Comparison of Hierarchical and Partitional Clustering in Multi-Source Phonocardiography

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***Abstract*—Phonocardiography (PCG) has proved a valuable tool over the years to monitor the status of at-risk patients for some cardiovascular diseases. Its multi-source version, consisting of the simultaneous recording of multiple acoustic signals from different points of the patient's chest, is currently under research as a solution to develop wearable devices based on PCG and bring PCG to the patient's domicile. When a high number of PCG signals are available, to define the most suitable auscultation area, depending on the clinical question, clustering comes into the picture. In this work, we applied agglomerative hierarchical clustering and k-means to multi-source PCG recordings. A similarity metrics based on the correlation of the signals was used to compare the signals based on their morphological characteristics. The two clustering methods resulted in a Rand Index averagely higher than 0.84, showing a high level of agreement and validating the usage of clustering for the application of interest. Hierarchical clustering allowed for obtaining a better trade-off between the intra-cluster variability and the inter-cluster distance. Adding to its deterministic nature, it should be considered as preferrable with respect to k-means. This work moves one step further to the development a reliable wearable device based on digital auscultation for the monitoring of the patient at its domicile.**

Keywords—heart sounds, multi-source phonocardiography, hierarchical clustering, k-means

I. Introduction

The constant ageing of the global population and the consequent rise of the prevalence of age-related pathologies has been driving a change in the healthcare paradigm in the latest years. The focus of medicine is moving from treatment to prevention and the center of gravity of the management of at-risk patients is shifted from the hospital to the patient's domicile [1], [2].

Technology plays a fundamental role in making this possible. The availability of sensors and wearable systems which can be used by the patient himself (or by a caregiver) enables interesting novel applications based on the remote monitoring of the patient's vital signs. This dramatically increases the chances for reaching the widest possible patients' population, even though the aspects of reliability and accuracy of the wearable systems need to be accurately faced to provide a real breakthrough in the clinical practice. What stated above is particularly true when considering the management of at-risk patients for cardiovascular diseases (CVDs), which are currently the number one cause of death worldwide [3].

In this context, phonocardiography (PCG, i.e., the digital recording of the heart sounds) is object of increasing research and has often proved a valuable tool to diagnose and monitor the health status of the heart [4], [5]. A main technical issue limiting its applicability in a domiciliary setting resides in the positioning of the electronic stethoscope. In fact, the quality of the signal, as well as the features extracted from it, strongly varies depending on the positioning of the microphone sensor over the chest, and finding a suitable positioning is not a trivial issue [6]–[8].

Multi-source phonocardiography may be a solution to the problem. On one side, the availability of simultaneous recordings of multiple PCG signals from different auscultation points is expected to strongly decrease the importance of the positioning of the sensors, by shifting the problem of the choice of the best auscultation point from the recording phase to the signal processing phase. On the other side, the information that signal conveys is different depending on the auscultation area: even in traditional auscultation, clinicians are trained to change the positioning of the stethoscope depending on the clinical question.

Some previous research works exist in the literature confirming the potential of multi-source PCG in improving the performances of their single-channel counterpart. In particular, features extracted from multi-source recordings were employed for the estimation of the Left Ventricular Ejection Fraction [9], for the estimation of the Pre-Ejection Period [10], for the classification of valvular disorders [11], [12] and for the classification of Coronary Artery Diseases [13]–[15].

When a high number of simultaneous recordings are available, typically only a subset of signals is really needed for the subsequent processing. For example, if the status of the mitral valve is under analysis, then the signals recorded over the heart apex are of particular interest, as traditional auscultation taught us. Nevertheless, detecting the correct subset of microphones depending on the application can raise some difficulties when the recording is performed by a naïve user, since the geometry of the positioning of the microphones over the chest is not necessarily the same across different recordings.

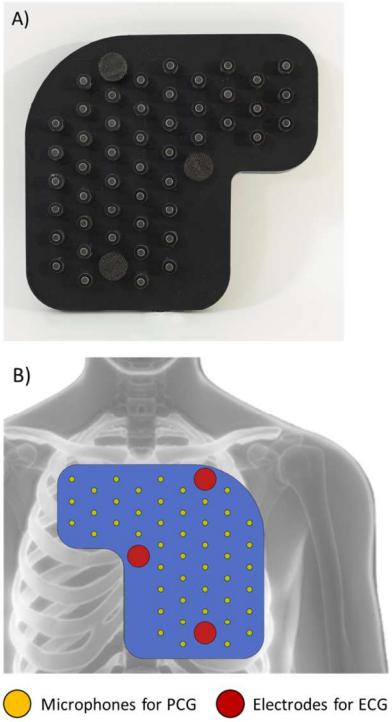


Fig. 1. Picture of the described wearable multi-sensors array device used for recording the signals (A) and distribution of the microphones and electrodes over the chest (B).

