

Multivariate Symbolic Aggregate Approximation for ECG Analysis

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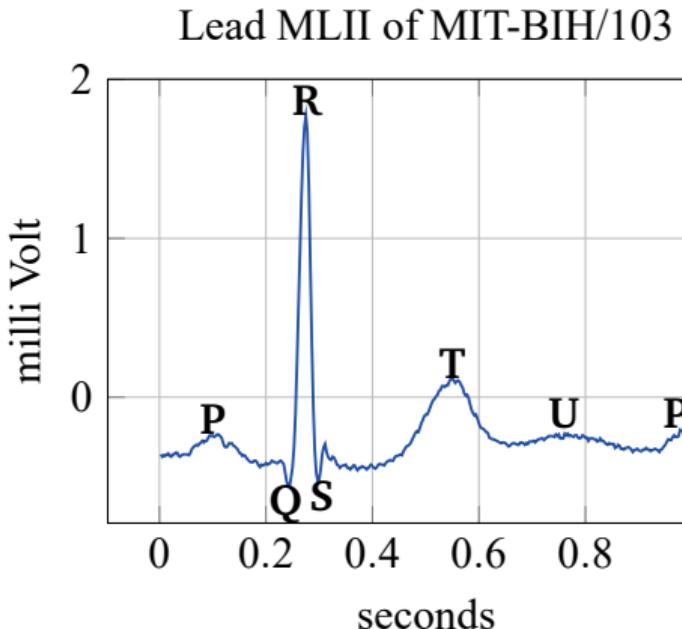
Outline

1 Introduction

2 Methods

3 Preliminary Results

What is an ECG?



- electrocardiogram (ECG or EKG) records the heart's electrical activity
- contains up to 12 simultaneous measurements—the leads
- common medical diagnostic tool

Figure 1: Annotated ECG of one heartbeat

ECGs as Time Series

Definition

A discrete time series is an ordered sequence which, at discrete points in time, has n values each. If $n = 1$, the series is univariate and if $n > 1$, it is multivariate.

- digital ECGs are discrete multivariate time series:
 - have > 1 value at each point, often $n = 12$
 - recorded at discrete, evenly spaced time points
- time series analysis methods can be applied to ECGs

ECG Analysis

- standard method: manual analysis by cardiologist
- automated or computer-assisted ECG analysis seeks to replace that
- multiple stages:(1) signal acquisition; (2) data transformation, processing, filtering; (3) waveform recognition, feature extraction; (4) classification
- current research focus: artificial neural networks

SAX, MSAX, and HOTSAX

- Lin *et al.* (2003):
Symbolic Aggregate Approximation (SAX)—simplified, symbolic representation
- Anacleto *et al.* (2020):
Multivariate SAX (MSAX)—expands SAX to multivariate time series
- Keogh *et al.* (2005):
Heuristically Ordered Time series using SAX (HOTSAX)—discord discovery algorithm for SAX

Time Series Discords

Definition

A time series discord is the subsequence of a time series that is most different from all other subsequences.

k time series discords are the k most different subsequences.

- discords represent anomalies in an ECG
- HOT SAX enables fast discord discovery

Hypothesis

HOTSAX with MSAX will increase the number of relevant discords detected compared to HOTSAX with SAX.

Step 1: Z-Normalization

Assumption

The time series values are normally distributed.

SAX

- normalize univariate time series
- uses scalar mean and variance

MSAX

- normalize multivariate time series
- uses vector mean and covariance matrix

Step 2: Dimensionality Reduction

PAA

Piecewise Aggregate Approximation (PAA) takes T time series points, splits them into w ($w < T$) segments, and averages each of them.

