Siemens Healthineers

Siemens Healthineers

Characterization and optimization of Biosensor Waveforms

Han (Eden) Chen, Dylan Longert, Nayeli Montiel, Nan Tang, Jinxin (Jessie) Wang

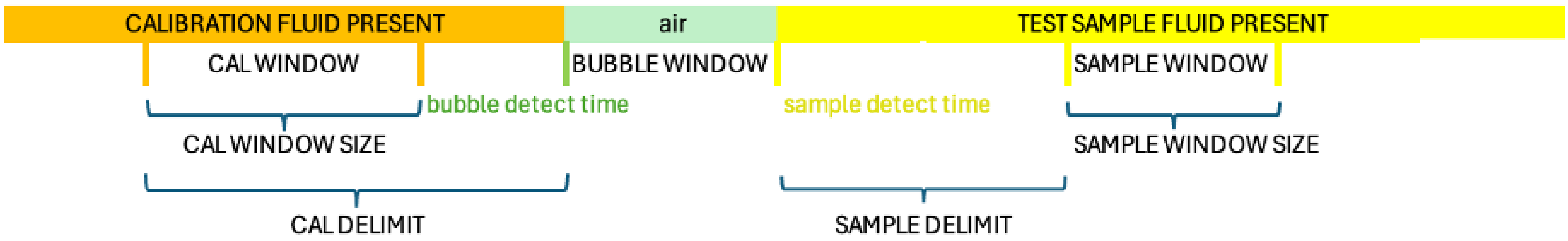
Agenda

- Objectives
- Datasets
- Methodology
- Timeline
- Deliverables

Objectives

Primary Question: How do biosensor waveform characteristics differ between System 1 and System 2?

- System 1 : Current market model [1]
- System 2 : Next-generation model with upgraded epoc Host, a different Reader, and a new type of Test Card.
- Measure the sensor values in both Calibration Period and Test Sample Period



Cal window start = bubble detect time – CalDelimit

Cal window end = cal window start + cal window size

Sample window start = sample detect time + SampleDelimit

Sample window end = sample window start + sample window size

Objectives

Additional Question: Can enhancements be made to current windows to improve their effectiveness?

- Window Placement Optimization
- Adjustment to both window size and position
- Improve the accuracy and precision of test results

Datasets

Multiple time-series of signals

Time in seconds

Electrical signal in mV

4-tables Approximately 22,000 time-series

Additional features

Fluid Type (Blood and Aqueous)

Type of sensor (either A or B)

Age card (in days)

Ambient temperature (in degree Celsius)