Clustering aims to divide the elements of a dataset into groups (*clusters*) based on their similarity. The latter is measured through an appropriate metrics, which is defined depending on the characteristics of the dataset and on the goal of the application of clustering [16], [17]. In the literature, clustering is typically used on unlabeled datasets, for the scopes of Knowledge Discovery in Data, Identification of Frequent Patterns and Data Mining [18], [19]. In the PCG context, clustering techniques could allow us to divide PCG signals into consistent subsets according on their shape similarity. Afterwards, the most suitable subset of signals can be chosen depending on the application.

The goal of this work is to compare and evaluate hierarchical and partitional clustering methodologies to divide simultaneously recorded PCG signals into morphologically homogenous subsets. In particular, agglomerative hierarchical clustering and k-means were taken into account.

II. Materials and Methods

A. Signals recording and processing

48 PCG signals were simultaneously recorded by means of a custom multi-sensor array. The array mounts 48 condenser microphones, for sensing the acoustic waves on the chest's wall, along with 3 electrodes for the simultaneous acquisition of an electrocardiogram (ECG). The ECG signal is used as reference for the robust segmentation of the PCG signals into heartbeats.

Fig. 1 shows the geometrical distribution of the sensors in the array. The microphones have a 4 mm diameter and are located over the nodes of a virtual grid, with a distance of 16 mm between closest neighbors. In this way, a properly high spatial resolution is reached (48 microphones located over an area of 172 cm^2), which makes an approximate positioning over the chest acceptable. The electrodes create a non-standard lead with the heart roughly at its center. This is possible because the information to be extracted from the ECG signal is the time of occurrence of the R-wave, which does not depend on the lead (contrarily to the signal's morphological features).

The device should be positioned over the left hemithorax of the patient, as shown by Fig. 1. The positioning is not required to be precise and can be successfully performed even by a naïve user (e.g., the patient himself or a caregiver). The array is flexible, so that it can best adapt to the morphology of the chest of the subject and is attached to the chest by means of an elastic band.

Both ECG and PCG signals are pre-amplified on board, simultaneously sampled at 1 kHz and multiplexed, to be A/D converted and transferred to a PC by a commercial I/O device (NI USB 6210 by National Instruments®).

The signal processing is performed on a PC using Matlab® routines. First, a pre-processing phase is carried out to obtain signals of reliable quality. The ECG signal is bandpass filtered between 10 Hz and 35 Hz. In this way, the frequency content of QRS complex is enhanced [20]. Afterwards, the R-wave peaks are identified through the signal using the Pan-Tompkins algorithm [20]. The PCG signals are bandpass filtered between 20 Hz and 100 Hz, which corresponds to the typical bandwidth of the two main heart sounds, generated by the closing of the cardiac valves [21]. The signals are segmented into heartbeats using the R-wave peak as reference, as shown by Fig. 2. In particular, the heartbeat i is defined as signal's samples within the interval $]R_i - 100;\ R_{i+1} - 100]$.

Lastly, the quality of each segment is assessed, and segments considered poor-quality are discarded. The quality assessment was performed on the basis of the signal's SNR, defined as:

$$SNR = 20\ \log_{10} \frac{A_S}{4\,\sigma_N}, \qquad (1)$$

where A_S is the peak-to-peak amplitude of the heart sound under analysis and $4\,\sigma_N$ is the amplitude of the 95% noise band, observed within the 70% and the 85% of the cardiac cycle, when no heart sound is expected to occur. Only segments with an SNR higher than 10 dB were used for clustering, which is considered to be sufficient for most applications [22].

B. Clustering and similarity measure

In our case, for each heartbeat, the elements to be divided into clusters are the signal segments recorded by the 48 microphones of the array.

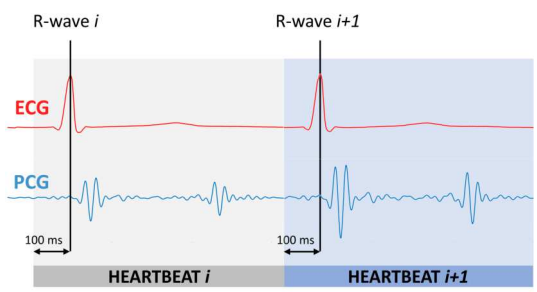


Fig. 2. Example of the segmentation of the heartbeats on the PCG signals using the ECG signal as reference.

