Fakultät für Informatik
Facoltà di Scienze e Tecnologie informatiche
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IoT – Hands-on Tutorial

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(based on a collaboration Unibz/Vertical-Life within the Salsa project)

18th User Conference for Software Quality, Testing and Innovation
November 11, 2020

Vertical-Life climbing
efre · fesr Südtirol · Alto Adige
Europäischer Fonds für regionale Entwicklung
Fondo europeo di sviluppo regionale
EUROPEAN UNION
AUTONOME PROVINZ BOZEN SÜDTIROL
PROVINCIA AUTONOMA DI BOLZANO ALTO ADIGE

Step counter

Sport skill assessment

Wii

Fitness coaching

Elderly assistant

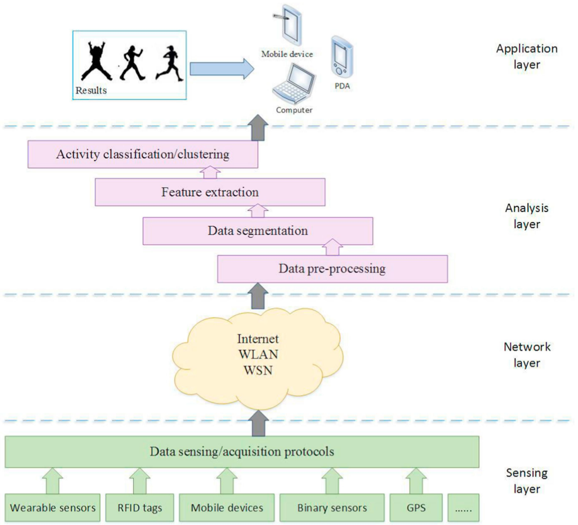
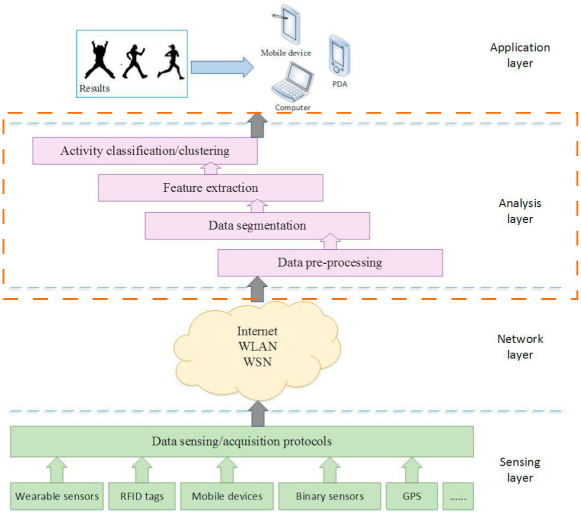


Figure from Qi et al. (2018). Examining sensor-based physical activity recognition and monitoring for healthcare using Internet of Things: A systematic review. Journal of Biomedical Informatics.


Results
Mobile device
PDA
Computer
Application layer
Activity classification/clustering
Feature extraction
Data segmentation
Data pre-processing
Analysis layer
Internet
WLAN
WSN
Network layer
Data sensing/acquisition protocols
Wearable sensors
RFID tags
Mobile devices
Binary sensors
GPS
......
Sensing layer

- Simple sensors (e.g. RFID) can provide a 'binary' information
  e.g. window contact RFID sensor detects activity window open/window closed,
  ADXL345 accelerometer ('freefall pin') can detect falls
- In general <activity-X> sensor does not exist
  - Sensor data must be interpreted
  - Multiple sensor must be combined (sensor fusion)
  - Several factors influence the sensor data
- Activity is recognized from the sensor data with
  - Signal processing
  - Machine learning
  - Reasoning (for context aware activity recognition)
- 'sensor node' or 'smart sensor'
  smart sensor = sensor chip + data processing in a device
  sensor node = sensor sends data to a remote station for processing

Introduction
- How to recognize activities?
- Sensor data
- Activity recognition chain
- Recognition system characteristics

Case study
- Sport climbing
- Sport climbing activities
- Data recording
- Gravity removal
- Segmentation
- Classification
- Results

Conclusions

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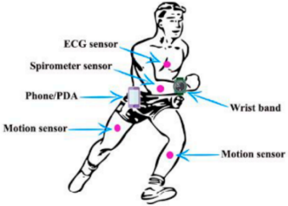
How to recognize activities?

