Heart Sound Segmentation using Switching Linear Dynamical Models

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Problem

Localization of exact positions of the fundamental heart sounds (FHS) is an essential step towards automatic analysis of heart sound phonocardiogram (PCG) recordings.

This is a difficult problem due to two aspects.

1. Noise: PCG segmentation is a difficult task in clinical environments when recordings are corrupted by in-band and background noise.
2. Regimes: A constrained non-ergodic Markov chain with limited number of states that represent the heart sound components.

Method

Let Y_t^k, $t = [1, 2, \ldots, T]$ and $k = [1, \ldots, K]$, where $K = 4$ corresponding to four heart sound components. consider AR (1)

$$Y_t^k = \sum_{p=1}^{P} \varphi_p Y_{t-p}^k + \varepsilon_t, \quad \varepsilon_t \sim N(0, R) \qquad (1)$$

Parameters Initialization:

The Ordinary least squares (OLS) method was used to estimate φ_p,such that

$$\hat{\varphi} = (XX')^{-1}(X'Y) \qquad (2)$$

where, φ is $1 \times P$ vector of AR coefficients, X is $P \times T$ contains the P lag observations of Y.

State-Space Model (SSM):

Equation (1) can be written as,

$$\begin{aligned} \mathrm{y}_t &= C\mathrm{x}_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, R) \\ \mathrm{x}_{t+1} &= A\mathrm{x}_t + \mathrm{w}_t, \quad \mathrm{w}_t \sim N(0, Q) \end{aligned} \qquad (3)$$

References

[1] Springer, DB and Tarassenko, L. Logistic Regression-HSMM-Based Heart Sound Segmentation. *IEEE TBME '16*

[2] Samdin, S. Balqis and Ting, Chee-Ming and Ombao, Hernando and Salleh, Sh-Hussain. A Unified Estimation Framework for State-Related Changes in Effective Brain Connectivity. *IEEE TBME '17*

Contributions

We develop a general framework for segmenting the fundamental components of heart sound data based on the SLDS. More precisely, we formulate a piece-wise stationary autoregressive (AR) process into a switching linear state-space representation to identify the change points in the auto-correlation structure to achieve segmentation of heart sound signals.

We adopt a four-states Markov-switching AR (MSAR) model to capture dynamic changes (cardiac events) between four important heart sound components.

We evaluate our proposed approach on a large heart sound dataset provided by Physionet/Challenge 2016.

MSAR

The switching AR process (1) is defined by

$$\mathrm{y}_t = \sum_{p=1}^{P} \varphi_p^{(S_t)} \mathrm{y}_{t-p} + \varepsilon_p^{(S_t)} \qquad (4)$$

The switching SSM model is defined as

$$\begin{aligned} \mathrm{y}_t &= C\mathrm{x}_t + \varepsilon_t^{(S_t)} \\ \mathrm{x}_{t+1} &= A^{(S_t)}\mathrm{x}_t + \mathrm{w}_t^{(S_t)} \end{aligned} \qquad (5)$$

- S_t indexes the switching SSM parameters $A^{(S_t)}$, $\varepsilon^{(S_t)}$, and $\mathrm{w}_t^{(S_t)}$.
- $\{x\}_t^{t-p+1}$ is the lagged state dynamics.
- $\varepsilon^{(S_t)}$ and $\mathrm{w}_t^{(S_t)}$ are the observation and state noise, which assumed to follow Gaussian, $\varepsilon_t \sim (0, R^{(S_t)})$ and $\mathrm{w}_t \sim (0, Q^{(S_t)})$.
- The matrix $A^{(S_t)}$ consists of the state-specific AR coefficients.
- $Q^{(S_t)}$ is a $P \times P$ sparse matrix with Q_{11} is the state covariance noise.
- The switching model parameters are denoted by $\Theta = \{A, Q, R\}$.

