NEAR REAL TIME NOISE DETECTION DURING HEART SOUND ACQUISITION

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ABSTRACT

Heart sound is a valuable biosignal for early detection of a large set of cardiac diseases. Ambient and physiological noise interference is one of the most usual and high probable incidents during heart sound acquisition. It tends to change the prominent and crucial characteristics of heart sound which may possess important information for heart disease diagnosis. In this paper, we propose a new method to detect ambient and internal body noises combined with heart sound. The algorithm is based upon the periodic nature of heart sounds and physiologically inspired criteria. A small segment of clean heart sound exhibiting periodicity in time as well as in the frequency domain is first detected and applied as a reference signal in sorting noise from the sound. The achieved average sensitivity and specificity are 94% and 97%, respectively.

1. INTRODUCTION

Cardiovascular diseases are the leading cause of death in developed countries. In Europe the prevalence of chronic cardiovascular diseases is between 20% and 45% of all deaths. Being a disease tightly connected to aging, it is observed that incidence is on the rising due to the extended life expectancy. The solution to this health problem is believed to be changing the focus from curative healthcare to preventive healthcare. This is commonly believed to be achievable by fostering preventive lifestyle as well as early diagnosis. In this sense long term tele-monitoring is a promising tool to achieve early diagnosis and, therefore, avoiding potentially life-critical situations as well as aggressive and expensive treatments. Therefore, current research trends in this direction are to integrate system solutions into ordinary daily objects, such as functional clothes with integrated textile or hard sensors. In order to be cost effective and usable for long time periods, these tools require intelligent data analysis algorithms to be able to autonomously perform diagnostic functions and to support users in solving problems, hence requiring low computational algorithms that could be run in real-time using low power processing devices. Under the analysis of vital signals (e.g. heart sound) using computational algorithm, the noise cancelation during signal acquisition is a primary and indispensable task. This task is imperative for reliable diagnostic feature extraction.

Heart sound is a valuable biosignal for early detection of a large set of cardiac diseases. Unfortunately, heart sound is more sensitive to noise than ECG. Many researchers have applied ECG as a reference or marker to find the ambient noise. In [1] an ECG was applied for heart beat detection. Subsequently noise presence detection was performed by beat by beat power spectrum cross correlation. A very well known method for speech enhancement based upon spectral domain Minimum-Mean Squared Error (MMSE) estimation was applied to reduce noise affect in heart sound [2]. This method reduces white noise from heart sound while S3 and S4 sounds were prevented using ECG gating. Another attempted method for noise cancelation in real time was developed using an extra acoustic sensor to capture the environmental noise. This additional signal provides a noise signal for subtracting environmental noise from the contaminated heart sound signal [3]. Other methods can be found in literature which involve filtering with a certain band of frequencies [4]. In order to develop cost effective, portable and practical systems, the noise removal algorithm must fully/paritally avoid to be dependent on ECG or any non-cardiac sound sensors.

In this paper, an algorithm is proposed for non-cardiac sound detection from heart sound during acquisition. The periodicity of heart sound components (namely S1 and S2) is an inspiration to detect non-cardiac sounds in heart sounds. The proposed method first searches for a clean heart sound segment as a reference signal based on periodicity. Afterwards, the spectral energy of the reference signal is correlated with the rest of heart sound in real time. The heart sound segments which exhibit low correlation coefficients with the reference heart sound signal are assessed as non-cardiac sounds. This method is able to detected almost every kind of physiological and environmental non-cardiac sound.

The paper is organized as follows: in the second section, the proposed method is thoroughly explained, the third section introduces results and discussion, and finally some conclusions are presented in the fourth section.

2. METHOD

In order to extract reliable diagnostic features from heart sound it is important to first suppress noise. During heart sound acquisition many external body noises such as ambient noise, as well as internal body noises such as heavy breathing, swallowing sound, speech etc., may be captured. These noises are linearly/nonlinearly mixed with heart sound. Therefore, the suppression of these noises in heart sound is not a straightforward problem. Furthermore, even a small ambiguity in suppression may lead to wrong diagnosis based on heart sound features. However, it is rather probable to assure that heart sounds used for diagnosis are not contaminated. The strategy proposed in this paper is to detect the contaminated sound segments and to exclude them from further processing.