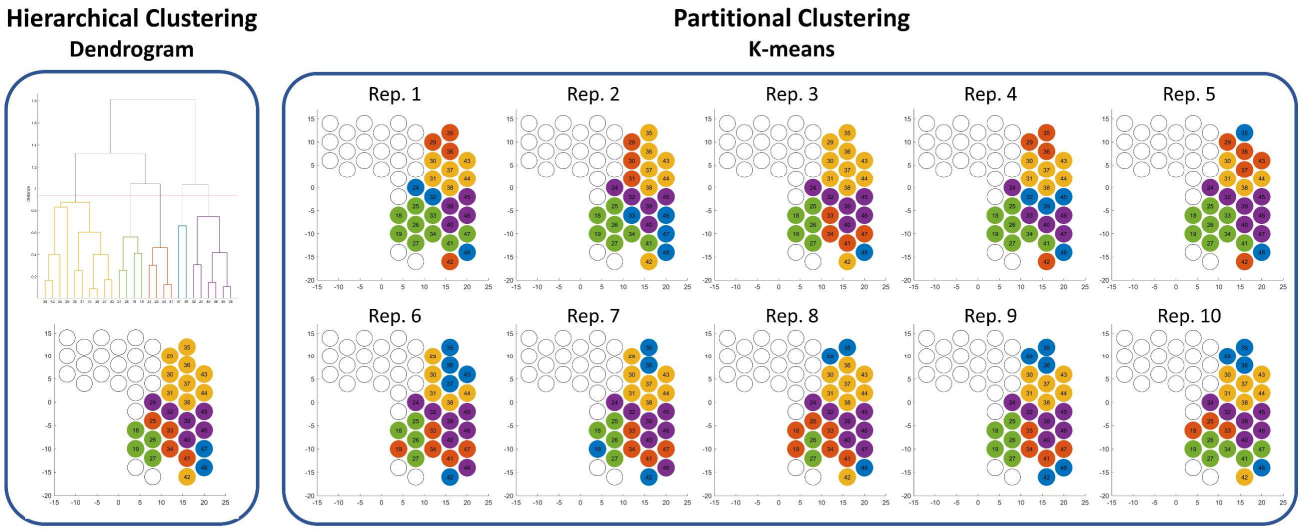


Fig. 3. Clustering obtained through hierarchical clustering (dendrogram) and partitional clustering (k-means, 10 repetitions) on a sample heartbeat.

To this set of signals, we applied two clustering methods: the agglomerative hierarchical clustering and the k-means. Both methods are iterative, but they differ on the way clusters are initialized and built up. However, their final aim is to obtain groups of elements with low intra-cluster variability, that is homogeneous clusters, and high inter-cluster distance, meaning that different clusters do not contain similar elements.

Since the clusters are expected to contain elements with a similar morphology, we used a similarity measure based on the correlation between signal segments from different channels. If x_i and x_j are two signal segments from different microphones, then the distance between x_i and x_j is defined as [23]:

$$d_{i,j} = 1 - \frac{(x_i - \bar{x}_i)(x_j - \bar{x}_j)'}{\sqrt{(x_i - \bar{x}_i)(x_i - \bar{x}_i)'}\sqrt{(x_j - \bar{x}_j)(x_j - \bar{x}_j)'}}. \quad (2)$$

In the following paragraphs details are provided concerning each of the two methods and their implementation for the scopes of this work.

C. Agglomerative Hierarchical Clustering

In agglomerative hierarchical clustering, each element of the dataset constitutes a separate cluster in the initial phase. Afterwards, iteratively, the two closest clusters according to the similarity metrics are aggregated together, until all the elements belong to the same cluster. In this way, a hierarchical tree called *dendrogram* is built [24]. The final clusters are obtained by cutting the tree at a certain level: the most appropriate cut is decided depending on the scope of the application of the clustering.

A main advantage of hierarchical clustering lies in the need for few initial parameters and a-priori knowledge. In particular, the algorithm requires to set the similarity metrics, the method to merge the clusters, also called linkage method, and the method to establish the cutting level. Another main advantage is that the method is completely deterministic [18], [24].

In this work, we used as metrics the similarity measure defined in (2) and as linkage method the "complete linkage", which uses the farthest distance among the elements in the different clusters as criterion for selecting the two clusters to be merged. This method allows to obtain more compact groups and to highlight outlier points [25]. The cutting level was automatically defined as the iteration where the two farthest clusters are merged.

