Mobile Health
IMU and
Human Activity

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Inertial Measurement Unit

- Accelerometer
- Gyroscope
- Magnetometer

Accelerometer

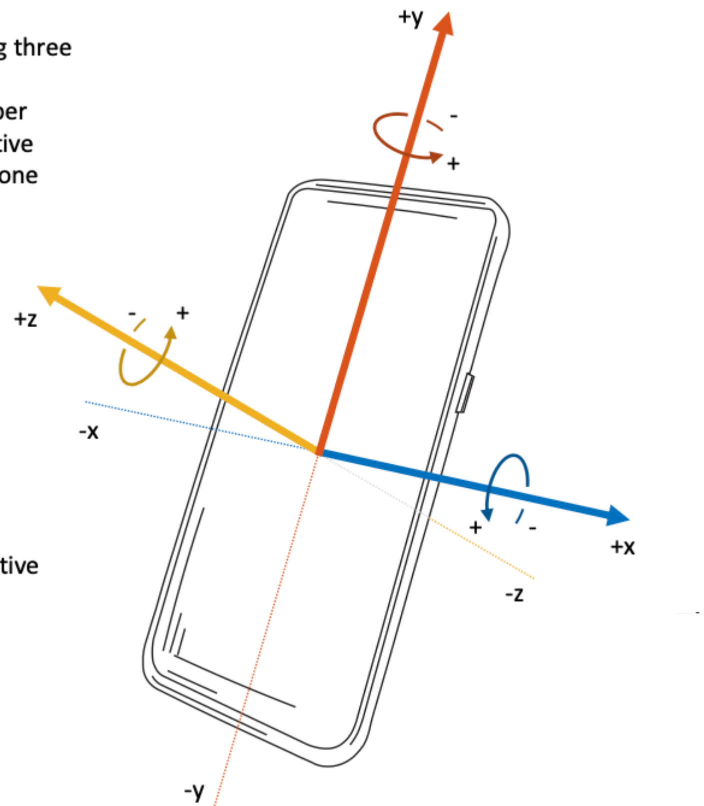
- Measures rate of change of velocity along three orthogonal axes of smartphone
- Output: gravitational units (g) or meters per seconds squared (m/s^2); positive or negative depending on the orientation of smartphone

Gyroscope

- Measures angular velocity around three orthogonal axes of smartphone
- Output: radians per second (rad/s); positive or negative depending on the direction of rotation

Magnetometer

- Measures strength of Earth's magnetic field relative to three orthogonal axes of smartphone
- Output: microtesla (µT); positive or negative depending on the orientation of smartphone



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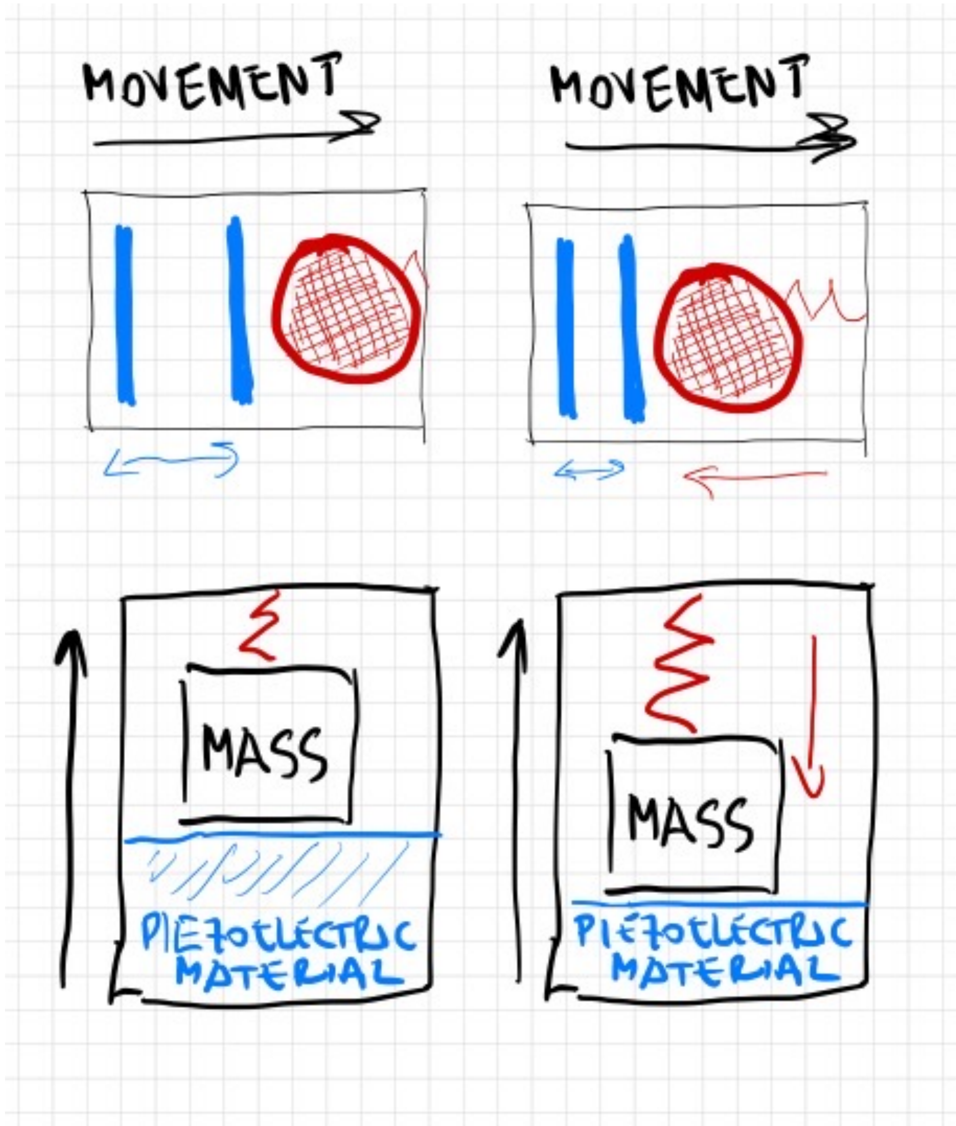
From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