Current window limits

Calibration limit

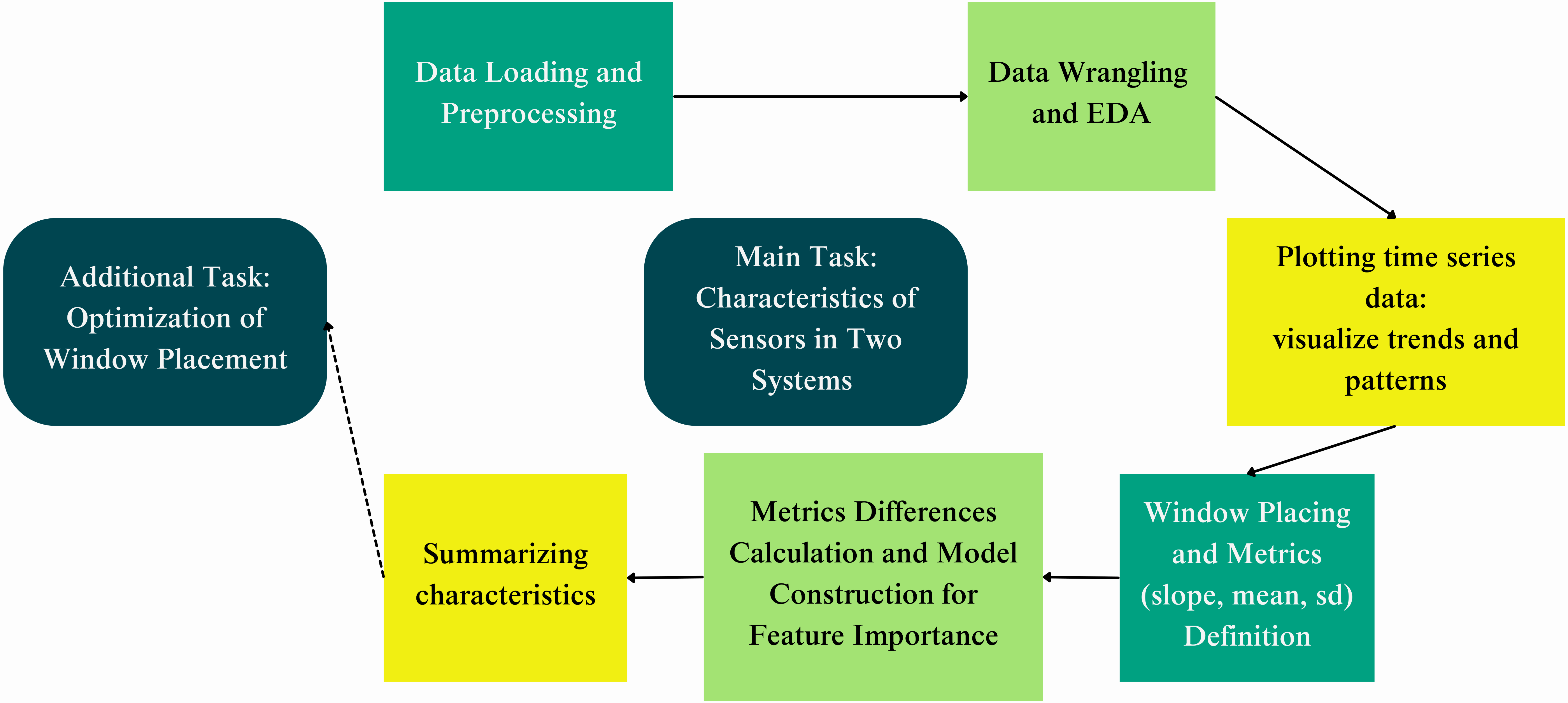
Sample limit

Calibration window size

Sample window size

Methodology

Overall Workflow

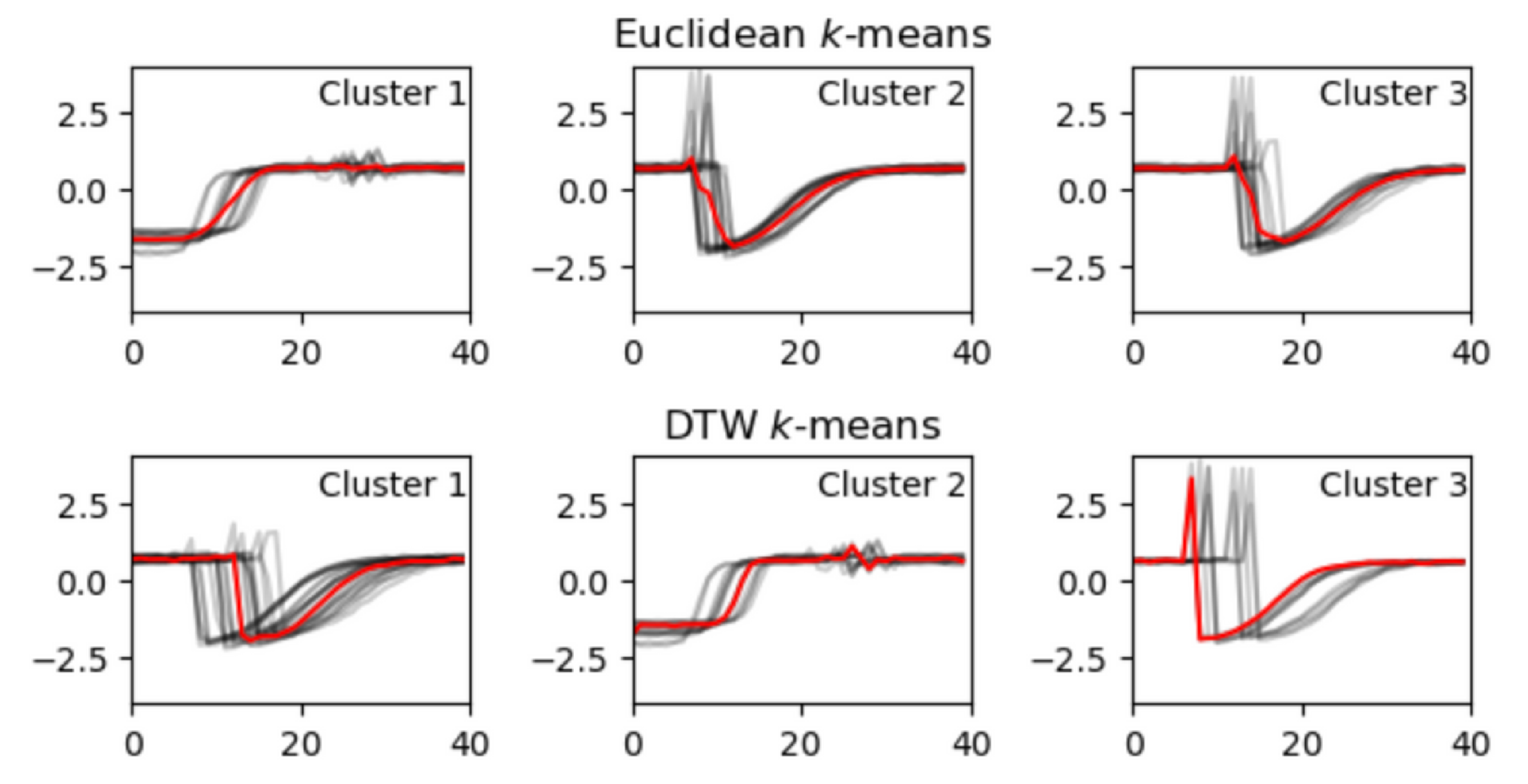


Methodology

Specific Techniques

Time Series Clustering

- Dynamic Time Warping (DTW) [2]
- Euclidean k-means v.s. DTW k-means
- Group similar tests into a smaller number of clusters



Methodology

Specific Techniques

Supervised Machine Learning

- Assuming the observations are independent
- Random Forests, Boosting, Support Vector Regression
- Fit curves with supervised modeling algorithms
- Can derive feature importance

ARIMA (AutoRegressive Integrated Moving Average)

- Autocorrelation exists/is of interest
- model linear relationships and stationary time series data with trends and seasonality

Methodology

Functional Data Analysis

A collection of methods for analyzing data in the form of things like functions, images or shapes (like curves or waveforms) [4]. Particularly useful to learn information about the rate of change (i.e. the derivatives) of the subject.

Functional PCA

A tool for reducing the dimensionality of multivariate data.

