Separation of the Valvular Contribution to Heart Sounds through Blind Source Separation in Multi-Channel Phonocardiography

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Abstract

The separation of the contribution of the left and right cardiac valves to heart sounds is an open challenge in the field of phonocardiography. Yet, reliably measuring their time of closure in a noninvasive fashion would open to novel monitoring possibilities. In this work, we explore the potentiality of Blind Source Separation applied to multi-channel recordings at high spatial resolution to separate the components of the two main heart sounds. Our pipeline involves a pre-processing stage to isolate the segments of interest, a dimensionality reduction stage performed via clustering, and the application of Independent Component Analysis. Our results on a sample population of 52 healthy volunteers show a successful separation of the components. The estimated time of closure is consistent with the physiology of the heart sounds, and the statistical difference between the contributes of the valves from the same sound was proved. We believe that this work makes a step further towards the clinical use of heart sound components and lays the foundation to novel possibilities of analysis.

1. Introduction

Heart sounds have been the object of a rise in popularity lately, particularly because of their applicability in home monitoring. Domiciliary telemonitoring could effectively improve the management of patients affected by chronic cardiovascular diseases (CVDs), such as heart failure [1]. In fact, it allows a timely recognition of the deterioration of the health status of the patient and the prevention of acute episodes. Phonocardiography (PCG) is a good candidate for use in telemonitoring, because of its non-invasiveness, portability, and low cost. Being the result of the contraction of the heart, heart sounds can provide unique information about its mechanical behavior. Currently, the hemodynamic assessment of the heart is carried out via echocardiography (ECHO) or right heart catheterization (RHC). Nonetheless, neither of these modalities suit for use in a home care framework.

At date, the analysis of the heart sounds still presents some open challenges. One resides in the separation of their components. The first (S1) and second (S2) heart sounds are generated by the closure of respectively the atrioventricular and semilunar valves. Nevertheless, the left and right sides of the heart are not perfectly simultaneous. Separating the components of heart sounds is hypothesized to have a strong clinical impact, allowing a precise non-invasive estimate of the Cardiac Time Intervals (CTIs), i.e., hemodynamic time measures, which proved to be correlated with the status of compensation of the heart [2]. Nevertheless, the separation of the components is not naïve, since they overlap in both the time and frequency domains. Previous works tackled the problem in two main ways: by optimizing the match of the recorded sounds to predefined [3]–[5] or data-driven waveforms [6], [7]; or by decomposing the signal exploiting wavelets [8] or time-frequency approaches [9].

In this work, we present a different approach based on multi-channel PCG and Blind Source Separation (BSS). The latter grounds on the assumption that the PCG signals that we detect on the chest surface are mixtures of the source signals generated by the closure of the cardiac valves, differently attenuated and filtrated by the biological tissues depending on the position of the microphone over the chest. To our best knowledge, a single previous study applied BSS to separate the components of S2 on 4-channel recordings [10]. In our study we aim at separating the components of both S1 and S2 from 48-channel recordings with a high spatial resolution, and use them to estimate the time of closure of the four cardiac valves.

2. Materials and methods

Figure 1 shows the pipeline of the proposed approach. Details are provided in the following paragraphs.

2.1. Recording system and pre-processing

Multi-channel PCG recordings were performed using a wearable array that we designed for this purpose. The

