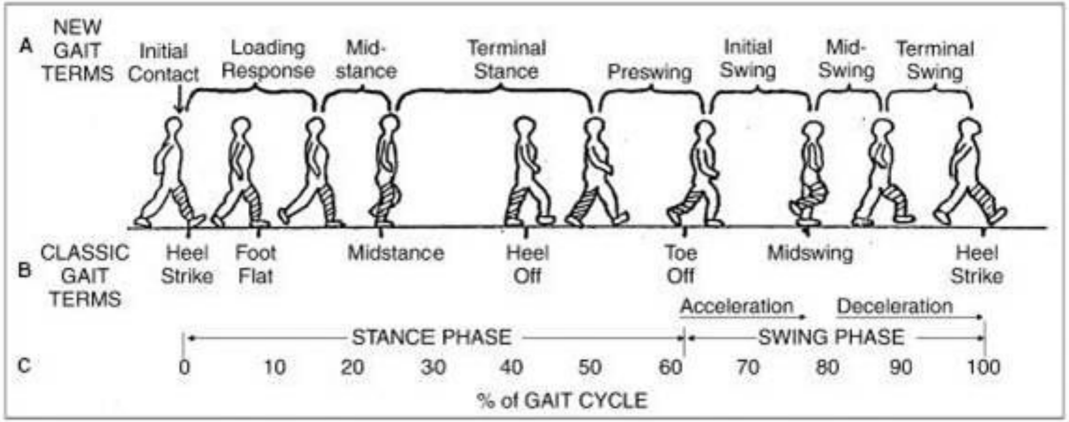
http://eldercarechannel.com/home-safety-tips-for-elderly/

Gait Analysis for Elderly

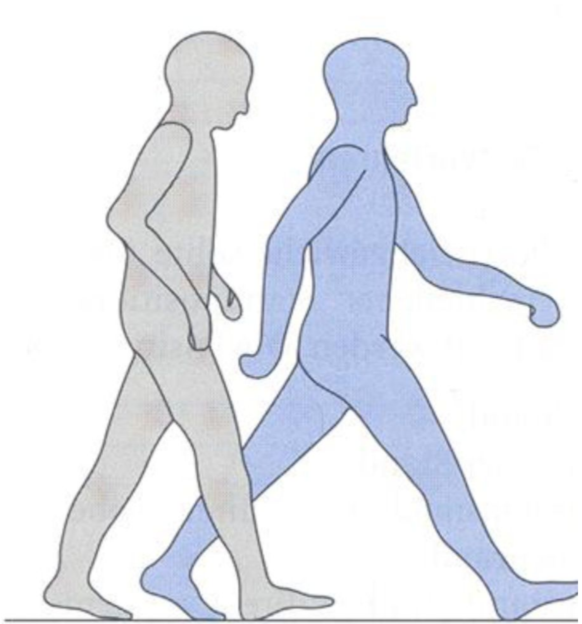
Using Wearable Sensors to Detect Gait Abnormalities

Team 6
Leonardo Hübscher, Martin Gerstmaier, Dennis Kipping

Gait Analysis



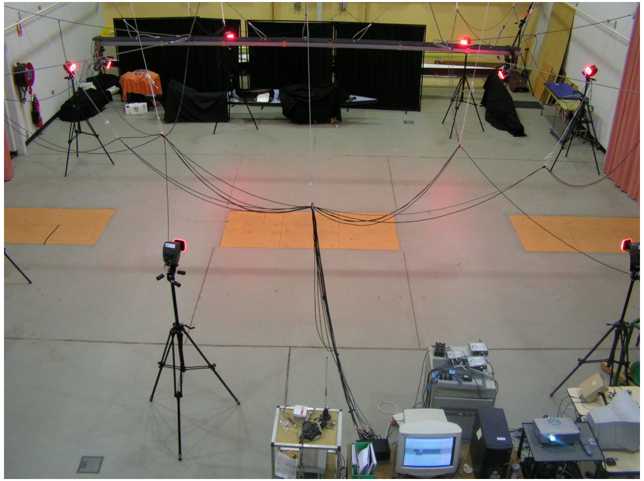
Typical Gait Issues of Elderly People



- slower walking speed
- reduced step length
- reduced activity
- overall feeling of weakness

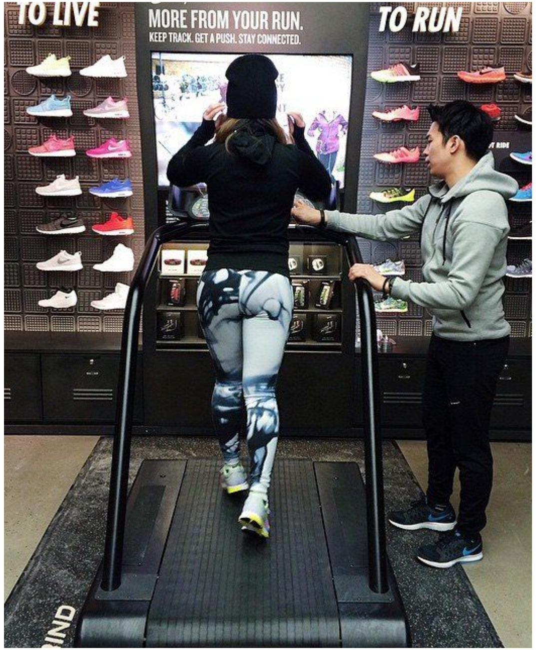
➔ general aging process
➔ musculoskeletal causes (e.g. Arthritis)
➔ neurological causes (e.g. dementia and Parkinson's disease)

Methods for Gait Analysis



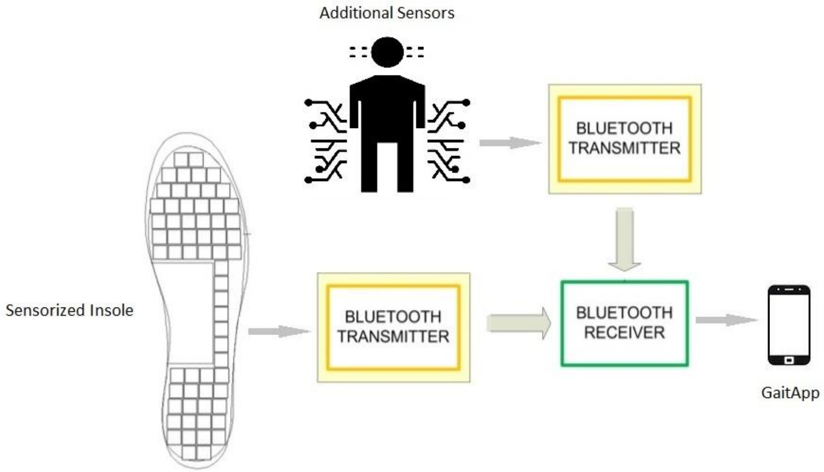
https://commons.wikimedia.org/wiki/File:Gait_laboratory.jpgf

https://www.flickr.com/photos/salforduniversity/14439337151



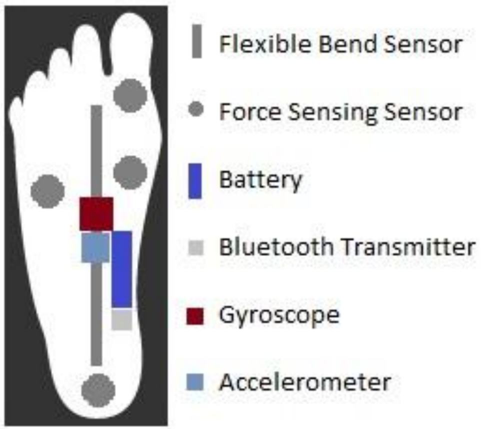
https://www.businessinsider.com/redesigned-seattle-nike-store-offers-gait-analysis-2015-8?IR=T

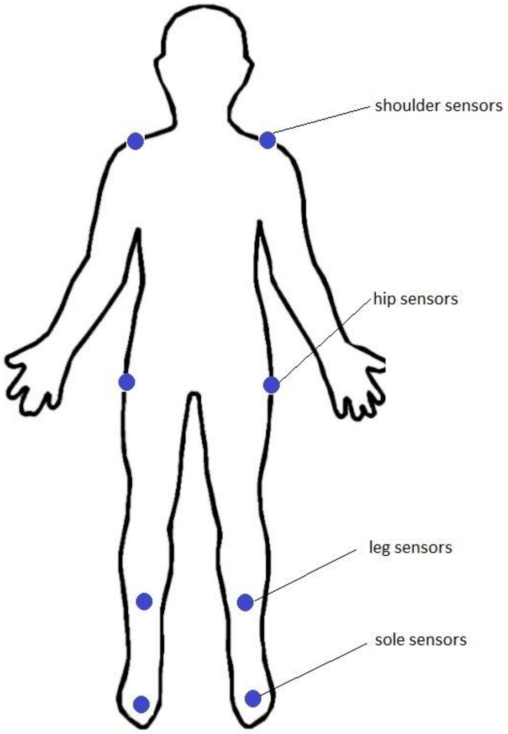
Gait Set



- multiple comfortable wearable sensors to detect conspicuous gait features
- longer monitoring during daily life activities
- intelligent evaluation of detected gait features
- (recommendations for further actions)