- With sensors (on-body, on-object, in the environment)
- Activities are represented by typical signal patterns
- Recognition: comparison between *template* and sensor data

How to recognize activities?

- With sensors (on-body, on-object, in the environment)

e.g.
drinking coffee, running

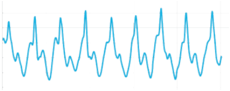


- Inertial sensors
- Physiological sensors
- Location sensors

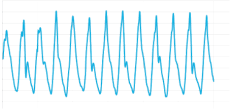
- Activities are represented by typical signal patterns
- Recognition: comparison between *template* and sensor data

How to recognize activities?

- With sensors (on-body, on-object, in the environment)
- Activities are represented by typical signal patterns



Slow walk pattern

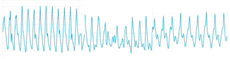


Fast walk pattern

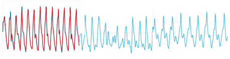
- Recognition: comparison between *template* and sensor data

How to recognize activities?

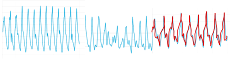
- With sensors (on-body, on-object, in the environment)
- Activities are represented by typical signal patterns
- Recognition: comparison between *template* and sensor data



sensor signal



Fast walk recognized

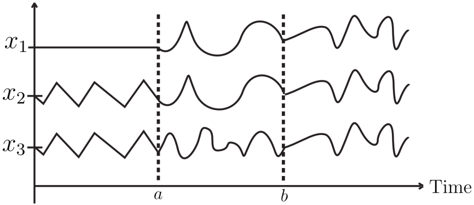


Slow walk recognized

Sensor data: Time series

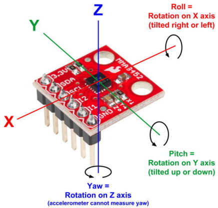
Time series

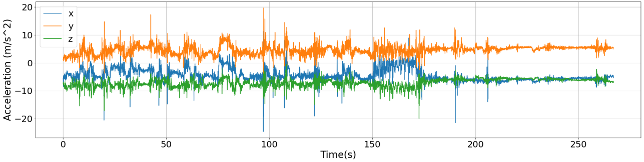
An ordered sequence of values of a variable at equally spaced time intervals.



- Multiple sensor, multiple dimensions
  $s_i = (d^1, d^2, d^3, \ldots, d^t)$, for $i = 1, \ldots, k$
  k denotes the number of sensors and d^t multiple values at time t.
- Sampling rate

Sensor data: Time series

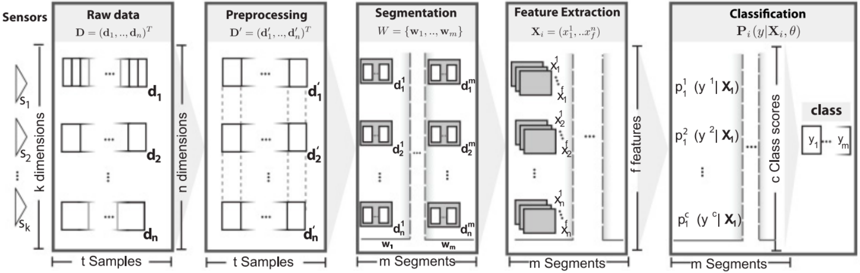




Examplary 3D acceleration time series.

