Automatic Identification of the Best Auscultation Area for the Estimation of the Time of Closure of Heart Valves through Multi-Source Phonocardiography

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Abstract

In the latest years, multi-source phonocardiography (PCG) is gaining interest in relation to the home monitoring of cardiovascular diseases. An application of interest regards the monitoring of the time of closure of the four cardiac valves, which would enable the follow-up of at-risk patients for heart failure. In this work, we propose a hybrid system based on hierarchical clustering and Multi-Criteria Decision Analysis (MCDA) for automatically selecting the best auscultation area for the mentioned application through multi-source PCG. We simultaneously recorded 48 PCG signals from the subject's chest and divided them into morphologically homogenous groups using agglomerative hierarchical clustering, based on their correlation. Then, we explored three different approaches to select the best auscultation area, based respectively on the minimum latency, on the maximum signal-to-noise ratio, and on multiple criteria using ELECTRE III. The results obtained on the follow-up of a healthy subject over consecutive days show that a) the selection of the auscultation area using MCDA overcomes the limits of single-criteria approaches, b) the estimate of the time of closure of the heart valves using the proposed system is more robust than what obtained through the state-of-the-art single-source methodology.

1. Introduction

In the latest years, phonocardiography (PCG), i.e., the digital recording of heart sounds, has often proved as a potentially valuable tool to diagnose and monitor a number of cardiovascular diseases (CVDs) [1]. When compared to other technologies (e.g., echocardiography, blood analysis), the main potentiality of PCG resides in its portability, which may lead to novel possibilities in the context of home monitoring. PCG proved particularly suitable to studying the progress of some CVDs which are difficult to monitor otherwise, such as congestive heart failure (CHF) [2]. In fact, keeping track of the status of an at-risk patient to prevent an acute episode is still challenging. Nonetheless, the monitoring of the electro-mechanical status of their heart can be suitably related to the monitoring of the time of closure of their heart valves [3]. The latter can be estimated through simultaneous recordings of ECG and PCG, by computing the latency of the two components of the two main heart sounds (mitral and tricuspid from S_1, aortic and pulmonary from S_2) with respect to the corresponding R-wave.

To date, some technical issues still limit the applicability of PCG in a home context. One of them is the need for a careful positioning of the digital stethoscope over the chest of the patient. As a matter of fact, both the quality of the PCG signal and the measured time of closure of heart valves strongly vary over different recording points [4,5]. Since the most suitable auscultation point depends on the application, as in traditional auscultation, the positioning of the stethoscope by a naïve user cannot be trusted to obtain reliable results.

Multi-source PCG is expected to provide a solution to this problem. By simultaneously recording multiple PCG signals from different points over the chest of the patient, the selection of the best auscultation point is shifted from the recording phase (i.e., from the user) to the processing phase (i.e., to the algorithm). One of the most important problems is how to choose, among the set of spatially distributed PCG signals, which signal or set of signals must be used to estimate the latencies of the heart sounds.

In this work, we present a hybrid system that first applies hierarchical clustering to divide the PCG signals of a multi-source recording into morphologically homogeneous subsets, and then Multi-Criteria Decision Analysis (MCDA) to select the best subset of signals. In particular, the goal is to explore the advantages of using MCDA for the selection of the best auscultation area, compared to single-criterion approaches.

2. Materials and Methods

2.1. Recording system

The recordings were performed through a custom multi-sensor array placed on the patient's chest. This array allows for recording 48 PCG channels along with an ECG signal.

The array was designed by our research group to enable an easy positioning on the chest of a high number of microphones. Figure 1 illustrates (A) the bottom side of the array showing the geometrical distribution of the sensors, and (B) the placing over the chest.

The sensing of the acoustic vibrations of the chest relies on 48 condenser microphones with a 4-mm diameter. They are homogeneously distributed over a grid with a 16 mm distance between closest neighbours. In this way, the entire surface of the left hemithorax of the subject is covered, even if the positioning is inaccurate. The signals are pre-amplified on board of the array. The ECG signal is recorded using a non-standard lead through custom electrodes. Both the ECG and PCG signals are simultaneously sampled at 1 kHz and transferred multiplexed to a commercial I/O device (NI USB 6210 by National Instruments®) that performs the A/D conversion and the acquisition through a personal computer. The multi-sensor array is flexible, to best adapt to the chest surface, and it is fixed to the chest using an elastic band.

2.2. Estimation of the latencies

First, the ECG signal is filtered between 10 Hz and 35 Hz, a suitable band to isolate the QRS complex, and R-wave peaks are identified by means of the Pan-Tompkins algorithm [6]. All 48 PCG signals are digitally bandpass filtered between 20 Hz and 100 Hz, frequency band that corresponds to the frequency content of the two main heart sounds [7]. The 48 signals from the are segmented into heartbeats, taking the R-wave peak as reference.

For each heartbeat, the quality of the signal segments was assessed by evaluating their SNR. We discarded the signal segments presenting a SNR value lower than 10 dB because we previously demonstrated that a lower SNR is not sufficient for the application of interest [8].

