Heart Sound Classification Based on Temporal Alignment Techniques

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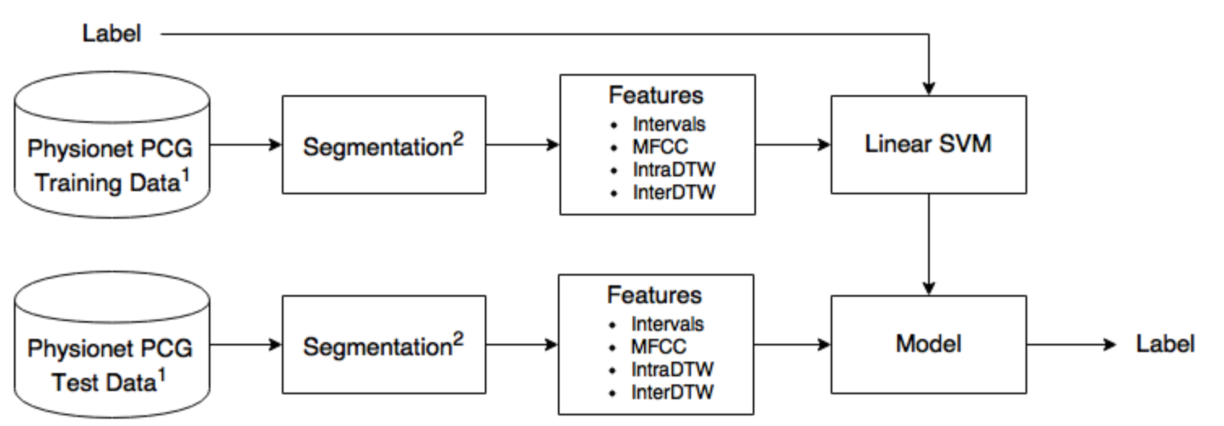
Introduction

- PhysioNet/CinC 2016 Challenge: automatically classify heart sound recordings collected from both clinical and nonclinical environments
- We explore temporal alignment techniques, in particular dynamic time warping (DTW), to address inter-patient and inter-population differences
- DTW-based features effectively reduce inter-patient variability and bias from heterogeneous data collection environments

Methodology

Our supervised learning system consists of three main stages:

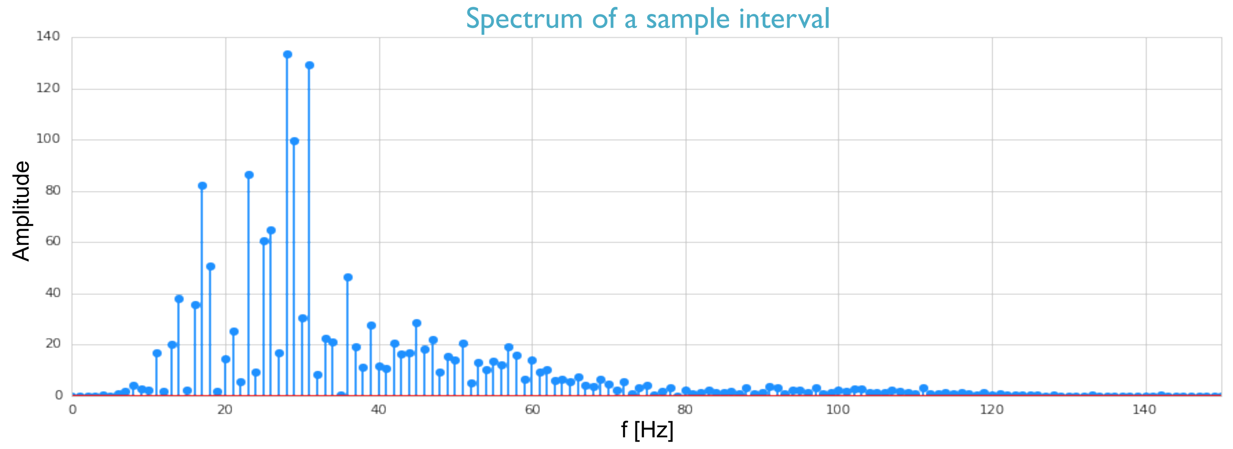
- **Segmentation** – PCG recordings are segmented into the fundamental heart sounds[1]
- **Feature Engineering** – Features pertaining to time intervals, spectral analysis and morphology are extracted from the segmented records
- **Classifier** – We learn a linear support vector machine (SVM) with asymmetric cost parameters to handle class imbalance