Activity Recognition Chain (ARC)

- A standard set of steps that is typically followed in activity recognition[1]:



[1]Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. ACM Computing Surveys, 46(3), 1–33.

Recognition System Characteristics

Execution	Offline	The system records sensor data first. The recognition is performed afterwards. Mostly used in **non-interactive** applications.
	Online	The systems acquires data and process it on the fly to infer activities. Mostly used in **interactive** applications.
Recognition	Continuous	The system detects activities in **streaming** data. It implements stream segmentation and classification.
	Isolated	The system assumes that the sensor stream is already segmented. It only classifies sensor data into activity classes.

Taxonomy of Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. ACM Computing Surveys, 46(3), 1–33.

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The Sport of Climbing

- Becoming increasingly popular competitive sport and recreational activity.
- There is a need for application:
  - Climbing skill assessment
    e.g. speed, stability, power, endurance, control
  - Usage analytics for climbing gym operators
    e.g. popularity of a route, number of falls

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Sport Climbing Activities (state-of-the-art)

activities

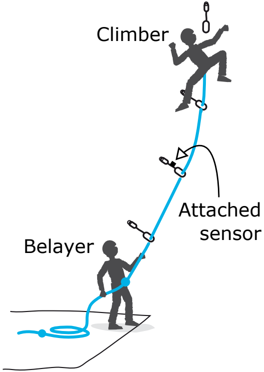
- gripping a hold **[Ladha et al, Boulanger et al]**
- immobility, traction, postural regulation **[Boulanger et al]**
- fall detection **[Tonoli et al'15, Tonoli et al'19]**
- resting, shaking arms for relief, chalking hands, clipping the rope, pulling the rope

performance indicators

- power, control, stability, speed **[Ladha et al]**
- endurance **[Pansiot et al]**
- fluency **[Seifert et al, Sibella et al]**
- exploratory and performatory movement ratio **[Boulanger et al]**

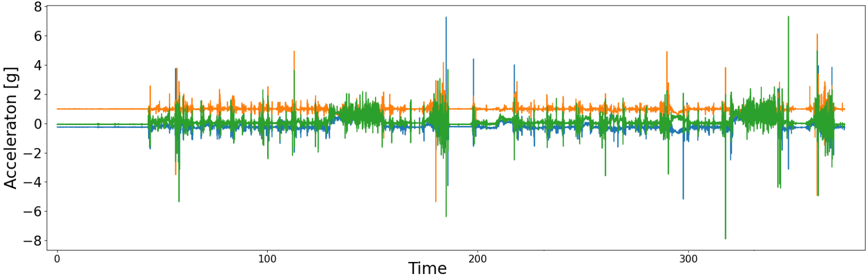
Data Recording

Smart quickdraw - a quickdraw equipped with a 3-axial accelerometer.