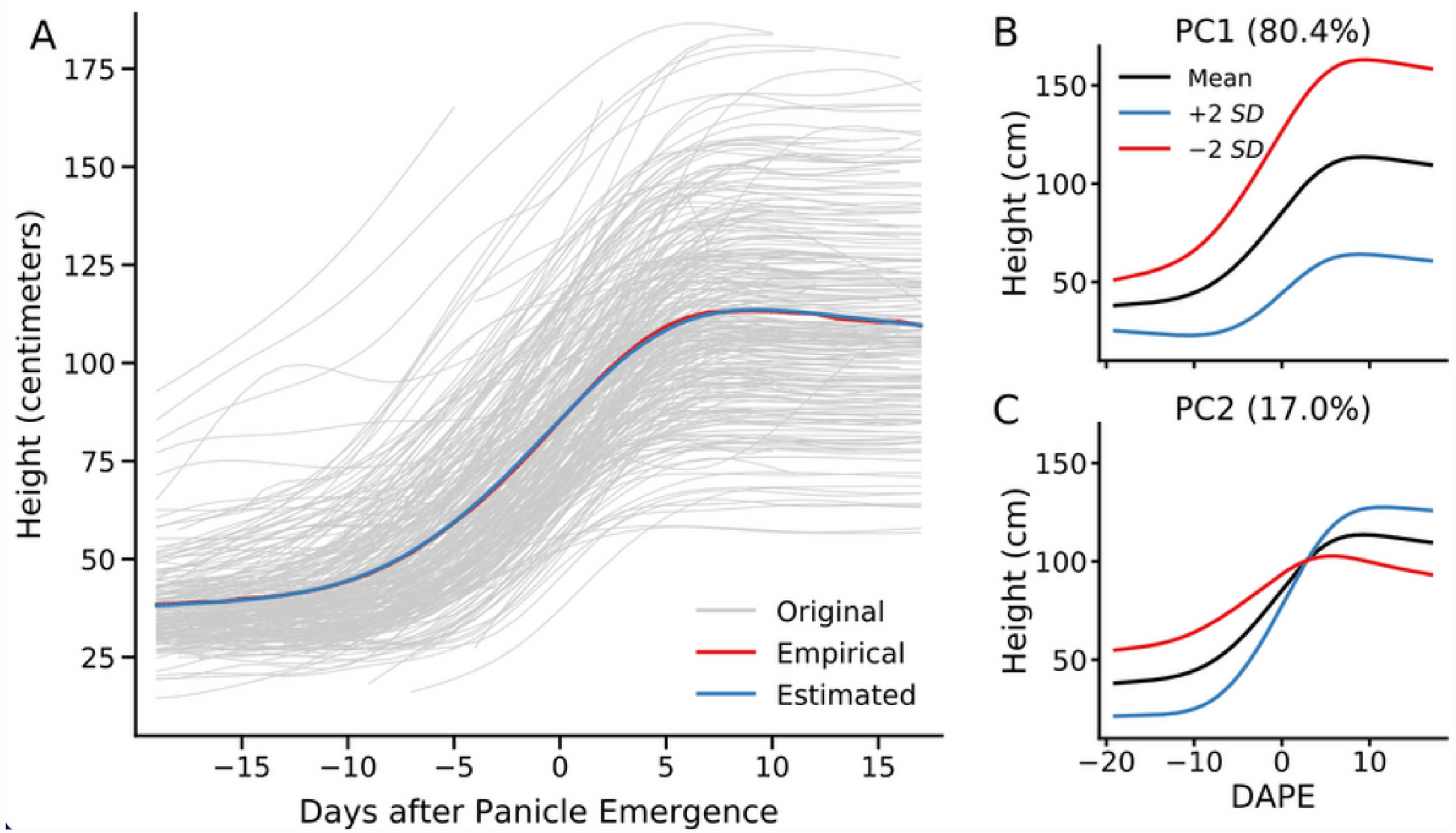


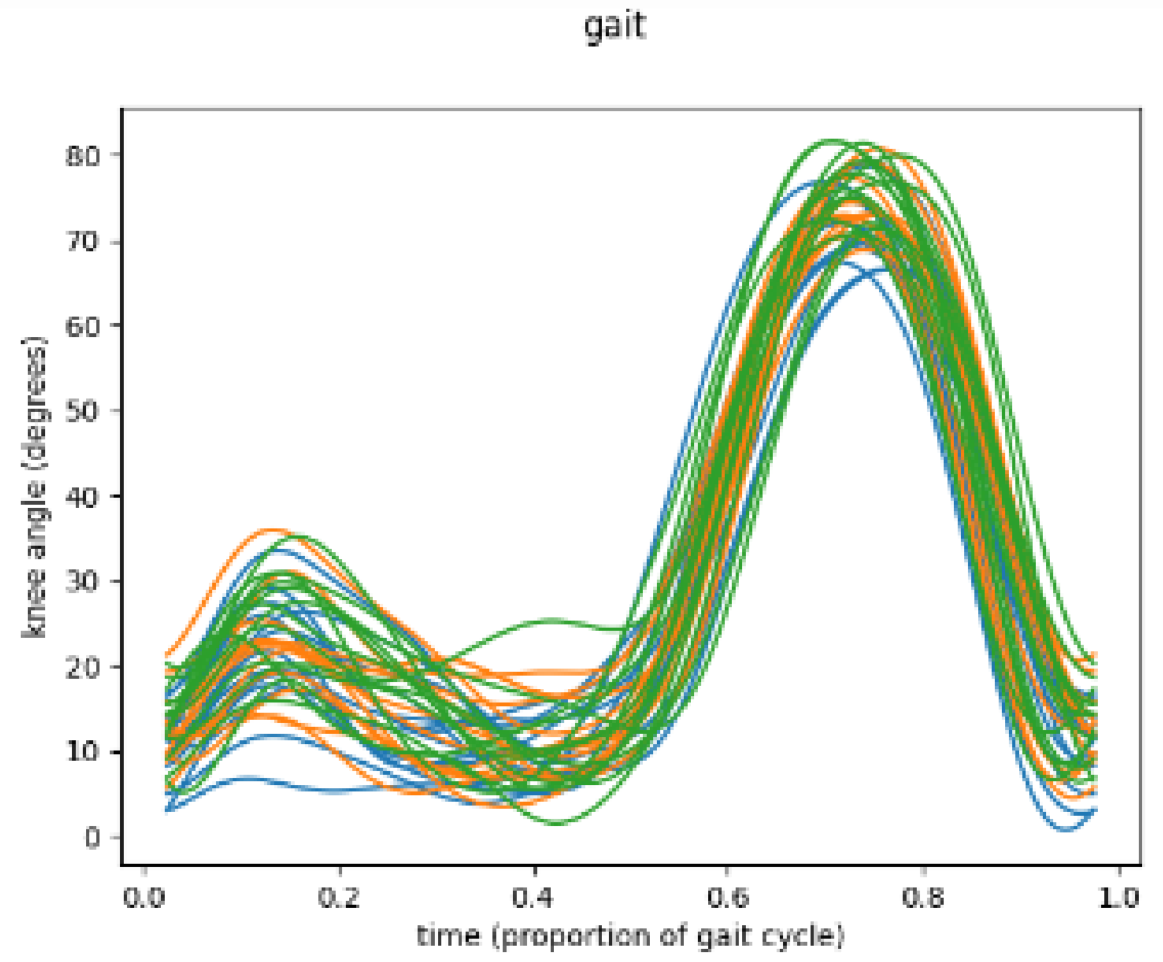
Figure 1. Two functional principal components explain >97% of variance in the sorghum growth curves observed in this study. Retrieved from [3].