SAX

- apply PAA to time series

MSAX

- apply PAA to each of the time series individually

SAX PAA of lead MLII of MIT- BIH/103

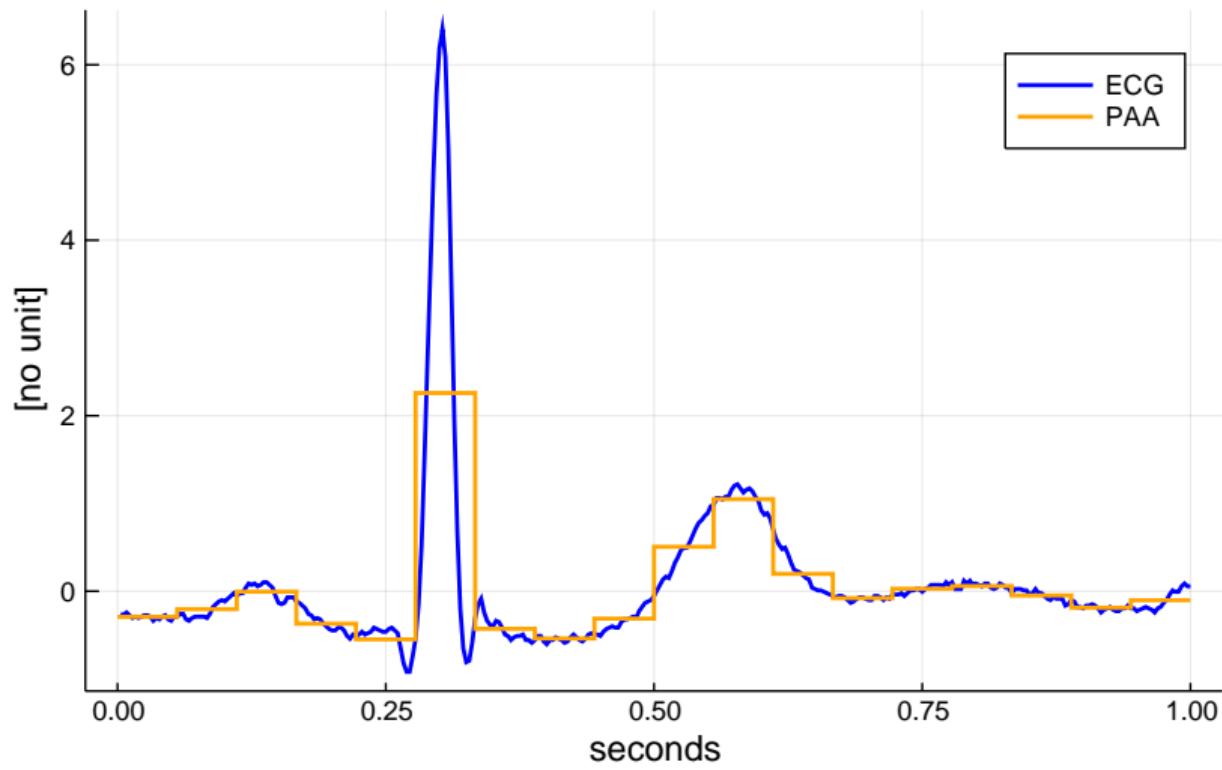


Figure 2: ECG with PAA (MITBIH/100, $w = 18$, $T = 360$)

Step 3: Discretization

SAX Discretization

Find breakpoints splitting $\mathcal{N}(0, 1)$ into B equiprobable segments.

Assign a letter to each area, starting with a to the left-most segment.

PAA segments get letters based on which area they are in.

SAX

- discretize the time series
- results in one *word*

MSAX

- discretize each time series
- results in one *word* with one letter for each time series