Data collection setup

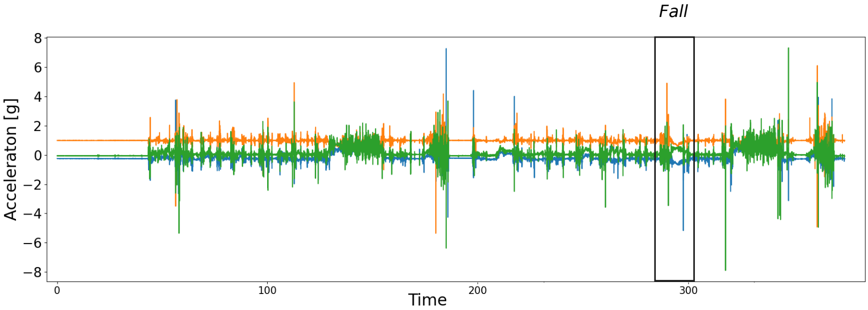
Data Recording



3-axial acceleration signal

Data Recording

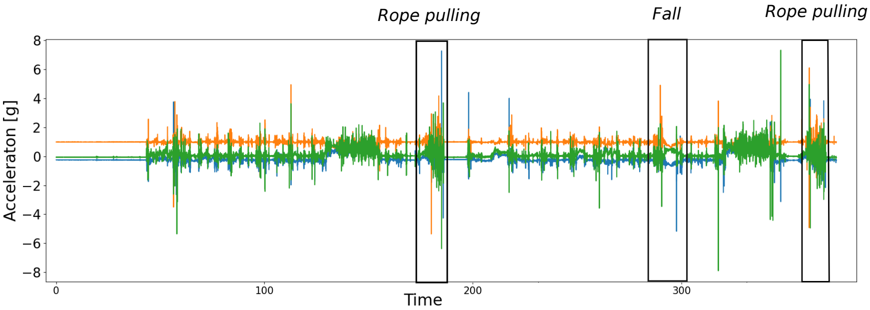
- Activities: *falling*



3-axial acceleration signal

Data Recording

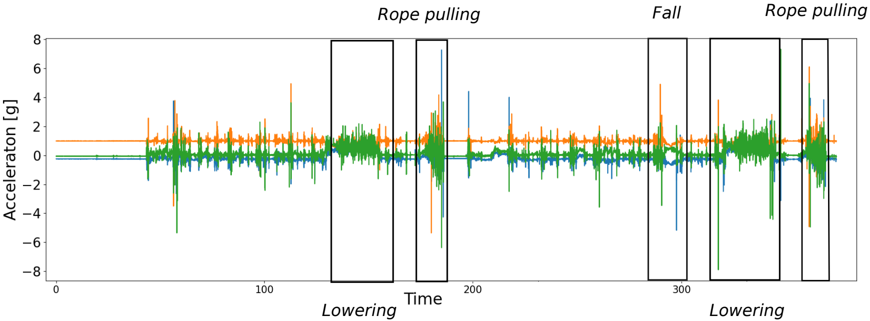
- Activities: *falling*, *rope pulling*



3-axial acceleration signal

Data Recording

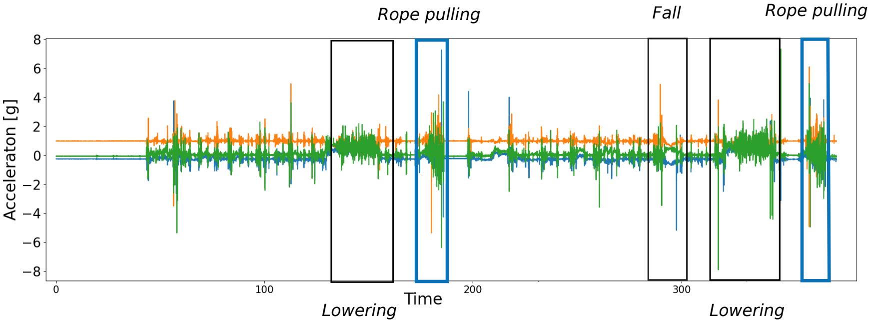
- Activities: *falling*, *rope pulling*, *lowering*



3-axial acceleration signal

Data Recording

- Activities: *falling*, *rope pulling*, *lowering*



3-axial acceleration signal

Dataset

- Data collection was performed in 2 climbing gyms, involving 2 participants, who climbed along 4 different lines.

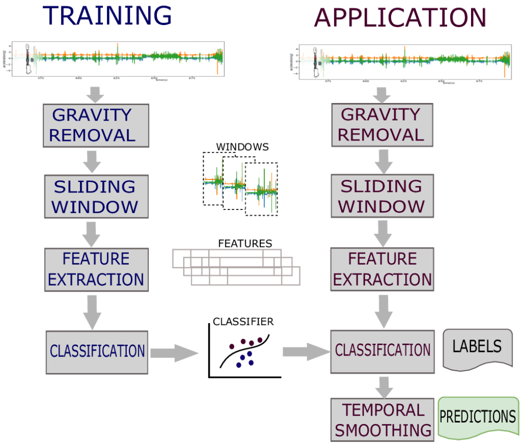
Summary of data collected on four different lines.