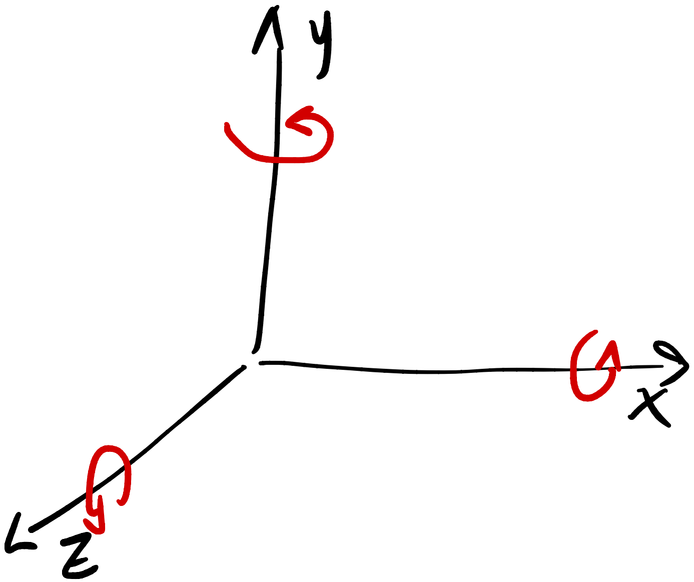
Accelerometer

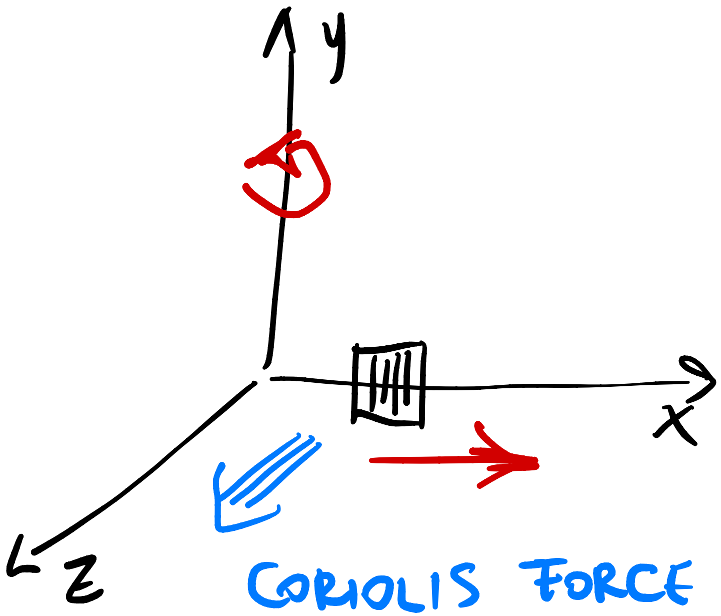
- Measures the change in speed with respect to time.
  - More informative than just speed as it can be linked to energy.
  - Speed can be deduced.
- Capacitor (vibration)
- Piezoelectric
- Current devices have accelerometers measuring movement in the three orthogonal axis.



Gyroscope: an intuition

- Gyroscopes use vibration to measures the rate of rotation.
- In practice it measures the rate of rotation wrt to each axis
- Unit deg/s





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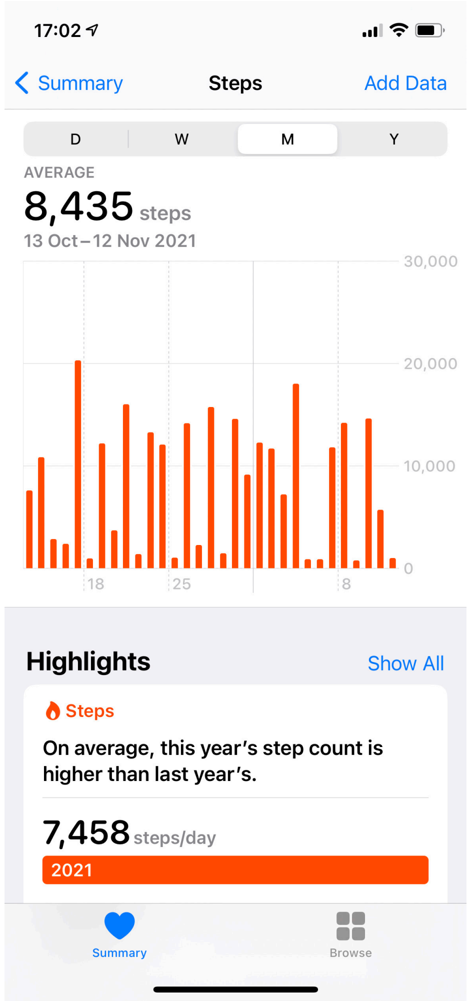
Step Count

- Wearables already use IMUs to offer activity indicators

- However no automatic (more refined) activity recognition in most cases…



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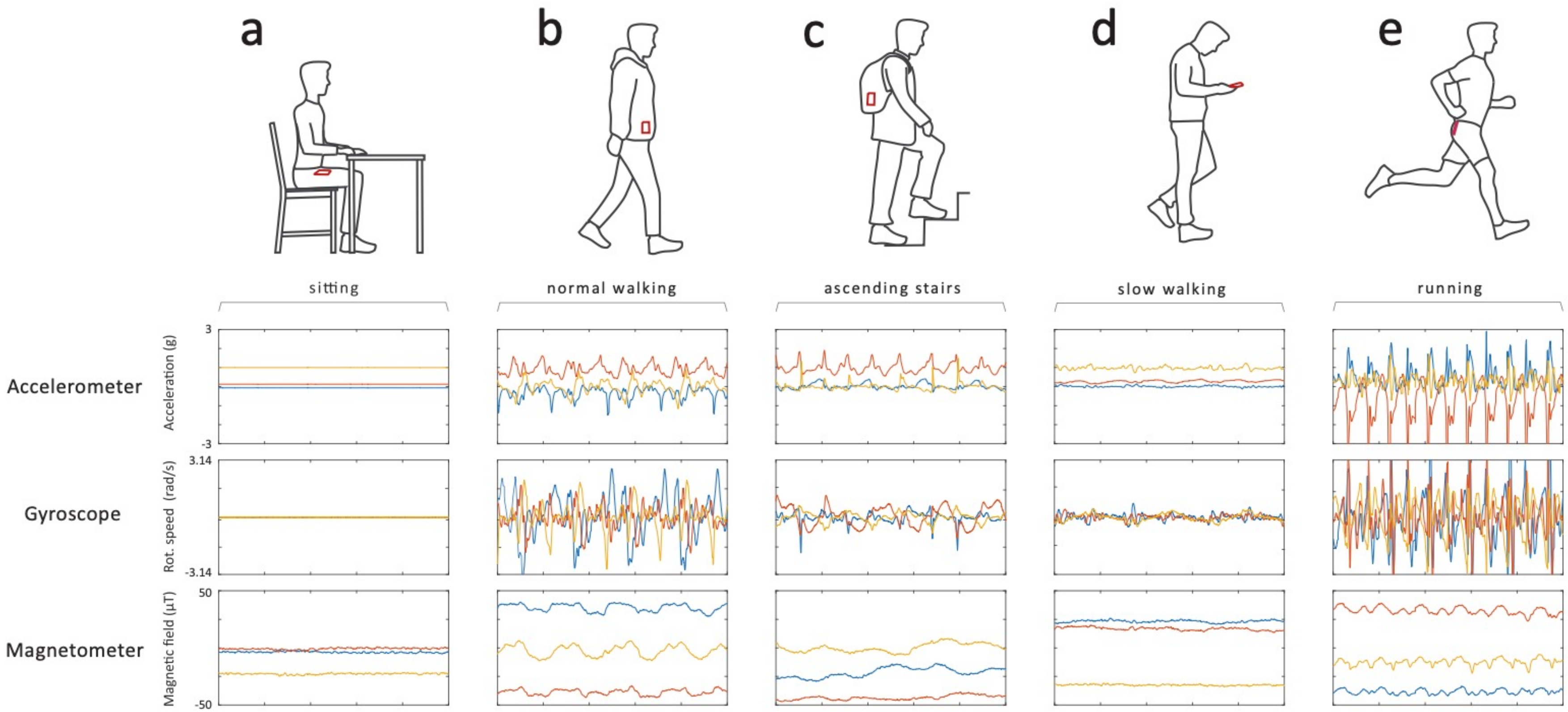
Activity Recognition



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From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

Considerations

- Position of the device might change the signals.
- Different sensors sense different patterns.
- Does it change from person to person.
- What about sampling?