SAX of lead MLII of MIT- BIH/103

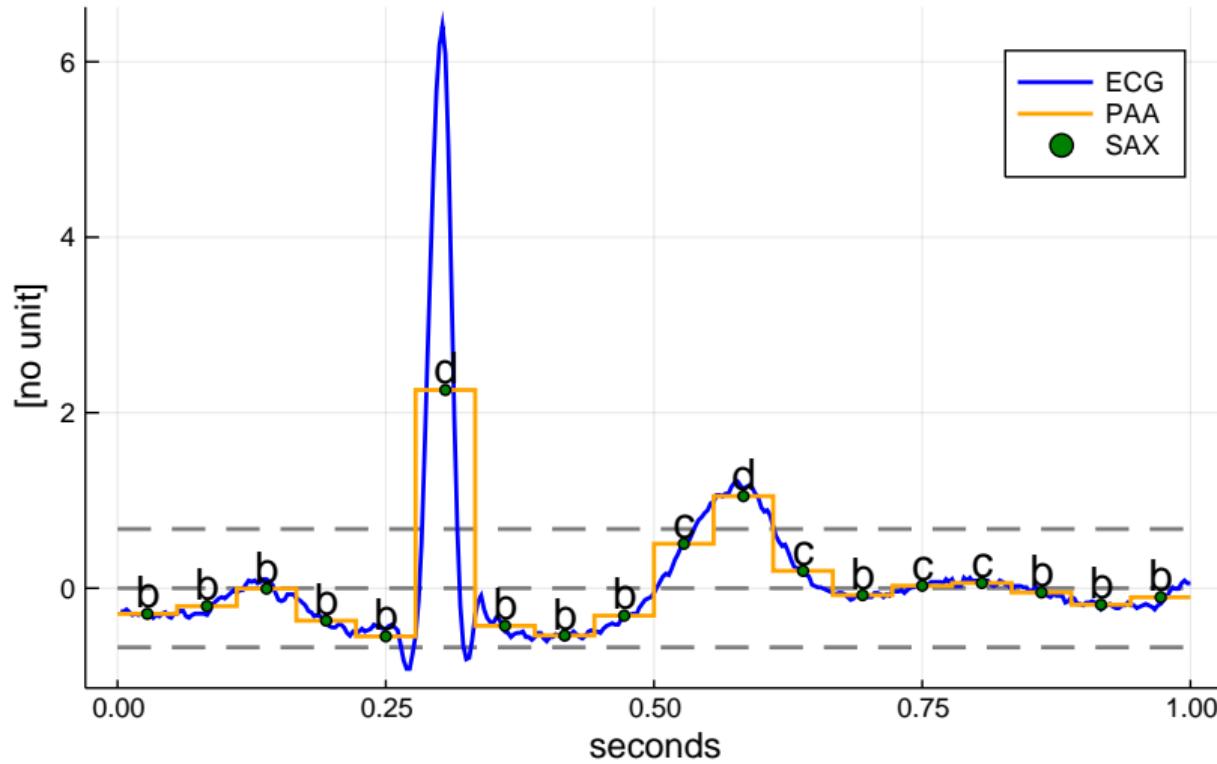


Figure 3: SAX (MITBIH/100, $w = 18, T = 360, B = 4$)

Step 4: Distance Measure

MINDIST

A distance measure is defined to compare two SAX words. It is defined for a pair of letters, distances between words are sums of distances between letters.

Table 1: Difference matrix for $B = 4$

	a	b	c	d
a	0	0	0.67449	1.34898
b	0	0	0	0.67449
c	0.67449	0	0	0
d	1.34898	0.67449	0	0

HOTSAX

- “brute-force” discord discovery is slow, needs T^2 operations
- HOTSAX speeds up discord discovery by considering:
 - discords are rare, start with rarest segment
 - similar segments have similar distances, consider together
- HOTSAX detects anomalies, it is not a classifier
- it uses SAX and MSAX for dimensionality reduction

Implementation

- SAX, MSAX, HOT SAX was implemented in Julia (scientific programming language)
- used annotated digital ECGs from the MIT-BIH arrhythmia database
- HOT SAX was performed for different w, B , subsequence lengths
- results were exported to CSV file and analyzed using the R programming language

Preliminary Results

- compared SAX and MSAX using the top $k = 80$ discords (816 sets of discords total)
- analyzed the relevance of results with recall (sensitivity)
- recall for MSAX is higher compared to SAX
- if SAX is applied to two leads and the results combined, it slightly outperforms MSAX

