CLASSIFICATION OF KNEE-JOINT VIBROARTHROGRAPHIC SIGNALS USING TIME-DOMAIN AND TIME-FREQUENCY DOMAIN FEATURES AND LEAST-SQUARES SUPPORT VECTOR MACHINE

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ABSTRACT

Analysis of knee-joint vibration sounds, also known as vibroarthrographic (VAG) signals, could lead to a noninvasive clinical tool for early detection of knee-joint pathology. In this paper, we employed the wavelet matching pursuit (MP) decomposition and signal variability for time-frequency domain and time-domain analysis of VAG signals. The number of wavelet MP atoms and the number of significant turns detected with the fixed threshold from signal variability analysis were extracted as prominent features for the classification over the data set of 89 VAG signals. Compared with the Fisher linear discriminant analysis, the nonlinear least-squares support vector machine (LS-SVM) is able to achieve higher overall accuracy of 73.03%, and the area of 0.7307 under the receiver operating characteristic curve.

Index Terms— Knee-joint vibration sounds, Wavelets, Matching pursuit, Turns count, Support vector machine

1. INTRODUCTION

Knee-joint vibration or vibroarthrographic (VAG) signals can be recorded by an accelerometer at the mid-patella position of the knee during flexion or extension movement of the leg. The articular cartilage surfaces of a normal knee are smooth and slippery. Vibrations generated due to friction between the articulating surfaces of degenerative cartilage are expected to be different in amplitude and frequency from those of normal knees [1]. Recent studies [2–9] reported that the VAG signal is associated with pathological conditions in the joint, so that computer-aided analysis of VAG signals is useful for screening and monitoring of articular cartilage pathology, which could help reduce the use of diagnostic open surgery with arthroscopy.

VAG signals are nonstationary and multicomponent due to the fact that the quality of the articular cartilage surfaces coming in contract may not be the same from one angular position to another during articulation of the joint. In most cases they contain significant transient structures that result in time-varying spectrum [9]. Due to the these characteristics, the VAG signal cannot be accurately analyzed by common digital signal processing techniques such as the Fourier transform or autoregressive (AR) modeling [4].

With the aim to distinguish abnormal signals from normal ones for further diagnosis purposes, we apply in this paper the joint time-frequency distribution (TFD) analysis based on the wavelet matching pursuit (MP) decomposition and the time-domain signal variability (SV) analysis. The features extracted from the wavelet MP decomposition and the SV analysis are used for the VAG signal classification with linear and nonlinear classifiers.

The remaining parts of the paper are organized as follows: Section 2 describes the details of the acquisition of the VAG signals studied. Section 3 and Section 4 present the features derived from the MP decomposition with the Daubechies wavelet packets and the SV analysis in the time domain, respectively. Section 5 uses the linear and nonlinear classifiers, i.e., the Fisher linear discriminant analysis (FLDA) and the least-squares support vector machine (LS-SVM), respectively, for classification of normal and abnormal VAG signals. Section 6 discusses the results of our experiments, in comparison with previous related studies. Section 7 concludes the present investigation.

2. VAG DATA ACQUISITION

The VAG data were collected by the research group of Rangayyan, University of Calgary, Calgary, AB, Canada [4]. During the data acquisition procedure, each subject was requested to sit on a rigid table in a relaxed position with the leg being tested freely suspended in air. The VAG signal was recorded by placing an accelerometer (model 3115a, Dytran, Chatsworth, CA) at the mid-patella position of the knee. The accelerometer measured the acceleration and deceleration of the knee movement when the subject swung the leg over an approximate angle range of 135^{o} to 0^{o} and back to 135^{o} in

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the duration $T = 4$ s [6], with an approximate motion speed at 67° per second. The VAG signal was prefiltered by a band-pass filter with a bandwidth of 10 Hz to 1 kHz so as to prevent aliasing effects, and amplified before digitizing at a sample rate $f_s = 2$ kHz with 12-bit resolution per sample. Auscultation of the knee joint using a stethoscope was also performed, and a qualitative description of sound intensity and type was recorded, together with their relationship to joint angle.