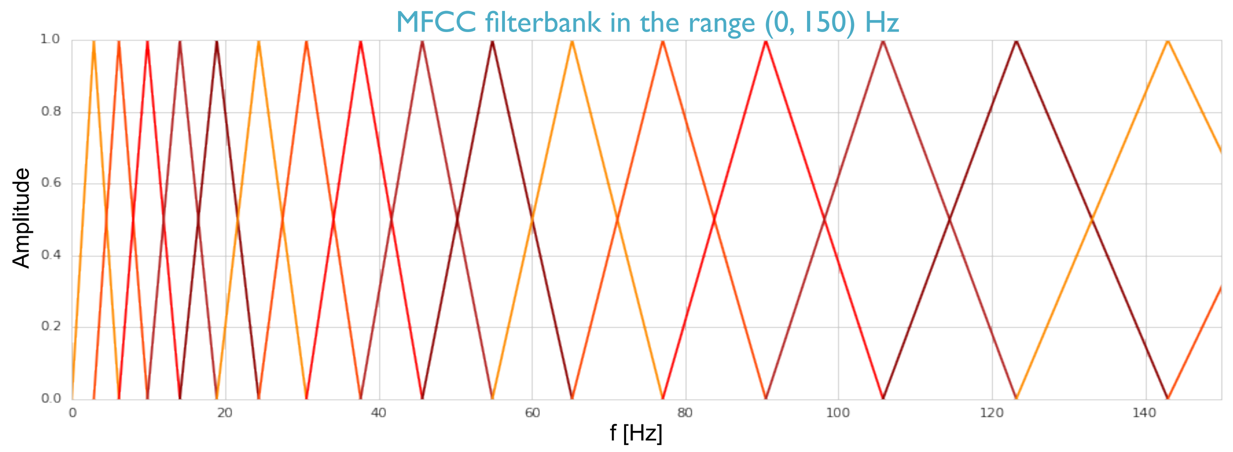
Overview of the supervised learning system

Mel-Frequency Cepstrum

Spectrum of a sample interval



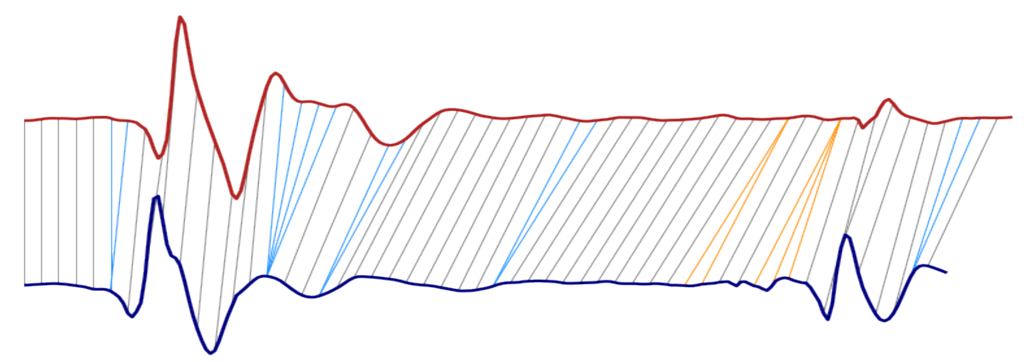
MFCC filterbank in the range (0, 150) Hz



- Mel-Frequency Cepstral Coefficients are computed for each heart sound cycle
- The logarithmic filterbank has higher resolution on low frequencies
- The MFCC mean and standard deviation of each record capture variability within each filterbank interval