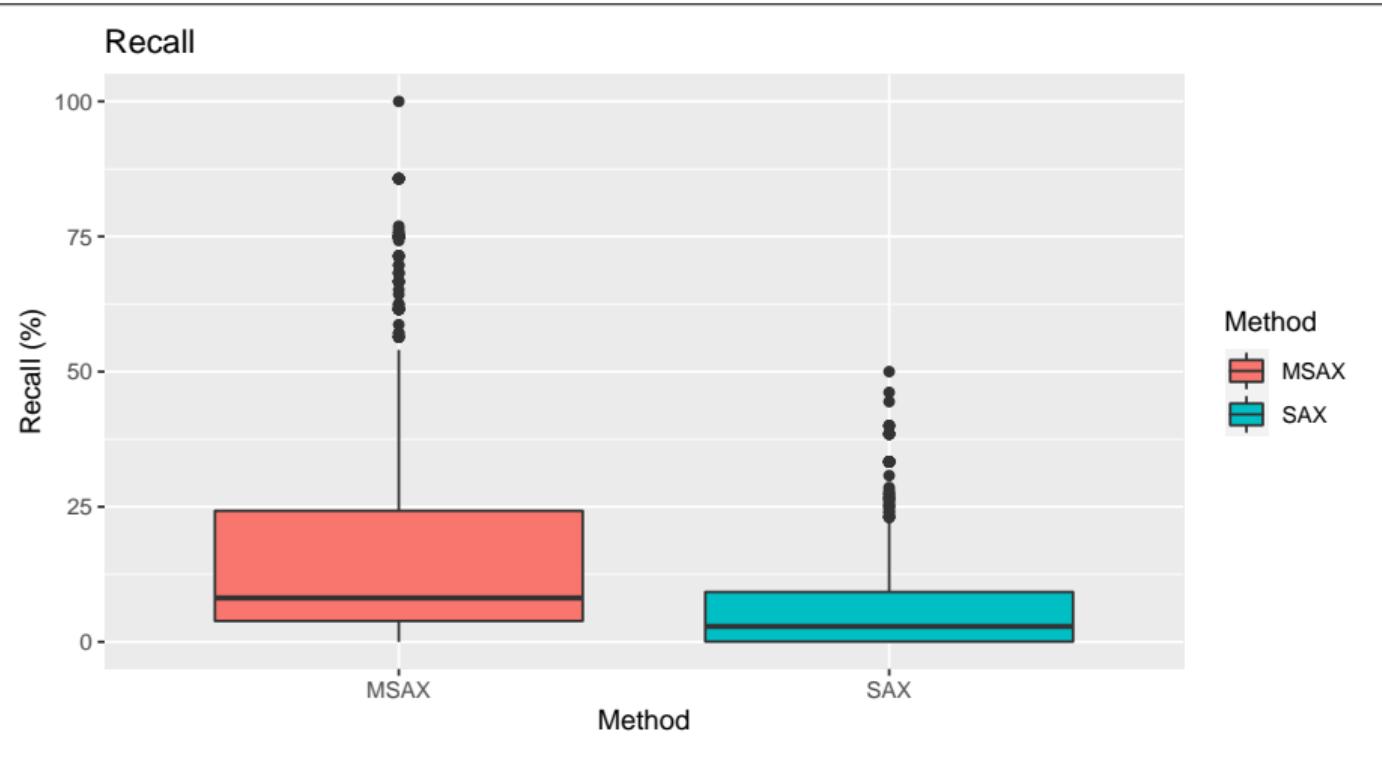


Figure 4: Boxplot comparing Recall for MSAX and single-lead SAX

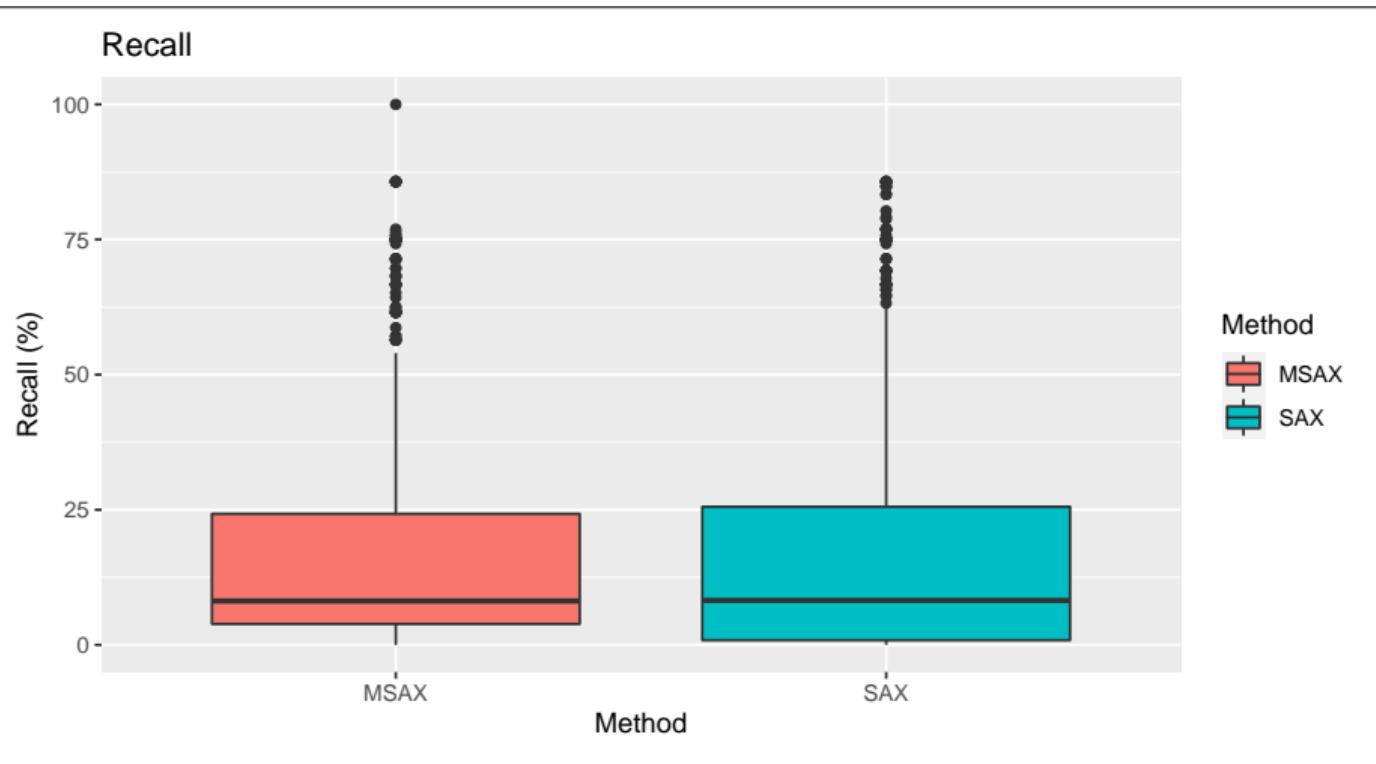


Figure 5: Boxplot comparing Recall for MSAX and dual-lead SAX

Remaining Tasks

- perform tests for statistical significance of the result
- analyze the outliers visible in the boxplots
- compute more sets of discords with different parameters
- explore the influence of the parameters on the result

Thank You!

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