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Method

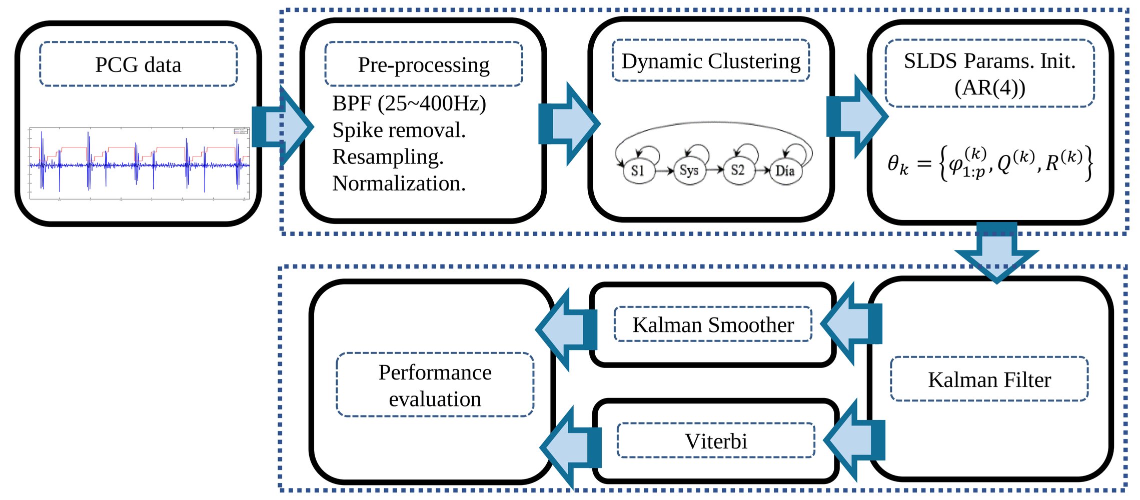


Fig.1 illustrates the proposed framework for heart sound segmentation based on SLDS.

State Estimation

Objective:

Given a sequence of observations $\{Y\}_1^T$, the problem of inference in SLDS models is to estimate the posterior probabilities $Pr(S_t = j | \{Y\}_1^T)$ of the hidden state variables S_t.

Switching Kalman Filter (SKF):

For each state $i, j = [1, \ldots, K]$ at time $t = [1, \ldots, T]$, Kalman Filter will iteratively compute the mean and covariance of the new predicted state, x_t^{ij} and P_t^{ij} respectively.

$$M_t^j = P(S_t = j | \{Y\}_1^T) \qquad (6)$$

where M_t^j (6) is the $K \times T$ probability that at each time $t \in [1, 2, \ldots, T]$, the observation y_t belongs to state j subject to $\sum M_t^j = 1$.

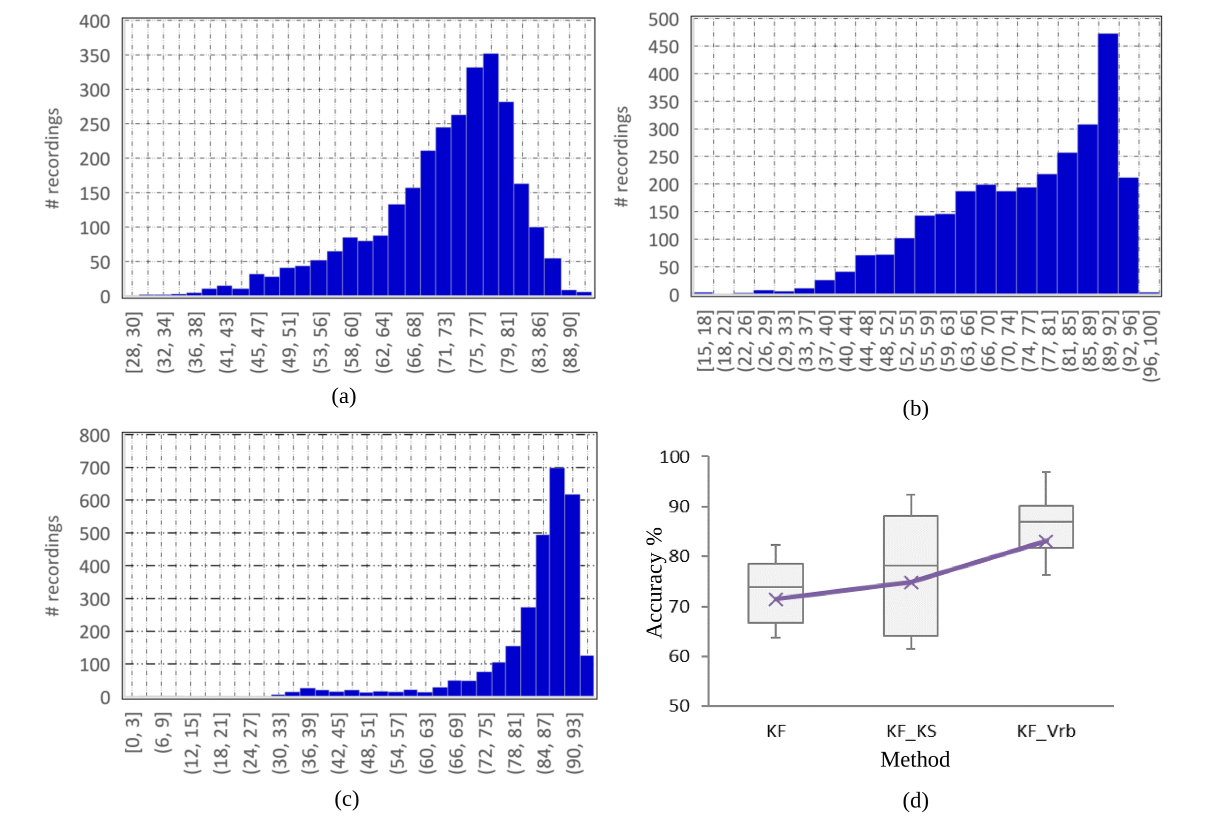
Switching Kalman Smoother (SKS):

The Kalman backward smoothing recursions use the filtered state probability $P(S_t | \{Y\}_1^t)$ and the filtered densities $\{\mathrm{x}^j\}_1^T, \{P^j\}_1^T$ to calculate the posterior distributions $P(\mathrm{x}_t | \{Y\}_1^T)$ conditioned to all the observations $\{Y\}_1^T$ starting from last time step T [2].