In order to accomplish the objective (see figure 1), first features are extracted which are used to detect a small segment of pure heart sound during acquisition. This segment is used as a reference signal and compared with the rest of the acquired heart sound in order to detect contaminated heart sound segments. The required features, i.e. zero crossing rate and periodicity of S1 and S2 heart sound components in time and frequency domain, and involved steps in the algorithm for the detection of the reference signal as well as its comparison with the subsequent heart sounds are elaborated in this section.

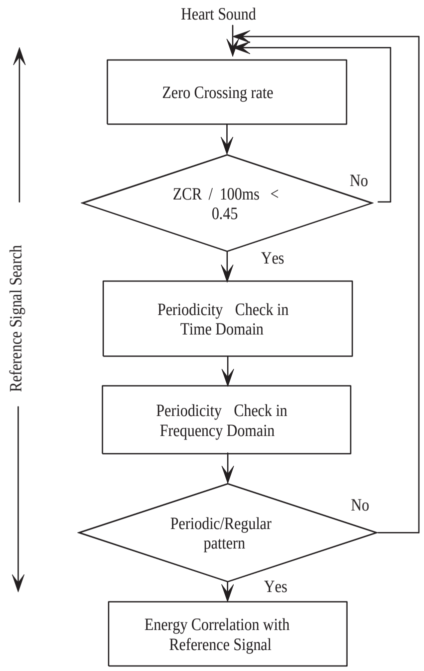

Figure 1: Flow Chart of the Proposed algorithm.

2.1 Feature Extraction

The core part of the proposed method is finding the reference signal. The reference signal must be highly representing the attained pure heart sound.

Two major features are taken into account in finding the reference sound:

- Zero-Crossing Rate
- Periodicity (Time/Frequency domain)

In the process of extracting these features, the applied analysis window are different based upon the prerequisites of the respective features.

2.1.1 Zero-Crossing Rate

Mostly heart sounds fall into low frequency range (40-200Hz), while in exceptional cases, e.g. heart sound produced by mechanical heart valves or severe murmur, this range may be increased. Withstanding this observation, it is found that almost every kind of human cardiac sound exhibits zero-crossing rate of 0.45 per 100 ms. This feature has the potential to discriminate noise sources with high frequency contents such as speech, coughing sound, rubbing sound, etc. The occurrence of these type of noise sources is highly probable during acquisition. Let $x(t)$ be the heart sound undergoing acquisition, the Zero-crossing rate of the i^{th} 100 ms segment is formulated as follows:

$$ZCR_i = \frac{1}{N_1}\sum_{j=1}^{N_1} |sgn(x(j)) - sgn(x(j-1))|, \qquad (1)$$

where N_1 is the number of samples in the selected window. The non-cardiac sound, namely very high frequency sounds are identified (see figure 2).

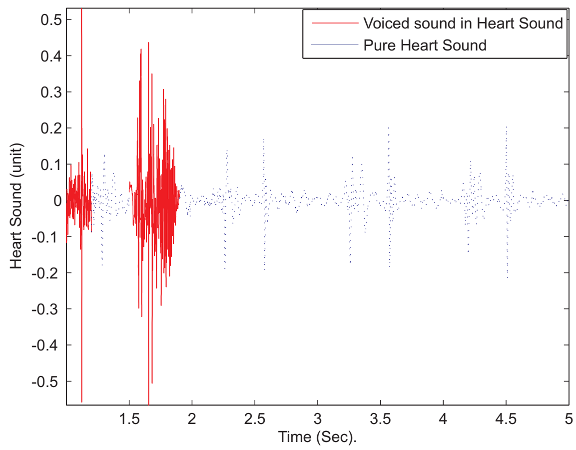

Figure 2: Zero crossing rate in due to speech segments presence in heart sound.

2.1.2 Autocorrelation based Periodicity

One of the most noticeable characteristic of heart sound is periodicity; even though heart cycles change with very unpredictable manner in arrhythmic heart patients, nonetheless periodicity/quasi-periodicity of its main components (S1 or S2 sounds) can be observed. Non-cardiac sounds immensely influence the identification of the regular occurrence of heart sound components. In absence of many non-cardiac sounds, it is straightforward to measure periodicity of pure heart sounds based on the autocorrelation function. Pure heart sounds exhibit periodicity/quasi-periodicity in time domain as well as in the frequency domain.