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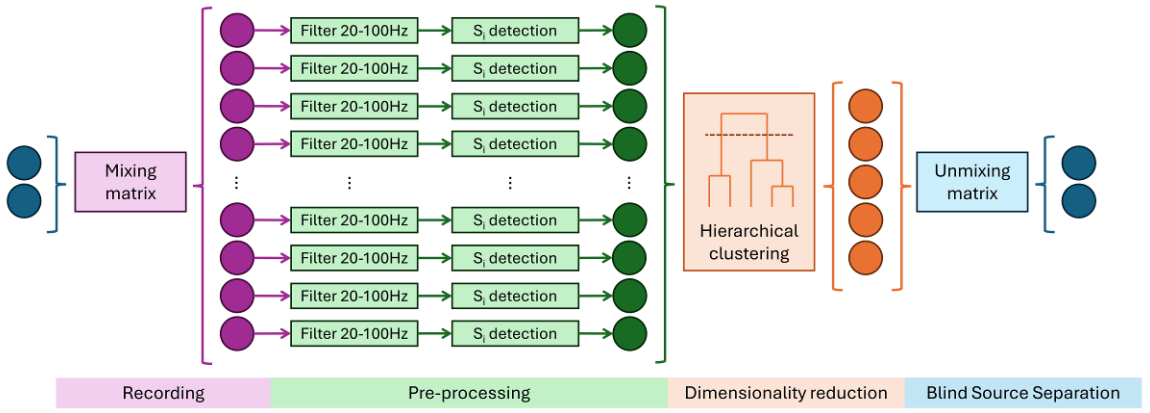

Figure 1. Pipeline of the proposed approach, consisting of four phases: 1) recording of 48 mixture signals; 2) pre-processing, involving filtering and the detection of either S1 or S2; 3) dimensionality reduction through clustering; 4) Blind Source Separation to recover the two original source signals. The same pipeline is repeated for S1 and S2.

array consists of a flexible pad embedding 48 microphones for PCG recording and 3 electrodes for a simultaneous ECG recording. The microphones are located over a 150 mm-by-140 mm L-shaped area and are distributed to cover the expected four auscultation areas. All signals are sampled simultaneously at 1 kHz and converted into digital with 16-bit dynamics. More details about the recording system can be found in [11].

The 48 PCG signals were bandpass filtered between 20 Hz and 100 Hz, to reduce the effect of noise while preserving S1 and S2. All channels were segmented into heartbeats by using the peak of the R-wave, extracted from the simultaneous ECG, as reference. The two main heart sounds, S1 and S2, are identified on the Shannon Energy Envelope (SEE). From each channel, two signals are created: one with zero samples everywhere except on the identified S1 segments, one with zero samples everywhere except on the identified S2 segments. The methods described in the following paragraphs are applied separately to S1 and S2.

2.2. Dimensionality reduction

A high spatial resolution enables inexperienced users to perform the recording in a home care setting [11]. On the other side, having a high ratio between the number of mixtures and the number of sources may result in a complex separation. For this reason, dimensionality reduction was carried out using clustering, a Machine Learning technique aimed at dividing the elements of a dataset into homogenous subsets based on their similarity. We observed in a previous work that clustering could separate our signals into groups while preserving their spatial relationships, even if no spatial constraint was set [12]. This is a fundamental characteristic when it comes to the use of BSS. For the purposes of this work, we used agglomerative hierarchical clustering, which does not require any a-priori hypothesis about the number of clusters. We used a correlation-based similarity measure, which reflects morphological similarity among signals. We constructed the dendrogram by iteratively merging the two closest clusters and automatically cutting it to the point where the clusters with the highest distance were merged. Then, we computed the cluster prototypes as the average of the elements belonging to clusters. The prototypes of the clusters are used as input for BSS.

2.3. Blind Source Separation

The goal of BSS is to identify the mixing source signals from a multi-channel recording without any a priori information about the geometry of the system or the mixing matrix. Mathematically, if $S(t)$ is a matrix where each row is a source signal, A is the unknown mixing matrix (mixing happens in the chest and depends on the filtering effect of the biological tissues), and $n(t)$ is the additive noise, then the matrix $X(t)$ where each column is a recorded signal can be defined as:

$$X(t) = AS(t) + n(t) \quad (1)$$

We can assume that $n(t)$ is removed by digital filtering. The aim of BSS techniques is to find the unmixing matrix W, which approximates the inverse of the mixing matrix A. Then, an estimate of the source matrix $\hat{S}(t)$ can be obtained as:

$$\hat{S}(t) = WX(t) \quad (2)$$

Among the available techniques to estimate the unmixing matrix W, we explored the use of Independent Component Analysis (ICA), which is one of the most

popular ones. In ICA, the multi-channel recordings are transferred into a suitable statistical domain where their mutual independence is maximized. We used the well-known FastICA algorithm because of its efficiency and set the number of sources to two, as we hypothesize that we can separate the contribution of the left and right valves. After applying ICA, we obtain two source signals for S1 and two for S2. In the end, the closure of each valve was identified beat-by-beat as the index of the maximum of the Shannon Energy Envelope (SEE) of its source, and the time of closure of each valve with respect to the corresponding R peak was computed.

