ASEPTIC: Aided System for Event-Based Phonocardiographic Telediagnosis with Integrated Compression

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Abstract

A general purpose system for telediagnosis of the valvular condition of the heart by analysing the phonocardiographic (PCG) signals generated by the heart is presented in this article. The system includes two main parts: a processing stage and a compression stage. The first one is arranged as a modular hierarchical structure with different abstraction levels, and performs a complete analysis of the PCG from the acquisition to the final diagnosis, following an event-based methodology. Analysis does not use auxiliary signals like ECG or pulse. The compression stage includes a lossy compression wavelet-based method with optimized parameters for an efficient transmission and storing of PCG signals. Results show a high degree of cardiac cycles in which all the events have been correctly delimited and identified, 91.27% and 65.65% for non-murmurs and for murmurs recordings, respectively, and compression rates between 2.6 and 5.6 times higher than the OGG Vorbis compression method.

1. Introduction

In the last 30 years, cardiac auscultation has been replaced by modern techniques (mainly echocardiography) to diagnose the valvular state of the heart, although it is still widely used as a screening technique. Nowadays, many efforts are being conducted to develop computer systems that can aid the physician to diagnose the state of the heart, and prioritize waiting lists according to the heart condition of the patient.

A complete system for telediagnosis of the valvular condition of the heart by analysing the phonocardiographic (PCG) signals generated by the heart is presented in this article. The system includes two main parts: a processing stage that analyses the PCG and determines the heart condition, and efficient algorithms that compress the PCG to transmit it remotely.

The processing stage is arranged as a modular hierarchical structure with different abstraction levels. Each level is associated to a basic signal, and includes several processing blocks. The analysis is performed by processing only the PCG, without using auxiliary signals like ECG or pulse. The system has been designed to work as a general purpose diagnosis system for cardiovascular pathologies, and follows an event-based methodology, trying to mimic the procedure carried out by the physician during auscultation. Transmission and storing of the PCG is made compressing the PCG with a specific method adapted specifically for this signal. The compression method is based in the wavelet decomposition, plus additional methods to increase the compression rate (CR) [1]. Information about the temporal delimitation of the cardiac events is also exploited to further increase CR.

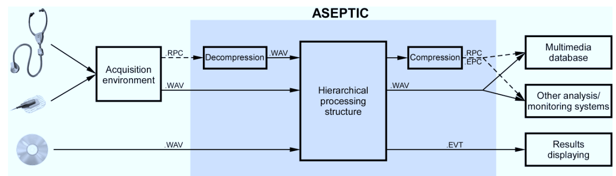

Figure 1. Internal structure of the ASEPTIC application.

2. Methods

The application developed, ASEPTIC (Aided System for Event-based Phonocardiographic Telediagnosis with Integrated Compression) includes a main stage that process the PCG signal, and compression/decompression stages that act as interfaces for receiving and sending signals to and from the application (Figure 1).

PCG signals are recorded at 8000 samples/s using a specific acquisition environment (Figure 2) that records, apart from the PCG, annotations about changes occurred during the auscultation process in the sensor (bell/diafragm), area of auscultation (apex, left lateral sternal border, right base, left base), and manoeuvrers (Valsalva, handgrip, . . .). The pulse signal is also recorded, but is used only for validating results and not during the analysis of the heart sounds. Annotations related to the auscultation process are stored

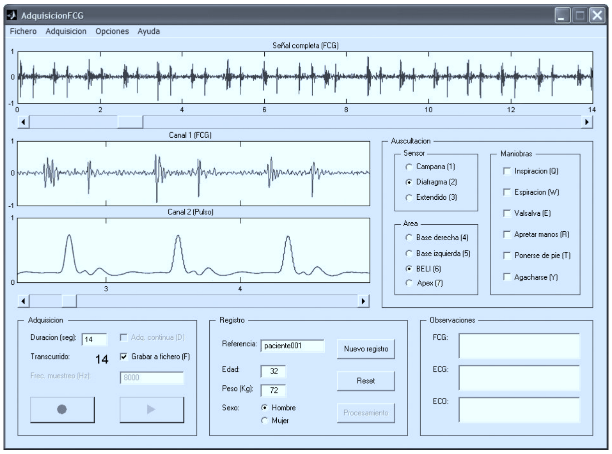

Figure 2. Specific environment for the acquisition of PCG signal.

