Biomedical Signal Processing and Control 44 (2018) 154–167

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Noise detection in phonocardiograms by exploring similarities in spectral features

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ARTICLE INFO

Article history:
Received 2 October 2017
Received in revised form 6 March 2018
Accepted 15 April 2018

Keywords:
Heart sound
Phonocardiogram
Noise detection
Spectral similarities

ABSTRACT

Analysis and interpretation of heart sounds (HSs) can be seriously hindered by noise contamination when signals are acquired in noncontrolled environments. Signal processing methodologies are then required in order to robustly analyse HSs collected in different recording settings. Some works already address this problem using complex calculus that are usually dependent on the accurate segmentation of the signals. As such, the aim of the present study is the development of a low-complex automatic algorithm able to discriminate clean from contaminated HS signals (or phonocardiograms) recorded in real-life situations.

Spectral features were used to characterize the different behaviours of clean and noisy HSs in phonocardiograms (PCGs) in noisy conditions. In particular, besides the normal interferences associated to the auscultation in a noncontrolled environment, other noisy sounds were purposely simulated and included vocalizations, ambient sounds and also other physiological interferences rather than HSs. The available signals were recorded in 24 healthy volunteers and in eight patients diagnosed with different cardiac disorders. The subjects included in the healthy dataset followed a pre-defined protocol, during which ambient, physiological and vocal interferences were simulated. A total of 288 PCGs, recorded in pulmonary and mitral auscultation positions, comprises the healthy dataset. The pathological dataset includes 16 PCGs, acquired in pulmonary and tricuspid chest locations.

The described approach was compared with two existent methodologies developed for the same purpose. Our algorithm was found to return the best performance regarding the different types of interferences, resulting in an average sensitivity and specificity of 88.4% and 85.6%, respectively, for healthy dataset and 84.3% and 85.8%, respectively, for the dataset with pathology. These results correspond to an increase of up to 4.7% in SE and 39.0% in SP when comparing to the two referred methodologies in healthy dataset. Regarding the pathological dataset our approach improved noise detection by up to 27.0% in SE and 34.1% in SP.

1. Introduction

Heart sounds (HSs) are produced by different events occurring during the heart cycle, namely opening or closing of valves and blood flow [1]. For example, the first (S_1) and second (S_2) HSs, being acoustically very prominent, can be easily identified at the beginning of the ventricular systole and diastole, respectively. Knowing that two sequential S_1 events define a cycle [1,2] it was possible to develop segmentation algorithms able to identify the heart cycles along phonocardiograms (PCGs). Third (S_3) and fourth (S_4) HSs are considered extra HSs that typically occur in early and late diastole. S_3 and S_4 can be produced by deceleration of mitral flow by ventricular walls [1,2], and their presence may have an ambiguous interpretation. Under certain circumstances, it is an indicative of cardiac abnormality and, in other cases, it is considered a sign of regular physiological activity [1].

Cardiovascular diseases directly affecting the heart, namely valvular heart disorders, can be identified by the occurrence of pathological HSs or murmurs which in turn are the result of blood flow turbulence and consequent vibration of the surrounding tissue. Murmurs can be detected resorting to cardiac auscultation, as it is a fast, non invasive and cheap method used in diagnosis [1,2]. It can be very effective in the early detection of the cardiac pathology, reducing the complexity and also the costs of the subsequent treatment [2].

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https://doi.org/10.1016/j.bspc.2018.04.015

Auscultation is performed by placing a stethoscope in specific areas near the heart, and by further evaluation of the acoustic properties of the HSs (e.g., intensity, duration, rhythm, etc.). However, the interpretation of the sounds is affected by the clinician's subjectivity which will be reflected in the final diagnosis [1,2]. As consequence, improvements have been made in the field of hardware electronics in order to obtain an objective assessment of the HSs. Nowadays, electronic stethoscopes and microphones are examples of devices used to record the PCG, i.e., a graphic representation of the HSs [1]. PCG carries information about the characteristic waveforms of the HSs, being however prone to be affected by different noise sources. Specifically, PCG can be contaminated by external (e.g., ambient music, doors closing, etc.) or internal physiological noise sources (e.g., cough, speech, stomach growls and breathing sounds). The presence of noise compromises the analysis of the signal and ultimately it can lead to erroneous diagnostics. This problem demands the development of algorithms able to detect and/or cancel noisy periods.