Since one abnormal signal in the original database of 90 signals was corrupted, we used in the present study the data set of 89 VAG signals, including 51 from normal health volunteers and 38 from subjects with knee-joint pathology. The normals were established by clinical examination and history. The abnormal signals were collected from symptomatic patients scheduled to undergo arthroscopy independent of the VAG studies. The abnormal subjects include chondromalacia of different grades at the patella, meniscal tear, tibial chondromalacia, and anterior cruciate ligament injuries, as confirmed during the arthroscopic examinations. The data set available only permits the normal versus abnormal binary classification, rather than diagnosis of various types or stages of pathology. Fig. 1 shows examples of normal and abnormal signals in the VAG data set studied. It can be observed that the abnormal signal exhibits a higher degree of overall variation, activity, or complexity than the normal signal in the time domain.

3. TIME-FREQUENCY DOMAIN FEATURE

The methodology of MP was proposed by Mallat and Zhang [10] with the aim to represent the signal using basis functions with good time-frequency properties (atoms). It is therefore a suitable candidate for analysis of the inherent nonstationary VAG signal. The MP method is a type of greedy algorithms that is able to approximate a N-sample signal $x(t)$ with orthogonal projections onto elements from a waveform dictionary $\mathcal{D} = \{d_r(t)\}_{r \in \Gamma}$ of P vectors and a unit norm. In the present study, we implemented the MP decomposition based on the Daubechies wavelets, because the Daubechies wavelets have a support of minimum size for any give number of vanishing moments [11], and such wavelets can be used to decompose the signal into components with excellent time and scale properties [12]. The projection of the VAG signal $x(t)$ using the dictionary of wavelet packet bases, $d_{r_m}(t)$, calculated with a Daubechies 8 (db8) filter, can be expressed as

$$x(t) = \sum_{m=0}^{M-1} a_m d_{r_m}(t), \tag{1}$$

where a_m are the expansion coefficients and M denotes the iterations of decomposition. The wavelet MP decomposition is implemented as follows: In the beginning, the wavelet MP projects $x(t)$ in the direction of $d_{r_0}(t) \in \mathcal{D}$ and also computes the residue $R^1 x(t)$, i.e.,

$$x(t) = \langle x,\ d_{r_0} \rangle\ d_{r_0}(t) + R^1 x(t), \tag{2}$$

where $\langle x,\ d_{r_0} \rangle$ denotes the inner product (projection). Since the first atom $d_{r_0}(t)$ is orthogonal to $R^1 x(t)$, we have

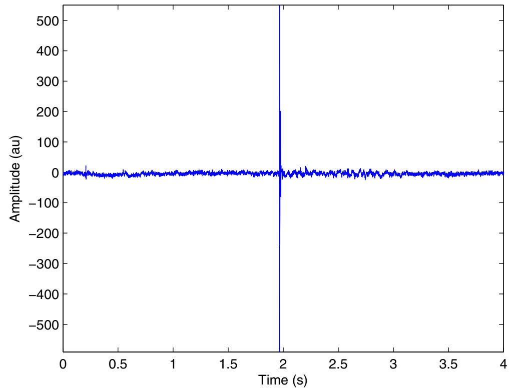
$$\|x\|^2 = |\langle x,\ d_{r_0} \rangle|^2 + \left\|R^1 x\right\|^2. \tag{3}$$

In order to minimize $\left\|R^1 x\right\|$, $r_0 \in \Gamma$ is then chosen such that $|\langle x,\ d_{r_0} \rangle|$ is maximum, i.e.,

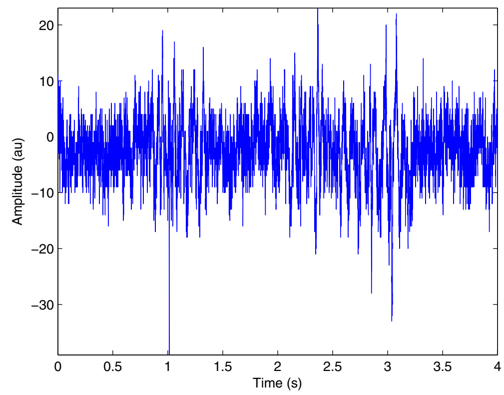
$$|\langle x,\ d_{r_0} \rangle| \geq \sup_{r \in \Gamma} |\langle x,\ d_r \rangle|. \tag{4}$$

Let $R^0 x(t) = x(t)$, the wavelet MP iterates this procedure by subdecomposing the residue, so that the VAG signal $x(t)$ after M iterations of decomposition can be formulated as

$$x(t) = \sum_{m=1}^{M-1} \langle R^m x,\ d_{r_m} \rangle\, d_{r_m}(t) + R^M x(t), \tag{5}$$



(a)



(b)

Fig. 1. VAG signal examples: (a) of a normal subject; (b) of a patient with knee-joint pathology. au: uncalibrated acceleration units.