For each remaining signal segment, we computed the latency of the closing of the four heart valves with respect to the R-wave peak. The two components of the two main heart sounds were identified within each signal segment by means of a method we previously developed and validated [9]. In the end, four latencies are computed for each signal segment: $RS_{1,M}$ (mitral valve), $RS_{1,T}$ (tricuspid valve), $RS_{2,A}$ (aortic valve), and $RS_{2,P}$ (pulmonary valve).

2.3. Hierarchical clustering

The aim of clustering is to divide a set of unlabeled elements in homogeneous subsets, based on a distance metrics which measures their similarity [10]. In our case, the elements to be divided into homogeneous subsets are the signal segments recorded by different microphones. Clustering is repeated separately for each heartbeat.

Among the existing clustering methods, we chose the agglomerative hierarchical method. Our choice fell on a

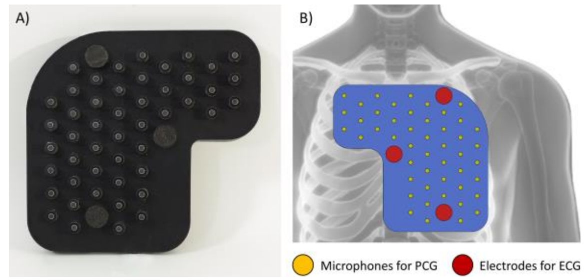

Figure 1. Picture of (A) the bottom side of the multi-sensor array and (B) approximate geometrical distribution of the sensors over the chest.

hierarchical clustering method, instead of on a partitional one, because the first does not need any initial definition of the number of desired clusters, which could influence the results [11]. To compute the distances, we used a similarity measure based on the correlation of two signal segments [12] because we wanted the clustering to be based only on the morphological features of the signals. We constructed the dendrogram by iteratively merging the two closest clusters considering their furthest elements. Then, we cut the dendrogram using an automated rule: the tree was cut in the point in which the algorithm merges clusters with the highest distance. The result of the clustering phase is, for each heartbeat, an array of labels which assigns each signal segments to a cluster.

2.4. Selection of the best cluster

After having divided the channels into homogenous subsets, the next step is defining which cluster is to be used to estimate the time of closure of each heart valve. What described in the following is repeated for each heart valve (the latency of an heart valve is generally referred to as $RS_{x,y}$ with $\{_{x,y}\} = \{_{1,M}\}, \{_{1,T}\}, \{_{2,A}\}, \{_{2,P}\}$).

The selection of the cluster, i.e., the selection of the best auscultation area, can be expected to depend on multiple different objectives. For this reason, we tested three different approaches:

1. Selection of the cluster with the minimum average $RS_{x,y}$ value.
2. Selection of the cluster with the maximum average SNR value.
3. Selection of the cluster performing MCDA through ELECTRE III [13].

The first approach theoretically allows us to minimize the time of propagation across the tissues and to obtain an estimate which is the closest possible to the real time of closure of the cardiac valves. The second approach allows us to use the signals with the highest quality, which is preferable from a signal processing point of view. Since both objectives are valid, the third approach allows us to explore the possibility of considering them simultaneously. We applied ELECTRE III using four criteria:

- **Criterion $RS_{x,y}$**: The average of the latency value estimated by each of the channels belonging to the cluster. To be minimized. Weight: 0.1.

- **Criterion $RS_{x,y\ var}$**: The difference between the maximum and the minimum latency values estimated by channels belonging to the cluster. To be minimized. Weight: 0.2.
- **Criterion SNR**: The average of the SNR values of the channels belonging to the cluster. To be maximized. Weight: 0.4.
- **Criterion SNR_{var}**: The difference between the maximum and the minimum SNR values of the channels belonging to the cluster. To be minimized. Weight: 0.3.

The evaluation matrix was built using as alternatives the identified clusters and as criteria the four above-mentioned ones. We defined the weight to be assigned to each criterion using the revised Simos' procedure [14]. The definition of ELECTRE III thresholds was guided by the experience on the variability of the values of the latencies and of the quality of the signals gained through previous work.

2.5. Sample population

We tested the proposed system on five 1-minute-long recordings from the same healthy volunteer, repeated on different days at roughly the same hour and in the same laboratory setting. A total of 721 heartbeats was analysed. The goal of the proposed experimental protocol is to simulate the application of interest, which is the home monitoring of the time of closure of the valves.

3. Results and Discussion

The application of the proposed system to the described sample population produced interesting results.

Clustering divided the signals into spatially coherent groups in all heartbeats. In other words, signals were automatically clustered into neighbors, even though no constraint about their spatial relationships was inserted. This is a proof of the reliability of the clustering phase.

With the scope of evaluating the agreement among the different approaches, we computed for each heart valve and for each recording, a map of the hits, i.e., a map showing the number of times each microphone was selected over the heartbeats of a 1-minute recording. Figure 2 presents an example for the mitral valve.

It can be observed that the best auscultation areas selected using either the minimum latency or the maximum SNR are quite different. In this situation, it is difficult to decide which criterion should be trusted. In fact, the minimum latency criterion allows for obtaining a significantly lower estimate of the time of closure, but the estimate is based on signals of sub-optimal quality. In this context, MCDA allows for achieving the best trade-off between good quality and minimization of the latency. This is coherent with the average $RS_{1,M}$ values obtained.