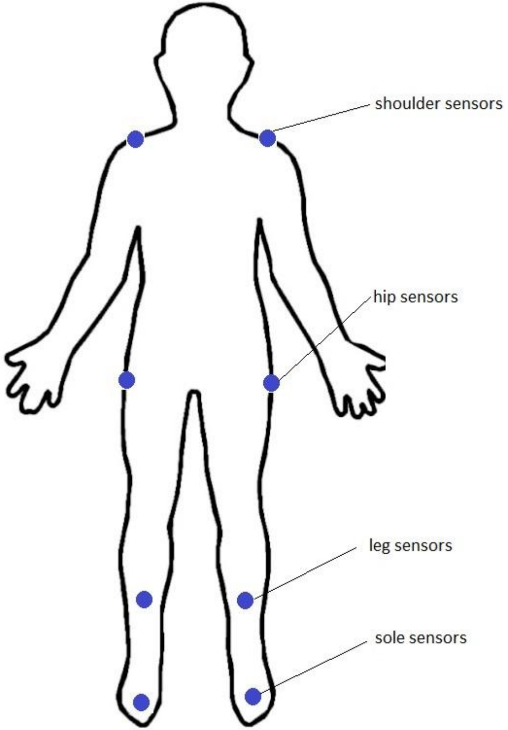
Wearable Sensors





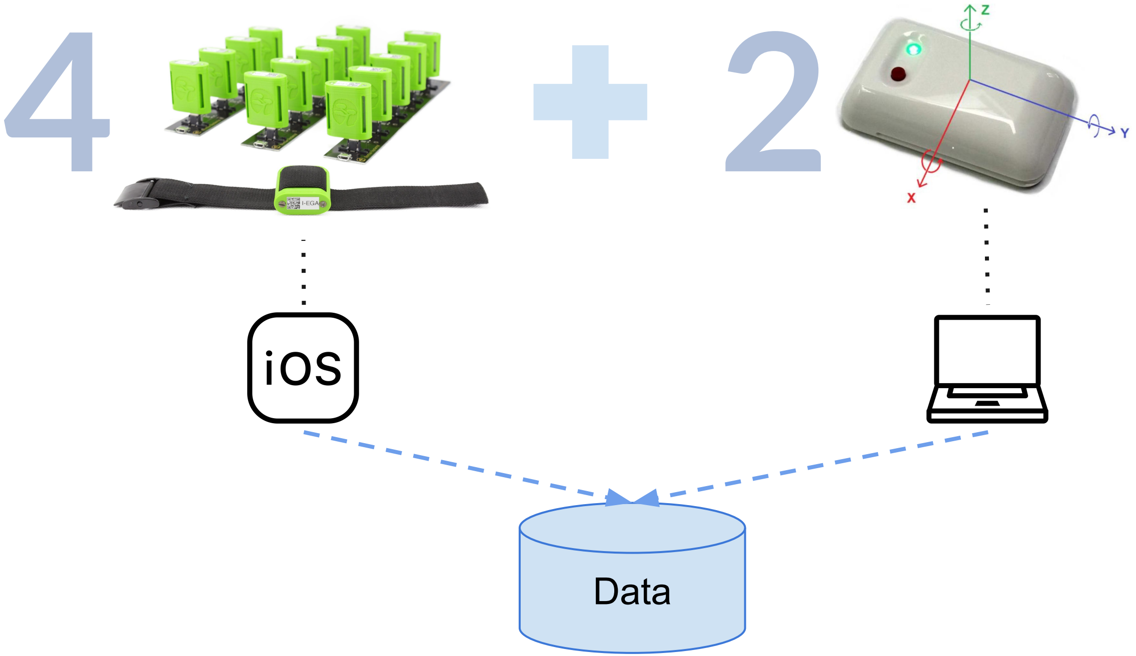
Feasibility Approach

Which sensors on which body parts are needed to achieve best possible results?



Experiment

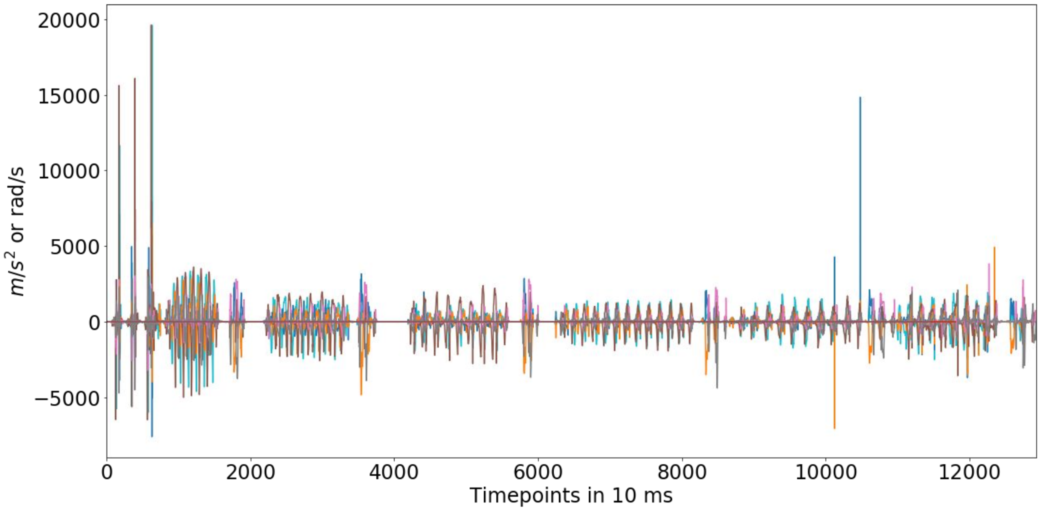
Experimental Setup



Experiment Procedure

Jumping → Normal → Pelvic → Limping → XS Steps → Shuffling → Insecure

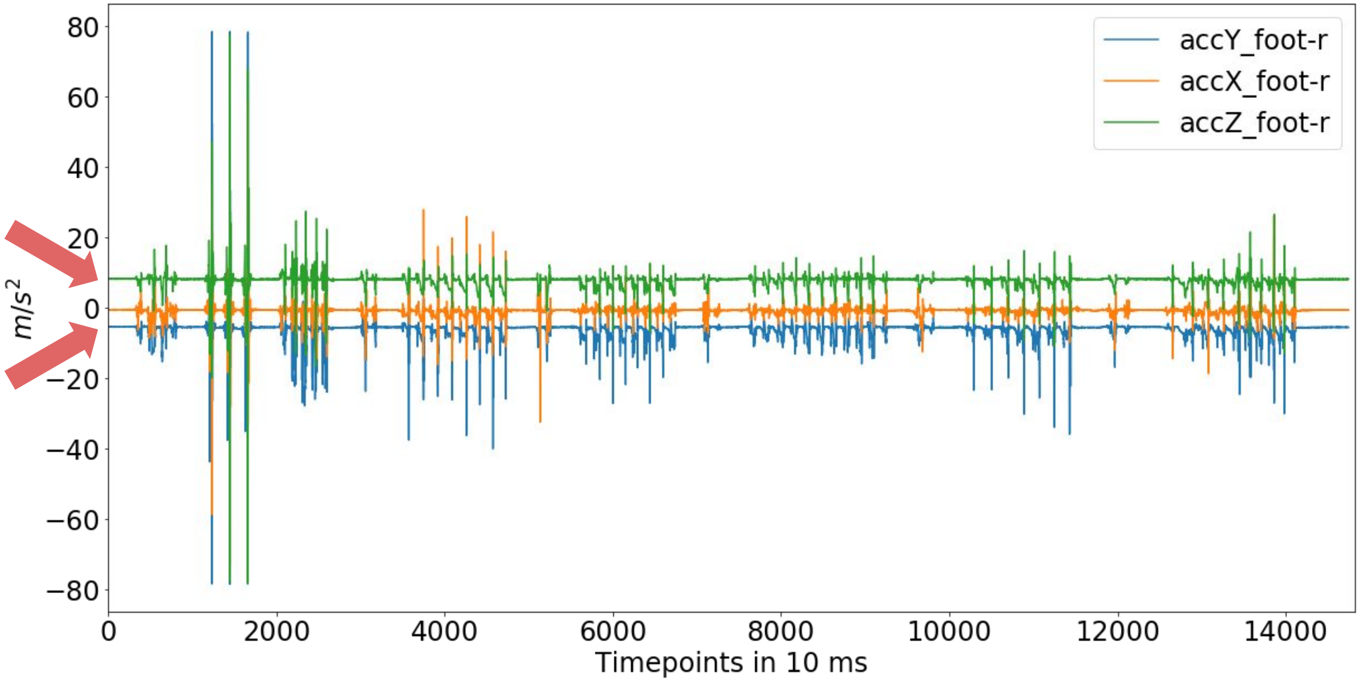
12	6
Runs	Sensors
15 M	**6**
Distance	Dimensions
5	**100 Hz**
Exercises	Sampling Rate



