Improved Parametric Estimation of Time Frequency Representations for Cardiac Murmur Discrimination

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Abstract

In this work a methodology of heart murmur detection by means of time–frequency representations (TFR) based on time–varying auto regressive (TVAR) modeling of phonocardiographic signals is proposed. Time–varying coefficients are estimated with Kalman smoother obtaining improved estimation precision and appropriate tracking of time–varying dynamics of phonocardiographic signals. TFRs derived from TVAR parameters are decimated with wavelet decomposition and taken to a feature space with PCA embedding (eigenfaces). Analysis of identification performance is accomplished for a database composed of 201 normal PCG records, and 201 murmurs. Results show that TFRs derived from Kalman smoother can discriminate normal heart sounds and murmurs better than other parametric TFRs obtained from LMS and RLS parameter estimation algorithms and non parametric TFRs based on Choi–Williams distribution.

1. Introduction

Cardiac mechanic activity can be estimated by means of auscultation and processing of heart sound records, known as phonocardiographic signals (PCG), a non–invasive low–cost technique. The importance of classical auscultation techniques has diminished because of its inherent restrictions, such as: human hear limitations, subjectivity of the specialist, the discernment abilities that can take years in being obtained, among others. Anyway, PCG records are very important in heart pathologies diagnosis [1], in evaluation of congenital heart defects [2], and in home health care, where an intelligent stethoscope with decision support capabilities can be helpful [2, 3].

Heart sounds consist of two regular consecutive thuds, known as S1 and S2, corresponding to closing of tricuspid and mitral valves and closing of aortic and pulmonar valves. Whenever a valvular pathology is present, blood flow in the heart becomes turbulent, causing vibration in the neighboring tissues and a perceptible noise called murmur. Heart murmurs are signs of pathologic changes in the heart, but their presence isn't easy to recognize because they are overlapped with normal heart sounds. The automatic detection of heart murmurs strongly depends on appropriate feature estimation, being timing, morphology and spectral properties of heart sounds most valuable features [4, 5]. Time–frequency representations (TFR) are capable of capture non–stationarity and frequency dynamical changes, being this the reason why they have been widely used to characterize non–stationary transients and fast changes of PCG signals [6–10].

Using time–varying auto regressive (TVAR) modeling for TFR estimation, several advantages can be obtained, such as [11]: representation parsimony (given that the signal is specified with a limited number of parameters), improved precision, improved resolution (due to underlying interpolation given by the model), improved tracking of time–varying dynamics, flexibility in analysis, as parametric methods are capable of directly capturing the underlying structural dynamics responsible for the non-stationary behavior, among others. In our work we use Kalman smoother as TVAR parameter estimator, because it can effectively estimate parameters of linear models and also can track time–varying dynamics of PCG signals [12].

The proposed method consists on estimation of TVAR parameters with Kalman smoother. From these parameters the TFR of the PCG signal is constructed. These surfaces are decimated with wavelet decomposition and taken to a feature space with PCA embedding (eigenfaces). Finally, samples in feature space are classified with k nearest neighbors. By means of wavelet decimation and PCA redundant information is reduced and most relevant features from TFRs are obtained, improving classification performance. We make cross validation of features obtained with our approach and compare with other methodologies, such as parametric TFR obtained with LMS and RLS algorithms and non parametric TFR obtained with Choi–Williams distribution (CWD). Results show that our approach can discriminate heart murmurs with best correct rate, sensitivity and precision of the methodologies.

2. Methods

2.1. Parametric TFR estimation

In a TVAR(p) model, time series $y[k]$ depends on the weighted sum of the preceding p values $\{y[k-n]\}_{n=1}^{p}$ and a random process $\xi[k] \sim \mathcal{N}\left(0, \sigma_{\xi}^{2}[k]\right)$, where the weighting values $\{a_n[k]\}_{n=1}^{p}$ can change along time:

$$y[k] = \sum_{n=1}^{p} a_n[k]y[k-n] + \xi[k] \tag{1}$$

The TFR $G(k, f)$ of the process $y[k]$ can be obtained with the following transformation [13]:

$$G(k, f) = \frac{\sigma_{\xi}^{2}[k]/f_s}{1 + \sum\limits_{n=1}^{p} a_n[k]e^{-j2\pi nf/f_s}} \tag{2}$$

where f_s is the sampling frequency. On difference with other TFR estimation methods, parametric TFR is superior due to implicit extrapolation of autocorrelation sequence.