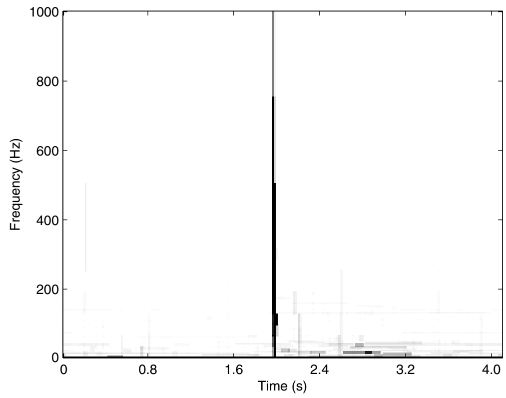
where $|\langle x,\ d_{r_m}\rangle| \geq \sup_{r\in\Gamma} |\langle x,\ d_r\rangle|$.

Since the residue term $R^M x(t)$ can be regarded as noise after sufficient iterations, one common approach to stop the iterative process depends on the convergence of residual energy, $\|R^m x\|^2$. In the previous studies, Krishnan *et al.* [3, 4] used the decay parameter defined by Mallat and Zhang [10] to end the MP decomposition based on the Gabor function dictionary. Although the decay parameter as an iterative indicator is well-devised in theory, for a wavelet packet dictionary that contains $P = N \log_2 N$ vectors, a single MP iteration then requires $O(N \log_2 N)$ operations. For the VAG data analyzed, each signal consists of $N = f_s \times T = 8000$ samples, and the wavelet MP decomposition becomes computationally expensive and works very slow.

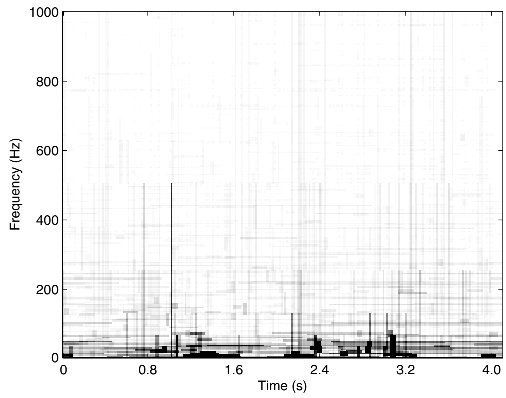
In the present study, we propose using signal-to-noise ratio (SNR) as an alternative indicator to determine the iterations of the wavelet MP decomposition. Referring to the VAG signals in Fig. 1, it can be inferred that, with a given SNR, the wavelet MP decomposition of an abnormal signal will require relatively fewer iterations than that of a normal signal, because the abnormal signal is much more noisy and also contaminated by a larger amount of artifacts such as muscle contraction interference. Thus the number of MP iterations can be considered as a potential feature for classification applications. On the other hand, the MP decomposition with a great many iterations can provide an excellent value of SNR and is also suited for de-noising applications [3], but such implementation is time consuming as mentioned above. It is therefore necessary to search for an appropriate value of SNR that makes a tradeoff between efficiency and effectiveness of a wavelet MP decomposition. After testing the SNR at different levels, we found that the SNR of 15 dB is an excellent indicator to determine the wavelet MP iterations.