Preprocessing Pipeline

Sensor Data Preprocessing

1 **Calibration**



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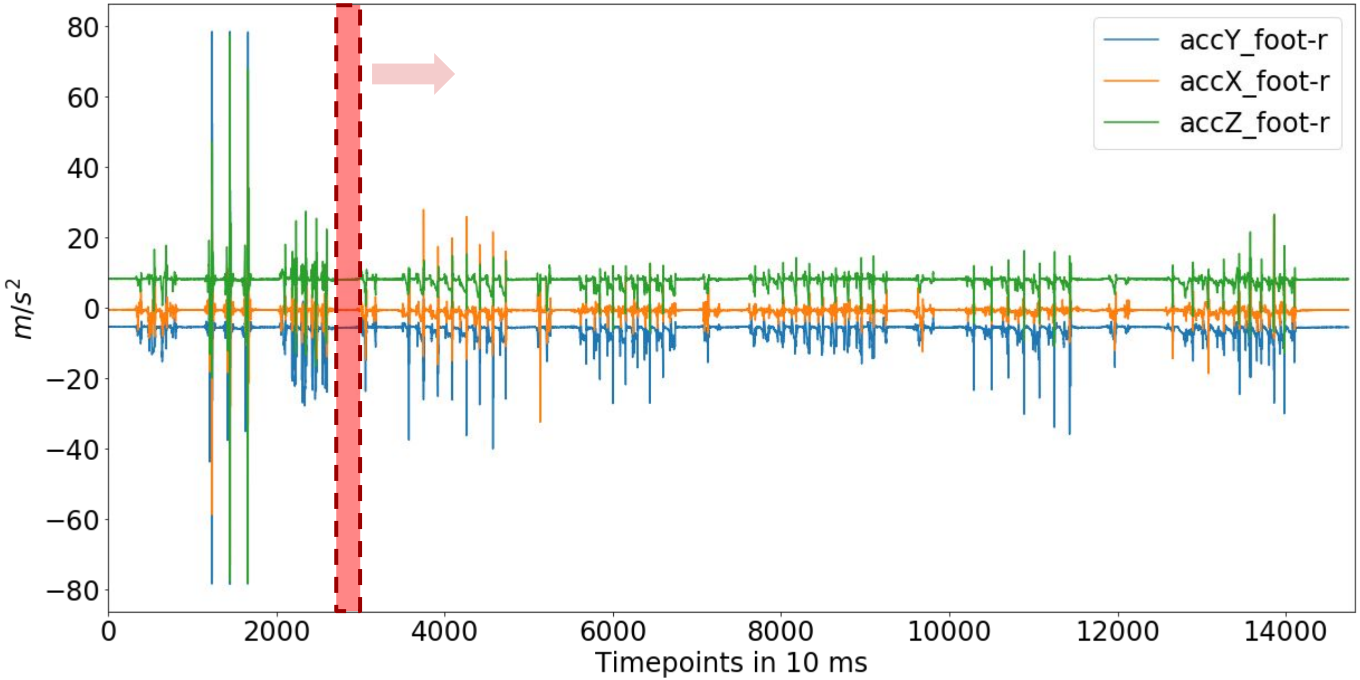

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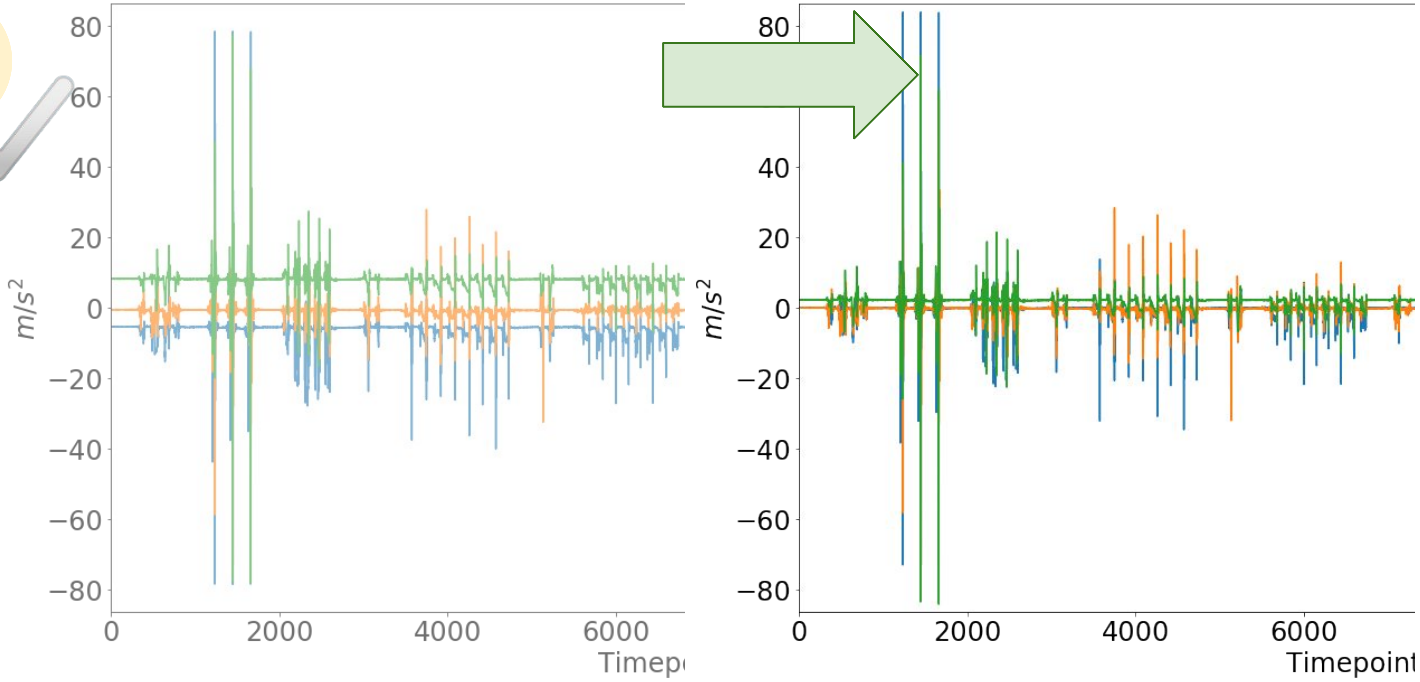
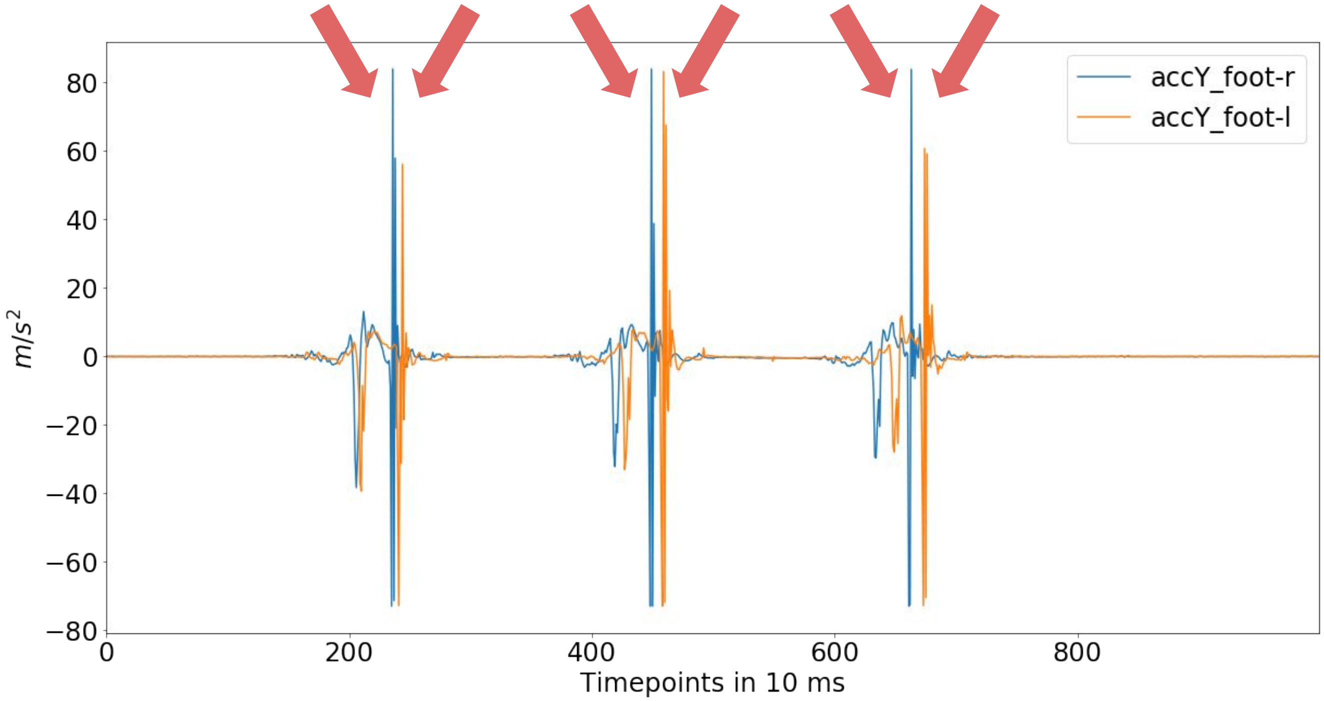


Sensor Data Preprocessing

1 **Calibration**

2 **Align Sensors**



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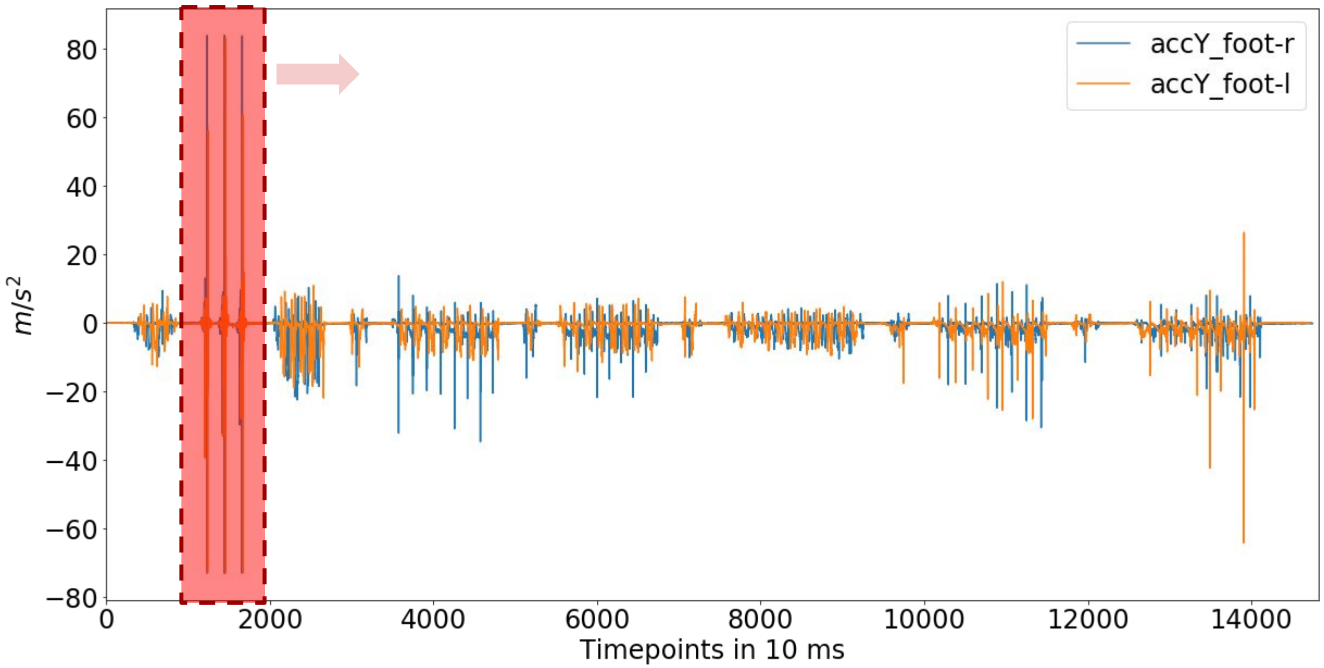