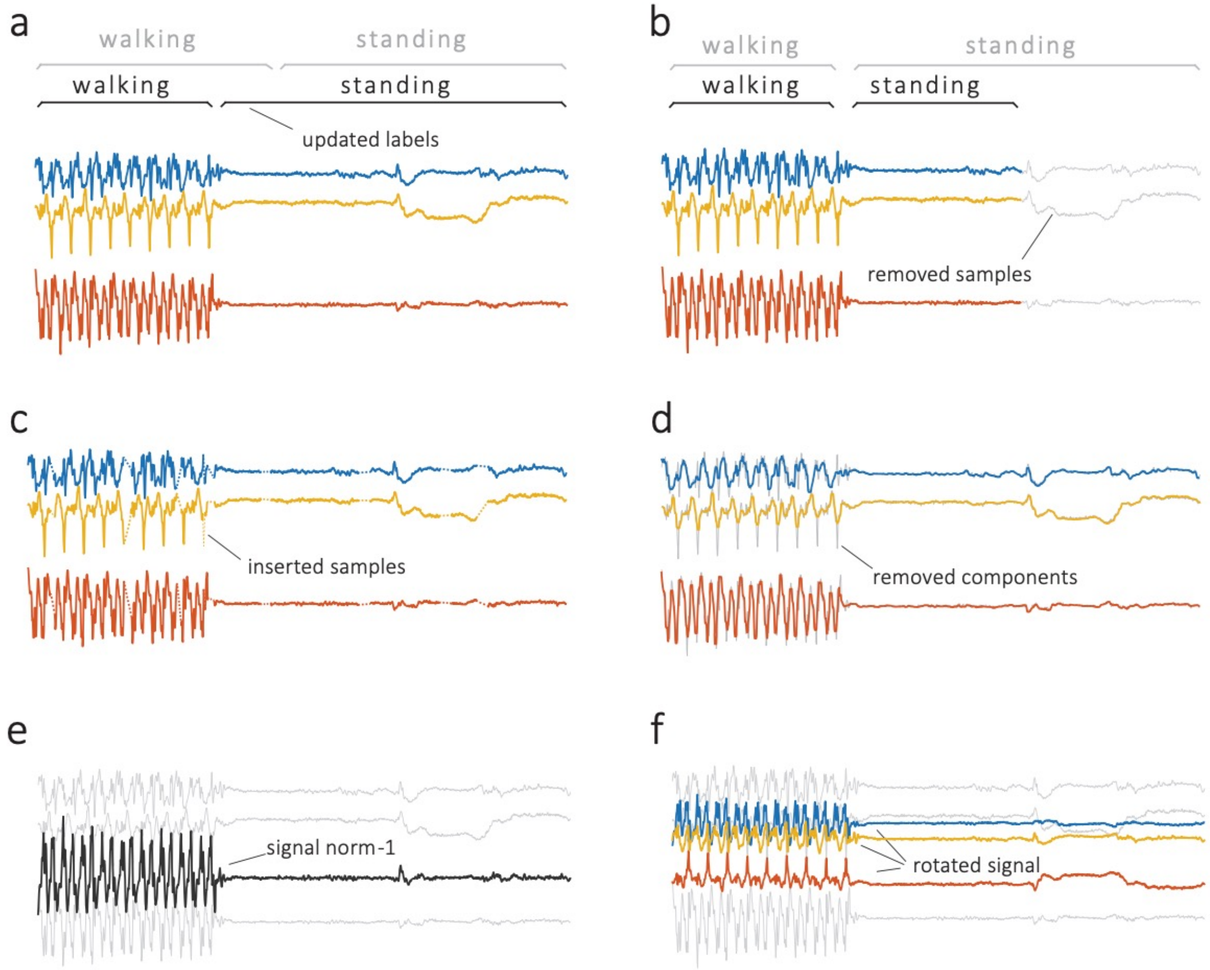
Sampling

- Generally between 20 and 30 Hz.

- Some studies try to research the trade offs of sampling frequency and activity detection because sampling affects device battery…
  - 10Hz enough to distinguish activity from smartphone IMUs and 20Hz for mode of transport [1].

[1] From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

Preprocessing



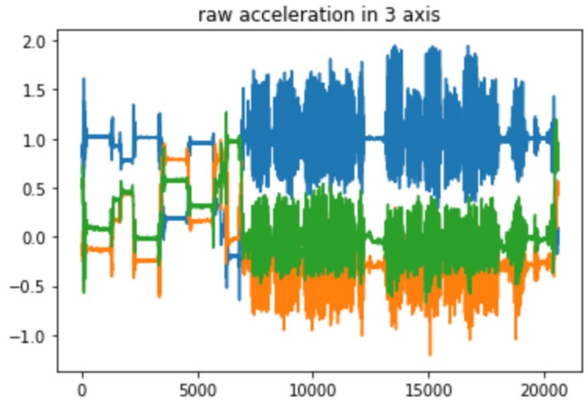
A labels are realigned (by eye)
B samples are removed to balance data
C missing data is filled with adjacent data
D removing components, denoising: high frequency noise cancellation.
E (see next slides ..magnitude): aggregation
F rotate to different coordinate system

From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

Signal Filtering

- Removing certain frequencies

- Example
  - Low pass filter: passes low frequencies and attenuates high frequencies.
  - Band-pass filter: only frequencies in a frequency band are passed.



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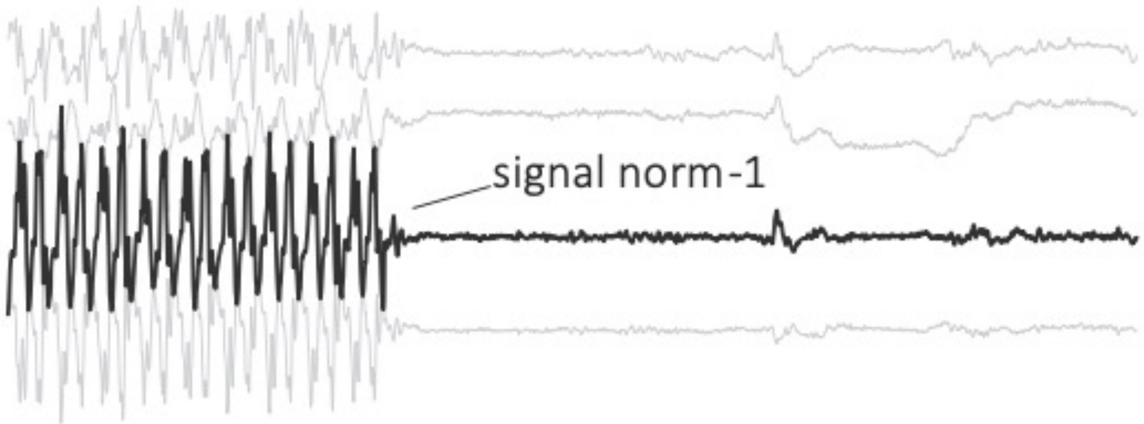
Preprocessing: Magnitude

$$\forall i : m_i = \sqrt{x^2 + y^2 + z^2}$$



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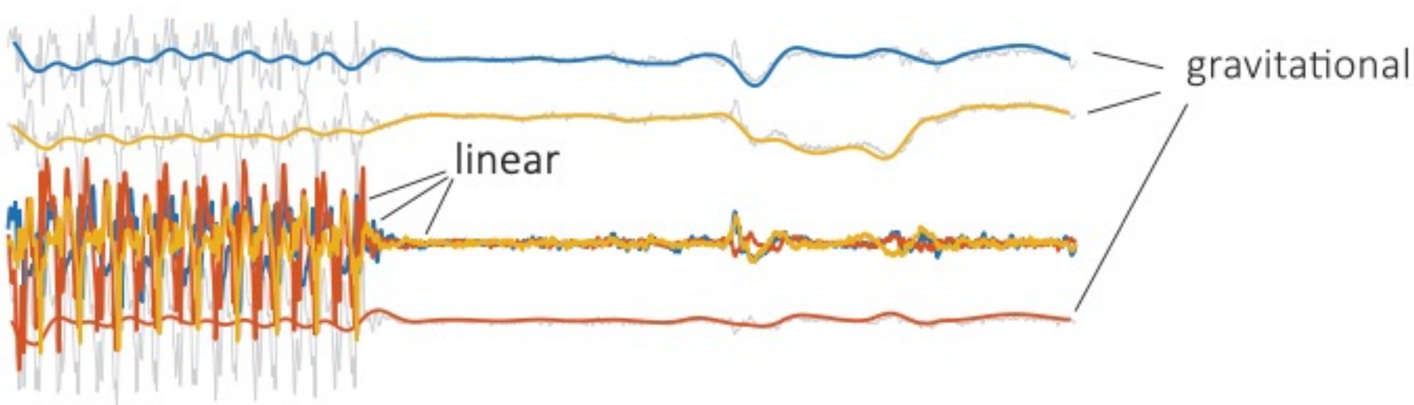
Gravitational and Body Force Separation



