Expert System for Phonocardiographic Monitoring of Heart Failure Patients Based on Wavelet Analysis

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Abstract

An expert system was developed basically for the phonocardiographic (PCG) monitoring in the coronary care unit and at home. The aim of the study was to examine the performance of wavelet transformation in a heart failure group with noisy environment. For detection and interpretation of heart sounds and murmurs two analysis mesthods were done. As first, with the Waveform Similarity Overlap-and-Add (WSOLA) algorithm, a better separation of sounds was achieved for determination of the gold standard to the cardiologist interpretators. For the time-frequency analysis of PCG signals in a special clinical settings (PCG monitoring of 52 heart failure patients (NYHA III-IV) with ejection fraction < 0.35*), various wavelets were compared to an autoregressive (AR) model to determine the better model. As a result the Morlet wavelet wave showed the best performance, so it will be used for the future in our PCG data-, and knowledge-base.*

1. Introduction

Cardiac auscultation is the most widely used clinical method, but the experience and expertise among today's practicing physicians are declining because the lack of training programs, and the widespread utilization of Doppler echocardiography. In digital phonocardiography, the short-time Fourier and the wavelet transformation (WT) are used for the time-frequency representation (TFR) of sounds and murmurs. The aim of the study was to examine the performance of WT in a heart failure group with noisy environment for each patient in different time (during hospital monitoring). Apart of these an expert system was developed basically for the phonocardiographic monitoring using our previous data [1].

Based on the literature [2, 3, 4, 5] the intensity of the first sound (S1), the third and fourth sound (S3, S4), and the systolic murmurs were analyzed. For PCG monitoring in the coronary care unit (and in home monitoring) the followings are important:

The faint S1 could be detected in the case of weak ventricular contraction as in LV systolic dysfunction or heart failure, in AMI, or in dilatative cardiomyopathy (DCM). Patients seen during an acute anginal attack may have tachycardia and hypertension with transient S4 and S3 gallop, (new or worsening) apical systolic murmur of MR (due to papillary muscle dysfunction), a paradoxically split S2, which disappears when the pain subsides. Patients with acute myocardial infarction a S4 gallop can be heard in almost all patients in sinus rhythm during or shortly after an acute ischemic event. Although the presence of an S4 gallop may not be specific enough to be diagnostic, its absence argues strongly against an AMI. S3 gallop may also be present in many pts after MI (approximately 25%) but only if significant LV systolic dysfunction along with an elevated LV filling pressure has developed (and, as such, portends an adverse prognosis). The atrial (S4) gallop is a good indicator of elevated LV end-diastolic pressure. Unlike the S3 gallop, the S4 gallop does not denote ventricular decompensation by itself. Systolic murmur occurred by papillary muscle dysfunction (PMD) is observable in 30% to 50% or more of patients within the first 24 hours, at least transiently. The sudden onset of respiratory distress/or shock and a new systolic murmur should alert the clinician to suspect one of two surgically remediable mechanical complications (i.e., VSD or acute MR caused by rupture of the papillary muscle). In the case of inferior-posterior AMI with concomitant RV infarction: S4, S3 gallop and systolic murmur of acute TR (short, soft, or absent during expiration, increasing or „brought out" during inspiration) may register.

The aim of our work was to translate the above mentioned complex parameters to the language of expert system. For the detection and interpretation of heart sounds and murmurs two methods were compared to each other. First, using the WSOLA algorithm, a better separation of sounds was achieved for determination of the gold standard to the cardiologist interpretators. For the time-frequency analysis of PCG signs in a special clinical settings (PCG monitoring of 52 heart failure patients (NYHA III-IV) with ejection fraction < 0.35), various wavelets were compared to an autoregressive model to determine the best model.

2. Methods

As a first step, the WSOLA (Waveform Similarity Overlap-and-Add) algorithm with the encapsulated Daubechies (Daub4) wavelet transform has been used for multiresolution time-scale modification (MTSM) [7, 8]. Behind the time-scale modification using time-segment processing, the basic idea is the time stretching of the analyzed segment without scaling the perceived frequency attributes, such as pitch. Several algorithms are referred to as OverLap-Add (OLA). To avoid phase discontinuities between segments, the synchronized OLA (SOLA) algorithm uses cross-correlation approach to determine where the segment boundaries have to be placed. The Time-Domain Pitch-Synchronous OverLap and Add (TD-PSOLA), an overlapping operation is performed pitch-synchronously. It works well with signals with a prominent basic frequency, but in other cases (e.g. noise) the size of the overlapping windows has to be increased, furthermore the phase error over a longer segment should be averaged, making it less audible.