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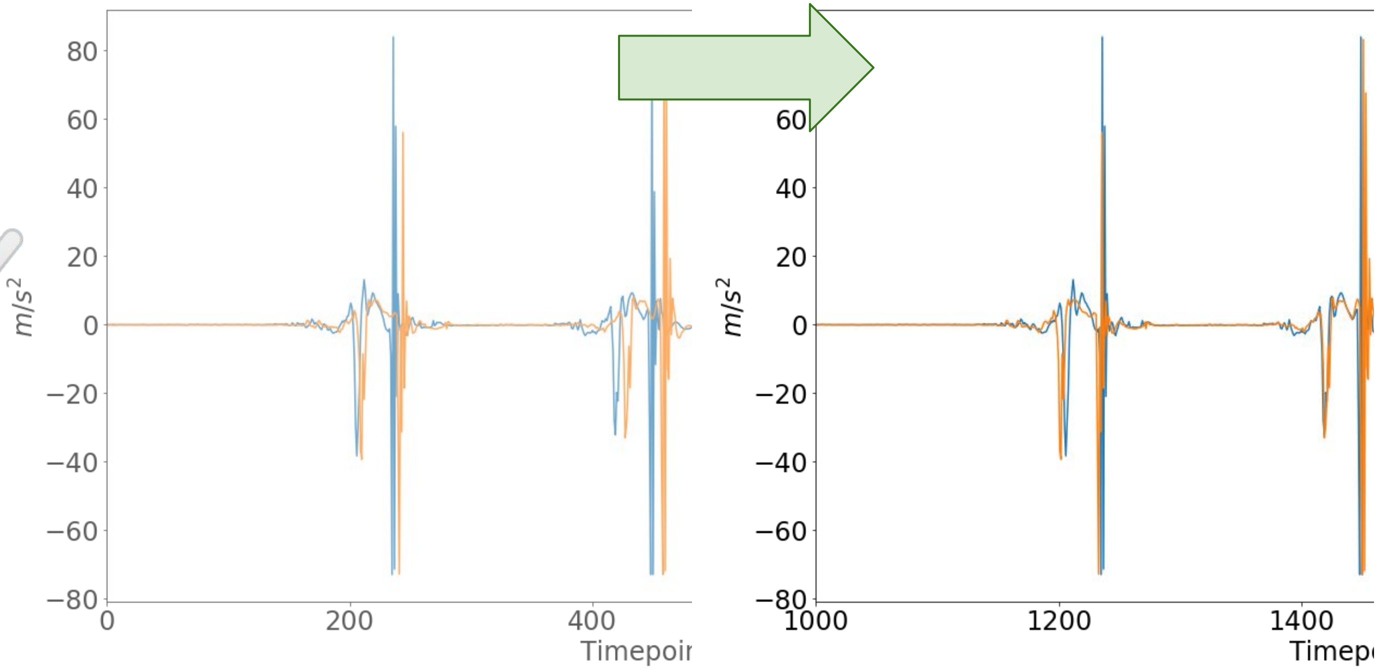
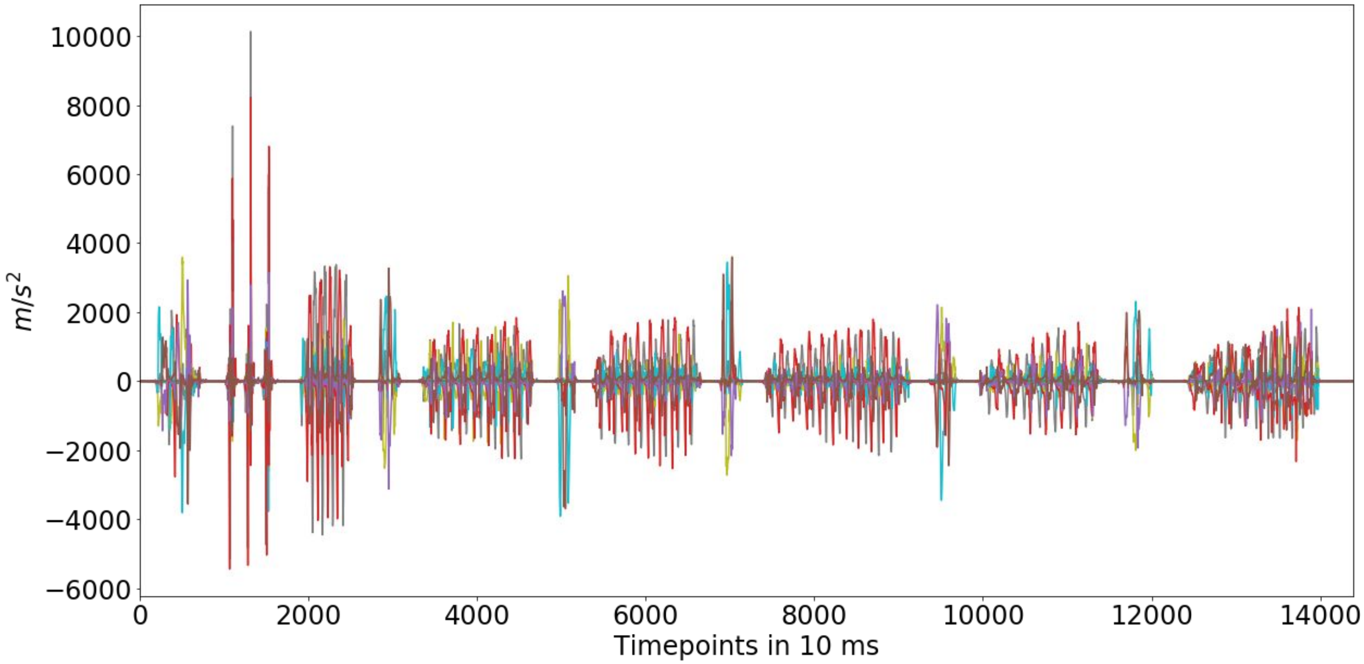


Sensor Data Preprocessing

1 Calibration

2 Align Sensors

3 Get Exercises



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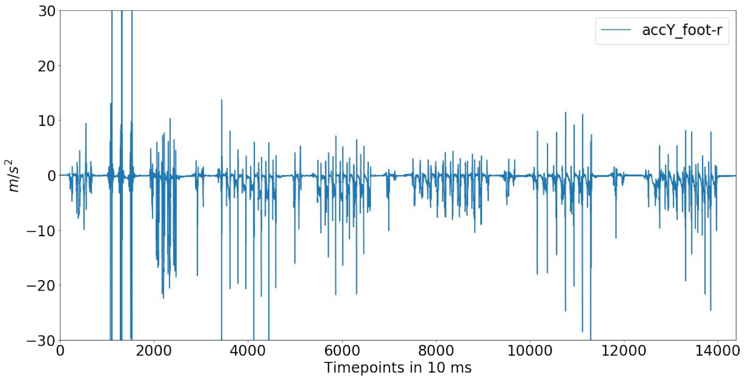
3 **Get Exercises**



Sensor Data Preprocessing

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2 **Align Sensors**

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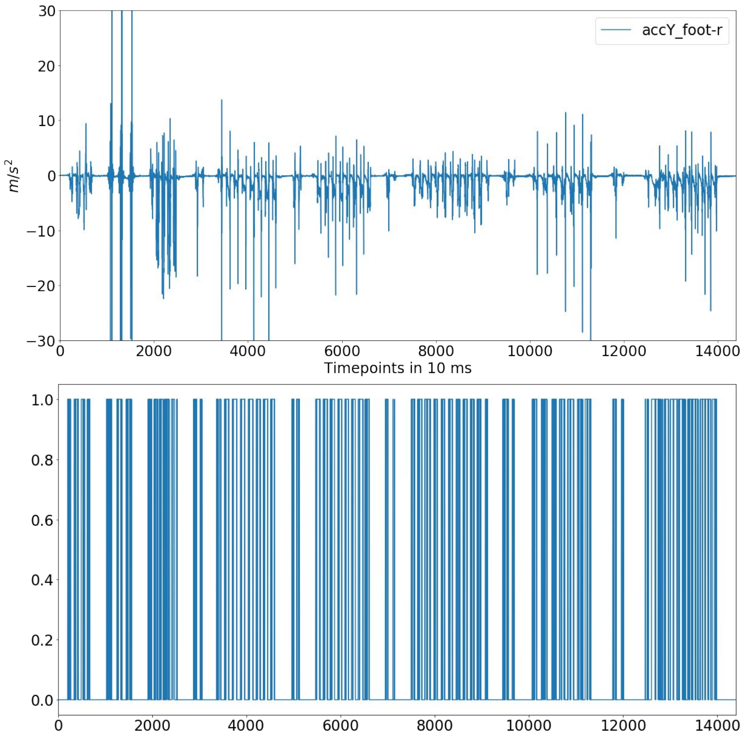