Dataset	Climbs	Climb time* (s)	Rope pulling time* (s)
Salewa	5	122.3 ($\pm$ 31.6)	10.4 ($\pm$ 2.6)
Vertikale1	4	145.5 ($\pm$ 46.1)	12.3 ($\pm$ 1.7)
Vertikale2	4	213.4 ($\pm$ 85.1)	12.4 ($\pm$ 1.1)
Vertikale3	4	147.7 ($\pm$ 47.1)	11.0 ($\pm$ 1.0)
Overall	17	155.2 ($\pm$ 64.6)	11.5 ($\pm$ 2.0)

*Average activity duration with the standard deviation.

Overview of Rope Pulling Detection Procedure

- Supervised machine learning
  Requires ground truth annotation
- Binary classification problem
  rope pulling class (6% to 8% of samples)
  non-rope pulling class



Gravity Removal

- Accelerometer generates three time series, each combines *linear acceleration* (due to body/object motion) and acceleration due to gravity.
- Low-pass filter **[Bayat et al]**:

A^X, A^Y, A^Z are composed of high frequency (AC) and low frequency (DC) components.

$$A^i_{DC}[n] = (1-\beta) \times A^i[n] + \beta \times A^i_{DC}[n-1] \qquad 1 \leq n \leq |A|,\ i \in \{X, Y, Z\}$$

$\beta = e^{-2\times\pi\times f_c \times \frac{1}{s}}$, f_c is cut-off frequency and s is sampling rate.

$$A^i_{AC}[n] = A^i[n] - A^i_{DC}[n] \qquad 1 \leq n \leq |A|,\ i \in \{X, Y, Z\}$$

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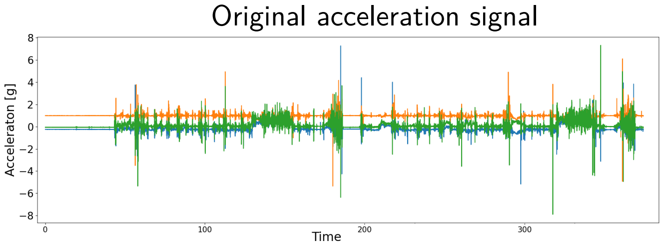
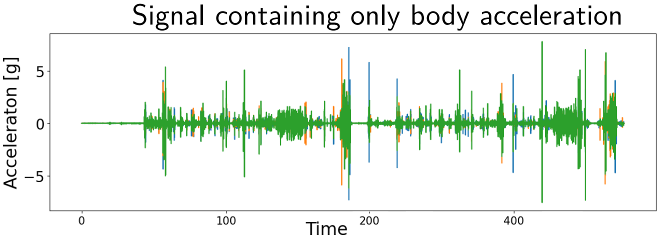
Gravity Removal





