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Stratification of Heart Sounds Morphology Through Unsupervised Learning

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Abstract. The use of heart sounds for the assessment of the hemodynamic condition of the heart in telemonitoring applications is object of wide research at date. Many different approaches have been tried out for the analysis of the first (S1) and second (S2) heart sounds, but their morphological interpretation is still to be explored: in fact, the sound morphology is not unique and this impact the separability of the heart sounds components with methods based on envelopes or model optimization. In this study, we propose a method to stratify S1 and S2 according to their morphology to explore their diversity and increase their morphological interpretability. The method we propose is based on unsupervised learning, which we obtain using the cascade of four Self-Organizing Maps (SOMs) of decreasing dimensions. When tested on a publicly available heart sounds dataset, the proposed clustering approach proved to be robust and consistent, with over 80% of the heartbeats of the same patient being clustered together. The identified heart sounds templates highlight differences in the time and energy domains which may open to new directions of analysis in the future.

Keywords. Heart sounds, clustering, unsupervised learning, Self-Organizing Map

1. Introduction

In recent years, heart sounds have been regarded as a promising alternative for the assessment and monitoring of cardiological health in telemedicine applications [1]. The advantages of the recording of heart sounds reside in its portability and low cost, which make it appealing with respect to echocardiography or right heart catheterization (RHC) which require expensive instrumentation and skilled clinical staff. Moreover, the analysis of heart sounds can provide valuable information about the hemodynamical behavior of the heart and the intracardiac pressures [2,3], which is difficult to obtain otherwise without subjecting the patient to invasive procedures. Despite being the object of wide research in the last decade, the analysis of the two main heart sounds still presents some open challenges. One resides in the separation and analysis of the heart sounds components. In fact, even though it is well known that the first (S1) and second (S2) heart sounds are generated by the closure of respectively the atrioventricular and the

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semilunar valves, the right and left sides of the heart are not exactly synchronized. Therefore, a clinical interest exists in separating the contributions of the mitral and tricuspid valves in S1, and of the aortic and pulmonary valves in S2 [4,5]. The task is not naïve given that the two components overlap both in the time and the frequency domains. Some existing methods to separate heart sounds components ground on modeling optimization [6,7], but the presence of comorbidities may affect the model and thus the separation. In this study we aim at proposing a ML-based approach to stratify the heart sounds according to their morphology and define some templates that can be analyzed separately and used in the future to improve the existing methods for heart sounds components identification.

2. Materials and Methods

2.1. Dataset and pre-processing

We used the SCG-RHC dataset, publicly available on PhysioNet [8]. The dataset contains signals from 73 patients undergoing RHC for heart failure assessment. A custom noninvasive wearable patch was used to record an electrocardiogram (ECG) and heart sounds, by means of a triaxial accelerometer, thus obtaining a seismocardiogram (SCG). Intracardiac pressures were recorded simultaneously. For this project, two 20-second segments were extracted from each procedure: one to study the closure of the tricuspid valve (contributing to S1), with the pressure catheter located in the right ventricle; and one to study the closure of the pulmonary valve (contributing to S2), when the catheter is in the pulmonary artery (PA). In this study, we focus on the noninvasive recording of heart sounds, therefore we considered the ECG and SCG signals. First, ECG signals were visually screened and patients whose rhythm was too complicated were discarded to avoid a negative impact in the subsequent phases of the analysis. The ECG was digitally filtered between 10 Hz and 35 Hz, and R-wave peaks were extracted and used to segment the signals into heartbeats. The SCG signal was filtered between 10 Hz and 80 Hz. In each heartbeat, 300-millisecod segments corresponding to either S1 or S2 were identified using time thresholding. The S1/S2 segments were aligned by taking the first segment as reference and shifting the remaining segments by a lag corresponding to the index of the maximum of the cross-correlation function. In the end, 419 S1 segments (from 29 patients) and 406 S2 segments (from 27 patients) were included in the dataset.