(A) Periodicity in the Time domain: The envelopes of heart sound components are extracted by applying the Hilbert transform followed by the Gammatone band-pass filter [5]. Next, the autocorrelation function of the envelope is computed. Typically, it will exhibit pronounced peaks for the main heart sound components, i.e. the S1, S2 and murmur components. The autocorrelated values are normalized by autocorrelation values of a chosen windowing function, e.g. the Hanning window. Let $x^e(t)$ be the envelope of the heart sound and let $y(t)$ be its autocorrelated function such that

$$y(t) = \frac{\int_0^N x^e(t)w(t) * x^e(t-\tau)w(t-\tau)d\tau}{\int_0^N w(t) * w(t-\tau)d\tau}, \qquad (2)$$

In equation (2), $w(t)$ is the the Hanning (windowing) function and N is the number of samples in a given segment of heart sound. The stronger peaks are detected using the algorithm described in [6]. This algorithm exhibits a high sensitivity in peak detection, therefore, usually several false weak peaks are detected. To solve this, the number of strong peaks in $y(t)$ are found using estimated duration (or heart rate) of heart cycles in a given segment of the analysis signal. Once all strong peaks have been detected, the periodicity is checked using radial distance between two contiguous heart cycles. The heart rate estimation and periodic cycles verification procedures are as follows:

(A1) Heart Rate Estimation: Heart rate, in a given segment of heart sound, is calculated using the large difference between two first singular values of rearranged autocorrelation function of the envelopes [7]. Let $y(t)$ be periodic with period T, i.e. $y(t+T) = y(t)$. At rest T is between 500 ms and 1200 ms (heart rate is between 50 beats/min and 120 beats/min) for the typical population in rest state. Let Y be the data matrix which is constructed by stacking $y(t)$ samples after every T ms using following arrangement,

$$Y = \begin{pmatrix} y(1)...y(T) \\ y(T+1)...y(2T) \\ . \\ . \\ y((m-1)T+1)...y(mT) \end{pmatrix}, \tag{3}$$

where m is the number of periodic analysis segments in a given segment of heart sound. If matrix Y has repeated rows, then it will have low (eventually one) non-zero singular values. The non-singular values are found by singular value decomposition (SVD) of Y, and rearranged such that $\sigma_1 \geq \sigma_2 \geq \sigma_3 ... \geq \sigma_m$. In case of periodic $y(t)$ the singular values rapidly decrease. Hence, periodicity can be measured using following relation,

$$\rho = (\sigma_2/\sigma_1)^2, \tag{4}$$

very low value of ρ implies strong periodicity in a signal. In the process of estimating the heart rate, Y is constructed varying T. The T, which is responsible for the minimum ρ, is the estimated duration of a heart cycle. The estimated heart rate enables to find the prominent peaks in $y(t)$. Since strong peaks are directly related to the main components in the heart sound which occur only once per heart cycle (see in figure 3).

(A2) Periodicity Check Criterion: The all stronger peaks of $y(t)$ are detected in previous step, which enables in finding shape similarity between two heart cycles (contiguous pair of stronger peaks). The similarity is measured by radial distance between two vectors. Let $y_1(t)$ and $y_2(t)$ be the two vectors, the radial distance is given by,

$$Cos(\theta) = \frac{< y_1(t), y_2(t) >}{|\, y_1(t)\, |\, |\, y_2(t)\, |}, \tag{5}$$

where $< . >$ is the inner product operator and $|\, .\, |$ represents mean square root value of the vectors. In all situations of similar periodic shapes, $Cos(\theta)$ value lies in the vicinity of 1.0, as is shown in figure 3(c).

(B) Periodicity in the Frequency domain: The periodicity of heart sounds in time domain may not be influenced by the presence of many non-cardiac sounds. For instance, swallowing, breathing or high pitched voice can not be identified using the time domain periodicity detection technique. However, the influence of the noise source in heart sound periodicity can be seen in the frequency domain. Therefore, spectrogram is adapted to find periodic patterns in frequency bands. Let $S(f,t)$ be the short Fourier transform of $x(t)$, i.e.

