Spatial Distribution of Seismocardiographic Signal Clustering

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Seismocardiographic (SCG) signals are chest wall vibrations that correlate with cardiac activity and often measured using accelerometers on the chest surface [1]. SCG may be generated by valve movements, heart muscle contraction and blood flow momentum changes. Respiration is a source of variability and studying the SCG signal "clustering" with respiration may help define physiological mechanisms related to this SCG variation [2]. Grouping similar SCG events into clusters may also help reduce SCG variability and possibly increase its diagnostic utility [1, 3]. Previous studies often measured SCG signals at one location that varied among studies (e.g., xiphoid process, 4th ICS, etc.) [2-4]. However, SCG clustering may depend on SCG measurement location. The objective of the current study is to investigate the dependence of SCG clustering on the measurement location. This distribution may be of diagnostic value and can help compare results from different studies. It may also help define locations where clusters are best separated, which may help optimize choices of SCG measurement location.

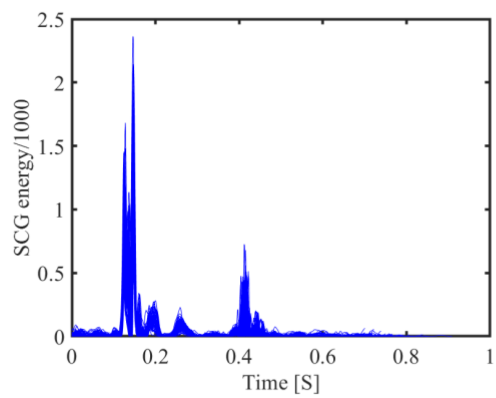

Figure 1. Energy of SCG events

SCG signals were measured by 36 accelerometers placed over the chest surface. ECG and spirometry were also acquired simultaneously in 15 healthy males (19-31 y/o) [1]. SCG, ECG, and respiratory flow rate were filtered using bandpass filters with pass bands of 1-150, 0.5-55, and 0.1-8 Hz respectively. The lung volume change was determined by integrating the air flow rate signal. SCG events were first segmented using the ECG-R wave (i.e. SCG events were chosen to start 100 ms before the R-wave) and then grouped into 2 clusters using the "k-medoid" algorithm and the dynamic time warping (DTW) to measure the distance between events [3]. Events were grouped into two clusters as recommended by the literature [3], which utilized the elbow method and average Silhouette value. The "decision boundary" between clusters and the classification accuracy were determined using linear support vector machines (SVM). The standardized flow rate and lung volume change at the ECG-R peak of each SCG event were used as features in the SVM and the decision boundary angle (in the feature space) was calculated. The decision boundary angle helps investigate the relation between the clusters, respiratory flow rate, and lung volume change (e.g., where in the feature space clusters will switch [3]).The signal-to-noise ratio (SNR) was also calculated as the ratio of the RMS in two windows: one representing the signal while the other represents the background noise. When plotting the local energy of the SCG events (as shown in Figure 1), a quiescent period was observed at the last 100 ms of SCG events. This period was selected to represent background noise, similar to what was done in [1]. The period representing the signal was chosen as a sliding window with a 100ms duration. As such, a local SNR can be defined using Equation 1:

$$SNR(t) = RMS(100\ ms\ window\ starting\ at\ time\ (t))/RMS(100\ ms\ window\ at\ the\ SCG\ event\ end)\ . \quad (1)$$

An example of the local SNR profile is shown in Figure 2(a) which shows that the local SNR is typically high around SCG1 and SCG2 waves when compared with Figure 2(b) which shows an example measured

SCG event after filtering and segmentation. The average SNR of the event could then be calculated using Equation 2:

$$SNR_{event} = \left(\int_0^{b=Event\ end\ timing-100\ ms} SNR(t)dt\right)/b\ . \quad (2)$$

Figure 3(a) shows the feature space at an example chest location (i.e. mid-sternum). Each event was designated by two features: the standardized respiratory flow rate and lung volume change at the corresponding ECG-R wave. As such, each event is represented by one point in the feature space. Clustering was then performed and the decision boundary between the two clusters at each location was drawn. In this figure, the red and blue dots represent the two clusters. The clustering process groups events into clusters where each cluster contains similar events. This grouping minimizes intra-cluster variability [3].

To better understand the physical significance of the clusters, plotting the timing of each event in the feature space (i.e., lung volume-respiratory flow rate space of Figure 3 (a)) is helpful. Here, clustering correlate with respiratory timing. Similar results were reported in previous studies [3]. Figure 3(b) shows the distribution of the decision boundary angle (i.e. the angle with the horizontal in the feature space). The values in Figure 3(b) are averaged over the fifteen study subjects. The average decision boundary angle at the 4th intercostal space and near the left sternal border was 131°, which is comparable with the 147° angle reported in [3]. Figure 3(c) shows the average percent of events in cluster 1 (the cluster that has the higher lung volume medoid). The % number of events in each cluster was comparable within the upper chest but tended to be different from the lower chest.