Fig. 2 displays the MP atoms decomposed from the VAG signals in Fig. 1 in the time-frequency plane, in which the darkness of a MP atom is proportional to the coefficient amplitude. It can be observed that the abnormal VAG signal has different time-frequency structures than the normal signal. For the normal VAG signal in Fig. 2 (a), most of the MP atoms with large amplitude congregate in the narrow range near the transient spike at 1.97 s (in relation to the significant click recorded by the auscultation of the knee). However, the dominant atoms of the abnormal signal are located in a broader range in the time and frequency scales, as shown in Fig. 2 (b). From Fig. 3, it can be observed that the VAG signals reconstructed with the MP atoms are notably noise-free. And the noise removed from the original VAG signals in Fig. 1 is depicted in Fig. 4, which is even better than that in the previous study using the Gabor function dictionary and the energy decay parameter [3].

In addition, the p value of the number of atoms (Natom) obtained with the Student's t-test is 0.0002, which implies that the Natom (numerically equal to M) presents a significant separability between normal and abnormal VAG signals. Such results also confirm our assumption described above.



(a)



(b)

Fig. 2. Wavelet matching pursuit atoms displayed in the time-frequency plane of the (a) normal and (b) abnormal signals.

4. TIME-DOMAIN FEATURE

Besides the wavelet MP decomposition in the time-frequency domain, variability analysis of the signal in the time domain may be useful for further classification as well. Thus the turns count method is worthy of consideration. According to Rangayyan [13, 14], a "turn" is referred to as a significant change in phase, direction, or slope in the signal, and only those turns that are in amplitude larger than the specified threshold are counted, in order to avoid the aliasing effects of noise.

In this investigation, we first normalized each VAG signal to the amplitude range from zero to unity, the same as in the recent studies [7, 8]. In each signal, the amplitude of all samples was amplified with the same scale so that the variability information of the signal can be preserved. Before counting the significant counts present in the VAG signal, we imple-

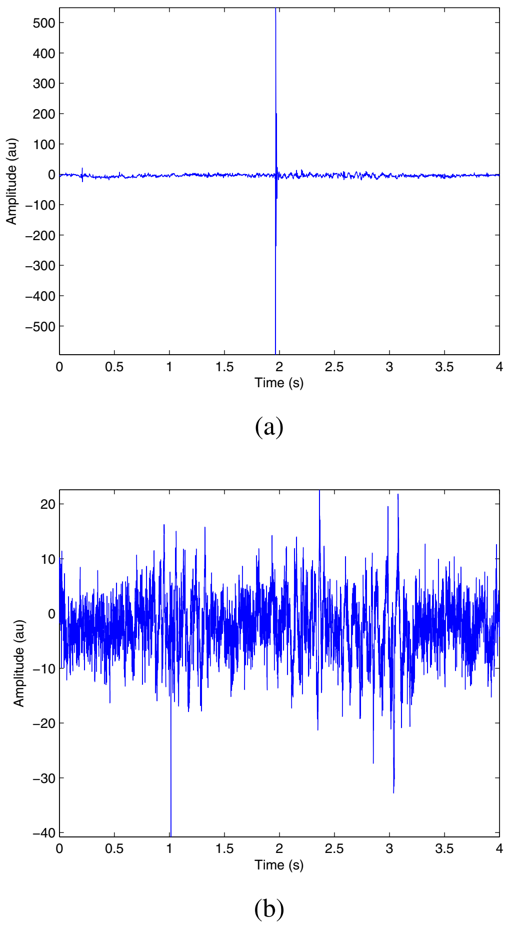


Fig. 3. Signal reconstructed with the wavelet matching pursuit atoms in regard to the original VAG signals in Fig. 1: (a) of a normal subject; (b) of a patient with knee-joint pathology. au: uncalibrated acceleration units.