We selected the WSOLA algorithm, which uses the concept of waveform similarity to ensure signal continuity at segment joints. This algorithm searches a new signal component to overlap and add with previous signal component in a given time duration around the synthesis time.

In its basic form, the overlap-add (OLA) strategy for time scaling consists of excising segments at time instants $\tau^{-I}(L_k)$ from the input signal $x\left(n\right)$, shifting them to time instants L_k, and adding them together to form the time scaled output signal $y(n)^I$:

$$y(n)^I = \sum_k x\left(n + \tau^{-I}\left(L_k\right) - L_k\right) w\left(n - L_k\right). \quad (1)$$

Yielding the output signal in this way, the individual segments will add incoherently, which introduces structural discontinuities at the waveform segment borders. WSOLA introduces tolerance parameters ($\Delta k \in [-\Delta_{\max}, \ldots, +\Delta_{\max}]$) on the desired time warping function to ensure that each new output segment $x(n+\tau^{-I}(L_k) - L_k)w(n-L_k)$ can be added coherently to the already formed- portion of the time-scaled signal. WSOLA ensures this signal continuity at segment joins by requiring maximal similarity between the new output segment and the segment that followed the previous output segment in the input signal.

To avoid problems of noisy PCG registrations the original fullband signal was decomposed into its sub-band components, prior to the WSOLA calculation. Some authors used the discrete Fourier transformation determining the sub-bands, we implemented the wavelet transformation [9].

The Daubechies-4 wavelet was applied in the multiresolutional time-scale modification (MTSM). The second tap wavelet transform blocks (after using the QMF structure in the first step) decompose the heart sounds into two sub-bands: high-pass filter ($h\left(n\right)$) is related to frequency band between 250-500 Hz, and low-pass filter ($g\left(n\right)$) between 0-250 Hz. Next, the WSOLA algorithm used for slowing-down, and finally the h', g' synthesis filters reconstruct the PCG signal. At the next step some wavelets (Haar, Meyer, Morlet, Mexican Hat, Daubechies(4)) were compared using an autoregressive (AR) model [6]. The following PCG data may represent the left ventricular dysfunction: faint first sound (fS1), S3 and S4 gallop sound, systolic murmur in the mitral auscultation area (MR). Using two observations, the change of these four entities were analyzed.

For a comparison we also analysed the input signal by the well known AR method, where each sample can be expressed as a linear combination of the previous samples and an error signal:

$$x(n) = -\sum_{p=1}^{M} a_p x\left(n-p\right) + e(n), \quad (2)$$

where $x(n)$ is the input signal, a_p is the AR coefficients, $e(n)$ is the estimated error signal, M denotes the model order.

The power spectral estimation (PSE) function of the AR method, $P_{AR}(w)$, is calculated:

$$P_{AR}(w) = \frac{\sigma_e^2}{\left|1 + \sum_{p=1}^{M} a_p e^{-jwp}\right|^2}, \quad (3)$$

where σ_e^2 denotes the noise variance (= we assumed to be constant), w the frequency, respectively. The modified Yule-Walker method was used (11 Kay), with a model order of 30. The continuous wavelet transform (CWT) was employed for the time-frequency representation, where five different wavelets functions (Haar, Meyer, Morlet, Mexican Hat, Daubechies(4)) were chosen.

To compare the frequency representations of the wavelets to the AR model, the Power Spectrum Estimation (PSE) of the latter to the Wavelet Power Spectrum Estimation of the wavelets were calculated:

$$WPSE(k) = \left| \sum_{n=1}^{N} CWT(n,k) \right|^2 , \qquad (4)$$

where N represents the number of points of the signal, k is the local frequency.

For the locations of the peaks in time are taken into consideration, the Energy Distributions (ED) of the wavelets have to determine. The ED of a signal is defined as the square of the modulus of the signal in time:

$$ED_{orig} = |x(n)|^2 \qquad (5)$$

and

$$ED_{wav}(n) = \left| \sum_{k=1}^{M} CWT\,(n,k) \right|^2 . \qquad (6)$$

While ED's of the original signal are obtained out of the CWT, PSE's of the AR modeling and obtained from CWT have to show the same variation at the maximum match; the normalized root-mean-square error (NRMSE) represents the similarity.