The majority of the studies found in literature intend to detect pathology in heart signals. In some of them, there is a previous step corresponding to the detection of noise. Furthermore, there are also algorithms developed to detect murmur which often rely on a segmentation process robust to noise. Such process has been improved over the last years in order to be efficient when dealing with PCGs acquired in noisy environments, and often with handheld stethoscopes. Towards that and in light of the quasi-stationarity behaviour of HSs, a wide variety of features have been used to distinguish noise from uncontaminated HS, such as, entropy gradient [3], variance fractal dimension [4], high frequency signatures [5] and features based on hidden Markov models [6,7], derived from simplicity measurements [8] and obtained from mel-scaled wavelet transform [9], among others. Wavelet denoising techniques have also been proposed [2,10–14]. Additionally, there are also noise reduction (or denoising) algorithms such as: the one proposed by Paul et al. that is based on the spectral domain minimum-mean squared error estimation [15], the Kalman denoising filters developed by Almasi et al. [16] and Yupapin et al. [17], the total variation filter designed by Varghees and Ramachandran [18], the noise versus HS separation performed in the joint cycle frequency–time–frequency domains based on fuzzy detection documented by Tang et al. [19] and also the adaptive overlapping-group sparse denoising algorithm proposed by Deng and Han [20]. The drawback of some of these noise reduction algorithms is closely related to an increase in signal's distortion (caused e.g. by reconstruction), with loss of the original properties of the HS. Finally, there are noise subtraction approaches, such the one described by Bai and Lu [21] and Zia et al. [22], that are known to use the information of an external sensor to record surrounding artifacts during acquisition. This approach usually relies on an extra microphone that captures only noise produced by external sources, neglecting other types of noise originated by internal body sources. To be noticed that, the majority of the aforementioned studies reported results obtained by applying the developed methodologies to HS recordings, to which artificial noise (e.g., white noise) has been added [2,9–14,16–20]. The evaluation of the performance of the algorithms is not conducted using recordings collected in noncontrolled environments, which fairly resemble the real scenarios of busy hospital rooms or in-home settings.

However, to the best of our knowledge, only few studies were found to report the implementation of signal quality evaluation step before the assessment of the presence of pathology in the heart signals [4,5,23–26]. Due to privacy and legal constraints, it was defined that HS collection has to be implemented under explicit control of the user. Therefore, these approaches to noise handling during collection were developed to detect contamination and to warn the user in order to avoid the noise source in case of noise persistence or to discard noisy segments from further processing.

In this context, Carvalho et al. [4] developed a signal quality evaluation methodology to be applied before the segmentation process. It involves the computation of a similarity measure which considers that a heart cycle (defined using the consecutive Q wave peaks from ECG's QRS complex) has been contaminated if the correlation between the spectral power distributions of that cycle and of a noise free cycle is lower than 0.995. If more than two cycles fall in this condition the entire signal is discarded.

Ramos et al. [24] explored the stationarity of the PCG in the context of noise detection, by assuming that the PCG comprises a quasi-stationary component associated with the HSs ($\sim$2–20 Hz) and a stationary component characteristic of lungs sounds. More precisely, this algorithm inspects the behaviour of the stationary property along the non-heart signal, in the presence of transient noise. This process is based on the implementation of a 1 Hz low-pass modulation filter in order to obtain temporal trajectories from the single-channel PCG. A different noise detection procedure, comprising two phases, was proposed by Kumar et al. [5,23,25]. The first phase consists in the identification of a noise-free window, obtained through a segmentation process based on periodicity inspection in both time and time-frequency domains. In a second phase, the uncontaminated window is compared with the remaining PCG signal, using energy features. Elgendi et al. developed a thresholding procedure able to identify blocks of noise that are further discarded [26]. Also in this case, the performance of the algorithm was assessed by adding white Gaussian noise to the acquired HSs.

Recently, the largest database of HS recordings has been made publicly available in the context of Physionet/Computing in Cardiology Challenge 2016 [27]. This database comprises 2435 recordings collected both in healthy and patients diagnosed with a wide variety heart conditions. Additionally, the acquisitions took place in both clinical controlled and noncontrolled environments, the latter leading to the existence of recordings contaminated with different types of noise. Each HS recording is annotated as "Normal" or "Abnormal" (redirect for further diagnostics) or "Unsure" (no quality signal, retake the recording). Based on this, it was not possible to use those recordings in our study, as no annotations are provided along the signals, not allowing a sample-by-sample analysis as is proposed hereby. Furthermore, no information is also provided regarding the amount of noise in a given recording which is also makes the dataset unsuitable to be used in our study. As result of this challenge (and as was previously performed by Springer et al. [28]), new methodologies have been developed in order to perform binary quality classification of HS recordings [29].

The noise detection approach described in the present paper was developed in order to automatically detect periods of noise in PCG signals, considering the computational cost and complexity required for its real-time applicability during long term tele-monitoring. As such, complex calculus corresponding to HS segmentation were replaced by a simpler approach based on rules. During acquisitions participants followed a protocol which comprises blocks of interferences deliberately produced either by the participant itself (e.g., vocal and physiological noise) or by external sources (ambient noise). Similarly to Kumar et al. [23], our approach also relies on the search of a reference window, that has not been contaminated with noise. Two features, namely the spectral energy similarity and the power spectral density (PSD) ratio, were then obtained by comparing the reference window with the remaining signal. The PCG segments classified as contaminated can be further discarded from the subsequent analysis, without the need to analyse a reconstructed and/or distorted signal. In order to prove the validity of our algorithm, the two previously described methodologies (modulation filtering algorithm – MFA by Ramos et al. [24] and