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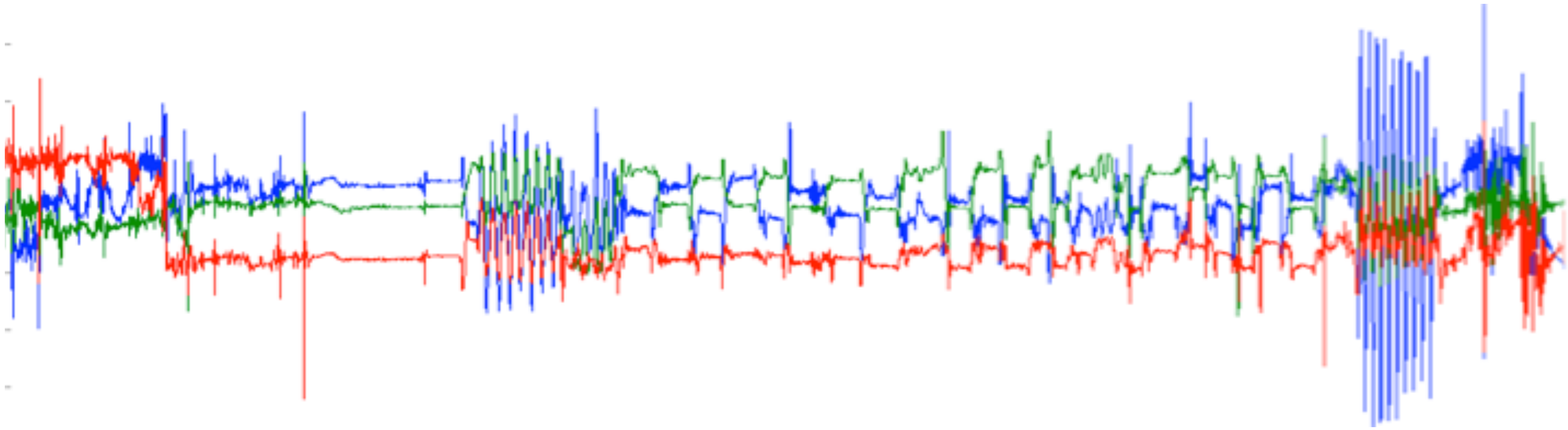
Data Segmentation

- Localize temporal patterns of interest
- But you do not know what/where these are…
- Sliding window approach
  - Issues: window length, overlap, window label choice…



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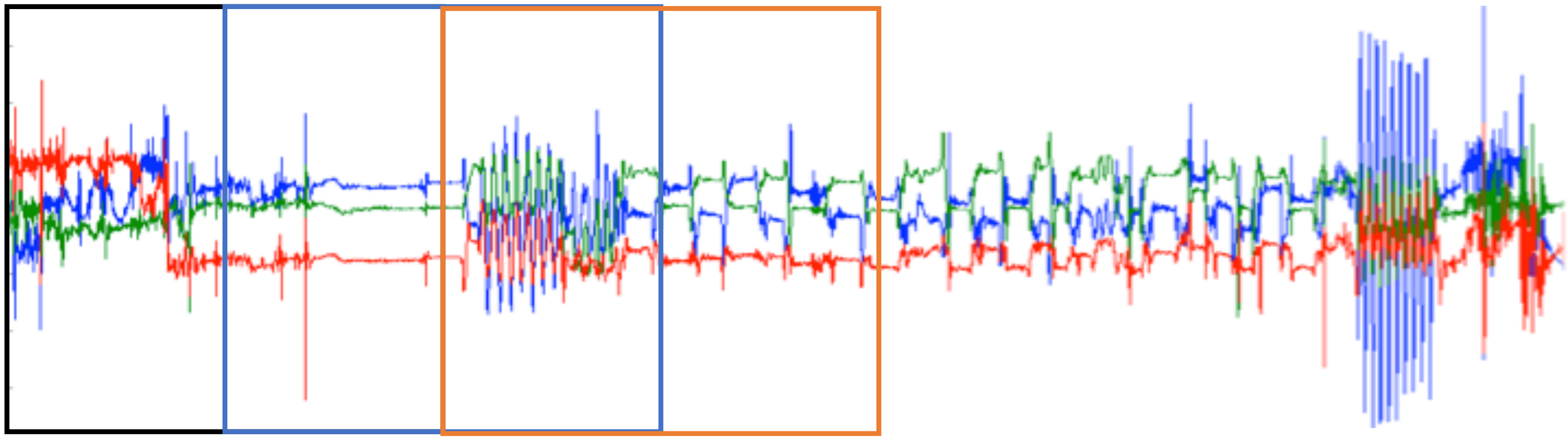
Sliding Window with 50% overlap

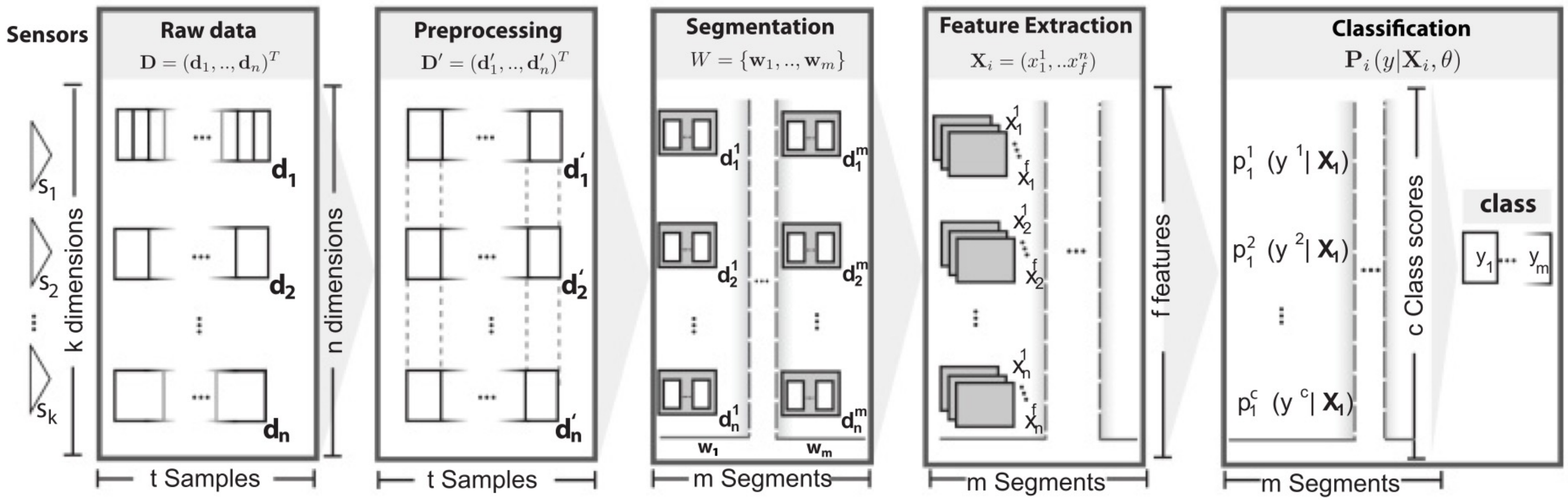
- Let's fix the window size, define a 50% overlap
- One can change window size and overlap