2.2. Template identification through unsupervised learning

The proposed pipeline is graphically described in Figure 1. Heart sounds segments are used as input for a cascade of four Self-Organizing Maps (SOMs) of decreasing size. SOM is an unsupervised neural network. The neuron model is based on the computation of a similarity measure of the input with the weight vector of the neuron. The structure is a 2D map, usually square. The training algorithm is based on competitive learning: the neurons compete among each other to win, the neuron with the highest similarity wins, the winner neuron weights and those of its neighborhood are updated. In this work the similarity measure is correlation. SOM are particularly useful when working with shapes because when the network is trained the weight vector is representative of the shape associated with the neuron. The cascade of SOMs is realized as follows. The input matrix is used as input to train the first SOM of the cascade, i.e., the 5-by-5 SOM. The map of

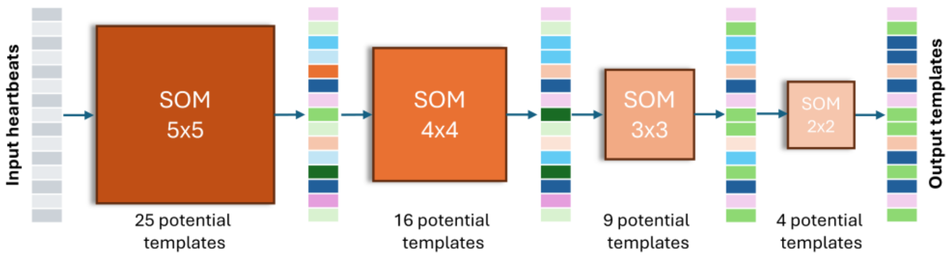

Figure 1. Pipeline of the proposed approach for heart sounds stratification.

the wins and the weights of the neurons are saved. Each element of the input matrix is replaced with the weights of corresponding winning neuron. The new matrix is used as input to train the next SOM. The process is repeated with the 4-by-4, 3-by-3 and 2-by-2 networks. The weights of the four neurons of the 2-by-2 SOM are candidate templates.

Characteristics of SOMs to consider are the stochastic nature of the initialization of the weights of the network and the randomness of the inputs order, which may produce different outputs in the presence of the same input matrix. The robustness of the learning phase was assessed by repeating the SOMs' cascade independently 100 times. The first repetition with a non-zero number of wins on all neurons is used as reference. Then, a matching matrix is produced for each validation SOM: the number in the cell (*i*,*j*) of the matching matrix represents the number of elements clustered in cluster *i* by the reference SOM and in cluster *j* by the validation SOM under analysis. The cells with the highest number of elements were used to match the clusters of the two SOMs. Then, the percentage of elements falling in different clusters was used as a metric of the repeatability of the clustering. In the end, each element is classified using the reference 2-by-2 SOM. In this way, heart sounds were stratified in consistent classes.

2.3. Analysis of the templates

The analysis of the templates was carried out in two phases. In the first phase, the distribution of the templates for each patient was assessed. We can hypothesize that heartbeats from the same patient have a similar morphology and thus belong to the same class, i.e., are similar to the same template. Therefore, the homogeneity of the patient-by-patient distribution of the classes is used to validate the consistency of the proposed stratification approach. In the second phase, the identified templates were represented in the time and in the energy domains. The representation in the energy domain was obtained through the point-wise computation of the templates' Shannon Energy. The latter is particularly relevant because some existing algorithms for the identification of the heart sounds components work on the energy envelope of the heart sounds [9].

3. Results and Discussion

Figure 2 shows the obtained templates for S1. The representation of the templates in the time domain (panel A), and in the energy domain (panel B) is proposed. Moreover, the patient-by-patient distribution of the heartbeats belonging to each class, i.e., similar to each template, is presented (panel C). The patient-by-patient distribution of the classes shows that, on average, 88% of the heartbeats from the same recording are classified as