TFR estimation with this method consists of two steps, estimation of model order and estimation of parameter vector $\boldsymbol{a}[k] = [a_1[k] \dots a_p[k]]^{\top}$ and variance $\sigma_{\xi}^{2}[k]$. Overall quality of TFR depends on the model order and estimation method.

Model order estimation can be done with information criteria, such as Akaike information criterion or Bayesian information criterion [14]. These criteria are based on minimization of a function related with the information content on the estimation residuals. Information criteria should be calculated on stationary segments, but still can be used for non–stationary environments, using [15]:

$$BIC(p) = \frac{N}{M} \sum_{k=1}^{M} \ln \hat{\sigma}_{p,k}^{2} + p \ln N \tag{3}$$

where $\hat{\sigma}_{p,k}^{2}$ is the variance of estimation residuals for a p order model, from sample y_k, M is the number of estimation windows used and N is the length of the window.

Time–varying parameters of TVAR model with Kalman smoother can be estimated by casting the problem into state space form, as follows [13]:

$$\boldsymbol{a}[k+1] = \boldsymbol{a}[k] + \boldsymbol{w}[k] \tag{4}$$

$$y[k] = \boldsymbol{H}[k]\boldsymbol{a}[k] + \xi[k] \tag{5}$$

where $\boldsymbol{a}[k]$ is the parameter vector of length p, $\boldsymbol{w}[k]$ is white Gaussian noise $\mathcal{N}(0, \boldsymbol{R_w})$ and $\boldsymbol{H}[k] = [y[k-1] \dots y[k-p]]$ is the regression vector. Equation (4) is known as process equation and defines how the parameters change along time, while equation (5) is known as measurement equation corresponding to a linear observation model of the parameter vector. Noise sources $\boldsymbol{w}[k]$ and $\xi[k]$ introduce uncertainty on the model, $\boldsymbol{w}[k]$ defines random changes of the parameter vector, while $\xi[k]$ defines the estimation residuals and also randomness in the TVAR model.

Equations (5) and (4) form the state space model of the TVAR process $y[k]$, which can be estimated with the Kalman filter [12]. After estimation with Kalman filter, it is possible to improve the estimation with a fixed interval smoothing, which also takes into account future values of $y[k]$ to estimate the state of the system.

Estimation residuals of Kalman smoothing are used to estimate the variance of the random process in (1), as follows:

$$\hat{\sigma}_{\xi}^{2}[k] = \frac{\alpha}{M} \sum_{i=1}^{M} g_i e[k-i]^2 + (1-\alpha)\hat{\sigma}_{\xi}^{2}[k-1] \tag{6}$$

where $e[k] = y[k] - \boldsymbol{H}[k]\hat{\boldsymbol{a}}[k-1]$ is the estimation error, $\boldsymbol{g} = [g_1 \dots g_M]$ is a smoothing window and α a smoothing parameter, both serve to diminish the effects of estimation error and high frequencies.

2.2. Dimensionality reduction scheme

TFRs obtained with any methodology, as those obtained with the parametric approach by equation (2) represent a features of a heartbeat which is difficult to classify due to its high dimensionality and redundancy. In order to reduce and select most effective features of the TFR we use wavelet decomposition and PCA analysis.

By means of wavelet decomposition the original TFR can be downsampled in a series of low–frequency and high–frequency components known as approximation and detail coefficients several times until the desired decomposition level is reached [16]. At each level of the decomposition, frequency resolution is doubled through filtering while the spatial resolution is halved by downsampling operation. Resulting coefficients are equally sized images four times smaller than the original one, which preserve information of low frequencies and high frequencies. As most information on TFRs is contained on low frequency components, only the approximation coefficients of the desired decomposition level are used.

Dimensionality and redundancy of resulting images from wavelet decomposition are still unappropriate, so a second step is needed. PCA is a technique that takes a set of points and transforms them to other space through a linear transformation which minimizes covariance between components. If we just take the components enclosing most of the information or variation, PCA would be a dimensionality reduction scheme as well. PCA on images can be done by the approach of eigenfaces [17]. The new representation space formed by the maximum variability components is the feature space which will serve to train classifiers.