$f_c = 0.25\text{Hz}$
$s = 52\text{Hz}$
$\beta = 0.984$

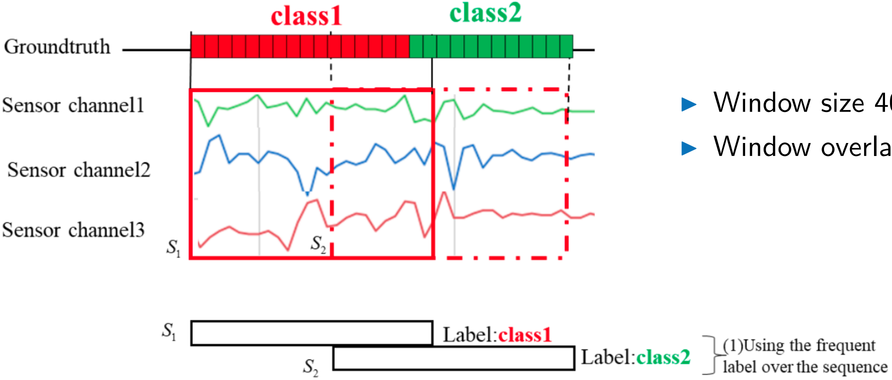
Segmentation

- Finding segments of preprocessed data stream that are likely to contain information about activities.
- Two general processing paradigms exist: i) explicit identification of start- and end-points of semantically contiguous segments and ii) implicit segmentation through extraction of windows and subsequent isolated classification regarding the patterns of interest.
- Sliding window technique
  - Data is divided into segments of fixed lenght (windows), with no gaps between consecutive windows.
  - A degree of overlap between individual windows may be included.
  - Window size typically ranges between 0.1s and 12.8s[2]

[2] Banos, O., Galvez, J.-M., Damas, M., Pomares, H., & Rojas, I. (2014). Window Size Impact in Human Activity Recognition.
Sensors, 14(4), 6474–6499.

Segmentation

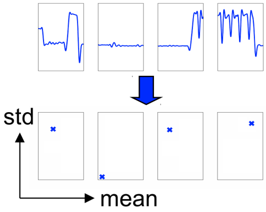
- Window labelling

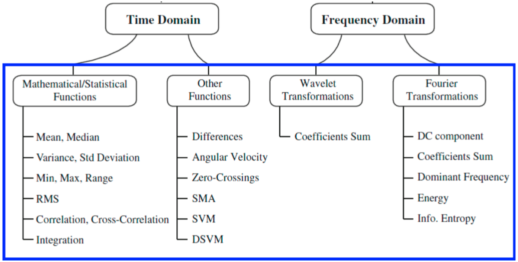


- Window size 400 samples (8s)
- Window overlap 95%

Feature Extraction

- Reduces the signals into features that are discriminative for the activities of interest.
- Trade-offs (minimize computation complexity, maximize separation between classes, robustness)
- Some common features for acceleration data[2]:





[2] Figo, D., Diniz, P. C., Ferreira, D. R., & Cardoso, J. M. P. (2010). Preprocessing techniques for context recognition from accelerometer data. Personal and Ubiquitous Computing, 14(7), 645–662.

Feature Extraction

- We chose a feature space of 60 dimensions for rope pulling recognition task.
  time-domain features: mean value, standard deviation, median, maximum, minimum, Pearson correlation coefficients between pair of time series (on different axis), number of peaks, kurtosis and skewness for x, y and z axes.
  frequency domain features: the five largest frequency values and the amplitudes of these values for x, y and z axes.
- A variety of methods for feature ranking and selection have been developed, e.g. Sequential Forward Selection (SFS) (see **[Guyon et al]** for an introduction).

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Classification

Table II. Examples of Activity Recognition Using On-Body Sensors to Illustrate the Diversity of Methods and Activities to be Recognised (Evaluation metrics are abbreviated: precision: "prec", recall: "rec", acccuracy: "acc", 1- equal error rate: "EER")