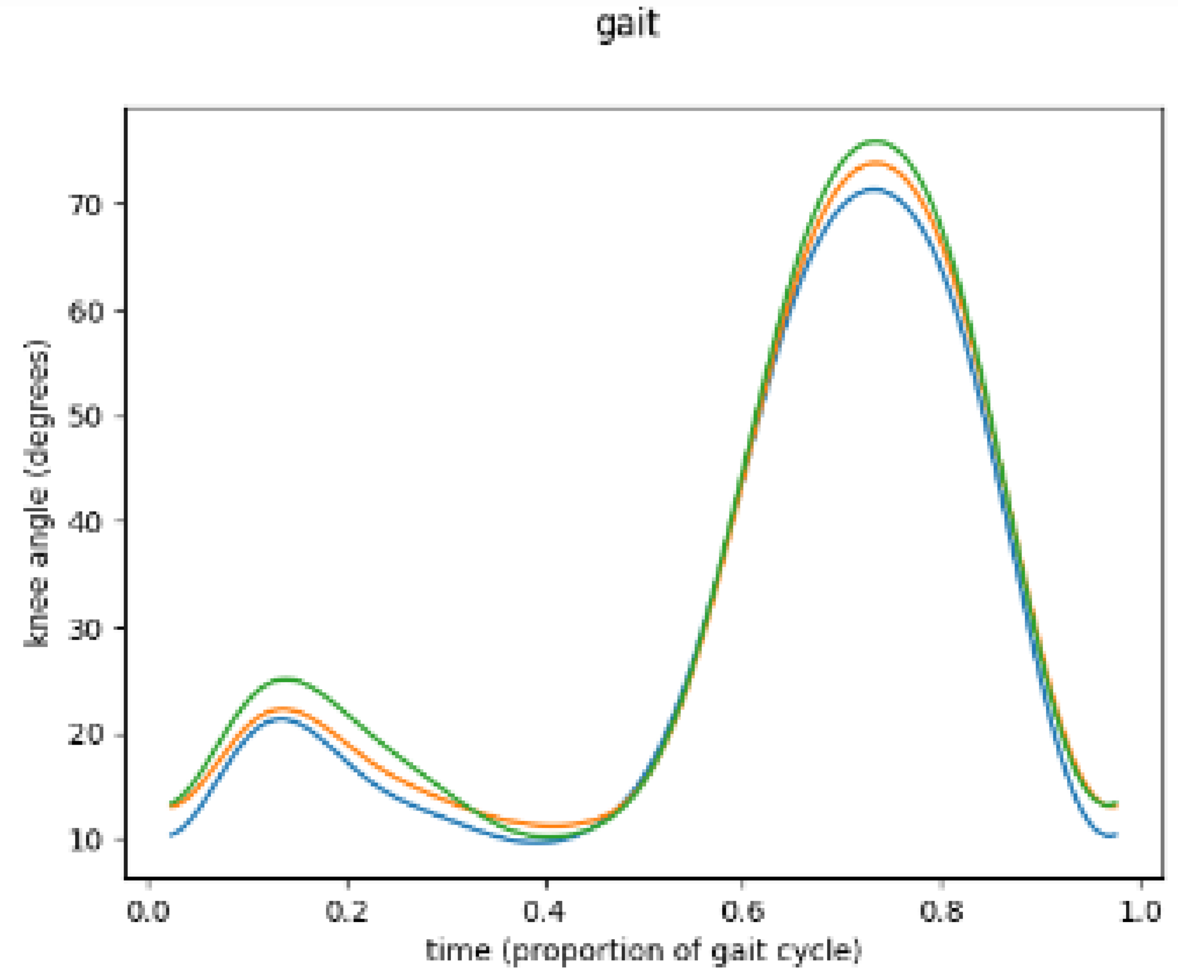
Methodology

One-way functional ANOVA [5]

Measure the variability

- After FPCA, get important component(s)
- Visualize among different systems/ variables
- Check P- value
  - H0: There are no significant differences in the mean electrical signals among different time points within the calibration/sample window.