Dynamic Time Warping

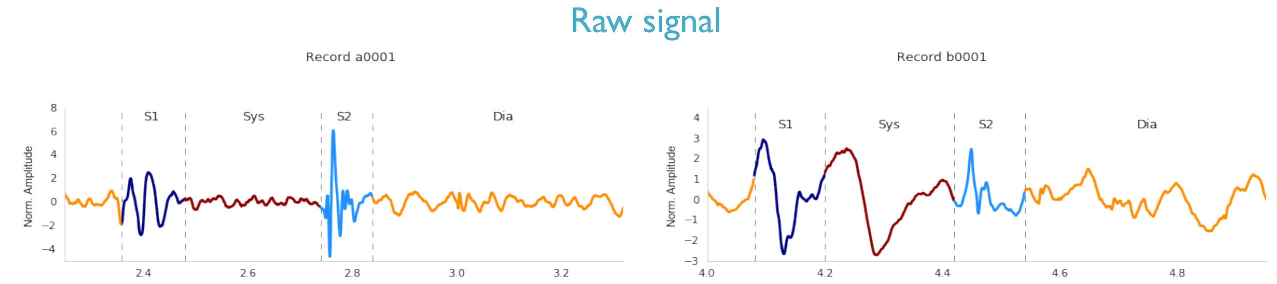
- DTW to compare intra- and inter-subject morphology of heart sounds
- DTW has obtained good results in the past in the domain of ECG classification[3,4]



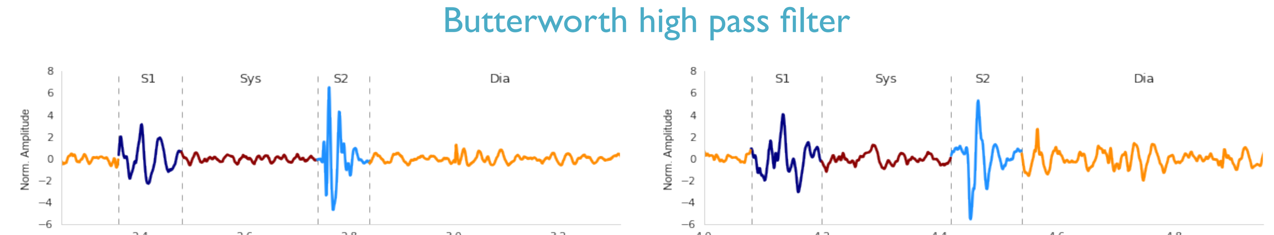
DTW finds an optimal alignment between two time-dependent sequences by warping the sequences in a nonlinear fashion

- Preprocessing steps applied prior to computing the DTW distances to reduce the noise
  i. Butterworth high pass filter (fc = 25Hz)
  ii. Homomorphic Envelogram
  iii. Z-standardization (zero mean, unit variance)