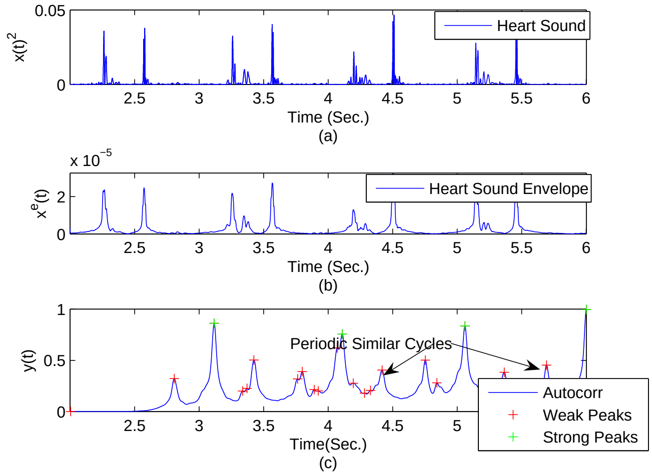

Figure 3: (a) Heart Sound Energy; (b) Heart Sound Envelope; (c) Autocorrelation function of the envelope with peaks identification.

$$S(f,t) = \int_0^M x(\tau) w(t-\tau) exp(\frac{-2jf\pi\tau}{M}) d\tau, \tag{6}$$

where M is the window size. It has been observed in normal/abnormal heart sounds that most power is concentrated up to frequency 1.2kHz. Hence, 15 frequency bands from the spectrogram matrix are taken for periodicity verification, as it is depicted in figure 4. It should be noticed that normal heart sounds exhibit regular patterns in these frequency bands which are linearly independent. These linear independencies may monotonically decrease/increase in different types of heart sound, i.e heart sounds from prosthetic valve click and native valve clicks. In this situation, the peaks in power are almost aligned. These phenomenons are seen in the heart sounds which exhibit periodicity in the frequency domain. The methods for the verification of S1 and S2 periodicity in frequency domain using 15 frequency bands and the criterion for power peaks alignment in these bands are explained next.

(B1) Pattern Detection in the Frequency Bands: In order to extract periodic patterns from spectrogram matrix, the rows are autocorrelated as given in equation (2). Let $S^k(f,t)$ be the autocorrelated function of the k^{th} frequency band in the spectrogram (see figure 4). Furthermore, it is depicted that autocorrelated power in 1-15 frequency bands are in regular patterns, where the stronger peaks occur almost at the same time, and widths of these peaks decrease in higher frequency bands. On the other hand, the peak widths increase in absence of signal power in the high frequency bands; usually, strong peak widths are absent in native heart valve click sound. Therefore, these observations inspire

in building the heuristic which may be applied to verify if the cardiac signal is clean from contamination. One of the observations is linear independence of the rows of $S^k(f,t)$. Regarding linear independency measurement, the SVD technique is applied again as was introduced previously. Since the peak widths in $S^k(f,t)$ increase or decrease in ascending frequency bands, therefore, each five contiguous ascending frequency bands are grouped according to equation (7) and singular values are computed using the previously described SVD technique.

$$Sg^{(k,k+4)}(f,t) = \begin{pmatrix} S^k(f,t) \\ S^{k+1}(f,t) \\ . \\ . \\ S^{k+4}(f,t) \end{pmatrix}, k = 1,6,11. \quad (7)$$

In equation (7) $Sg^{(k,k+5)}$ is the matrix formed by grouping of $S^k(f,t)$ rows for each five ascending frequency bands. The SVD of matrix $Sg^{(k,k+5)}(f,t)$ provides singular values which reveal linear independence. In the equation (4), ρ exhibits low value for linear dependent rows. Let ρ_1, ρ_2 and ρ_3 be the singular values ratios of the matrix $Sg^{(1,5)}(f,t)$, $Sg^{(5,10)}(f,t)$ and $Sg^{(10,15)}$ respectively, then the most significant observations regarding pure heart sounds are: $\rho_1 > \rho_2 > \rho_3$ or $\rho_1 < \rho_2 < \rho_3$. In the situations of non cardiac sounds these sequences are violated. It should be noted that the strong peaks are due to heart valve clicks. S1 and S2 sound in native valves, it is observed that the width and hight of the peaks decrease in high frequency bands while in prosthetic valve heart sound peak widths decrease but peaks heights increases due to high power availability in high frequency bands. Therefore, in prosthetic valve heart sounds linear independency monotonically decreases in the high frequency bands.