in the annotations file, and the PCG signal is compressed and stored in the signal file. Both files are transmitted to the computer where the ASEPTIC application is running. The PCG is then decompressed and analyzed, and results are displayed. If necessary, the PCG signal together with analysis results can be transmitted to other systems (annotated multimedia databases, hierarchical superior analysis/monitoring systems, . . .). In that case, the PCG is compressed again, using information about the temporal delimitation of the cardiac events.

2.1. Processing stage

The processing algorithms developed perform a complete analysis of the PCG signal from the acquisition to the final diagnosis. These algorithms are arranged as a hierarchical structure formed by four levels (1 to 4). Each level is associated to a main signal: envelopes of the PCG (level 1), detected events (2), identified events (3), and diagnosis (4). Each levels is also formed by several processing modules that perform specific tasks over the PCG or over the other main signals (Figure 3). As signals pass from the lowest level to the highest level, they are involved in a data abstraction process that transforms progressively quantitative data into qualitative data.

Next we describe briefly the processing algorithms for each level in the hierarchy.

2.1.1. Level 1

Firstly, the PCG is decimated by a factor 2 (from 8000 samples/s to 4000 samples/s), and scaled in the range [+1,-1] by dividing the PCG by its maximum absolute value. The resulting signal is digitally filtered using two IIR (Infinite Impulse Response) Chebyshev type I 3rd. order filters, with cutting frequencies $f_{c1} = 40\,Hz$ (high-pass)

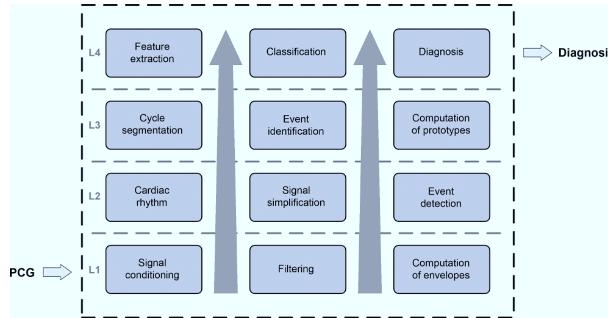

Figure 3. Processing modules of the hierarchical structure used to analyze the PCG.

and $f_{c2} = 800\,Hz$ (low-pass). Finally, three instantaneous magnitudes are derived from the PCG (instantaneous amplitude, IA, energy, IE, and frequency, IF) and their envelopes are computed using a moving average filter [2].

2.1.2. Level 2

The autocorrelation signal of the product of the three envelopes provides a symmetric signal with its maximum in the central point. The main relative maximum peaks detected in either of the halves of the autocorrelation signal are used to define the average cardiac rhythm as the mean value of the segments defined by these main peaks. An events detection method is then used to detect the basic cardiac events. This method is based in the detection of the relative maxima in the amplitude envelope and the computation of a set of associated points [3]. They define the temporal limits of the events, and a basic identification of them as *sounds* or *murmurs* is provided [4].

2.1.3. Level 3

From the computed average cardiac rhythm and the detected events, the PCG is segmented in cardiac cycles, beginning with a first heart sound (S1). Then the detected events are identified using the following information: events duration, amplitude and maximum frequency, relative distance between events, number of events in the cardiac cycle, and situation of the middle point of the event (only for murmurs). Algorithms have been developed to identify the following events: S1, S2, S3, S4, midsystolic clicks (MSC), and murmurs. In this last case, information about the relative situation of the murmur in the cardiac cycle is also provided (early/mid/late/holo and systolic/diastolic). Identification is based in three methods, used sequentially until one of them provides the identification of all the events in the cardiac cycle (if all the methods fail to identify the events in the cycle, these are marked as *non identified*): energy envelope, spectral-based energy tracking [5], and the application of the IF to A5 subband of the wavelet decomposition of the PCG.