In the end, we compared the average latency values obtained through multi-source PCG recordings, processed with the proposed system, against the state-of-the-art single-source methodology. The results are illustrated by Figure 3. The plots show that multi-source PCG, independently on the approach for selecting the best auscultation area, allows for obtaining a more stable and accurate estimate of the time of closure of the heart valves over the days. When comparing the different approaches for the automatic selection of the best auscultation area, it can be observed that the maximum SNR approach leads to the most unprecise estimates. On the other side, the estimates obtained through MCDA are coherent to what obtained selecting the cluster with the minimum latency.

4. Conclusion

In this work, we presented a methodology to improve the estimation of the time of closure of the four cardiac valves through multi-source PCG. The method allows for automatically selecting the best auscultation area using a high number of microphones spatially distributed over the chest. This enables naïve users to perform the recording

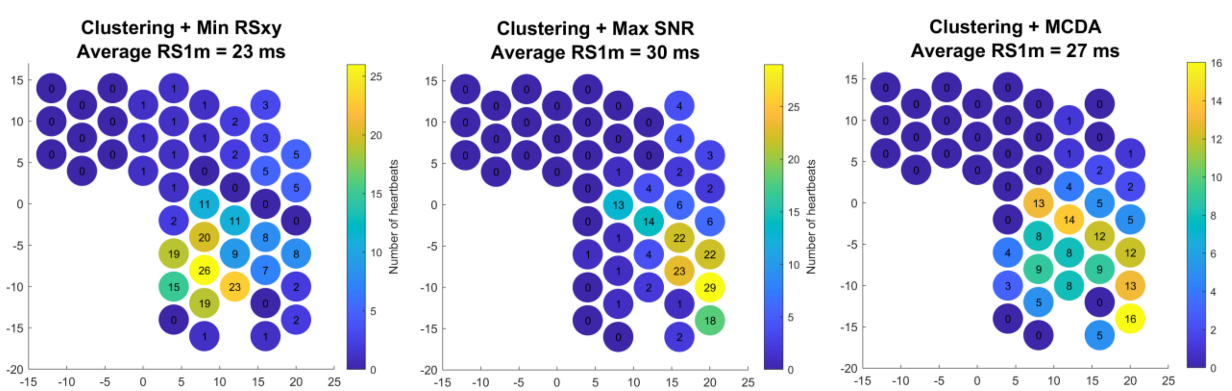

Figure 2. Example of a map of the hits, i.e., the number of times each microphone was selected, for the mitral valve and for each of the tested approaches for the selection of the best auscultation area.

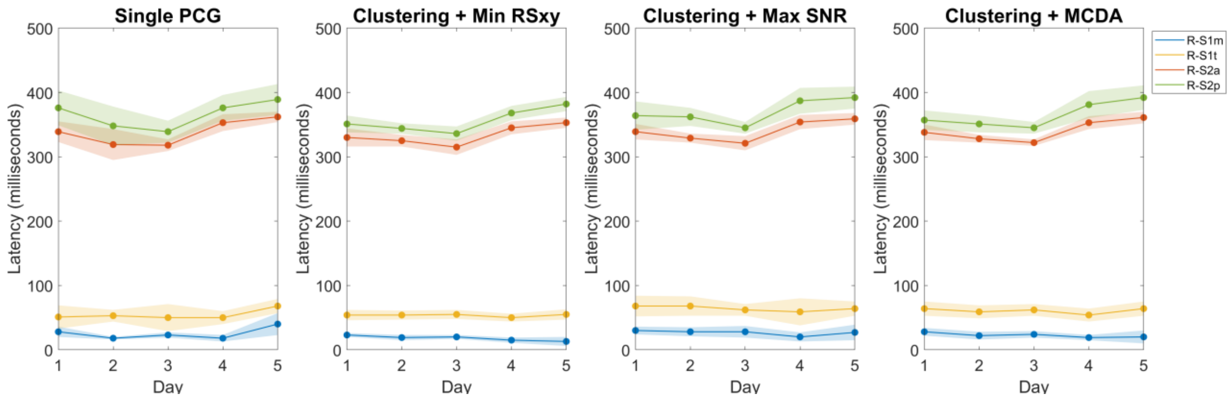

Figure 3. Comparison among the final latency values obtained through each tested approach. The dots represent the mean value, interpolated by the lines, whereas the dashed area represents the standard deviation band the recordings.

and thus the application of PCG to home monitoring.

We explored different approaches for the selection of the best auscultation area and preliminary results on recordings resulting from the daily follow-up of a healthy subject show that a multi-criteria approach overcomes the limits of single criteria and allows for obtaining more reliable estimates. Moreover, a comparison against the traditional single-source approach confirms the validity of the method in increasing the robustness of the estimate.

Having assessed the validity of the proposed method in this pilot study, further studies will focus on the tuning of the ELECTRE III parameters and on its validation on recordings from both healthy and pathological subjects. Even though further validation will be needed, this work lays the first foundation for the application of multi-source PCG in domiciliary settings.

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