3. Results and discussion

We present the results of the application of our methodology to a sample of 52 volunteers with no history of CVDs subjected to a 5-minute recording. The device was located by a fellow volunteer to test its feasibility in a home care setting. In this scenario, we have no information about the geometry of the system with respect to the source, which is a typical use case for BSS. The experimental protocol was approved by the Ethical Committee of Politecnico di Torino (prot. 27801/2023).

3.1. Separation of the components

The results of the separation of the mitral and tricuspid components from S1, and the aortic and pulmonary components from S2 are presented in Figure 2 for a recording included in the sample population. Similar results were obtained for all the recordings. Panels A-B-C represent the SEE of respectively S1, the extracted mitral component, and the extracted tricuspid component. In the images, each row represents a heartbeat. The segments were aligned for better visualization. Panel D shows the corresponding SEE for a sample heartbeat. Panels E, F, G and H provide the same information for S2 and the extracted aortic and pulmonary components.

The SEE of the recorded S1 segment shows a wide colored band with a peak around 40 milliseconds. The latter peak is preserved in the SEE of the mitral component, but with a narrower colored band. On the other side, the peak disappears in the tricuspid image, but a novel peak arises at around 60 milliseconds. A 20-millisecond split is consistent with physiology. We can hypothesize that the tricuspid energy was masked by the mitral one in the recording, which made it difficult to detect. The BSS approach proved capable of separating the two contributions and making the second detectable.

Similar conclusions can be drawn from the analysis of S2. The SEE of the recorded S2 segment shows a clear single peak. Nevertheless, the two extracted components show narrower, more distinct peaks with a split of around 10 milliseconds. The energy of the recorded S2 segment spans the time interval covered by the combination of the two extracted components, which strongly overlap.

3.2. Time of closure of the cardiac valves

Figure 3 shows a plot of the time of closure of the four cardiac valves with respect to the corresponding R-wave peak. The mean value of the four curves is compatible with what is expected from physiology. Also, the split between the components of the same sound is consistent with our hypothesis. Moreover, all the curves present a