D. K-means

K-means is one of the best known partitional clustering algorithms. First, k clusters centroids are initialized by arbitrarily assigning random elements to them. Then, each element of the dataset is assigned to the cluster corresponding to the closest centroid according to the similarity metrics. The new centroids of the clusters are computed again, usually as mean of the elements inside the cluster, and the elements are reassigned to the closest cluster. The process continues iteratively until the assignment of all the elements to clusters ceases changing or if after given number of iterations [18].

It should be highlighted that the k-means algorithm is typically repeated more than once to obtain robust results due to the stochastic nature of the initial assignment of the elements to clusters [18]. Moreover, k-means requires the number of clusters k to be defined a priori, which is not always easy to define, depending on the clinical problem [26].

In this work, we tested k values between 5 and 10 and run the k-means algorithm 10 times for each value of k. The final clustering was chosen as the one resulting in the highest minimum inter-cluster distance.

E. Evaluation of the results of clustering

We tested both hierarchical agglomerative clustering and k-means on a dataset of 721 one-heartbeat-long recordings, each involving 48 PCG signals recorded simultaneously from the chest of the subject. The heartbeats were extracted from 6 recordings one to five minutes long belonging to two healthy volunteers. The recordings were performed in a laboratory setting, with the subjects in a supine position and the multi-sensor array positioned on the left hemithorax by the subjects themselves. The algorithms were applied separately beat by beat.

We performed two kinds of analysis on the results.

In the first place, we evaluated the agreement among the clusters resulting from the two methods. To do so, we constructed for each heartbeat a contingency matrix, i.e. a matrix where each cell contains the number of elements clustered in the cluster p by the hierarchical approach and in cluster q by k-means, where (p,q) are the coordinates of the cell. Then, the Rand Index is computed, according to the formula [18]:

$$RI = \frac{a+b}{\binom{n}{2}}, \tag{3}$$

where a is the number of pairs of elements that are clustered together from both approaches, b is the number of pairs of elements that are clustered apart from both approaches and n is the total number of elements in the dataset. The RI index ranges from 0 to 1 and high values correspond to high agreement between the two approaches.

To best evaluate the agreement among two clustering methods, we required the number of clusters to be equal. Therefore, we repeated the analysis twice: (1) by choosing the number of clusters through the dendrogram and running the k-means with the same number of clustering and (2) by choosing the number of clusters through k-means and applying the corresponding cutting level on the dendrogram.

In the second place, we evaluated the actual results of each clustering approach on their own optimal number of clusters. The evaluation takes in account three factors:

- The intra-cluster variability (varIntra), defined as the average distance between two elements belonging to the same cluster. We consider the highest value over the clusters, i.e. the worst case.
- The inter-cluster distance (distInter), defined as the minimum of the distances between two centroids of two different clusters. A centroid is a prototype of the cluster and is computed as the median of its elements, in this case.
- The Silhouette Coefficient, which simultaneously consider the intra-cluster variability and the inter-cluster distance. It is based on a Silhouette value which is defined for each element of the dataset as [27]:

$$s(r) = \frac{\min_{M \neq R} \frac{1}{N_{C_M}} \sum_{m \in C_M} d(r,m) - \frac{1}{N_{C_R}-1} \sum_{m \in C_M, m \neq r} d(r,m)}{\max\left(\frac{1}{N_{C_R}-1} \sum_{m \in C_M, m \neq r} d(r,m), \min_{M \neq R} \frac{1}{N_{C_M}} \sum_{m \in C_M} d(r,m)\right)} \tag{4}$$

where the first term in the numerator is the distance from the closest element not belonging to the same cluster and the second term in the numerator is average distance from the elements of the same cluster. The Silhouette Coefficient is the average of the Silhouette values of all the elements of the dataset. High values of the Silhouette Coefficient are found for clustering where both the intra-cluster variability is low and the inter-cluster distance is high, i.e. for clustering which allows obtaining a good tradeoff between the two parameters.

III. Results and Discussion

In this section the main results of the application of both hierarchical agglomerative clustering and k-means to the PCG dataset are presented. For the sake of brevity, hierarchical agglomerative clustering will be referred to as *dendrogram* in the following.