Apply Threshold Filter

Sensor Data Preprocessing

1 **Calibration**

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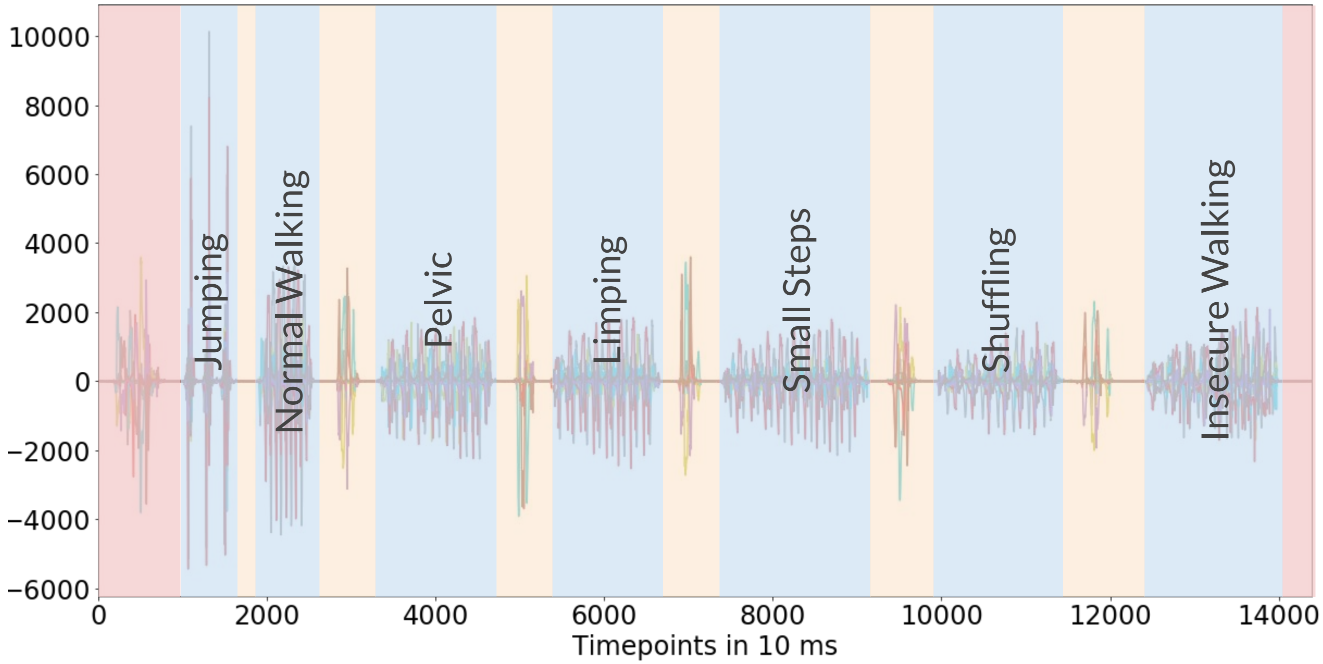


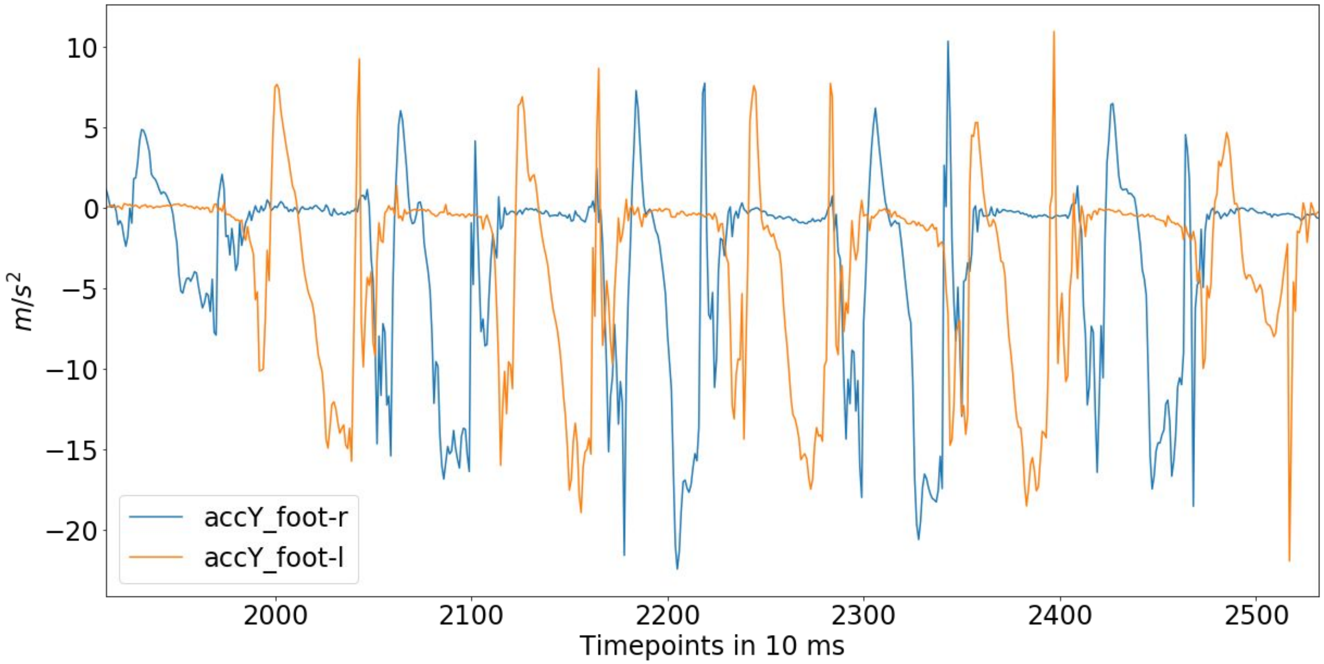
Sensor Data Preprocessing

1 Calibration

2 Align Sensors

3 Get Exercises

4 **Get Strides**



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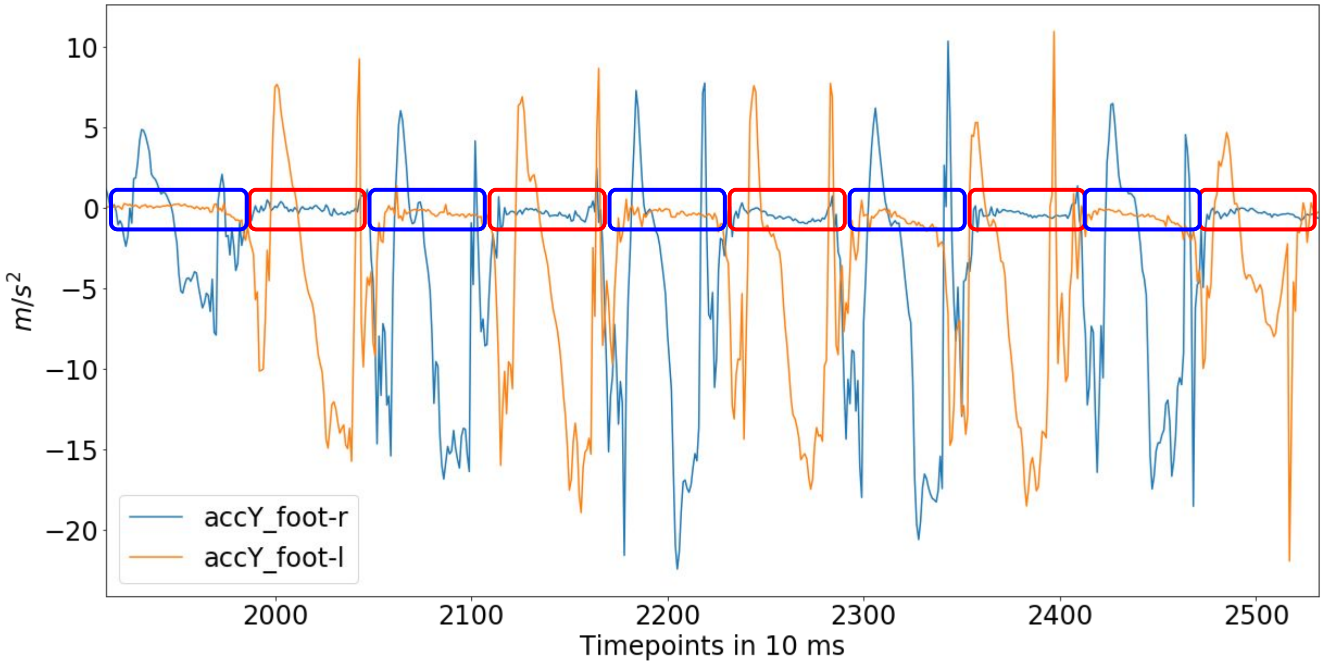

