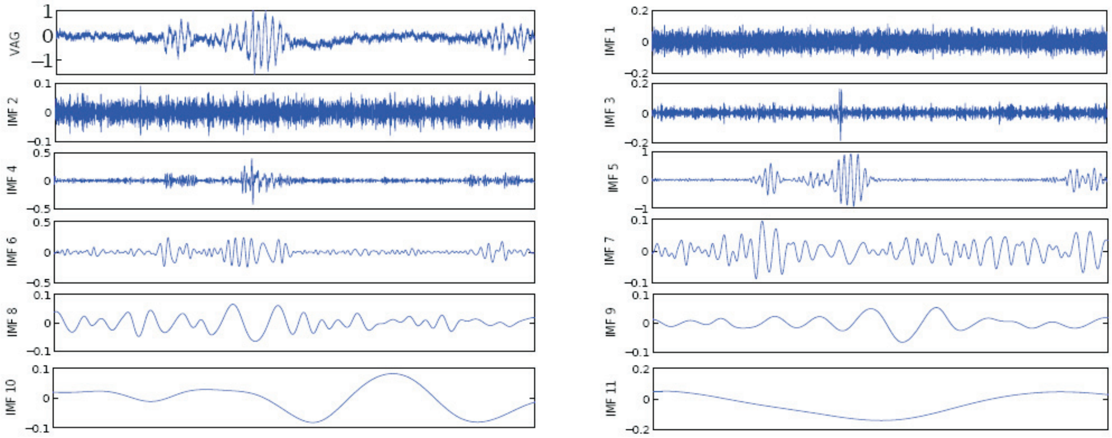


Fig. 2. IMFs Obtained using EEMD of a Patient with Knee Joint Pathology.

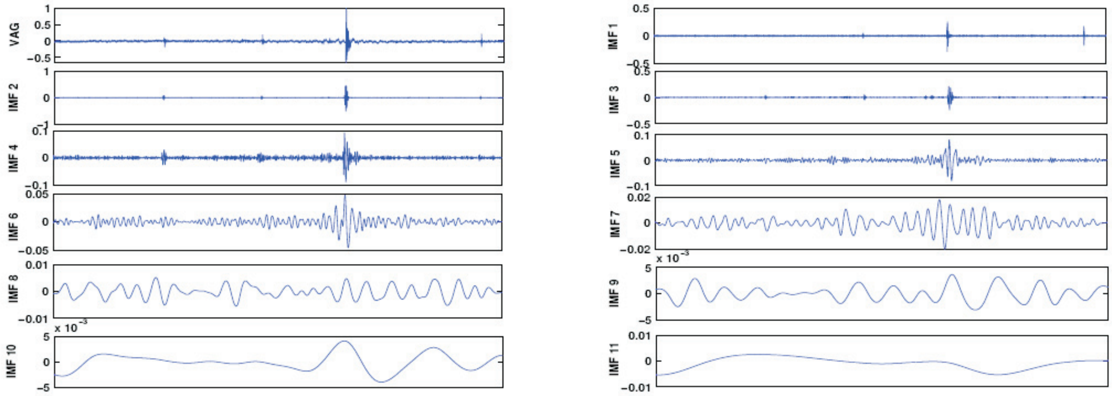
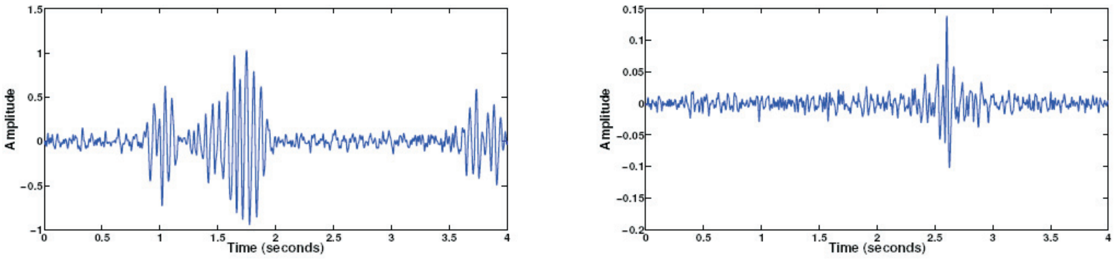


Fig. 3. IMFs Obtained using EEMD of a Normal Subject.



(a) Signal of a Subject with Knee Joint Pathology

(b) Signal of a Healthy Subject

Fig. 4. Normalized Reconstructed Signals.