3. Results

3.1. Database

The database used in our tests consists on 148 PCG from individuals with possible valvular pathologies, acquired with an electronic stethoscope (WelchAllyn® Meditron model). Records are digitized at 44.1 kHz with a resolution of 16-bits per sample. Eight recordings of twelve seconds corresponding to the four traditional focuses of auscultation (mitral, tricuspid, aortic and pulmonary areas) were taken for each patient in the phase of post-expiratory and post-inspiratory apnea. A group of cardiologists labeled the records, obtaining 50 normal PCG and 98 records with evidence of valvular disorders (aortic stenosis, mitral regurgitation, etc). The records are filtered to diminish effects of acquisition noise, resampled at 4KHz and segmented by beat. After a second inspection, the best of the segmented records where taken, thus obtaining 201 normal beats and 201 pathological beats.

3.2. TFR estimation

TFRs are obtained with four methods: Choi–Williams distribution, and parametric TFR estimated with least minimum squares (LMS), recursive least squares (RLS) [18] and Kalman smoother (KSm). The parameter values for each one of the algorithms are shown in Table 1. For parametric TVAR models the estimated order with Bayesian information criterion in equation (3) is 6, and TFRs are obtained for frequencies between 0 and 400Hz. Resulting surfaces have 4800×512 points. Examples of TFRs obtained with the methodologies are shown in Figure 1.

Methodology	Parameters
CWD	$\sigma = 2, N_{fft}$=1024
LMS	$\mu = 2$
RLS	$\lambda = 0{,}99$
Kalman Smoother	$\lambda = 0{,}99$
Variance estimation	$g = gausswin(200, \sigma), \sigma = 1/2,$ $\alpha = 0{,}98$

Table 1. Estimation parameters of the studied methods.

3.3. Classification results

Dimensionality reduction was made as explained in Section 2.2. We used Daubechies 2 wavelet family and two levels of decomposition in the wavelet decomposition scheme and 15 principal components in PCA analysis, which gave, in the worst case, 90 % of the variability. We made cross validation of *k* nearest neighbors classifier

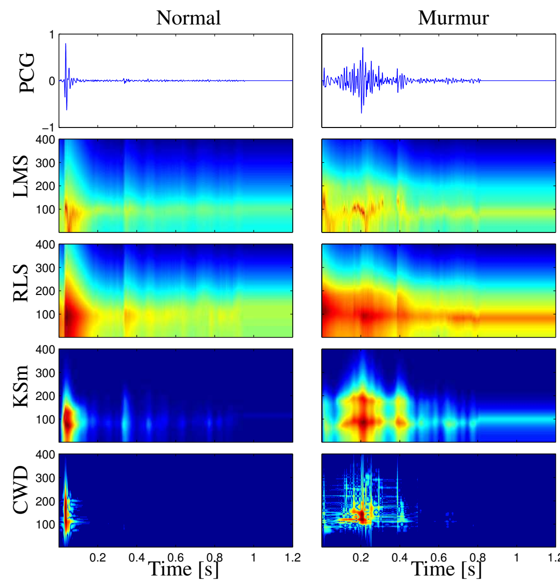

Figure 1. Obtained TFRs for normal PCG and murmurs.

on the feature space obtained after dimensionality reduction, taking on 11 folds, 70 % training and 30 % validation sets obtained by random sampling. Figure 2 shows cross validation results.

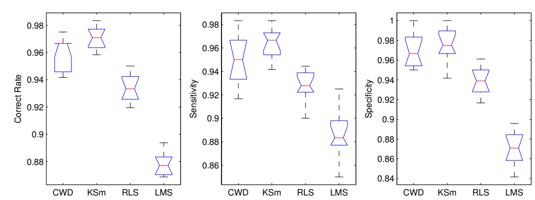

Figure 2. Cross validation results.

4. Discussion and conclusions

In this document it has been proposed a methodology for PCG signals characterization with parametric TFRs. Results show that parametric TFRs estimated with Kalman smoother extract time–frequency information from PCG signals that can discriminate between normal beats and murmurs. In comparison with other estimators of TVAR models, Kalman smoother can estimate, with improved accuracy, time–changes of TVAR parameters and, therefore, frequency changes of the PCG signal.

The parametric approach has shown that can appropriately embed time–frequency information of a signal with a reduced number of parameters. Also, this approach is less computationally demanding, even with the most elaborated estimator, the Kalman smoother. Obtained classification results show that parametric TFR estimated with Kalman smoother is more informative than Choi–Williams distribution.

Dimensionality reduction scheme for TFRs has shown that can effectively extract information from these surfaces, allowing good classification performance. It also shows that TFR are highly redundant, because it was possible to classify TFR with 4800×512 points, just with 15 derived features.

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