	Methods	Activities	# classes	# participants	Results	Reference
1	HMM	daily situations	12	1	85.8% - 99.7% acc	[Clarkson et al. 2000]
2	Topic models	daily routines	4	1	77% prec, 66% rec	[Huynh et al. 2008]
3	Joint boosting	daily routines	4	1	88% prec, 90% rec	[Blanke and Schiele 2009]
4	CRF/HMM	daily home activities	7	1	96%/95%	[van Kasteren et al. 2008]
5	Decision tree	selected daily activities	20	20	84% acc	[Bao and Intille 2004]
6	AdaBoost+HMM	selected daily activities	8	12	90%	[Lester et al. 2006]
7	HMM	eating and drinking arm gestures	5	2	87% acc	[Amft et al. 2005]
8	SVM	office activities from eye movements	6	8	76.1% prec, 70.5% rec	[Bulling et al. 2011]
9	String matching/SVM	reading from eye movements	2	8	88.9% prec, 72.3% rec / 87.7% prec, 87.9% rec	[Bulling et al. 2012]
10	HMM/LDA	assembly tasks	9	5	63% prec, 66% rec	[Ward et al. 2006]
11	CRF	composite and low-level DIY activities	10 and 6	6	75% EER and 88% EER	[Blanke and Schiele 2010]
12	String matching	bike maintenance tasks	5	3	82.7%	[Stiefmeier et al. 2007]
13	naive Bayes/kNN	car maintenance tasks (person dependent)	20	8	48% prec, 71% rec	[Ogris et al. 2008]
14	Joint Boosting	car maintenance tasks (person independent)	20	8	93% EER	[Zinnen et al. 2009b]
15	kNN	Tai Chi movements	3	4	85% acc	[Kunze et al. 2006]
16	HMM	American sign language	40	–	around 95%	[Starner et al. 1997]
17	–	walking styles	4	4	–	[Lukowicz et al. 2006]
18	HMM	self-stimulatory behaviour in autism	8	1	68.57%	[Westeyn et al. 2005]

[1] Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. ACM Computing Surveys, 46(3), 1–33.

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Activity Recognition Results

Classification performance metrics:

- Confusion matrix
- $Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$
- $Precision = \frac{TP}{TP+FP}$
- $Recall = \frac{TP}{TP+FN}$

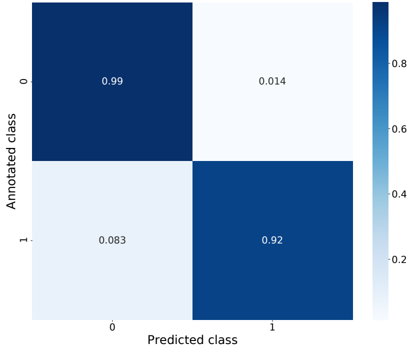
		Predicted class	
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

Activity Recognition Results

- Results are based on stratified 10-fold cross-validation.

Method	Precision	Recall
Random forest (n=100)	0.85	0.87
CatBoost	0.57	0.92
AdaBoost	0.70	0.93
Logistic regression	0.72	0.78

Performance of rope pulling detection using different classifiers on raw prediction results.

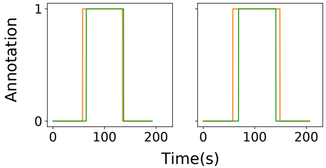


Normalized confusion matrix

Activity Recognition Results

Dataset	GT	TP	JI	FP
Salewa	5	4	0.86	0
Vertikale1	4	4	0.92	0
Vertikale2	4	4	0.99	0
Vertikale3	4	4	0.95	0
Overall	17	16	0.93	0

Performance of random forest classifier.
GT : ground truth, TP : true positives,
FP : false positives, JI : Jaccard index.



Jaccard index of similarity for two sets:

$$J(A, B) = \frac{A \cap B}{A \cup B}$$

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- Sensor signal to activity class mapping is identified at the design time. Can't displace sensors, Can't change the way activities are done.
- A large body of data is typically required to develop an application suitable for practical deployment.
- It is often worth applying both exhaustive and non-exhaustive evaluation methods (i.e. leave-one-out cross-validation).
- To separate gravity component from acceleration may require sensor fusion approach. (e.g. **[Madgwich]**)
- Find optimal sensor sampling rate for accelerometry based human activity recognition. (e.g. as done in **[Khan et al]**)
- Encouraged by first results we plan to further explore the potential for using smart quickdraw for climbing applications i.e., climbing performance assessment and climbing gym usage analytics.

References

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on time series segmenation

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on activity recognition in climbing

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on sampling rate optimization

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Thank you for your attention.

Questions?

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