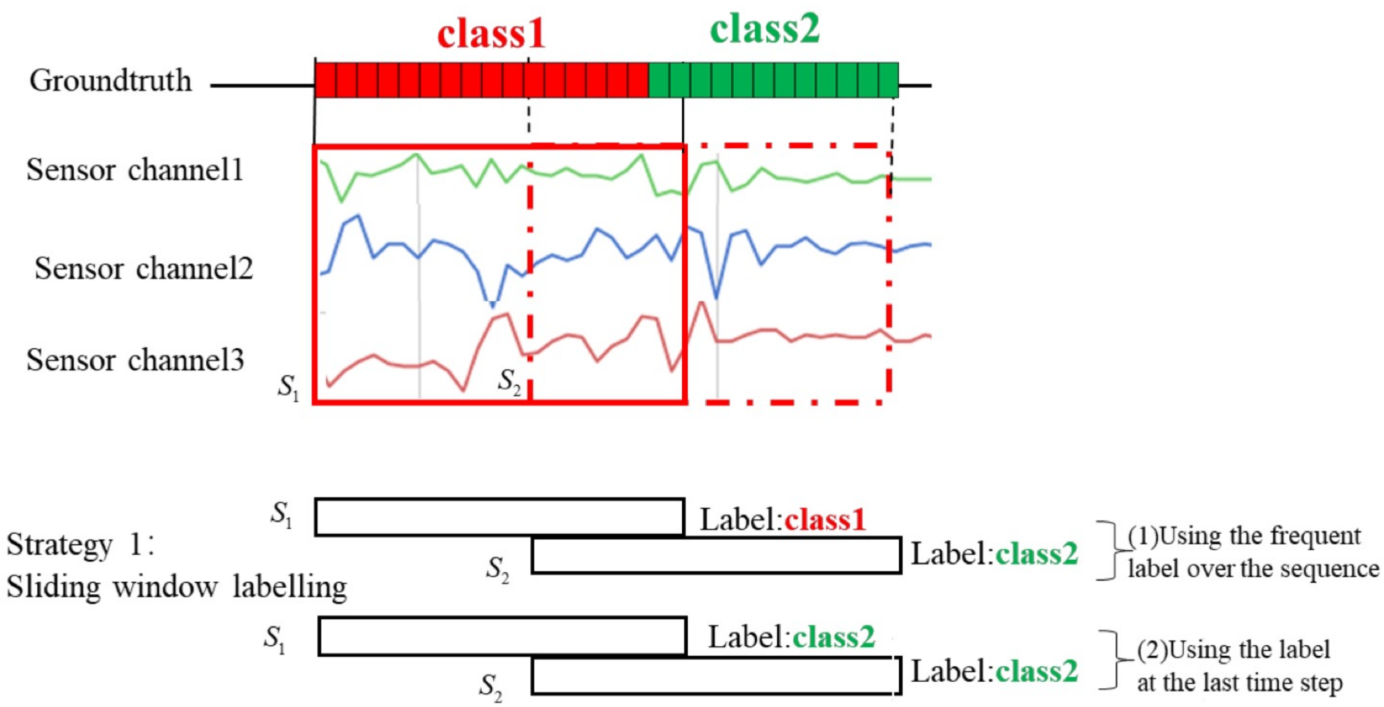
Segmented Samples to Prediction

- For each sample further analysis is applied to reach a prediction, for example:
  - A number of features are extracted on a sample and a classifier is used to use these to decide on the class label for a sample.
  - The sample row data is fed into a deep learning network which gets to a softmax probability offering a classification output.

Traditional Inference Pipeline



Mapping Classes with Windows



Zhang, Yong & Zhang, Yu & Zhang, Zhao & Bao, Jie & Song, Yunpeng. (2018). Human activity recognition based on time series analysis using U-Net.

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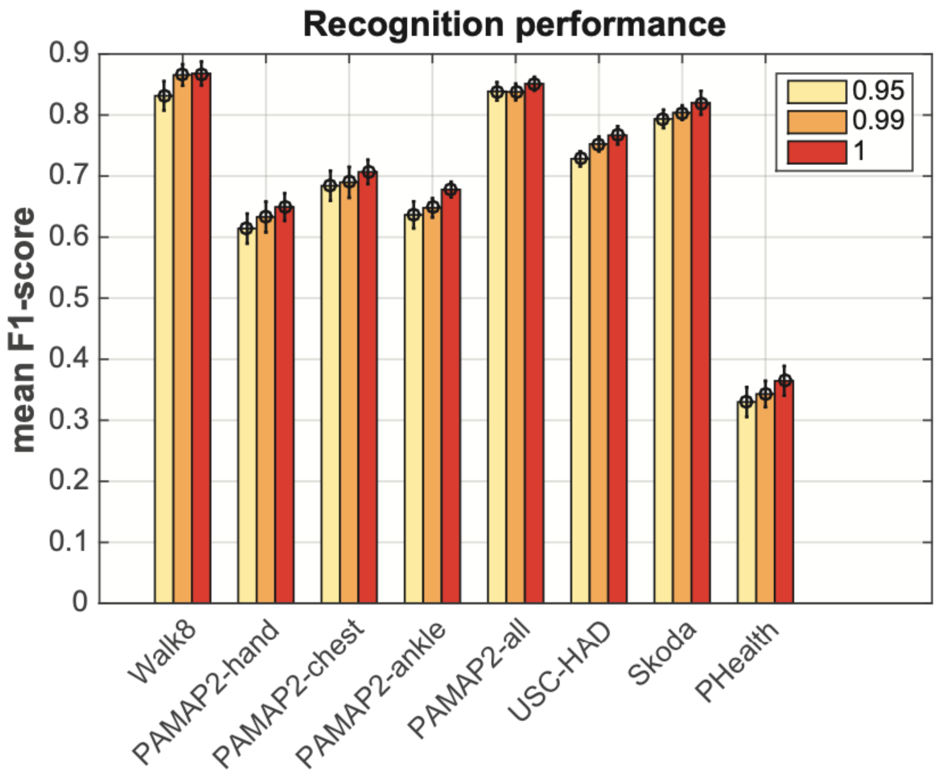
Sampling Rate

Sampling rate has impact on battery
Here is an approach that defines a function to allow lowering sampling rate while keeping a similarity with the original curve.

Histogram shows that when using this method the performance are not affected much.

Dataset	#Classes	Original	Optimal sampling rates	
		$Q(Hz)$	$\hat{q}$ ($\mathcal{S} = 0.95$) (Hz)	$\hat{q}$ ($\mathcal{S} = 0.99$) (Hz)
Skoda	11	96	12	22
PAMAP2-Hand	13	100	32	56
PAMAP2-Chest			33	57
PAMAP2-Ankle			42	63
USC-HAD	12	100	17	30
PHealth	10	100	15	26
Walk8	4	250	18	35



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[A. Khan, N. Hammerla, S. Mellor, and T. Ploetz, “Optimising sampling rates for accelerometer-based human activity recognition,” Pattern Recognition Letters, 2016.]