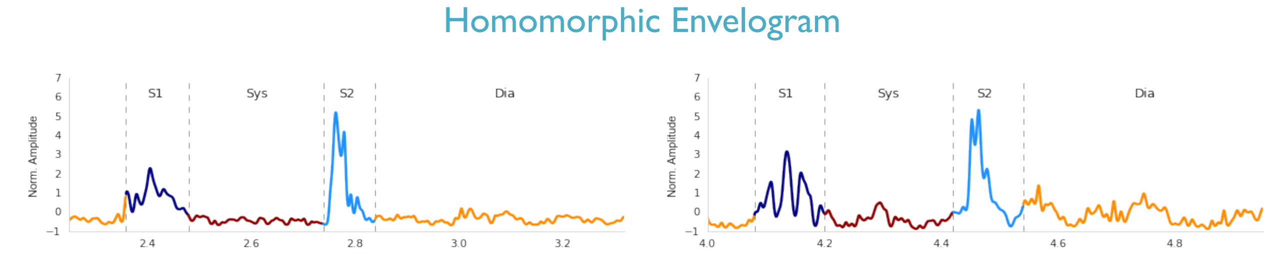
Raw signal



Butterworth high pass filter

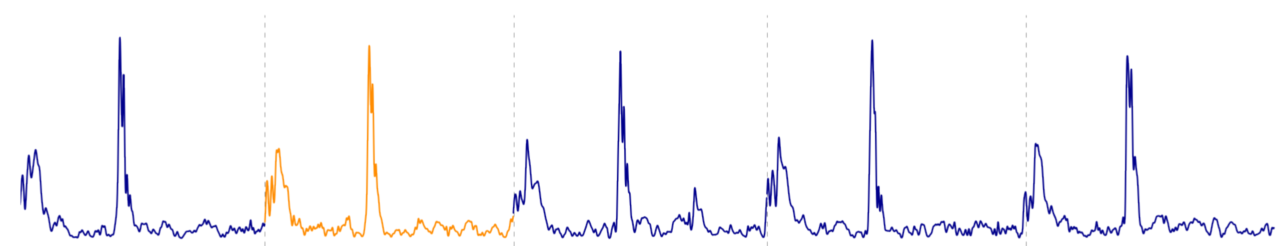


Homomorphic Envelogram



Computing Medoid Beats

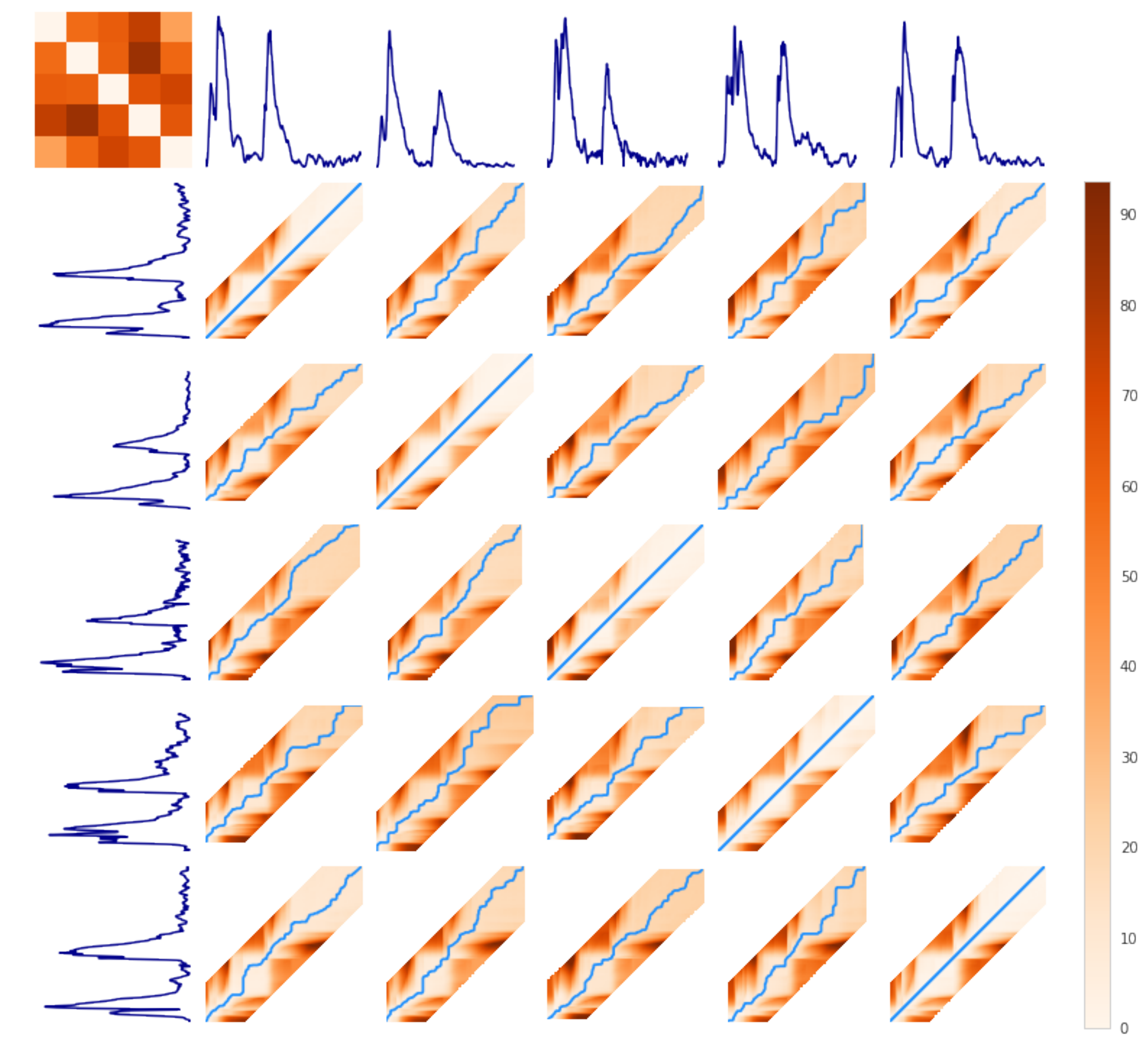
- To construct a representative heartbeat for a given record we use the medoid heartbeat
- This is the heartbeat whose average DTW distance to all the other in-record heartbeats is minimal