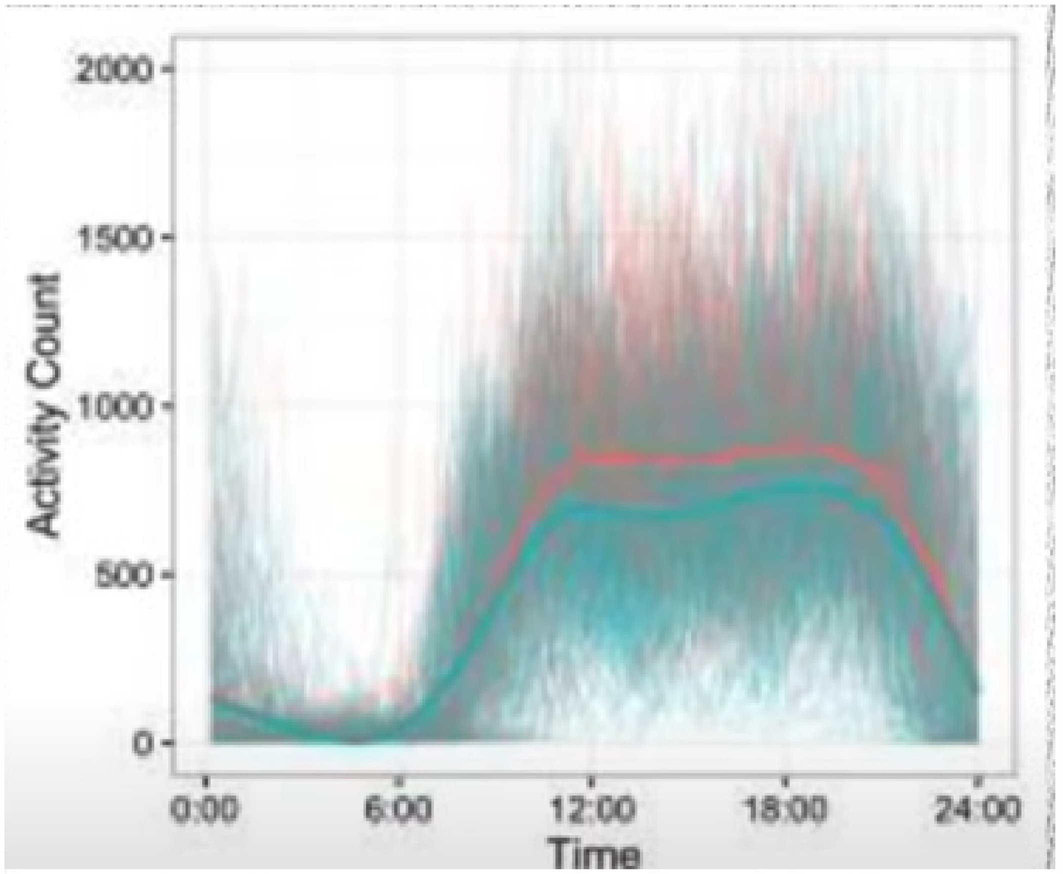


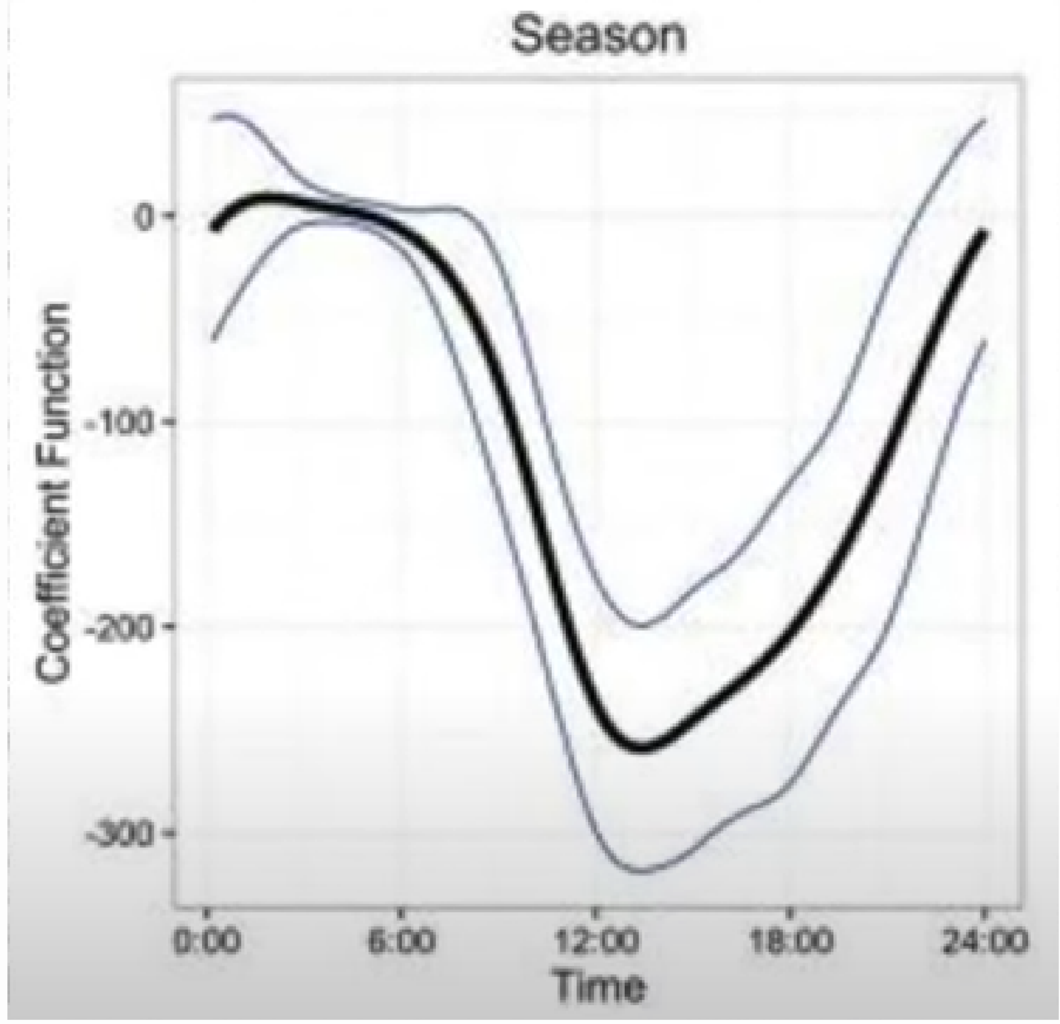
Methodology

Function-on-Scalar Regression [6]