52 heart failure patients (NYHA III-IV) with ejection fraction < 0.35, and 50 age matched control subject without significant heart disease were examined. The phonocardiograms (PCG) was registered with an own developed electric stethoscope with a sampling rate of 20 to 8000 Hz. The measurements were repeated twice in a day and in three consecutive days. The data - with the ECG - was stored for the further analysis. The following PCG data may represent the left ventricular dysfunction: faint first sound (fS1), S3 and S4 gallop sound, systolic murmur in the mitral auscultation area (MR). These four entities were searched manually and with automated detection in the wavelet TFR maps of the signal. Two cardiologists evaluate the signals independently. The accuracy of the observers in identifying the four signs as compared with the PCG gold standard was expressed as positive and negative predictive values (PPV and NPV). The intraobserver agreement between pairs and groups of observers and the gold standard was quantified using the weighted kappa statistic; a kappa (κ) value of < 0.20 indicates poor or slight agreement, 0.21 to 0.60 is fair moderate, and 0.61 to 1.00 is substantial to almost perfect agreement [7, 8, 10, 11].

3. Results

The six registrations of the 52 heart failure patient (312 cases) were analyzed in the WSOLA study. Two independent cardiologist analyzed the PCGs, the original and the MTSM +WSOLA registrations. The rate of concordance for S3, S4, and a systolic regurgitant murmur were 62%, 59%, 69%, respectively for the original PCG, and 76%, 89%, 71% for the MTSM +WSOLA data. The best performance was achieved in the detection of S4 ($p < 0.001$), for S3 the value was also significant ($p < 0.01$).

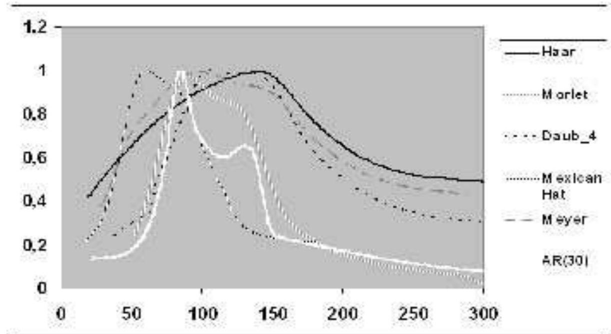

Figure 1. WPSE (wavelet method) vs. PSE (AR model)

Figure 1 shows the results of the autoregressive/wavelet analysis study for the heart sound and systolic murmur analysis comparing the WPSE's to PSE using AR modeling.

All wavelets, except the Morlet shows an incorrect spectrum. At the frequencies near to 100 Hz, the Daub4 spectrum is acceptable, but at higher frequencies the values of the Haar and Meyer are wrong. When the localization of the peaks in time is taken into consideration, the lower values of the NRMS shows better prediction. One can pick the NRMSE values for the different wavelets from Table 1.

Table 1. The NRMSE values

Wavelet	NRMSE value
Haar	92.33
Meyer	79.33
Morlet	39.45
Mexican Hat	86.54
Daubechies(4)	69.29

The least NMRSE value of the Morlet transformation represents the best similarity. In identifying fS1, the mean PPV was 36%, the mean NPV was 61, for S3 (59%, 78%), for S4 (51%, 69%), for MR (62%,81%); The overall interobserver agreement was $K = 0.31$ in the case of simple auscultation, and was 0.69 using the wavelet TFR.

4. Discussion and conclusions

The two studies showed several problems in real-life PCG monitoring. The registration in noisy environment, the comparation on various days result very hybrid PCG data. The more sophisticated signal analysis methods give some possibilities to manipulate the data, but these transformations do not give the „Road of Kings". Our results confirm the necessity collecting huge PCG database for expert system learning with or without neural network. The WSOLA method is suitable to improve the diagnostic confidence of the cardiologist, which is important creating the reference („output layer") of the database. Using the autoregression modeling, the undesired attributes in the CWT representation are observed on for all wavelets, the Morlet wavelet is the only exception. These two studies are the beginning of a real-life expert system of automated PCG monitoring, where the we would solve other important problems, namely how the define for the computer some features of auscultation (e.g. harsh, blowing, musical, vibratory, buzzing quality, measuring the effect of respiration, how to define the Levine-Harvey grading of loudness, or the „band-like"/crescendo-decrescendo fashion).

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