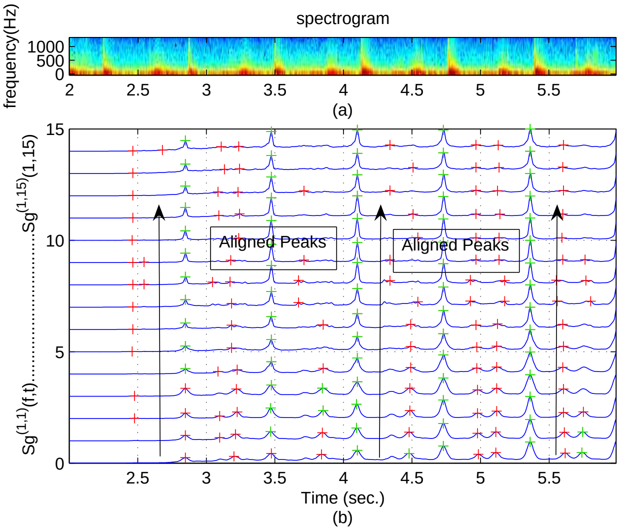

Figure 4: (a) Spectrogram of a pure heart sound exhibiting 1-15 frequency bands; (c) Autocorrelation function $S^k(f,t)$ of spectral power in 15 frequency bands, in this situation ρ increases in high frequency bands.

(B2) Peak Alignment in the Frequency Bands: As it has already been explained the peaks are due to S1 and S2 heart sounds, therefore, they should exhibit alignment in $Sg^{(k,k+5)}(f,t)$ frequency bands. Otherwise, it is considered that these peaks are due to noise. In order to check the alignment, all main peaks are found using the previously described peak detection technique. Afterwards, defining a time tolerance ($\pm 5\%$ of the time of first peak), all peaks alignment are inspected.

2.2 Proposed Algorithm

The previous subsection introduced the feature extraction procedure as well as the preparation phase required to detect the reference heart sound. In this section, the actual detection procedure applied for this purpose as well as the detection method of the contaminated heart sound segments are described. The detection of the reference heart sound includes the following steps:

Step1: In the first step, zero crossing rate per 100 ms window is computed. If ZCR/100 ms is greater than 0.45 then the segment is classified as noise.

Step2: If the heart sound segment verifies the periodicity constraints, then a similar heart sound window to the left is searched in order to establish the end of the reference signal.

Step3: After selecting the reference signal, it is treated as an ideal signal to assess the rest of the heart sound segments. In this step, spectral root mean square of the heart sound signal is calculated from following equation,

$$S_{rms}(f,t) = \sqrt{\int_0^{T_w} | S(f,t) |^2 dt}, \quad (8)$$

where T_w is the size of the reference signal. The reason of applying the root mean square over the spectrogram is to avoid signal power estimation. Root mean square of the spectrogram provides an estimate of the power distribution in frequency domain, see figure 5(c). Let $S^{ref}_{rms}(f,t)$ and $S^{test}_{rms}(f,t)$ be the spectral root mean square for the reference and the test heart sound signals respectively, then validation is performed using the following condition,

$$CorrCoef(S^{ref}_{rms}(f,t), S^{test}_{rms}(f,t)) > th, \quad (9)$$

where $CorrCoef$ is the correlation coefficient between two signals. The threshold th value is defined as 0.99 in the equation (9).

In order to apply the described algorithm, the analysis window size is first decided which is chosen 100 ms in the present work. Hence, the algorithm starts after acquiring 100 ms of heart sound. However, the periodicity validation starts after 3 seconds. This analysis window can be physiologically justified with the duration of heart cycles. It requires to consider sufficient signal duration in order to check convincing periodicity. An interesting example is presented in figure 5, where the reference signal is found and subsequently contaminated heart sound segments are detected.

