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.

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.

METHOD

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

\[
Y^k_t = \sum_{p=1}^{P} \varphi_p X^k_{t-p} + \varepsilon_t, \quad \varepsilon_t \sim N(0, R)
\]

Parameters Initialization: The Ordinary least squares (OLS) method was used to estimate \( \varphi \), such that

\[
\hat{\varphi} = (XX')^{-1}(XY)
\]

where, \( \varphi \) is a \( 1 \times P \) 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,

\[
y_t = Cx_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, R)
\]

\[
x_{t+1} = A(S_t)x_t + w_t, \quad w_t \sim N(0, Q)
\]

The switching AR process (1) is defined by

\[
y_t = \sum_{p=1}^{P} \varphi_p^S y_{t-p}^S + \varepsilon_t^S
\]

The switching SSM model is defined as

\[
x_t^S = Cx_t^S + \varepsilon_t^S
\]

\[
x_{t+1}^S = A(S_t^S)x_t^S + w_t^S
\]

- \( S_t \) indexes the switching SSM parameters \( A(S_t), \varepsilon_t^S \) and \( w_t^S \).
- \( \{x_t^S\}_{1}^{T} \) is the lagged state dynamics.
- \( \varepsilon_t^S \) and \( w_t^S \) are the observation and state noise, which assumed to follow Gaussian, \( \varepsilon_t \sim N(0, R(S_t)) \) and \( w_t \sim N(0, Q(S_t)) \).
- The matrix \( A(S_t) \) consists of the state-specific AR coefficients.
- \( Q(S_t) \) is a \( P \times P \) sparse matrix with \( Q_{tt} \) is the state covariance noise.
- The switching model parameters are denoted by \( \Theta = \{A, Q, R\} \).

STATE ESTIMATION

Objective:

Given a sequence of observations \( \{Y_t\}_1^T \), the problem of inference in SLDS models is to estimate the posterior probabilities \( Pr(S_t = j|\{Y_t\}_1^T) \) 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, \( \hat{x}_t^j \) and \( P_t^j \) respectively.

\[
M_t^j = P(S_t = j|\{Y_t\}_1^T)
\]

where \( M_t^j \) 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 \( P(S_t|\{Y_t\}_1^T) \) and the filtered densities \( \{x_t^S|\{Y_t\}_1^T\} \) to calculate the posterior distributions \( P(s_t|\{Y_t\}_1^T) \) conditioned to all the observations \( \{Y_t\}_1^T \) starting from last time step \( T \).

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 \( M_t \). 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 segmentation 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.

REFERENCES


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