Class Prediction Problem

- Predict activity given a window of movement data.
- Predict activity given multiple windows of movement data.
- Predict the activity sequence given multiple windows of movement data.
- Predict activity given a sequence of movement data for a pre-segmented activity.
- Predict activity cessation or transition given a window of movement data.
- Predict a stationary or non-stationary activity given a window of movement data

Feature Extraction

- Distribution of x,y, z axis acceleration per window for various activities

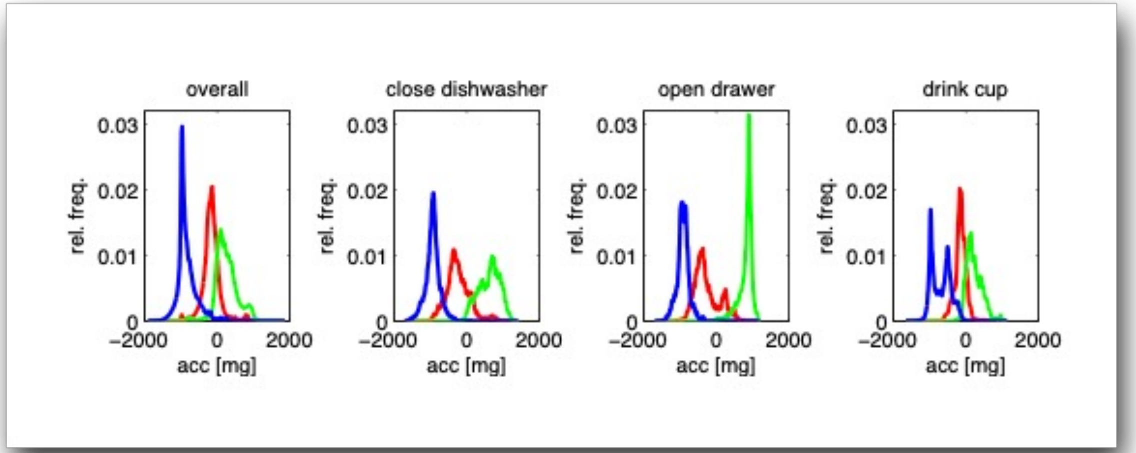
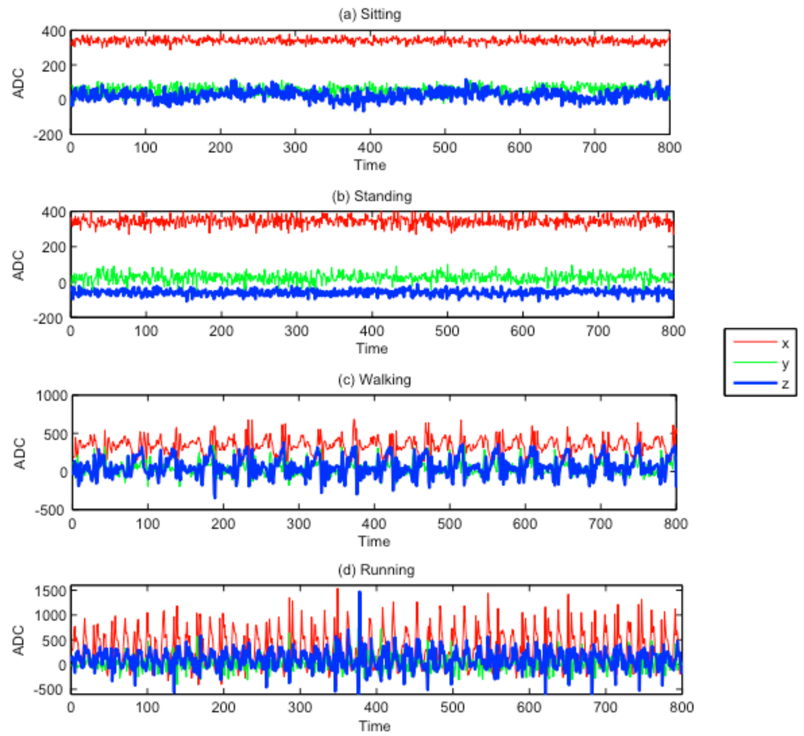


Figure by Thomas Ploetz

Physical Activity using Accelerometer

- Activities: sitting, standing, waking, running

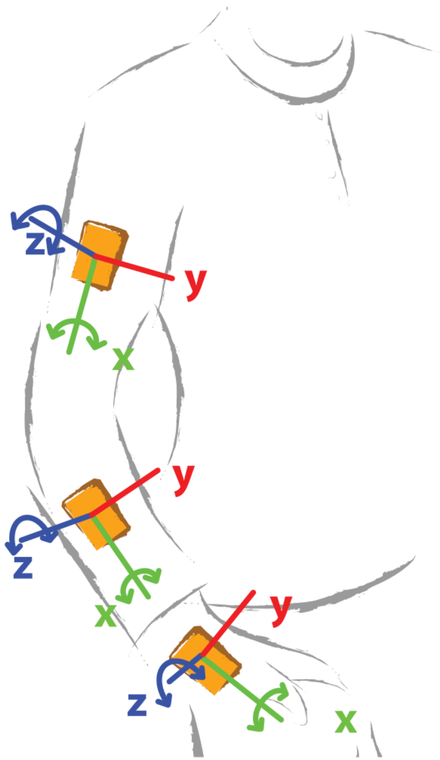
- Feature examples:
    - **Mean** (can help distinguish between standing and sitting).
    - Standard deviation
    - **Number of peaks** (can help distinguish between waking and running).



Classification: a Recap!

- Feature extraction produces a feature vector.
- The classification matches the feature vector to a pre-defined set of classes.
- The classification engine is typically based on machine-learning techniques and is trained using labelled training data.
- Common classification algorithms include:
  - K Nearest Neighbour.
  - Naive Bayes classifier.
  - Decision Trees.
  - Hidden Markov Models.