Medoid heartbeat in a sample recording

Intra-patient Variability

- Cardiac conditions may manifest by higher than usual variability in heartbeat shape and frequency
- To capture intra-patient variability, DTW distance is computed for each combination of heartbeats

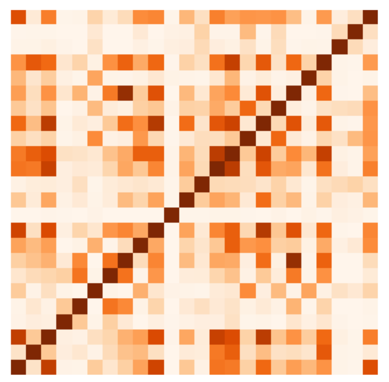


Pairwise DTW matrices for the heartbeats in a sample record

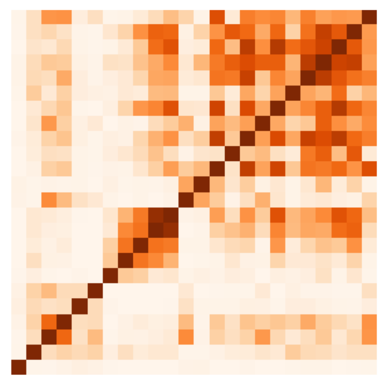
- Features are obtained from the distances to the medoid heartbeat
- Features are also extracted from contiguous heartbeats to capture time evolution

Inter-patient Variability

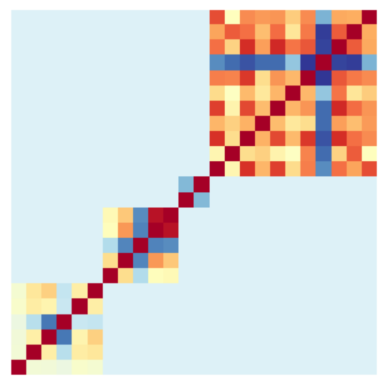
- Intra-DTW features fail to capture abnormalities that manifest consistently
- Inter-patient DTW distances aim to capture canonical patterns based on a beat's similarity to a set of template heartbeats