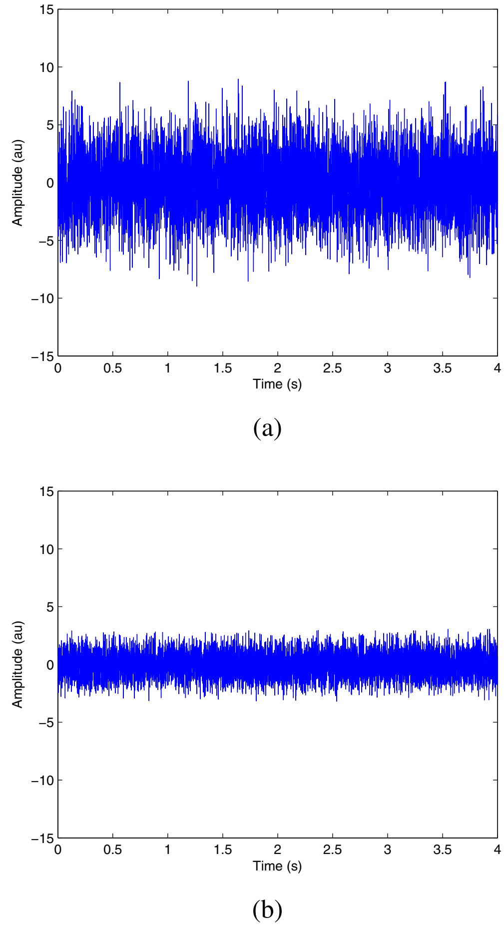
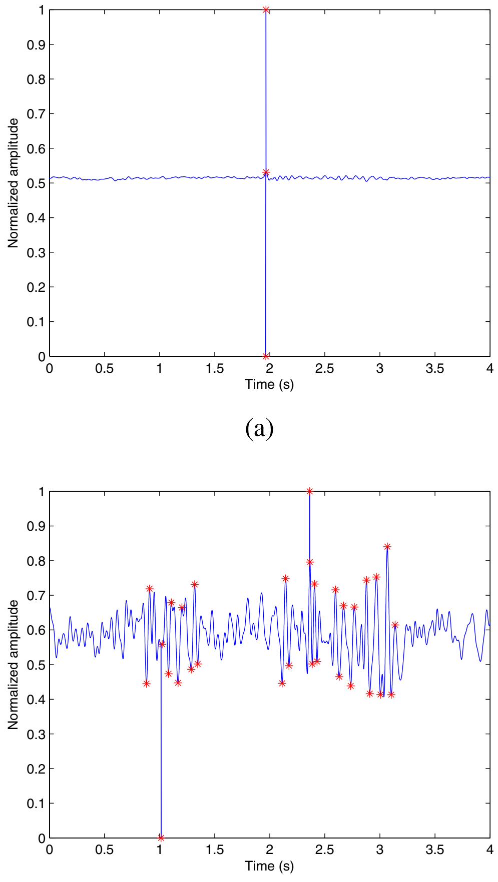


Fig. 4. Noise extracted by the wavelet matching pursuit decomposition method in regard to the original VAG signals in Fig. 1: (a) of a normal subject; (b) of a patient with knee-joint pathology. au: uncalibrated acceleration units.

mented a filtering procedure using a 10th-order lowpass Butterworth filter (-3 dB cutoff at 50 Hz) with unit gain at DC. This lowpass Buttworth filter causes a delay of 100 samples (or 0.05 s), which was calibrated after the filtering procedure in our experiments. We did not use the signal reconstructed with the MP atoms, as shown in Fig. 2, for the variability analysis, because the MP method cannot remove the interference caused by muscle contractions or 50 or 60 Hz power-supply lines.

In the past work of Rangayyan and Wu [8], the threshold to determine a significant turn was adaptively set to be $0.5\sigma_{\rm v}$, where $\sigma_{\rm v}$ denotes the standard deviation of the VAG signal analyzed. Although the turns counted with the adaptive threshold provide good discriminant information for classification of VAG signals, the number of turns computed from a normal signal is larger than an abnormal one, because the variance of the normal VAG signal is usually lower than that of the abnormal signal [8]. Such a result, however, is somewhat deviating from our expectation that the turns associated with an abnormal VAG signal would be larger in number due to a higher degree of variability. In the present study, we fixed the amplitude threshold at 0.2 to compute the turns over the normalized VAG signals.

Fig. 5 gives the results of the turns count with the fixed threshold (TCFT) method for the VAG signals in Fig. 1 after being normalized and filtered. Compared with Fig. 3, it is clear that the interference in the VAG signal has been filtered. And as expected, more significant turns have been detected in the abnormal VAG signal, as marked in Fig. 5 (b). In addition, the p value of the TCFT obtained with the Student's t-test is 0.0013, better than the result of the adaptive threshold approach (p value: 0.0098) reported by Rangayyan and Wu [8].