Activity Recognition Classification

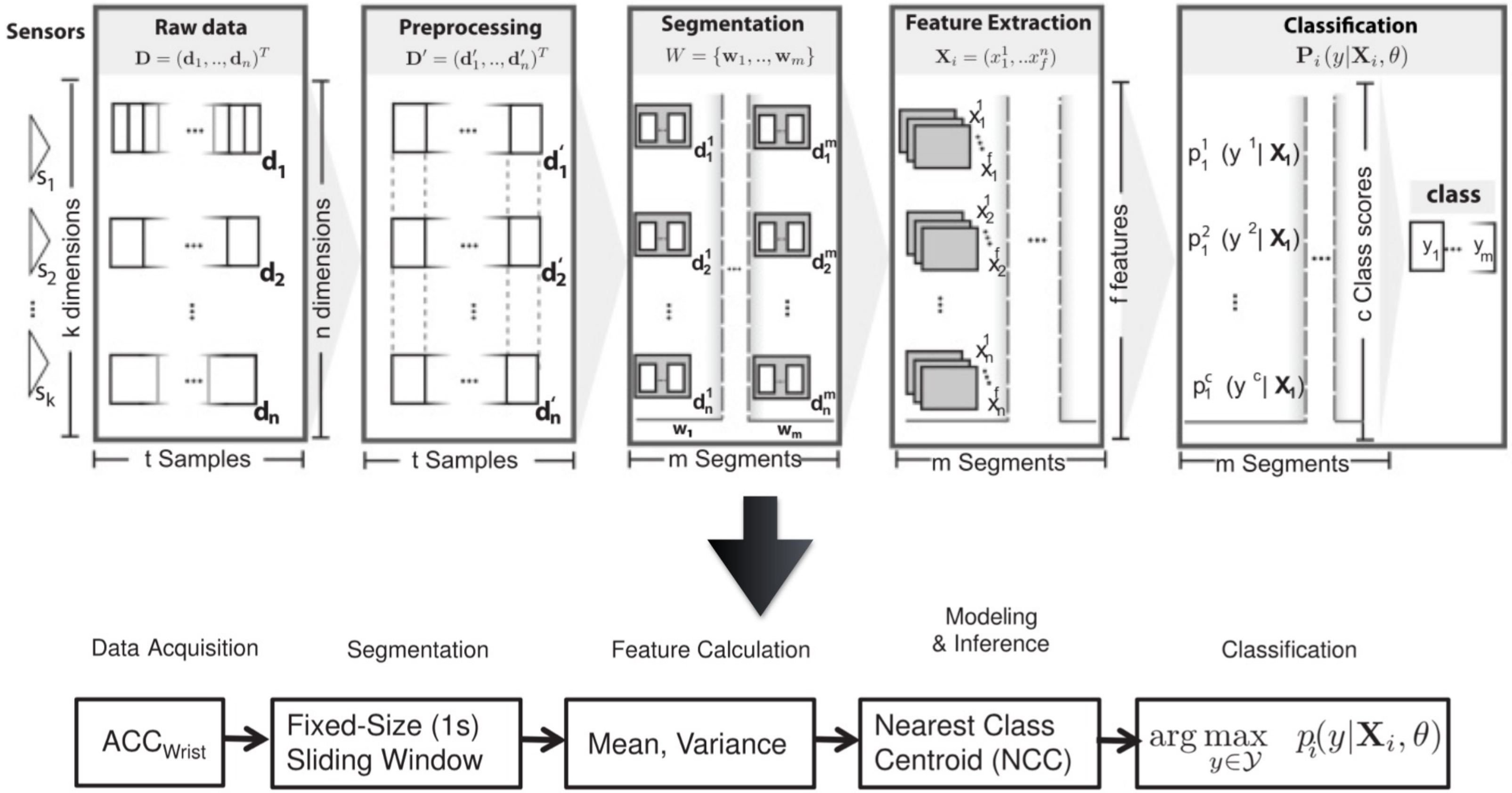


Activities

opening a window
closing a window
watering a plant
turning book pages

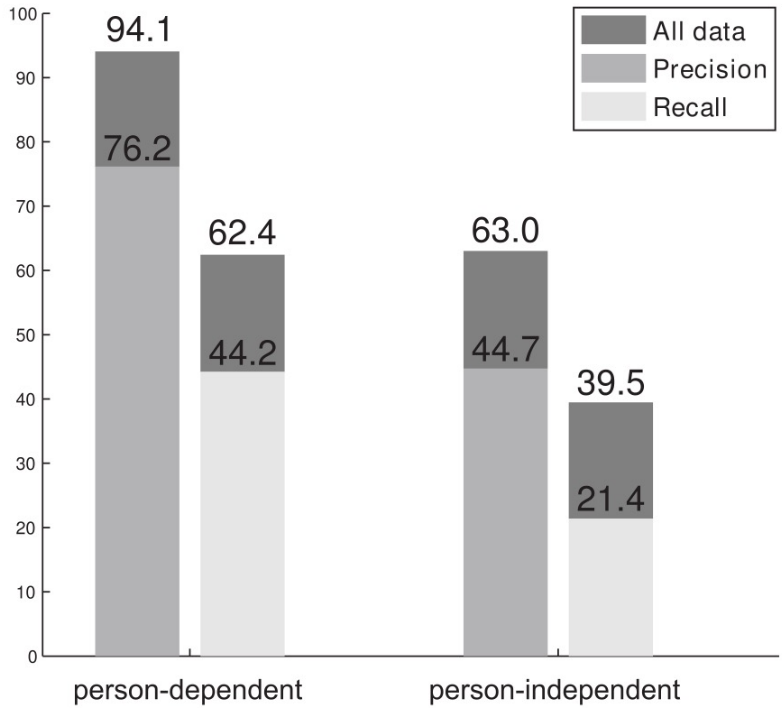
drinking from a bottle
cutting with a knife
chopping with a knife
stirring in a bowl

forehand
backhand
and smash



Sensors
Raw data
$\mathbf{D} = (\mathbf{d}_1, .., \mathbf{d}_n)^T$
Preprocessing
$\mathbf{D}' = (\mathbf{d}'_1, .., \mathbf{d}'_n)^T$
Segmentation
$W = \{\mathbf{w}_1, .., \mathbf{w}_m\}$
Feature Extraction
$\mathbf{X}_i = (x_1^1, ..x_f^n)$
Classification
$\mathbf{P}_i(y|\mathbf{X}_i, \theta)$
k dimensions
n dimensions
f features
c Class scores
class
t Samples
t Samples
m Segments
m Segments
m Segments
Data Acquisition
Segmentation
Feature Calculation
Modeling & Inference
Classification
ACC_{Wrist}
Fixed-Size (1s) Sliding Window
Mean, Variance
Nearest Class Centroid (NCC)
$\arg\max_{y \in \mathcal{Y}} \; p_i(y|\mathbf{X}_i, \theta)$

Classification Results: Person Dependence and Multiple Sensors



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Confusion Matrix on Activities

classification

groundtruth	NULL	Open window	Drink	Water plant	Close window	Cut	Chop	Stir	Book	Forehand	Backhand	Smash	*recall*
NULL	24267	216	444	3228	48	24	60	75	45		3		85.42
Open window	3849	1938	453	291	48	12	9		24				29.26
Drink	3984	927	3780	321	3	9							41.89
Water plant	3984	726	774	3735	21	57	15						40.11
Close window	3891	381	1173	945	1533								19.35
Cut	2940		264	450		6585	456		3				61.55
Chop	2895	168	435	153		909	5742		126				55.06
Stir	4947	39	135	42	21	474	561	4392	207				40.60
Book	4560	27	144	951		354	1725	60	6687				46.09
Forehand	3195	330		144	609	9	66		3	969	6	3	18.17
Backhand	3003	207	21		21	3	6	24	33		1302		28.18
Smash	1860	57		78	185		42	45		1567	137	230	5.47
precision	38.29	38.64	49.59	36.13	61.59	78.06	66.14	95.56	93.81	38.21	89.92	98.71	

Gait analysis

- Gait is indicative of musculoskeletal and neurological diseases such as Parkinson's disease, Alzheimer's disease, multiple sclerosis and osteoarthritis.

M. Ullrich, A. Kuderle, J. Hannink, S. Del Din, H. Gaßner, F. Marxreiter, J. Klucken, B. Eskofier,F. Kluge. Detection of Gait From Continuous Inertial Sensor Data Using Harmonic Frequencies. JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS. 2020.