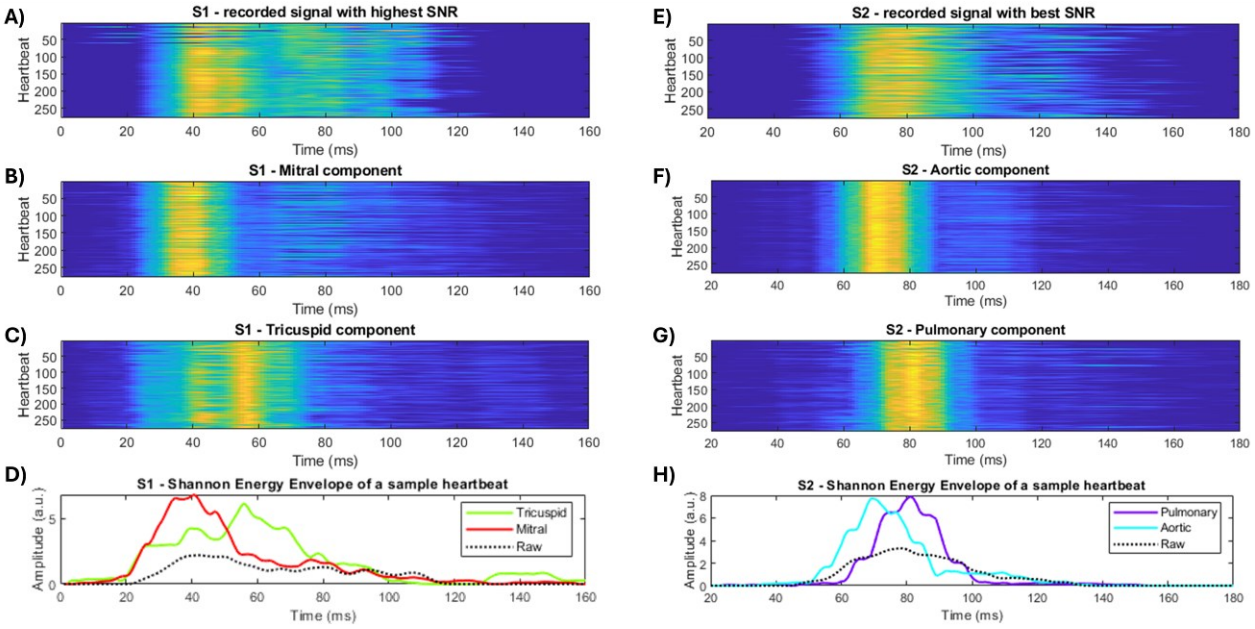

Figure 2. Separation of the S1 and S2 components achieved through the proposed BSS method on a sample recording.

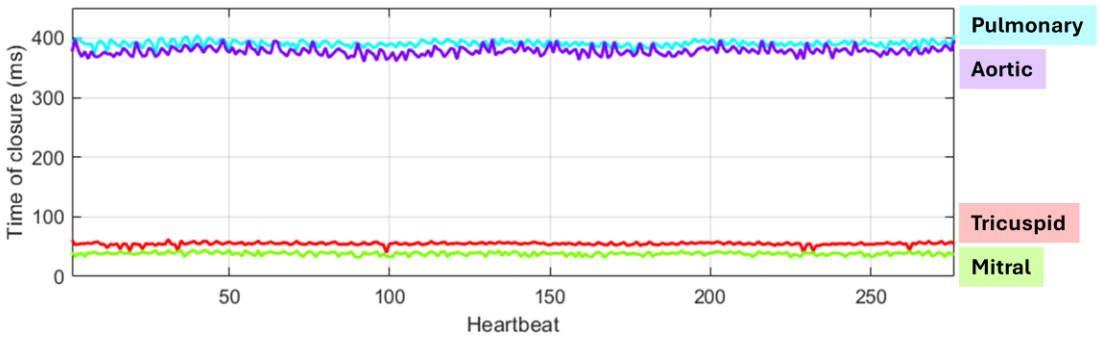

Figure 3. Time of closure of the four cardiac valves estimated using the proposed approach on a sample recording.

periodic oscillation which is compatible with the respiration cycle and further confirms the validity of the proposed approach. In the end, Table 1 shows aggregated results over the sample population. Results prove that the obtained mean values over the sample population are consistent with what expected from the literature. The observed high variability depends on the physiological differences in the cardiac cycle among subjects. We applied a paired Student t-test ($\alpha = 0.05$) to the values obtained for the two components of the same sounds and obtained a p-value lower than 0.001, which confirms that the two estimates are significantly different and due to different physiological phenomena.

Table 1. Obtained time of closure of the valves.

Valve (Sound)	ToC mean ± std (ms)	p-value
Mitral (S1)	39 ± 15	< 0.001
Tricuspid (S1)	57 ± 18	
Aortic (S2)	340 ± 77	< 0.001
Pulmonary (S2)	352 ± 75	

4. Conclusions

In this work we explored the possibility of separating the contributions of the left and right heart valves from the two main heart sounds. We obtained promising results on a sample of 52 healthy volunteers. Our future steps will focus on validating our approach against an ECHO or RHC gold standard. Moreover, we will explore the generalizability of the methods on subjects affected by CVDs. We believe that this work moves a step further towards the use of the CTIs in monitoring applications.

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