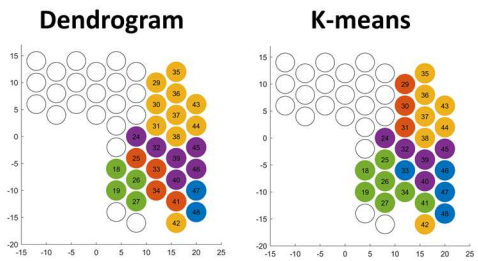
A. *Agreement between hierarchical and partitional clustering*

For a visual comparison of the results of clustering, Fig. 3 presents an example on a random heartbeat, comparing the clustering obtained through the *dendrogram* and by k-means with an equal number of clusters over 10 repetitions. The blank circles represent microphones that recorded signals with a SNR lower than 10 dB.

It can be observed that clustering performed through both approaches resulted in spatially coherent groups of microphones. In other words, the signals belonging to the same cluster were typically recorded by neighboring microphones. This can be seen as a confirmation of the significancy of the obtained results since no a-priori knowledge about the spatial relationships among the signals was used for defining the similarity metrics. It can also be observed that there is a certain degree of variability of clustering among different repetitions of k-means. This is due to the stochastic nature of the k-means algorithm. In this example, the second repetition was selected as the final k-means clustering because it has the highest inter-cluster distance.

The contingency matrix in Fig. 4 summarizes the information about the agreement of the two clustering. Because of the contingency matrix, the Rand Index is computed twice for each heartbeat, choosing the number of clusters using the dendrogram and the k-means, respectively. Fig.5 shows the two values over the heartbeats. The blue solid line represents the value when the number of clusters is selected via dendrogram, whereas the red dashed line represents the value when the number of clusters is selected via k-means.

The average value of the Rand Index was found as high as 0.88 when the number of clusters is selected via the



K-means

Dendrogram	Cl 1	Cl 2	Cl 3	Cl 4	Cl 5
Cl 1	2	0	0	0	0
Cl 2	1	0	0	0	3
Cl 3	0	3	7	0	0
Cl 4	1	0	0	5	0
Cl 5	0	0	0	0	4

Rand Index = 0.86

Fig. 4. Contingency matrix and Rand Index for summarizing the agreement of the dendrogram and k-means clustering on the sample heartbeat.

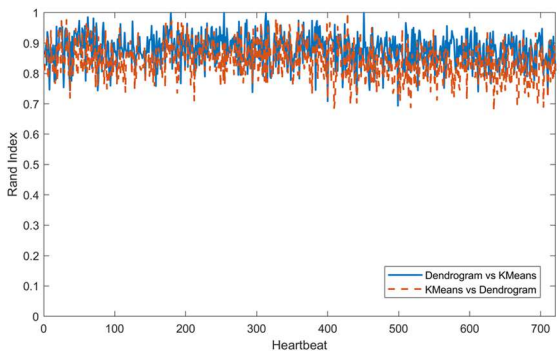


Fig. 5. Rand Index over the heartbeats of the sample population computed when the number of cluster is decided either by th dendrogram (blue solid line) or the k-means algorithm (red dashed line).

dendrogram (stdev = 0.05) and 0.84 when the number of clusters is selected via k-means (stdev = 0.06). The value is higher than 0.7 for all heartbeats in both cases, which we can consider as a good agreement. This suggests that, in the overall, clustering is an appropriate technique to divide the simultaneously recorded PCG signals into significant groups based on their morphology.

It should be highlighted that the optimal number of clusters selected by either dendrogram or k-means is equal only in 26% of the heartbeats. In the vast majority of cases (70%), dendrogram selects a higher number of clusters. Nevertheless, the agreement between the two approaches is statistically significantly higher when the cut is selected via dendrogram ($p < 0.001$ using paired Student t test). This suggests that a slightly higher number of clusters is a better choice in this context.

B. *Comparison of the results of each clustering approach*

The results of clustering using dendrogram with its optimal number of clusters and using k-means with its optimal number of clusters are compared in terms of intra-cluster variability, inter-cluster distance and Silhouette Coefficient. The distribution of the three parameters over the heartbeats is presented in Fig. 6, along with the corresponding boxplots.

When applying paired Student t-test with a significance level $\alpha = 0.05$, all the three comparisons are found statistically different ($p < 0.001$).

From the observation of the plots, it can be derived that the inter-cluster distance obtained through k-means is higher than the one obtained using the dendrogram. Nevertheless, also the intra-cluster variability obtained through k-means is higher. This suggests that k-means favors the maximization of the inter-cluster distance at the expense of the minimization of the intra-cluster variability.