2.1.4. Level 4

After the PCG is completely segmented in cycles and identified events, several features are extracted from the events (from the envelopes of IA, IE and IF). Principal Components Analysis (PCA) reduced the 13 features computed initially for each event to 5 features/event. The feature vector for each cardiac cycle is formed by the 5 PCA features for each one of the events in the cycle. Classification of these feature vector is done with a multilayer perceptron (MLP) neural network trained with the Levenberg-Marquardt algorithm. Each training was done in two phases: 1) using one half of the data to train the network and the other half to test the network, and 2) swapping the halves for training and testing. Final diagnosis is obtained from the identified events, the classification results, and patient data (age, sex, . . .).

2.2. Compression stage

Compression of the PCG is based in zeroing the wavelet coefficients whose magnitude is below a threshold. This generates two vectors: the coefficient vector, TC, (representing the coefficients as float numbers), and the significance map, SM, which is a binary vector that represents with '0' those positions in the coefficient vector where coefficients were zeroed, and with '1' those positions where coefficients were not modified. Zeroed coefficients and the last block of 0's are then removed from vectors TC and SM, respectively, and further compression is achieved using linear quantization for the remaining wavelet coefficients, and Run-Length Encoding (RLE) and Huffman encoding for the significance map. This method is called Raw Phonocardiogram Compression (RPC), and its flowchart is represented in Figure 4.

After the events detection carried out during the analysis, the temporal delimitation of the events is used to obtain two signals: the *events signal*, formed by all the events segments placed one after another, and the *noise signal*, formed by the noise segments (the segments between the events segments) place one after another. These two signals are then compressed independently using the RPC method, in the so-called Event-based Phonocardiogram Compression (EPC) method. The compression error for the noise signal can be greater than that of the events signal, since the important information for the diagnosis is included in the events segments and not in the noise segments. This allows increasing CR of the global signal (events signal + noise signal) without increasing the compression error of the events.

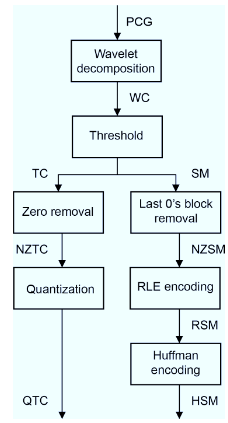

Figure 4. Raw Phonocardiogram Compression (RPC) algorithm.

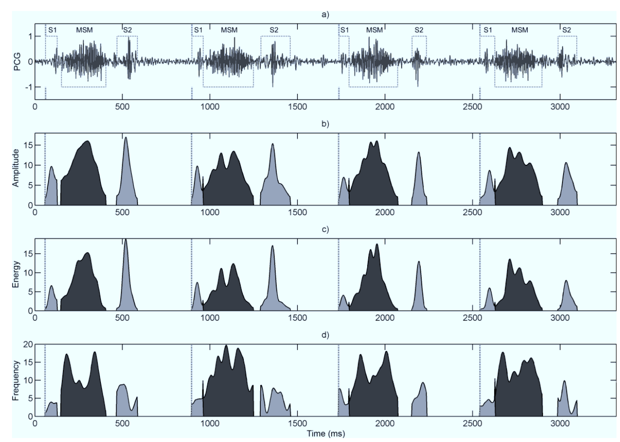

Figure 5. Cardiac cycles segmentation and events identification results for a PCG record with midsystolic murmur (MSM). From top to bottom: PCG signal, IA envelope, IE envelope, and IF envelope.

