Multivariate Symbolic Aggregate Approximation for ECG Analysis

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Outline

Introduction

- ischemic heart disease (IHD) makes up 16% of global deaths but can be diagnosed using an electrocardiogram (ECG or EKG)
- manual ECG analysis is slow and error-prone, computers can help
- long ECGs are problematic even for computers → simplification through representation
- such representations should be simpler, but still correspond to the original data

What is an ECG?

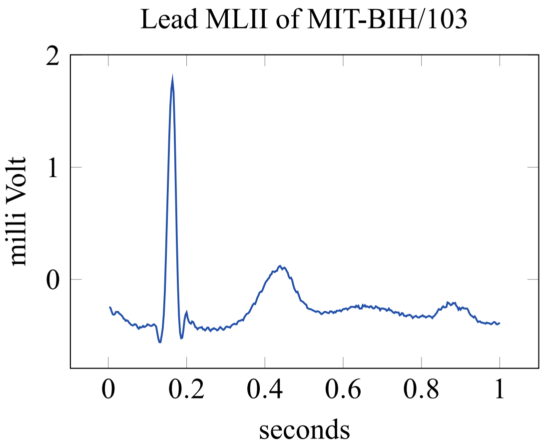


Figure 1: ECG of one heartbeat.

- records the heart's electrical activity
- contains up to 12 leads (simultaneous measurements)

Representation and Classification

- for simplification, time series can be represented, e.g. as SAX or MSAX
- then, the representation can be analyzed instead of the raw data
- HOT SAX can be used to classify ECG segments into discord and non-discord
- this work uses HOT MSAX to combine MSAX and HOT SAX
- effectiveness of the methods will be judged by recall and precision

Research Questions & Hypothesis

- Using the MIT-BIH ECG database, what parameters maximize HOT SAX and HOT MSAX recall?
- Which is better: optimal HOT SAX or optimal HOT MSAX?

HOT MSAX should have higher recall than HOT SAX if both use their best parameters

Novel Contributions

- application of MSAX to ECG discord discovery and medical data in general
- the HOT MSAX algorithm, a modification of HOT SAX that uses MSAX
- the expansion of HOT SAX to multivariate time series through HOT MSAX

Method Background

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

SAX and MSAX – Overview

SAX	MSAX
Application	
univariate time series, e.g. a single ECG lead	multivariate time series, e.g. multiple ECG leads (whole ECG)
Steps	
(1) univariate z-normalization	(1) multivariate z-normalization
(2) PAA dimension reduction (w)	(2) PAA dimension reduction (w)
(3) SAX discretization (a)	(3) SAX discretization (a)

SAX and MSAX – Step (2)

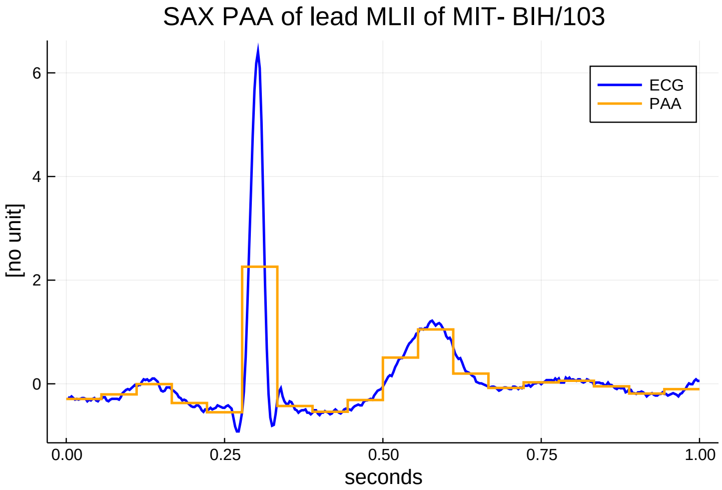


Figure 2: ECG with PAA, $w = 18$

SAX – Step (3)

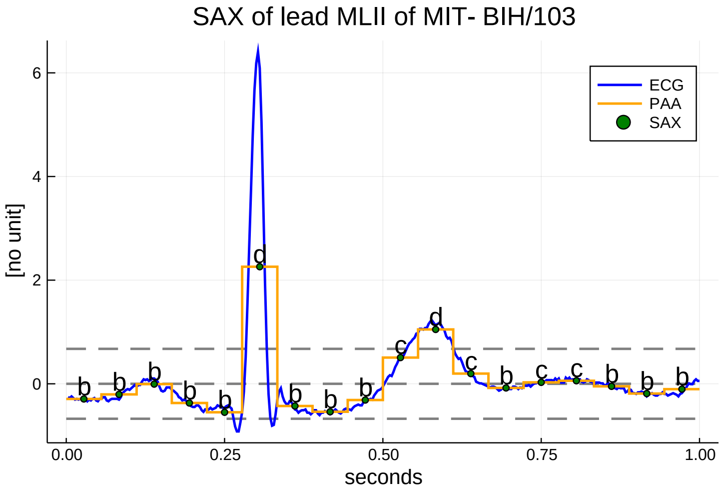


Figure 3: ECG with SAX, $w = 18$, $a = 4$

MSAX – Step (3)