Sensitivity (SEN) and Specificity (SPE) were calculated. The Confusion matrix was computed for evaluating ACC, SEN and SPE. Figure 5 describes the Receiver Operating Characteristics (ROC) curve for IMFs 5, 6 and 7. ROC curve plots true positive rate against the false positive rate for different IMFs[19]. The green, red and blue curves depict the ROC plots for IMFs 5, 6 and 7 respectively. Figure 6 describes the confusion matrix's structure. It depicts four

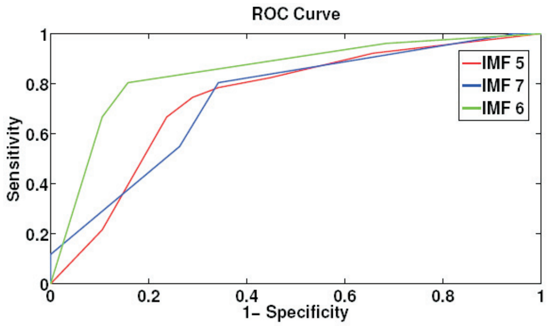


Fig. 5. ROC Curves of IMFs 5-7.

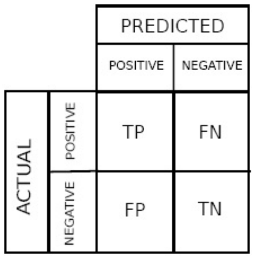
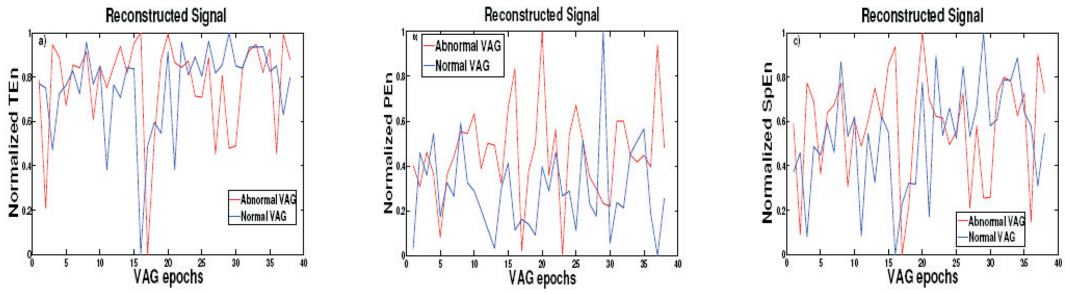


Fig. 6. Structure of Confusion Matrix.



(a) Tsallis Entropy (b) Permutation Entropy (c) Spectral Entropy

Fig. 7. Scatter Plots of Abnormal and Normal Signals.

values namely True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN). Our work has concentrated on deriving entropy based features as a measure to quantify the complexity of the VAG signals. The entropy measures were computed for the reconstructed signal using equations (4)–(10). Figure 7(a), (b) and (c) depict the scatter plot of the reconstructed signal for different entropy measures. The scatter plot describes the difference in TEn, SpEn and PEn for the two sets of signals namely abnormal and normal. The extracted features were used to train the RF classifier for classifying the VAG signals. 10 fold validation has been performed while the size of the tree was selected as 8 for the RF classifier. The values obtained for ACC, SEN and SPE are 86.52%, 94.12% and 76.32% respectively.

In this paper, we proposed a unique technique to extract features and screen VAG signals. As Wu suggested, the proposed methodology uses EEMD and DFA to remove baseline wander and random noise from VAG signals. This work models a reconstructed signal using EEMD and DFA. The reconstructed signal is used to extract entropy based measures as features to train a random forest classifier. Tsallis entropy, Permutation entropy and Spectral entropy measures were extracted for all the signals for classification. The values obtained for accuracy, sensitivity and specificity are 86.52%, 94.12% and 76.32% respectively.

4. Conclusions

This paper describes a unique approach towards feature extraction and classification of VAG signals using EEMD and DFA. The proposed methodology provides a more accurate method for classification of VAG signals as normal and abnormal. The proposed methodology uses IMFs obtained from EEMD and the scaling exponent obtained from DFA for modeling the reconstructed signal. The reconstructed signals were used to extract features. Non-linear features such as TEn, PEn and SpEn were found to be good measures for segregation of VAG signals into abnormal and normal set. The entropy measures extracted were then converted to vectors for inputs to the Random Forest Classifier. Parameters such as Accuracy, Sensitivity and Specificity were extracted to indicate the efficacy of the proposed methodology. ROC curves were plotted to interpret the accuracy of the test. The proposed methodology has produced an accuracy of 86.52%, sensitivity of 94.12% and specificity of 76.32%. Future work can be directed towards automated estimation of the degree of damage that the knee joint has undergone.

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