On the other side, dendrogram allows for obtaining a better tradeoff between the minimization of intra-cluster variability and the maximization of the inter-cluster distance. This is confirmed by the Silhouette Coefficient, which is higher in dendrogram than in k-means.

The presented results show that hierarchical and partitional clustering techniques allow for obtaining clustering with a high agreement. Therefore, both methods should be considered reliable to divide the simultaneously recorded PCG signals from multi-source recordings into consistent groups. When it comes to choose the most suitable method, results show that hierarchical clustering presents some advantages with respect to k-means. In particular, it allows obtaining a better tradeoff between having homogeneous groups and having groups the farthest possible from each other. Together with the appealing deterministic nature of hierarchical clustering and the non-necessity to fix the number of clusters a priori, the choice for the latter in the context of multi-source phonocardiography looks natural and supported by data.

IV. Conclusions

The application of multi-source phonocardiography to the remote monitoring of the cardiological health status of at-risk patients is expected to grow in importance in the future. Nevertheless, its clinical impact will be limited as long as a patient himself or a caregiver could effectively perform the monitoring.

The possibility of dividing the high number of signals recorded in a multi-source setting in spatially consistent subsets in the processing phase overcomes the need for a precise positioning over the chest and allows to identify the auscultation area of interest a posteriori. In this work we analyzed the validity of clustering to perform such a task and we compared hierarchical and partitional clustering methods. Our results show that both hierarchical and partitional

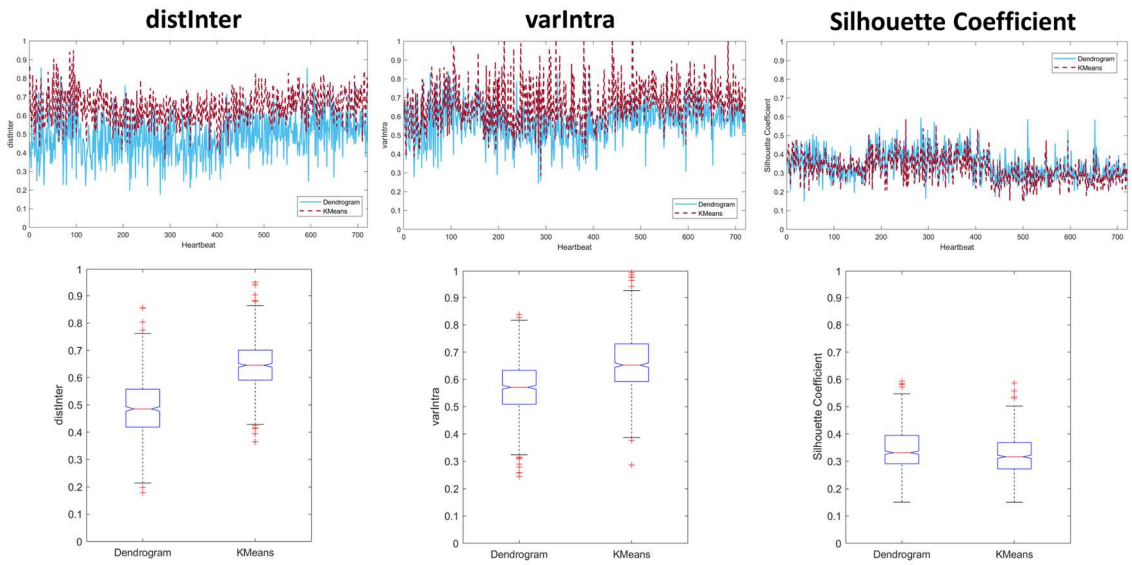


Fig. 6. Value of the inter-cluster distance, the intra-cluster variability and the Silhouette Coefficient obtained through the two clustering approaches over the beats of the sample population. It must be noted that the inter-cluster distance must be high, while intra-cluster variability must be low.

clustering allow for obtaining spatially consistent groups using a similarity metrics based on the signal's morphology. Moreover, the two approaches were found to have a strong agreement, which validates the applicability of the clustering methodology to a multi-source dataset with reliable outcomes.

When hierarchical and partitional clustering were compared, hierarchical clustering was found to produce a better tradeoff between having a good homogeneity within the clusters and a high distance among different clusters. Adding to its deterministic nature and the non-necessity to define the number of clusters a priori, hierarchical clustering can be regarded as a reliable method to divide multiple simultaneously recorded PCG signals into homogenous groups. This could help in the future in identifying the proper auscultation area depending on the clinical question without the need for using anatomical landmarks for the positioning of the sensors.

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