3. RESULT AND DISCUSSION

3.1 Material and Data Collection

Heart sounds were recorded from different patients with prosthetic valve implants (both Mechanical and Bioprosthetic) one month after surgery using an electronic stethoscope from Meditron in University Hospital of Coimbra, Portugal. The data set is collected using patients with arrhythmic and non-arrhythmic hearts. These heart sounds include several non-cardiac sounds. The used stethoscope has an excellent signal to noise ratio and extended frequency range (20 - 20,000 Hz). All sound samples were digitized with 16-bit resolution and 44.1 kHz sampling rate.

3.2 Experimental Results

The algorithm was tested with several heart sound signals which were contaminated by several types of non-cardiac sounds. The tested data set includes 86 heart sound samples. Each sound sample includes regular heart sound as well as mixtures with non-cardiac sounds, such as high/low pitch speech, several types of environmental sounds, human made ambient noise, and internal body sounds (swallowing, heavy breathing, speech). The recording length of all heart sounds was not more than 2 minutes. In sake of algorithm validation, some heart sounds purposely recorded with several no-cardiac sounds. The algorithm performs with the noticeable average sensitivity of 97% and average specificity of 94% regardless of heart sound types.

The main challenge in the proposed approach is the selection of the reference heart sound. In the performed tests the algorithm was always able to find an appropriate reference signal, even in those situations when noise was present at the beginning of the heart sound.

4. CONCLUSIONS

A new algorithm for non-cardiac sound detection, without using ECG as a reference signal, in realtime heart sound acquisition was proposed. The algorithm is composed by two main step: first a reference signal composed by a complete heart cycle is detected. Secondly, this reference signal is compared to subsequent heart sound segments. The first phase of the algorithm is slightly computationally intensive. However, once the reference signal has been detected, subsequent processing is of low complexity. At this stage, non-cardiac sounds are segregated from heart sound, subsequently analysis of heart sounds can be performed. Furthermore, the method enables near-real time application using low power embedded systems, such as those require to implement in eHealth solutions.

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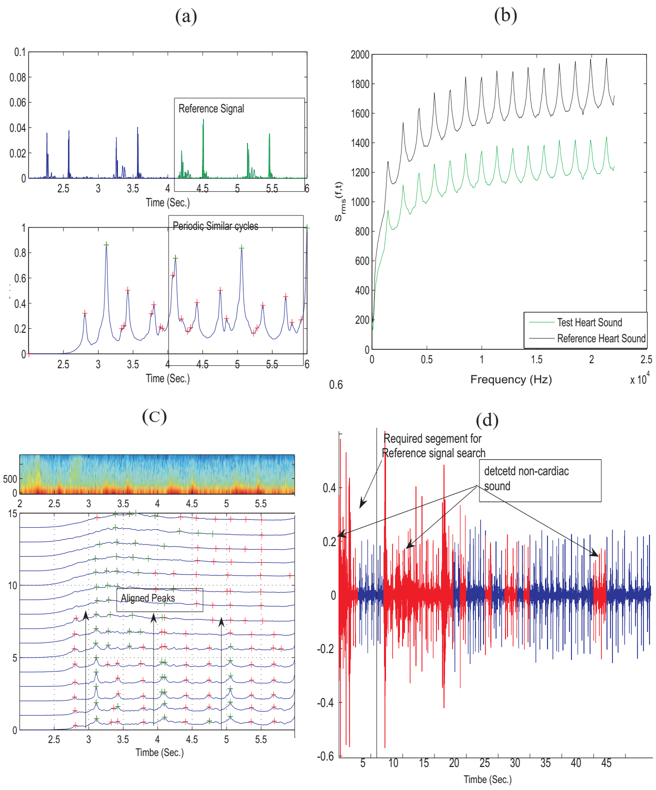

Figure 5: (a) Reference sound in Heart Sound; (b) Periodicity/Regular pattern based on ρ decrement and peaks alignment; (c) $S_{rms}(f,t)$ of Reference and test heart sound; (d) All noisy detected noisy segments.