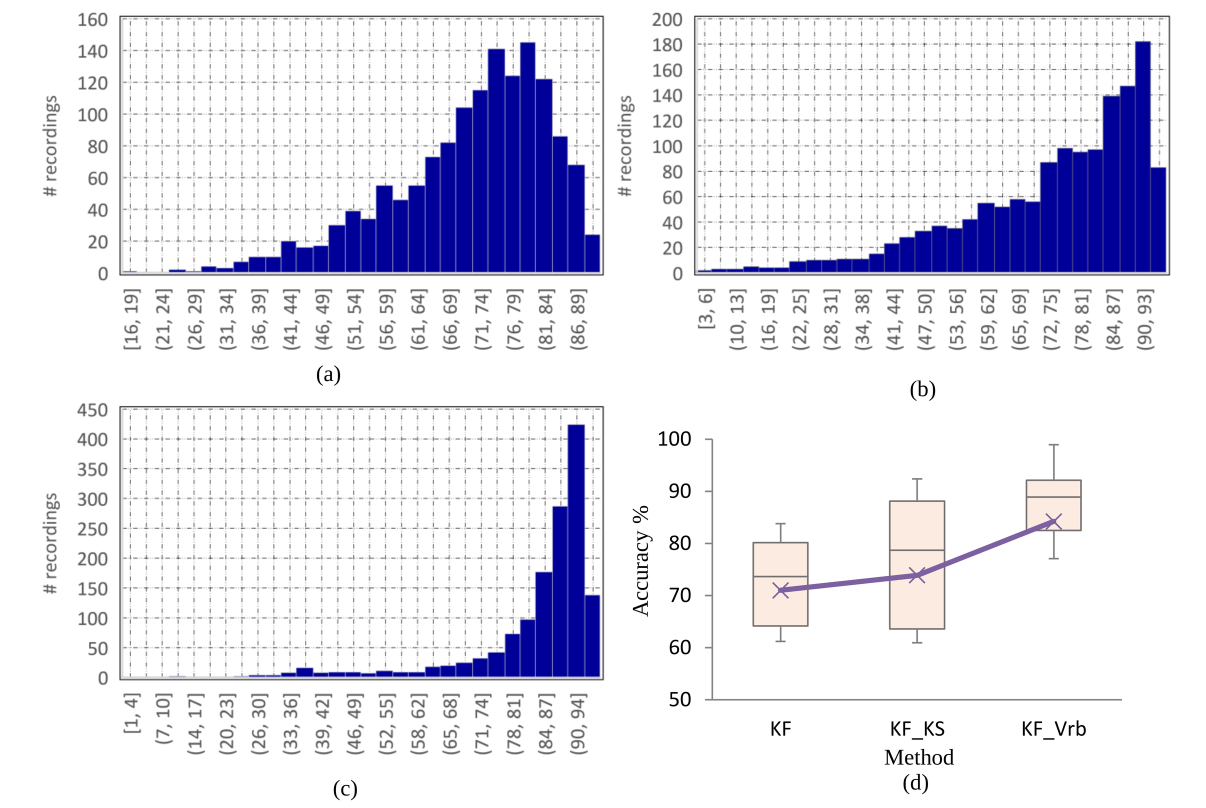
Duration-Dependent Viterbi Algorithm:

The modified Viterbi algorithm was proposed by [1]. Which decodes the most likely sequence of states, given the SKF posterior probabilities M_t^j. The duration-dependent Viterbi algorithms forces the state to remain in the correct sequence (the fundamental heart sound components).

Results & Conclusions



Percentage histograms of non-split dataset segmentation. (a) SKF; (b) SKS; (c) SKF-Viterbi. (d) Distribution of accuracies for different segmentation methods.



Percentage histograms of test dataset segmentation. (a) SKF; (b) SKS; (c) SKF-Viterbi. (d) Distribution of accuracies for different segmentation methods.

- The segmentatin accuracies of unseen dataset dropped slightly in both SKF and SKS, while the Viterbi maintained the same performance 84.2%.
- The fusion of SKF and duration-dependent Viterbi based heart sound data labeling results in improving the average performance in SKF form 71% to 84.2%.
- The study presented here investigated new approaches for the segmentation of fundamental heart sounds from a single channel PCG recording without using any reference signals