The Sensor and the Setting…

- Training set: 150 gait analysis recordings of 121 patients in hospital
- Validation set: 203 gait recordings from 7 PD patients at their home
- Exercises:
    1. 2x10 m walk with a break at the turning point (*2x10m*) 2)
    2. 4x10 m walk without stops at turning points
    3. (*4x10m*) 3) 2-minute walk back and forth along a straight path of 25 m (*2min*)
    4. Tapping on the ground with the heel (*heel)*
    5. Tapping on the ground with heel and toes alternately (*heel-toe*)
    6. Circular movement of the foot (*circling*)

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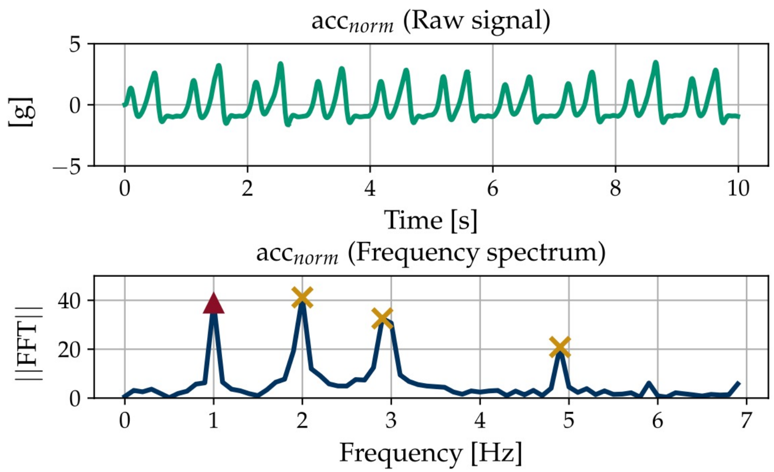
Data Processing

- Norm of accelerometer and gyroscope for window used to detect movement. If above a threshold accept sequence.
- Low pass filter (cut off 6Hz).
- Use FFT to find important frequencies.
- Uses autocorrelation to measure peaks (and harmonic frequencies)

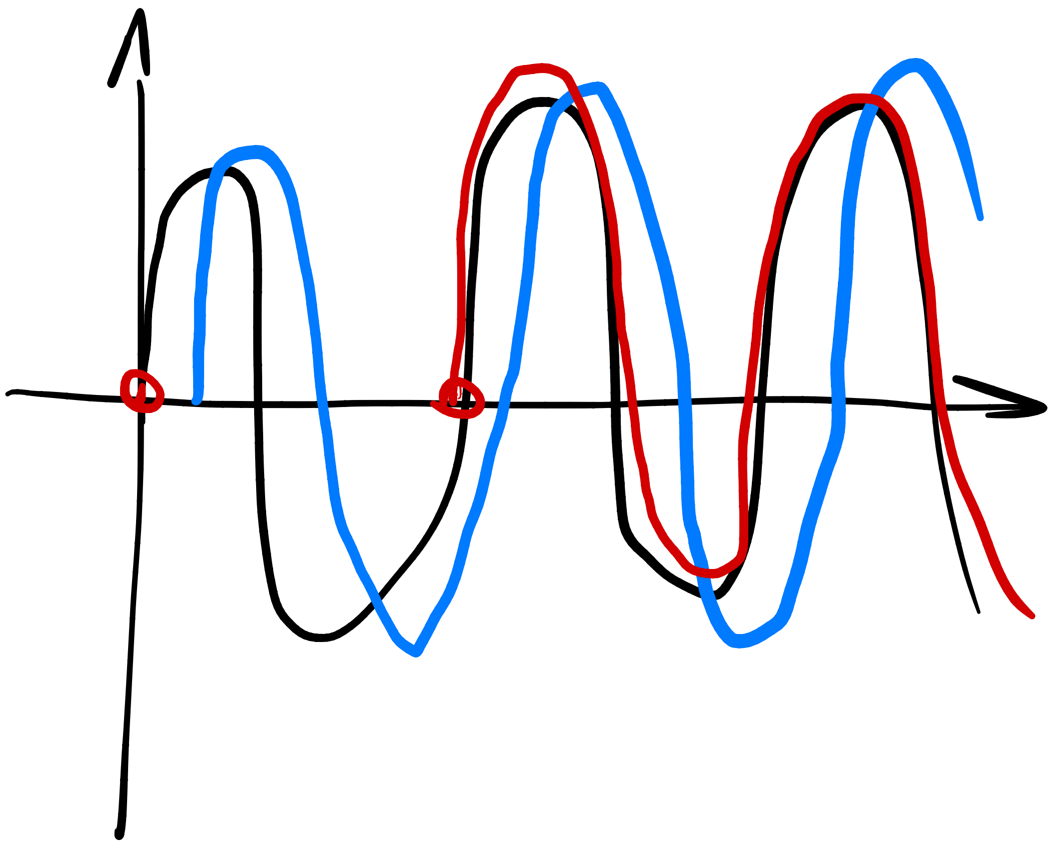
$$R(m) = \sum_{n=0}^{N-1-m} s(n)s(n+m)$$

- Use these to decide if to keep this window.

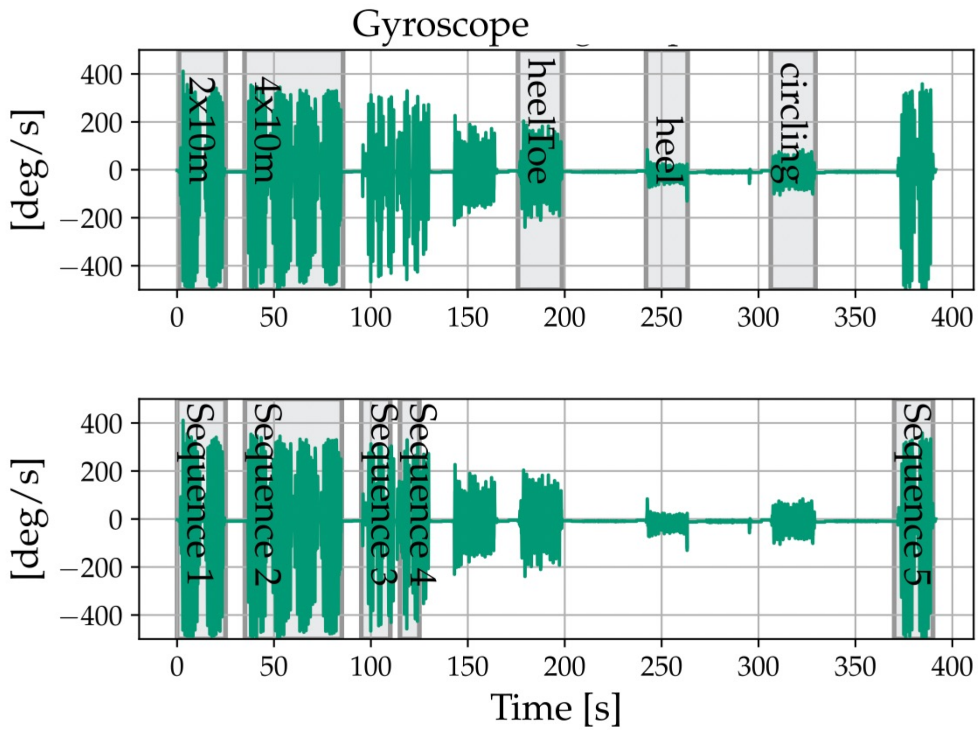
$$|s^{3d}| = \sqrt{s_x^2 + s_y^2 + s_z^2},$$



Autocorrelation to measure period



Some Results



	acc_v	acc_{norm}	gyr_{ml}	gyr_{norm}
Lab Data Set				
Sensitivity	0.97 (0.03)	0.94 (0.04)	0.98 (0.01)	0.89 (0.04)
Specificity	0.95 (0.02)	0.96 (0.01)	0.96 (0.02)	0.81 (0.04)
Youden index	0.92 (0.02)	0.90 (0.04)	0.94 (0.01)	0.70 (0.06)
Opt. Peak Prom.	8	13	17	11
Val. Data Set				
Sensitivity	0.50	0.70	0.97	0.89

Questions

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