(a)

(b)

Fig. 5. Illustration of significant turns in the filtered (a) normal and (b) abnormal VAG signals, in which the significant turns detected have been marked with asterisks. The delay of 0.05 s caused by the lowpass Butterworth filter has been calibrated.

5. CLASSIFICATION

To perform the VAG signal classification based on the time-frequency domain and time-domain features, we applied the Fisher linear discriminant analysis (FLDA) and the least-squares support vector machine (LS-SVM).

The FLDA is a commonly used statistical method which finds the linear combination of features to best separate two or more classes of instances in the data studied [15]. The FLDA is similar to principal component analysis (PCA) in that both look for linear combinations of variables which best explain the data. The FLDA explicitly attempts to model the difference between the classes of data, whereas the PCA does not take into account any difference in class [15].

The support vector machine is an elegant and highly principled learning method for the design of a feedforward neural network with a single nonlinear hidden layer [16]. Its derivation follows the principle of structural risk minimization that is root in Vapnik-Chervonenkis (VC) dimension theory [17]. As the name implies, the design of the machine hinges on the extraction of a subset of the representative training data that is called "support vectors" and also considered to be informative for the classification task. By choosing the nonlinear inner-product kernels in the network, the SVM is able to perform the same function as the polynomial learning machine, radial-basis function network, or multilayer perceptron with a single hidden layer [18, 15]. The SVM provides the learning method based on optimization to control model complexity independently of dimensionality. In particular, the model complexity problem is solved in a high-dimensional space by using a penalized hyperplane defined in the hidden space as the decision surface. The curse of dimensionality is bypassed by focusing on the dual problem for performing the constrained optimization problem. An important reason for using the dual problem setting is to avoid having to define and compute the parameters of the optimal hyperplane in a data space of possibly high dimensionality. The LS-SVM proposed by Suykens *et al.* [19] is a reformulation to the standard SVM, with an improvement of moderate complexity. The learning of the LS-SVM is implemented by minimizing a regularized least squares cost function with equality constraints, under the Kuhn-Tucker condition.

To determine the kernel function most suited for VAG signal classification, we implemented the LS-SVM using the linear, polynomial, sigmoid, and Gaussian kernels, one by one specified by different values of model parameters. By checking the accuracy and the optimal separating hyperplane provided by each LS-SVM, we chose the polynomial kernel function whose the degree and intercept parameters equal to 2 and 1, respectively, and set the regularization parameter of the LS-SVM to be 5 to perform the classification task. Both of the FLDA and the LS-SVM was tested with the leave-one-out (LOO) cross validation method [15], and then labeled as FLDA/LOO and LS-SVM/LOO, respectively.

6. RESULTS

Table 1 lists the performance of the linear and nonlinear classifiers. The accurate classification rate in percentage obtained with the FLDA/LOO method is only 65.17%. the LS-SVM/LOO method on the other hand reaches 73.03%. It is clear that the nonlinear classifier outperforms the linear classifier for the analysis of VAG signals. In addition, we also tested the overall diagnostic performance of the LS-SVM/LOO using the receiver operating characteristic (ROC) curve. The area under the ROC curve (*Az*) obtained with the LS-SVM/LOO is 0.7307 with a standard error (SE) of 0.0540. The results of the LS-SVM/LOO are better than the previous studies using the logistic regression analysis with AR coefficients as features (accuracy: 68.9%) [2], or with the energy, energy spread, frequency, and frequency spread features derived from the Gabor MP method (accuracy: 68.9%, *Az*: 0.68) [3].

Table 1. Classification results

Classifier	Accuracy (%)	*Az*	SE
FLDA/LOO	65.17	0.6692	0.0578
LS-SVM/LOO	73.03	0.7307	0.0540

7. CONCLUSION

Analysis of VAG signals using the signal processing and machine learning techniques has high potential for noninvasive detection of degenerative articular cartilage surfaces so that the diagnostic use of arthroscopy can be reduced. In this paper, we developed two distinct features with excellent p values, i.e., the Natom and TCFT derived from the time-frequency wavelet MP decomposition and time-domain signal variability analysis, respectively. With these features, the nonlinear classification using the LS-SVM/LOO is superior to the logistic regression analysis used in the past studies, with higher accuracy and larger *Az* value under the ROC curve, over the data set of 89 VAG signals.

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