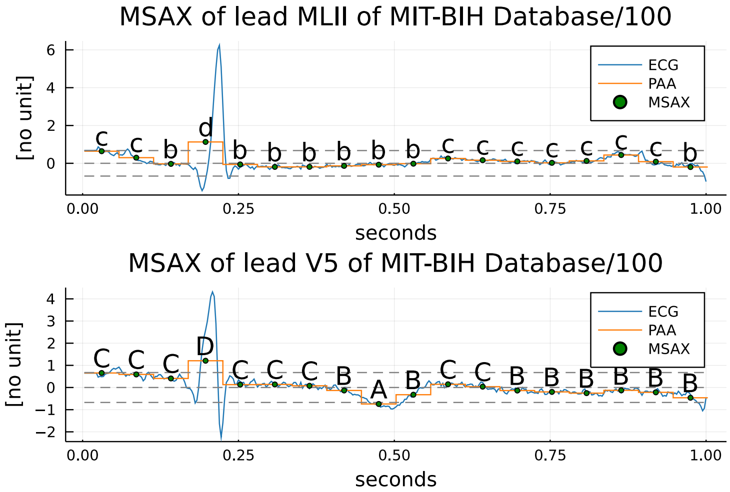


Figure 4: ECG with MSAX, $w = 18$, $a = 4$

SAX and MSAX – Distance Measure

- needed to compare two SAX/MSAX segments
- sum of distances between symbols
- symbol distance is based on difference of breakpoints
- lower-bounds Euclidean Distance, i.e. corresponds to "real" distance

HOT SAX and HOT MSAX – Overview

- HOT SAX: find discords in SAX-represented time series
- classifies time series segments into “discord” and “non-discord”
- HOT MSAX: uses MSAX instead of SAX
- HOT MSAX can work with multivariate time series

HOT SAX and HOT MSAX – Heuristic

- two parameters: m and k
- two assumptions:
  - time series discords are rare
  - segments similar to discords may also be discords
- speed up discord discovery:
  - consider rarest segments first
  - consider similar segments together

Analysis Process

(1) perform HOT SAX and HOT MSAX for many parameter combinations for all ECGs in the MIT-BIH database

(2) find recall, precision for each combination

(3) set recall threshold of 95%, then sort by precision

(4) choose top 10 of those parameters for each method

(5) choose best parameters for each method using box plot, interquartile range, outliers

Three Datasets

(1) S-SAX: data for HOT SAX algorithm, considering each lead separately

(2) D-SAX: data for HOT SAX, considering both leads combined

(3) MSAX: data for the HOT MSAX algorithm

Overview of Results

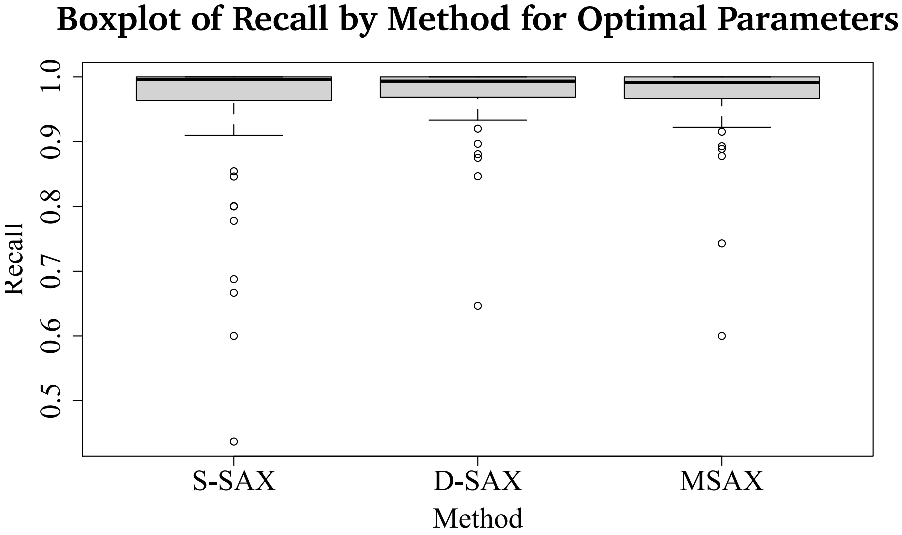
Table 1: Coarse Overview of Results. Shown are sets of parameters for each method that satisfy the recall threshold of 95%.

Method	Total Sets	Sets Satisfying recall $\geq$95%
S-SAX	4,968	99 (1.2%)
D-SAX		192 (3.9%)
MSAX		255 (5.1%)

Best Parameter Sets by Method

Table 2: Best Parameter sets for each of the methods. Best overall parameters highlighted in bold.

Method \ Parameter	k	w, m	a
S-SAX	-1	36	21
D-SAX	-1	**12**	24
MSAX	-1	**12**	**17**


Boxplot of Recall by Method for Optimal Parameters
Recall
1.0
0.9
0.8
0.7
0.6
0.5
S-SAX
D-SAX
MSAX
Method

Comparing Best Parameter Sets – Recall

Table 3: Statistical measures for recall of optimal parameter sets. Best overall values highlighted in bold.

Method \ Measure	IQR	Median	Outliers
S-SAX	0.035	**99.60%**	11
D-SAX	**0.030**	99.35%	**6**
MSAX	0.033	99.13%	**6**

Discussion

- no statistically significant difference in recall for the methods

→ hypothesis cannot be supported

- MSAX has both the smallest alphabet size and highest dimension reduction

→ this points to MSAX being more efficient in achieving the same results

- Anacleto, Vinga, and Carvalho [5] showed similar performance for ECG classification, supports this work's conclusion

Conclusion

- could not demonstrate superiority of HOT MSAX for best parameters
- contributed the HOT MSAX method to literature
- showed viability of a discord classifier for ECG analysis
- in future research: different ECG data, different detection criteria

References I

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[2] J. Lin, E. Keogh, S. Lonardi, and B. Chiu, "A symbolic representation of time series, with implications for streaming algorithms," in *Proceedings of the 8th ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery - DMKD '03*, San Diego, California: ACM Press, 2003, pp. 2–11. DOI: 10.1145/882082.882086.

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Thank You!