Figure 4(a) shows that the classification accuracy is highest in the 4th quadrant of the chest near the left sternal border, which may be attributed to the higher SNR in this region as shown in Figure 4(b). More investigations are needed to study physiological reasons, which may include heart position and

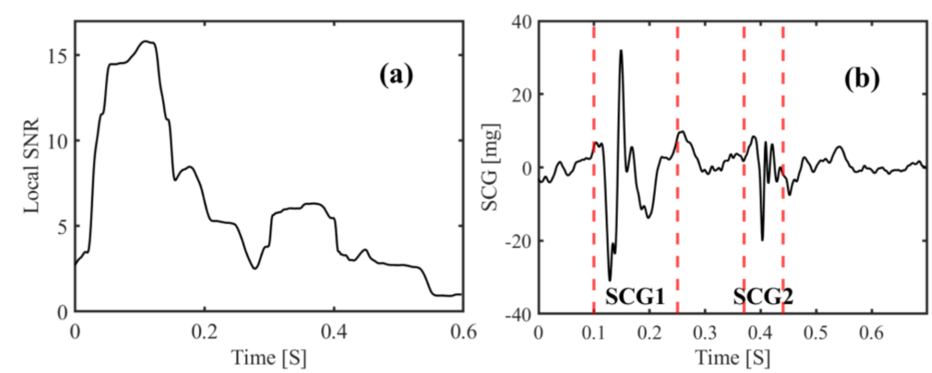

Figure 2. (a) Example local SNR profile (b) Typical SCG event. mg is 1/000 of the gravitational acceleration

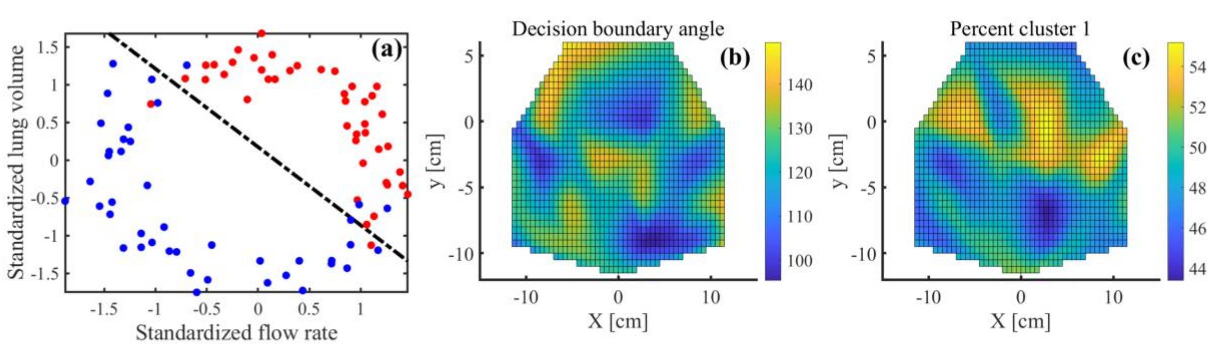

Figure 3. (a) Example of the decision boundary in the feature space at the mid-sternum (b) Spatial distribution of the average decision boundary angle (c) % number of events in cluster 1 (the cluster where the medoid has the higher lung volume)

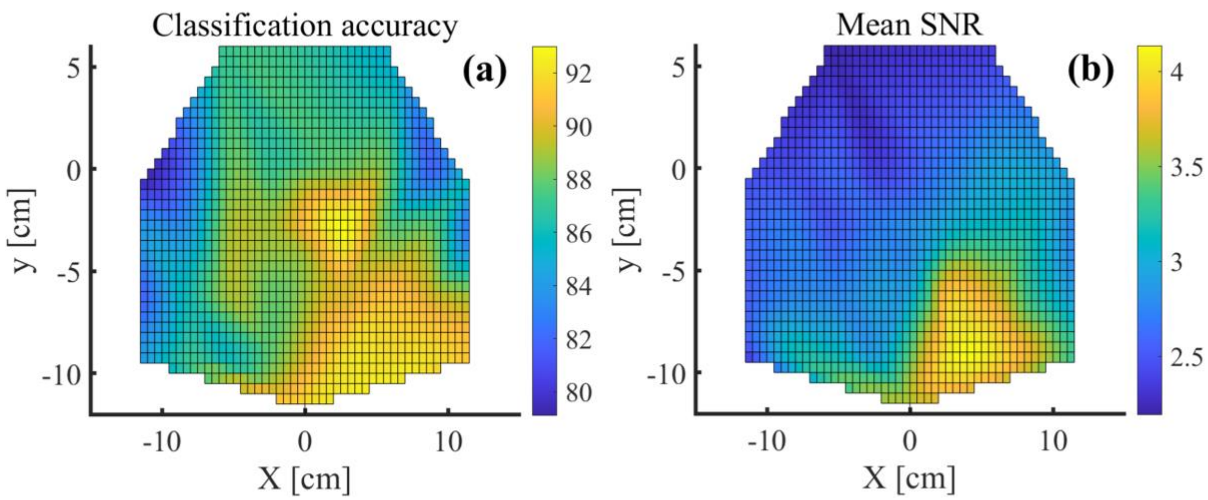

Figure 4. Spatial distribution of (a) mean classification accuracy (b) mean SNR

cardiopulmonary physiology. This trend suggests that the 4th quadrant may be a better location for acquiring the SCG signal. The values in Figure 4 are also averaged over the fifteen study subjects.

The results demonstrated the dependence of SCG clustering on measurement location, which suggests that care needs to be taken when comparing results of studies that recorded SCG at different locations. Results also showed that the highest classification accuracy and SNR occur at the 4th quadrant near the left sternal border, which suggests that this region would be optimal for measuring SCG. More studies are needed to explore the utility of the observed clustering differences in assessing cardiac health.

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