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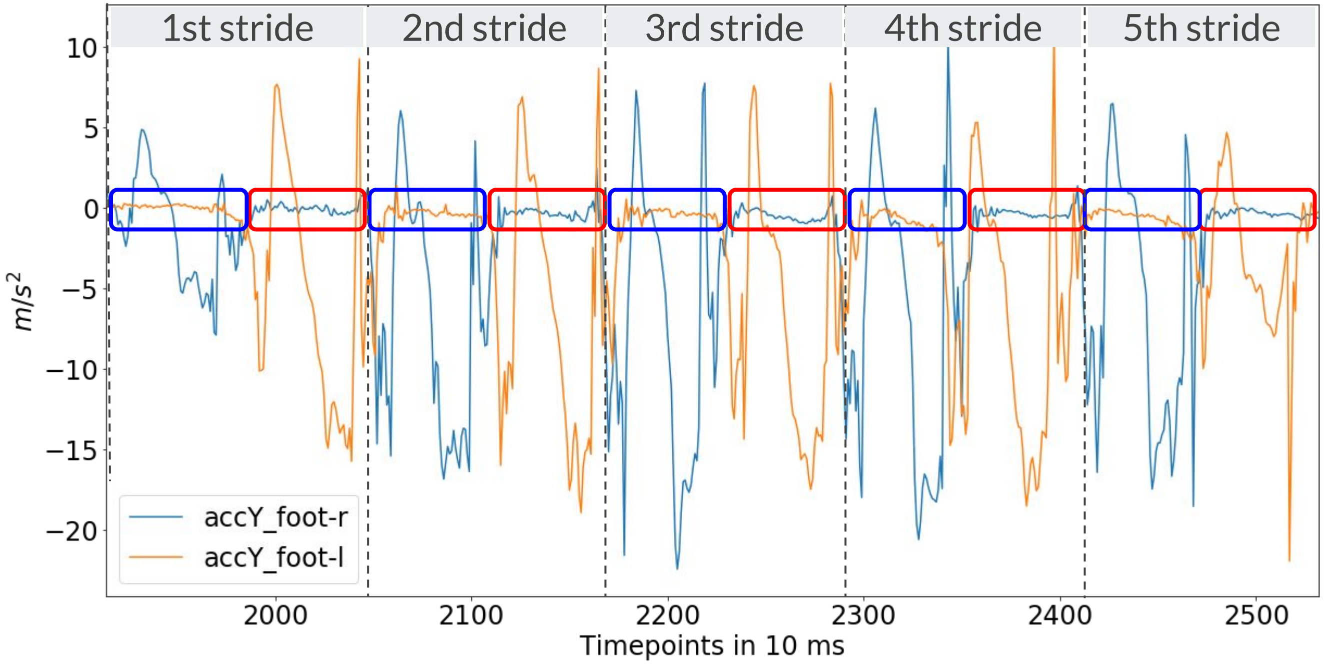

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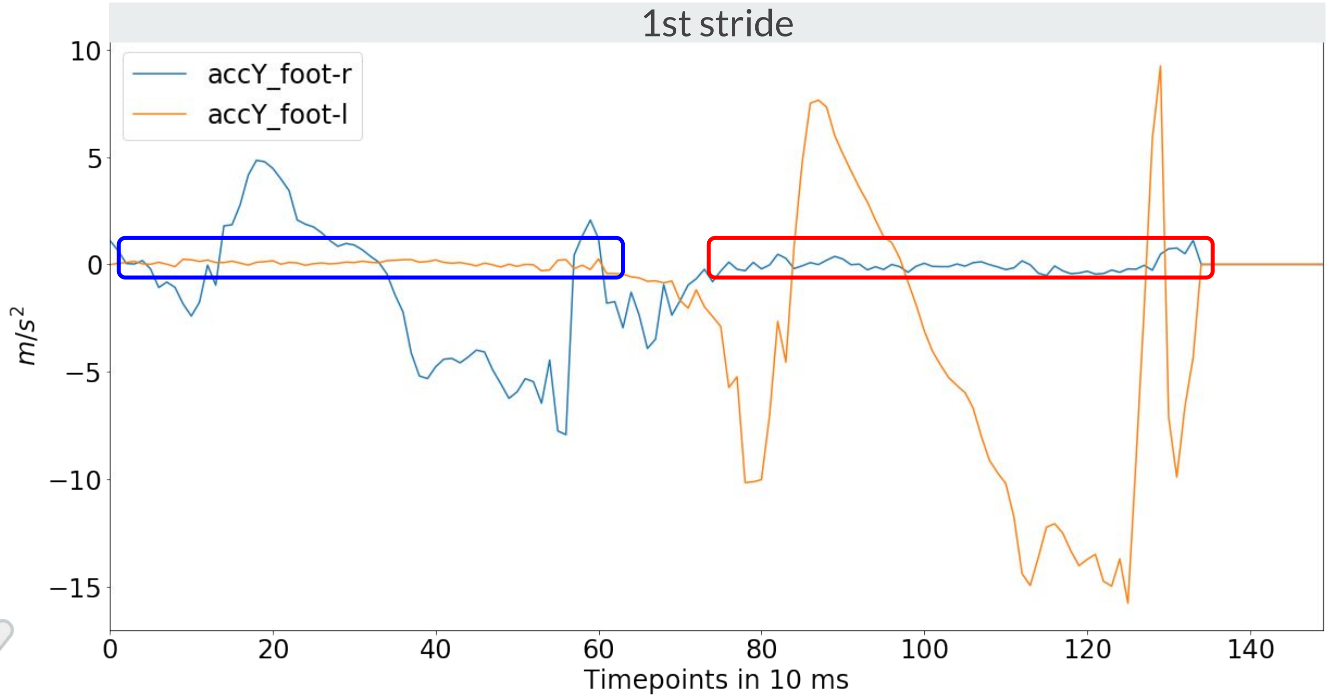
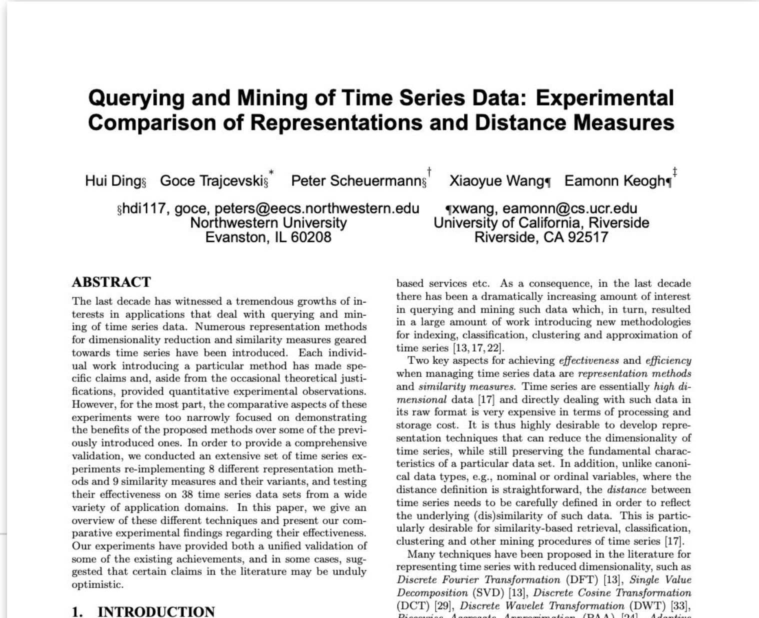


Stride Classification

Classification Algorithm

- Stride classification via k-nearest neighbours
- Performed for each sensor separately
- Can achieve state-of-the-art performance with Dynamic Time Warping



Querying and Mining of Time Series Data: Experimental Comparison of Representations and Distance Measures

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Evanston, IL 60208

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ABSTRACT

The last decade has witnessed a tremendous growths of interests in applications that deal with querying and mining of time series data. Numerous representation methods for dimensionality reduction and similarity measures geared towards time series have been introduced. Each individual work introducing a particular method has made specific claims and, aside from the occasional theoretical justifications, provided quantitative experimental observations. However, for the most part, the comparative aspects of these experiments were too narrowly focused on demonstrating the benefits of the proposed methods over some of the previously introduced ones. In order to provide a comprehensive validation, we conducted an extensive set of time series experiments re-implementing 8 different representation methods and 9 similarity measures and their variants, and testing their effectiveness on 38 time series data sets from a wide variety of application domains. In this paper, we give an overview of these different techniques and present our comparative experimental findings regarding their effectiveness. Our experiments have provided both a unified validation of some of the existing achievements, and in some cases, suggested that certain claims in the literature may be unduly optimistic.

1. INTRODUCTION

based services etc. As a consequence, in the last decade there has been a dramatically increasing amount of interest in querying and mining such data which, in turn, resulted in a large amount of work introducing new methodologies for indexing, classification, clustering and approximation of time series [13, 17, 22].

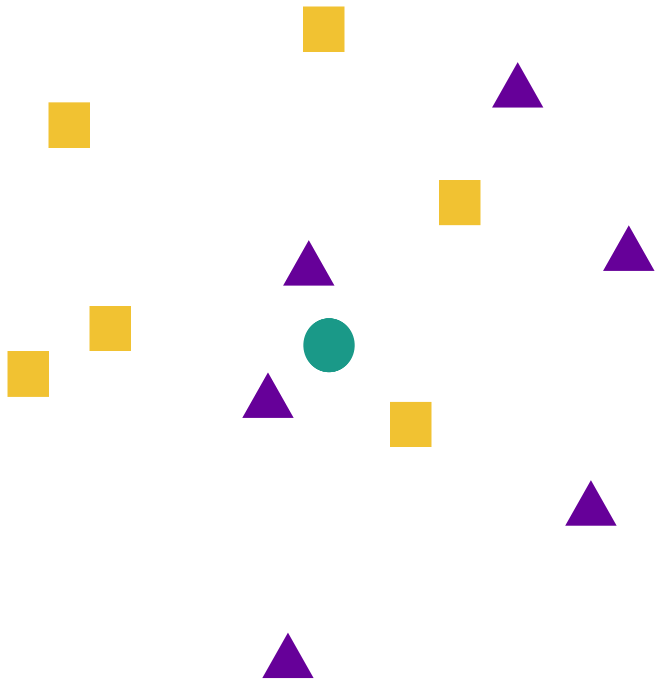
Two key aspects for achieving *effectiveness* and *efficiency* when managing time series data are *representation methods* and *similarity measures*. Time series are essentially *high dimensional* data [17] and directly dealing with such data in its raw format is very expensive in terms of processing and storage cost. It is thus highly desirable to develop representation techniques that can reduce the dimensionality of time series, while still preserving the fundamental characteristics of a particular data set. In addition, unlike canonical data types, e.g., nominal or ordinal variables, where the distance definition is straightforward, the *distance* between time series needs to be carefully defined in order to reflect the underlying (dis)similarity of such data. This is particularly desirable for similarity-based retrieval, classification, clustering and other mining procedures of time series [17].