Affinity Matrix



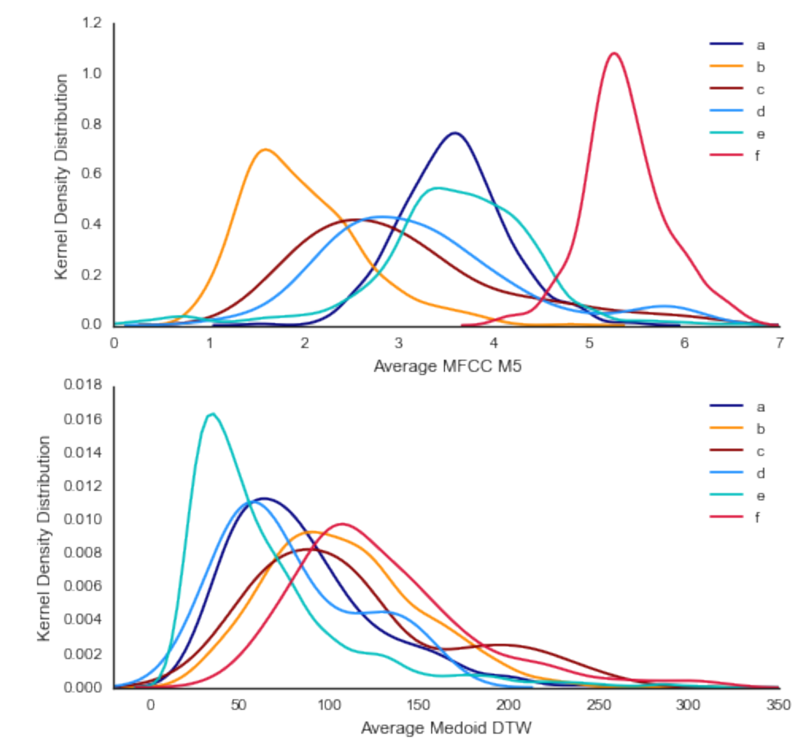
Clustered Matrix



Clusters with Centroids

- For each population and class, spectral clustering is performed using the representative heartbeats of each recording.
- Templates are selected from the centroids of each cluster
- DTW distances between templates and heartbeats are computed

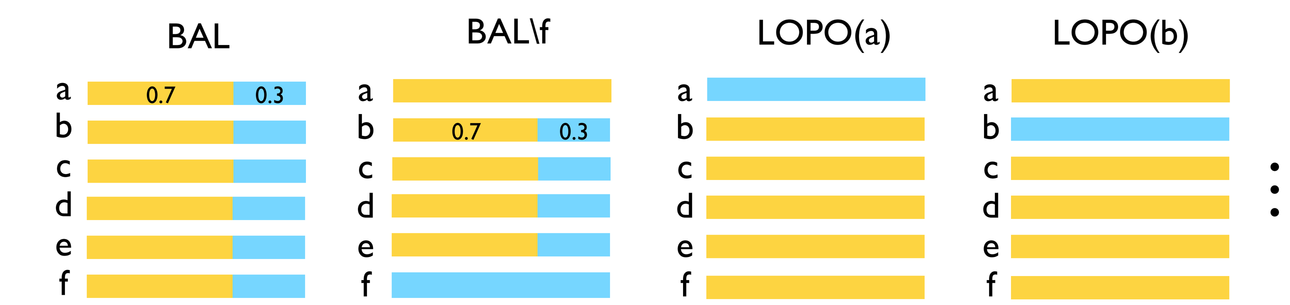
DTW Robustness



- Kernel density estimates are computed to assess the robustness of DTW-based features to inter-population differences
- DTW based features consistently reduce inter-populational variability, producing more homogeneous distributions

Cross-Validation Setup

We considered a number of experimental setups that differ in the way data are split into training ( ) and validation ( ) sets



$$\overline{L} = 1/N \sum_p \mathrm{LOPO}(p) \qquad \overline{wL} = \sum_p 1/|p| \cdot \mathrm{LOPO}(p)$$

Results

Features	BAL	BAL\f	$\overline{L}$	$\overline{wL}$	$[L_{\min}, L_{\max}]$	Challenge
Interval Wavelet	74.22 ± 0.63	76.41 ± 0.86	58.27	52.35	[48.20, 76.50]	78.1
Interval MFCC	77.68 ± 0.48	79.66 ± 0.72	60.90	54.91	[51.70, 73.80]	
MFCC interDTW	85.73 ± 0.48	79.72 ± 1.04	66.03	64.64	[58.50, 75.70]	79.5
MFCC* intraDTW	85.18 ± 0.74	84.89 ± 0.43	68.37	68.81	[61.10, 77.40]	82.4
MFCC intraDTW interDTW	85.63 ± 0.42	84.42 ± 0.49	66.95	67.78	[60.60, 75.30]	78.9

* This set of features includes also Systole and Diastole in addition to S1 and S2

1. Liu C, Springer D, Li Q, Moody B, et al. An open access database for the evaluation of heart sound algorithms. Physiological Measurement 2016.
2. Springer DB, Tarassenko L, Clifford GD. Logistic regression-hsmm-based heart sound segmentation. IEEE Transactions on Biomedical Engineering 2016.
3. Wiens J, Guttag JV. Active learning applied to patient-adaptive heartbeat classification. NIPS, 2010.
4. Syed Z, Guttag JV. Identifying patients at risk of major adverse cardiovascular events using symbolic mismatch. NIPS, 2010.

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