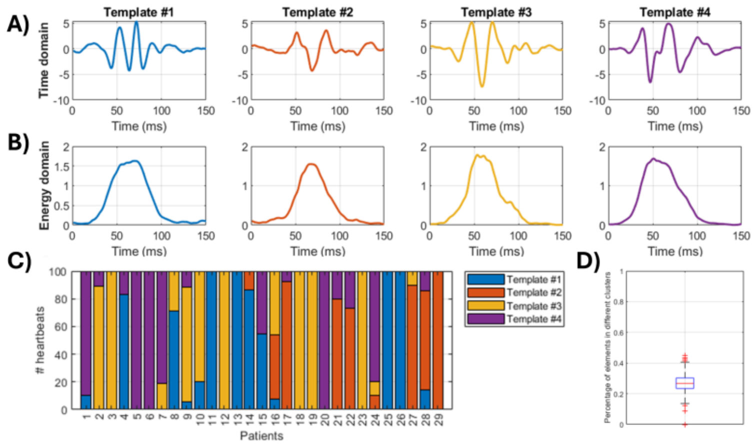

Figure 2. Templates identified for S1 in the time (A) and energy (B) domains, distribution of the templates each patient’s heartbeats (C), and boxplot of heartbeats clustered differently over 100 repetitions (D).

similar to the same template. This proves the consistency of the proposed method to stratify S1 sounds according to their morphology. The results of the robustness analysis (panel D) confirm this point: the median of heartbeats classified differently by the SOM cascade equals 26% over 100 repetitions, which make the resulting templates encouraging in terms of robustness. The analysis of the templates in the domains shows that even if the templates present relevant morphological differences in the time domain, the energy envelope is not dissimilar. This may give an explanation to the well-known difficulty in separating the components of S1 and open to novel directions in its analysis.

Figure 3 presents the templates identified for S2 in the time (panel A) and energy (panel B) domains, along with their distribution over the patient-specific recordings (panel C) and the results of the robustness analysis (panel D). Also in this case, a homogenous distribution of the templates over the heartbeats from the same patient (average 84%) validates the consistency of the stratification over the sample population.

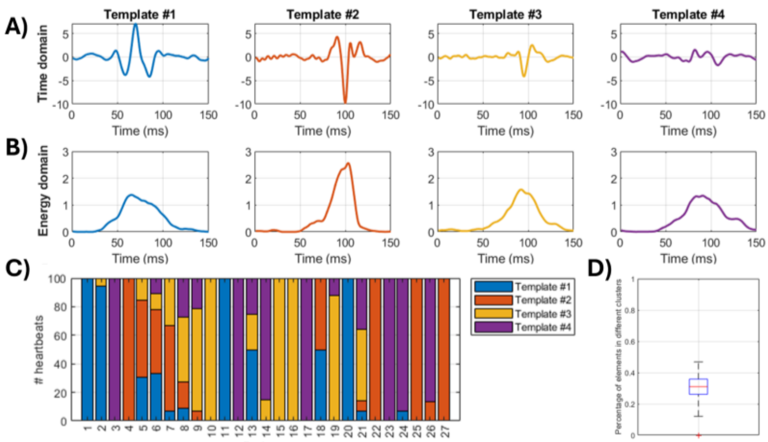

Figure 3. Templates identified for S2 in the time (A) and energy (B) domains, distribution of the templates over each patient’s heartbeats (C), and boxplot of heartbeats clustered differently over 100 repetitions (D).

Also the robustness analysis confirms that the stochastic nature of the initialization of the SOMs does not strongly impact on the resulting clustering, with a percentage of heartbeats clustered differently equal to 31% (median value). It should be highlighted that, contrarily to S1 where often one neuron yielded no wins, showing that a number of templates equal to four is sufficient to represent the diversity of the input samples, in S2 all the neurons were used: a higher number of templates may help in stratifying the S2 sound morphologies even better and increase the robustness of the analysis. The analysis of the templates in the energy domain opens to interesting considerations which may result in clinically relevant conclusions. In fact, different templates result in a rather different morphology of the energy envelope. This may be explained by a different relative contribution of the aortic and pulmonary components to the sound. In this sense, the obtained stratification may improve the separability of the two components in a future study.

4. Conclusions

The presented study proposes an automated method to stratify the two main heart sounds according to their morphology. The proposed approach grounds on the use of unsupervised learning techniques, such as SOMs, to build a fully data-driven model of the heart sounds. The resulting stratification highlights the diversity of the heart sounds and enhances the possibilities of analysis of the different identified types. This may open to new directions in the analysis of heart sounds and their components in the future. Next steps include tuning SOMs' hyperparameters and the number of templates to be searched for, and analyzing the relationship between the templates and relevant clinical parameters.

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