Many techniques have been proposed in the literature for representing time series with reduced dimensionality, such as *Discrete Fourier Transformation* (DFT) [13], *Single Value Decomposition* (SVD) [13], *Discrete Cosine Transformation* (DCT) [29], *Discrete Wavelet Transformation* (DWT) [33],

Classification Algorithm

Quick recap of *k*-NN

- Non-parametric classification
- Training: examples in feature space
  → store feature vectors
- Classification algorithm:
  - Compare input to training data
  - Find *k* nearest samples
  - Assign most frequent class label



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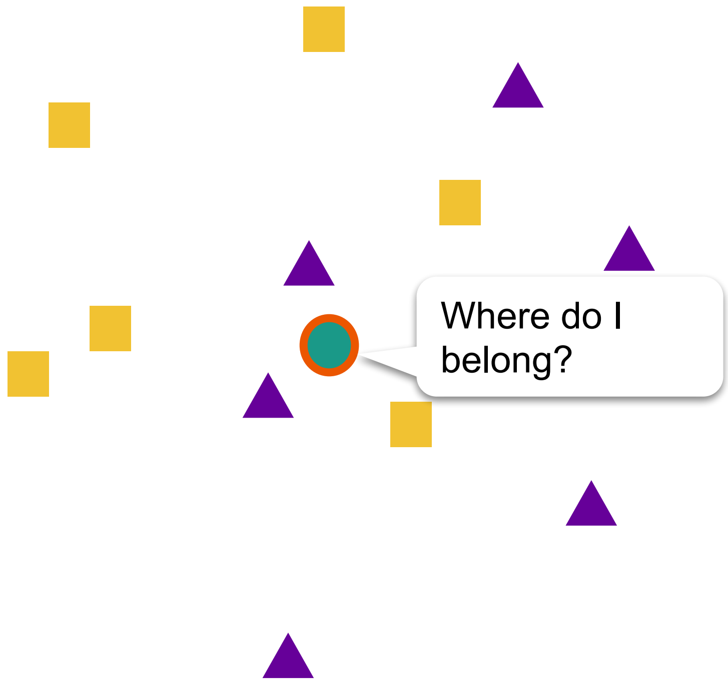

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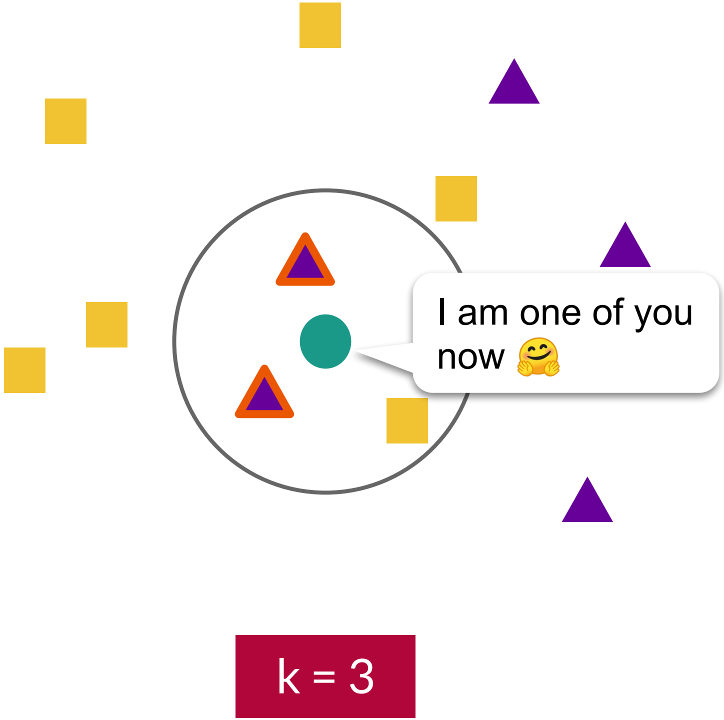

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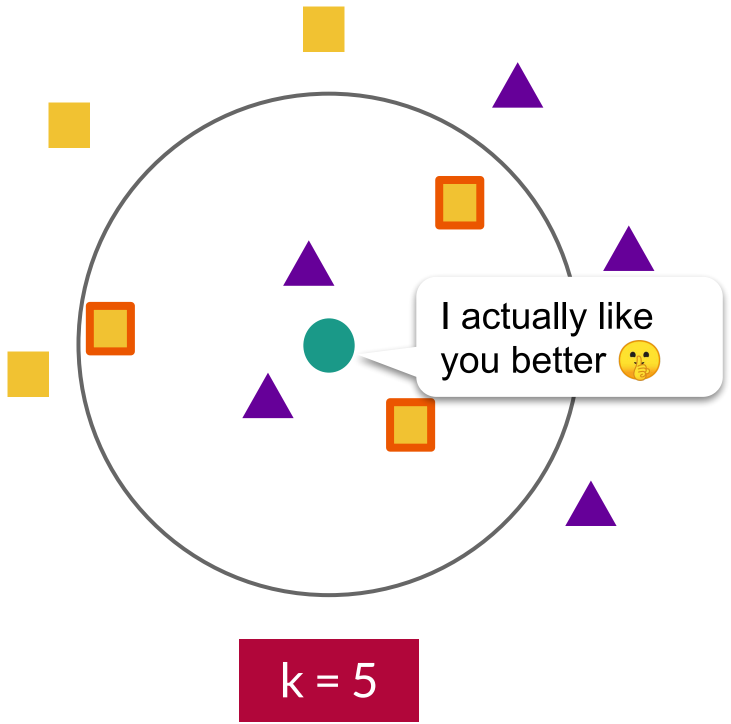


Compute Similarity

- Commonly used:
  Euclidean Distance
- Issue:
  Linear alignment
  → Not robust to stretching or compression of time axis

$$d(Q, C) = \sqrt{\sum_{i=1}^{n} [Q(i) - C(i)]^2}$$

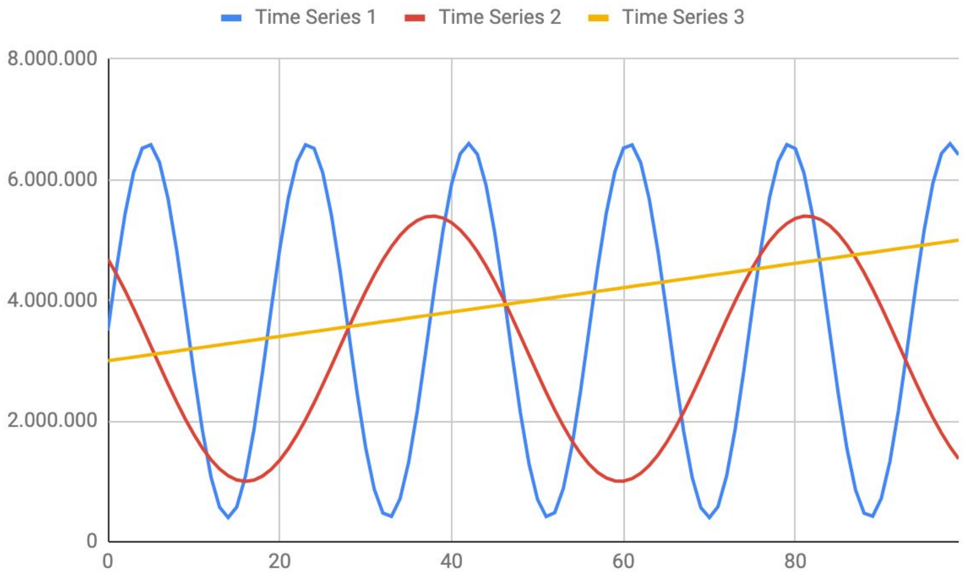
Compute Similarity

Example

- Time Series 1 & 2 naturally more similar than Time Series 1 & 3

Euclidean Distances

26.96	**23.19**
Time Series 1 to 2	Time Series 1 to 3



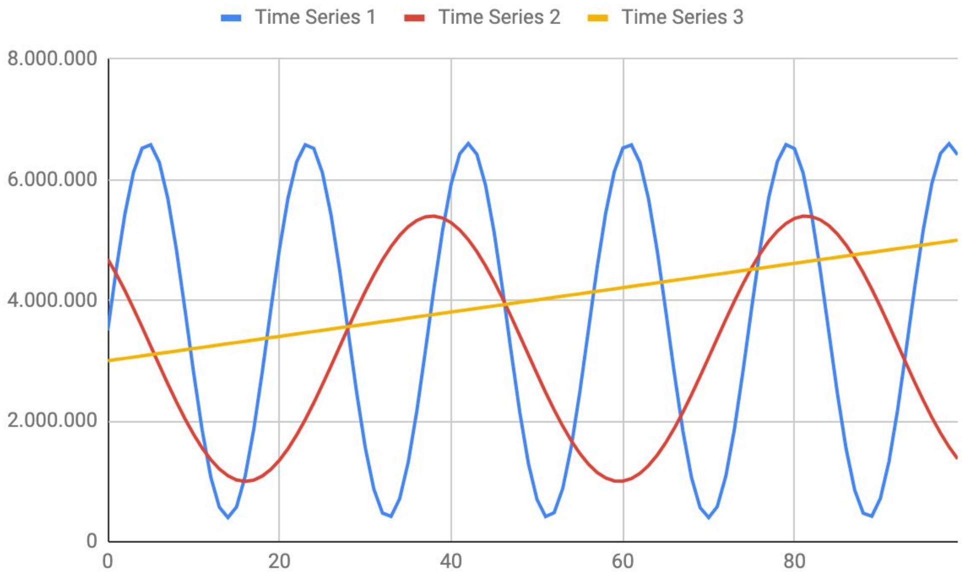
Compute Similarity

Solution: Dynamic Time Warping

- Finds optimal non-linear alignment between two time series
- Robust to time stretching