$$Y_i(t) = \beta_0(t) + \int \beta(t) X_i dt + \epsilon_i(t)$$

- Add predictor into the model
  - FluidType/CardAge/Temperature
- Plot marginal coefficient curve with confidential interval.
- Compare with system 1 and system 2
  - Which time will have huge difference among two systems





Summary of the techniques

Time-Series clustering

- Efficiently groups similar tests into a small number of clusters making easily to identify patterns and differences.
- Provides effective visualization of plots for each cluster allowing easy comparison of data trends.

Supervised Machine Learning

- Provides feature importance scores, helping understand which features are most important in determining differences.

Time-Series models

- Characterize multiple time series by capturing temporal dependencies and patterns present in the data.

Summary of the techniques

Functional Data Analysis

- Focuses on analyzing the entire shape of waveforms, capturing time-dependent variation effectively.

Functional PCA

- Allows for dimensionality reduction of the data while retaining most of the variability in the waveform.

Functional Regression

- Incorporates predictors to account for their effects in the waveform characteristics.
- Provides insights into how waveform characteristics vary over time through the coefficients of the regression model.

Timeline

Project Start: 29 Apr, 2024
Project End: 25 Jun, 2024

Weekly:
Monday - Data Science Team
Tuesday - UBC instructor
Weekday - Group meeting

Biweekly:
Thursday - Advisory Commitment

Time	Theme	Date Goals
2 weeks	Initiation	Define goals/ Data Preparation/ Research Retrieval
2 weeks	Characterization I	Visualize waveform/ Implement FDA & Clustering/
2 weeks	Characterization II	Testing & Validation (new methods)
1 week	Window Optimization	Improve window effectiveness.
1 week	Conclusion	Further improvements/ Final Report and Presentation

Deliverables

Content:

- characterization of biosensor waveforms (mainly)
- suggestions for improved window placements

Format:

- A final presentation.
- A comprehensive report
- Python script for the Siemens team to replicate the pipeline on all the other sensors according to their demands.

Thank you for your attention

References

[1] Epocal Inc., "System Manual with Epoc NXS Host," Siemens Healthcare Diagnostics Inc., Ottawa, ON, Canada, 2023. [Online]. Available: https://siemens-healthineers.com/epoc

[2] "tslearn contributors, 'Time Series Clustering — tslearn 0.5.2 documentation,' tslearn: A Machine Learning Toolkit for Time Series Data, 2023. [Online]. Available: https://tslearn.readthedocs.io/en/stable/user_guide/clustering.html#time-series-clustering. [Accessed: May 7, 2024].

[3] "Functional principal component based time-series genome-wide association in sorghum," Scientific Figure on ResearchGate. [Online]. Available: https://www.researchgate.net/figure/Two-functional-principal-components-explain-97-of-variance-in-the-sorghum-growth-curves_fig1_339329925. [Accessed: May 8, 2024]

[4] J.-L. Wang, J.-M. Chiou, and H.-G. Müller, "Functional Data Analysis," Annual Review of Statistics and Its Application, vol. 3, pp. 257-295, 2016, doi: https://doi.org/10.1146/annurev-statistics-041715-033624. [Online]. Available: https://www.annualreviews.org/content/journals/10.1146/annurev-statistics-041715-033624

References

[5] Grupo de Aprendizaje Automático - Universidad Autónoma de Madrid: One-way functional ANOVA with real data.[Online]. Available: https://fda.readthedocs.io/en/latest/auto_examples/plot_oneway.html

[6] "What is functional data analysis?", YouTube. Available: https://www.youtube.com/watch?v=U2TvHLA18lo