3. Results

Results obtained for the processing modules represented in Figure 3 showed that the signals derived from the PCG (IA, IE and IF) provides enough information to discriminate and identify the events. To illustrate this, Figure 5 shows clearly how the envelope of the IF for the midsystolic murmur (MSM) takes greater values than for the two main sounds (S1 and S2), although the amplitude and energy of the murmur are sometimes lower than for the sounds (first and second cycles).

The method used to compute the average cardiac rhythm has proven to be very robust, not only for normal records (with S1 and S2), but also for records with additional sounds (S3, S4, MSC) and murmurs. The application of this method is limited to records without severe arrhythmias, since the average cardiac rhythm would then not lead to valid results. The cardiac events detection method achieves also good results, separating the individual events even in the case that two or more events appear joined (like S1 and the murmur in cycles 2, 3 and 4 of Figure 5) or when the murmur has greater amplitude than S1 or S2 (cycles 1 to 4 in Figure 5).

Automatic segmentation shows also great accuracy with respect to manual segmentation (mean and maximum errors of 1.67% and 4.16% of the cardiac cycle duration for a normal record). Identification results achieved a high degree of cardiac cycles in which all the events were correctly delimited and identified: 387 from 424 cycles (91.27%), and 258 from 393 cycles (65.65%) for non-murmurs and for murmurs recordings, respectively.

Concerning pattern recognition, the 5 most discriminant features for each event were the duration, mean values of the event for AI and FI envelopes, and the area enclosed by the event for the AI and FI envelopes. To get a first impression of the classification performance of the system, 94 cardiac cycles were classified into three classes: normal record (with S1 and S2), record with holosystolic murmur, and record with midsystolic murmur, using a MLP neural network with 15/40/3 neurons for the input/middle/output layer. The output layer is of type winner-take-all. Correct classification results were 100.00%, 92.69% and 97.57% for the normal, holosystolic murmur, and midsystolic murmur classes, respectively.

Finally, compression results of methods RPC and EPC have been compared to those obtained with OGG Vorbis compression method. Comparing CR obtained for similar compression errors, RPC achieves CR values between 1.8 and 4.5 times those achieved with OGG Vorbis. EPC achieved between 2.6 and 5.6 times the CR of the OGG Vorbis method. Finally, EPC method compress PCG between 20% and 70% more than RPC method for the same compression error in the events segments. Figure 6 represents CR values obtained for a normal record for the three compression methods evaluated for different PRD (Percent Root-mean-squared Difference) compression errors.

4. Discussion and conclusions

A complete application for the telediagnosis of the cardiovascular condition of the patient has been presented in this article. It includes a processing stage that analyzes the PCG signal without auxiliary signals using an event-based approach, and a compression stage that provides an efficient method to store the PCG and transmit it remotely. Results achieved for the identification of cardiac events and classification of records into different classes have been very promising, and compression rates obtained are very superior to other audio compression methods applied to the PCG.

Future works include testing the algorithms with a larger records database to adjust accurately the design parameters of the algorithms in order to improve the identification rate. Taking into consideration the annotations generated during auscultation is also planned to increase the accuracy of the diagnosis.

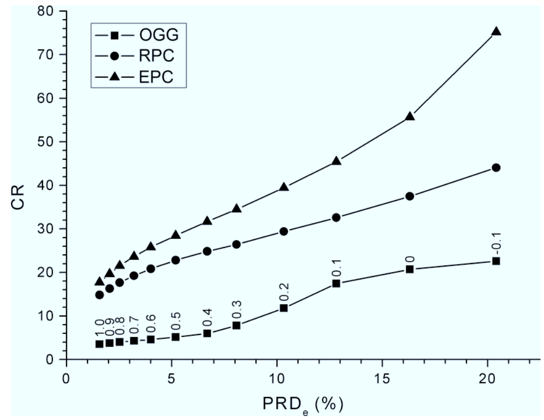

Figure 6. CR versus PRD error compression results for the OGG Vorbis, RPC and EPC compression methods.

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