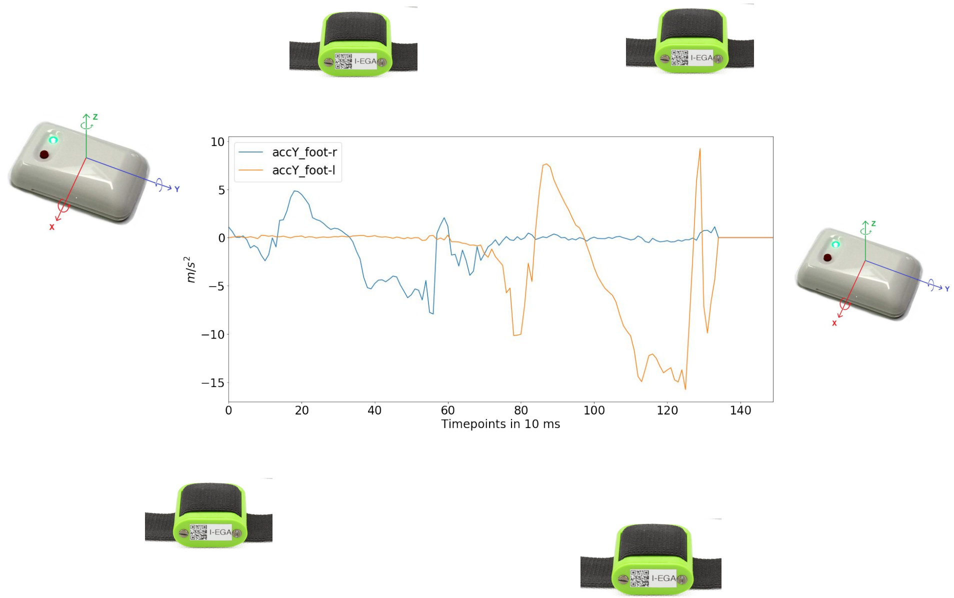
DTW Distances

17.93	21.55
Time Series 1 to 2	Time Series 1 to 3



Majority Vote

- Data only comparable to data from same measurement point and same measure
- Majority vote of sensor measures decides on final class of stride



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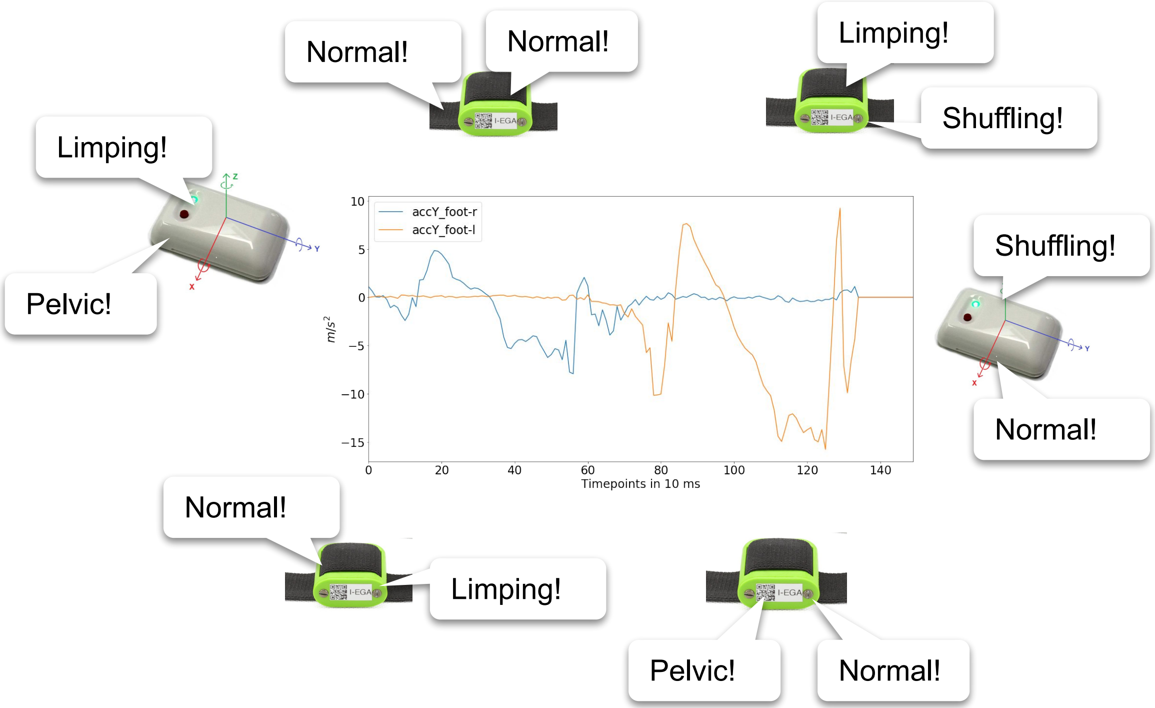

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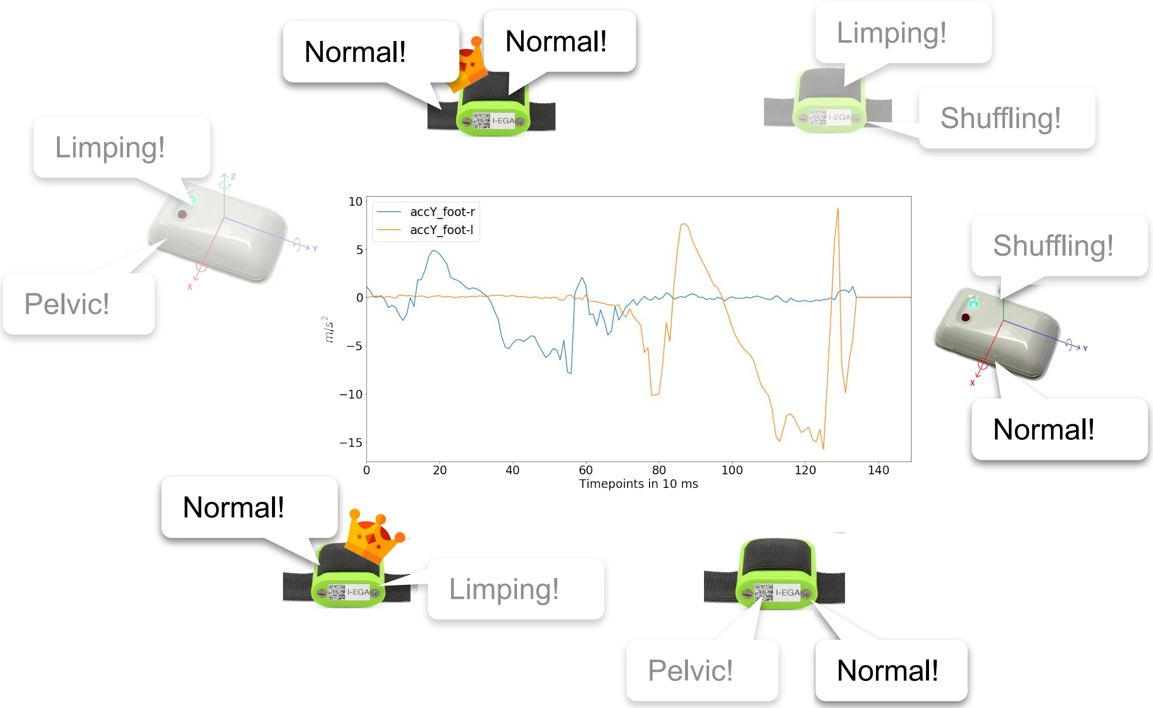

Performance

Class	Precision	Recall	F1-Score
Normal	1.00	1.00	1.00
Pelvic	1.00	0.67	0.80
Limping	1.00	0.82	0.90
Small Steps	0.88	1.00	0.93
Shuffling	0.62	1.00	0.76
Insecure Walking	1.00	0.43	0.60
Weighted Avg	0.89	0.84	0.84

For all measures:
Higher is better

Performance

Conclusion on Sensors

- Experiment allows for automated classification of gait abnormalities
  → enables automated & continuous monitoring
- Combination and majority voting of sensors significantly increased precision
- Sensors have differing performance in different gait abnormalities:
  - Hip:
    - higher performance for limping, pelvic displacement & insecure walking
    - lower performance for small steps & shuffling
  - Feet:
    - higher performance for small steps & shuffling
    - lower performance for pelvic displacement & insecure walking

Improvements

Experiment:

- More measurements to improve data diversity
- Real subjects for training, simulation differs with style of actor
- Cleaner measurements with strict pauses for training

Technical:

- Higher range & compatibility of wireless sensors needed

https://www.green-hill.com/wp-content/uploads/2018/06/senior_fall_prevention.jpg