LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

Praktikum Mobile und Verteilte Systeme

Mobile Sensing

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http://www.mobile.ifi.lmu.de

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Technische Universität München

Zuverlässig an Ihrer Seite

AUSSCHREIBUNG

Ort

Lehrstuhl für Sozialpädiatrie der Fakultät für Medizin der Technischen Universität München, ansässig am kbo-Kinderzentrum München

Aufgabe

Entwicklung einer Ratgeber-App für Eltern von Säuglingen mit Regulationsstörungen (exzessives Schreien, Schlaf- und/oder Fütterstörungen)

App-Funktionen

- Rubriken mit Fachinformationen
- Integrierung von Interviews in Text- und Videoformat
- Dokumentation und Auswertung des Schrei-, Schlaf- und Essverhaltens des Säuglings
- Erfassung und Auswertung des Stresslevels der Eltern anhand digitaler Fragebögen
- Chatforum zum Austausch der app-nutzenden Eltern

Ihr Profil

- Erfahrungen in der Entwicklung von Apps (vorzugsweise für Android und iOS)
- Begonnenes Masterstudium gewünscht
- Hohe Motivation und Eigeninitiative

Wir bieten

- Eine verantwortungsvolle und abwechslungsreiche Tätigkeit
- Arbeit in einem interdisziplinären, aufgeschlossenen, motivierten jungen Team
- Einblicke in die Arbeit mit durch Regulationsstörungen stark belastete Familien
- Flexible Arbeitszeiten

Kontakt

Svenja Scheel (M.Sc.) • email: svenja.scheel@kbo.de

Praktikum Mobile und Verteilte Systeme

Today: Mobile Sensing

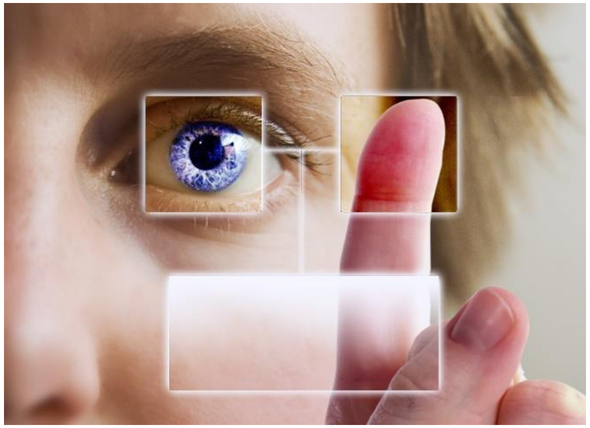
- Smartphones as **multi-sensor platforms**
- **Processing** of continuous streams of sensor data
- **Segmentation** of discrete events within time-series
- **Comparison** and **classification** of sensor events
- **Describing** sensor events with a numerical representation

Sensors of a modern smartphone

- Todays smartphones are multi-sensor platforms, featuring

    1. Cameras and microphones
    2. Connectivity (bluetooth, WLAN, cell receivers, etc.)
    3. Outdoor Positioning (GPS, etc.)
    4. Motion and orientation sensors (e.g., rotation, acceleration, etc.)
    5. Environmental sensors (barometer, humidity, therometer, etc.)

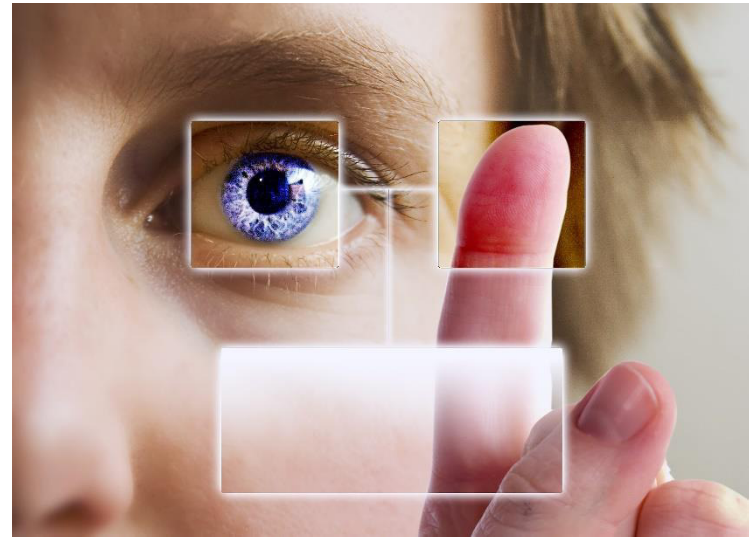
...and much others



Cameras and microphones as mobile sensors

Cameras as a sensor for

- Visual positioning and navigation
  - E.g., MoVIPS
- Visual identification
  - license plates, biometric features
  - human facial features
- Much more…



Source: http://www.biometricupdate.com/201301/biometric-technology-of-the-future-today

Implementation example

- Feature extraction (e.g., via SIFT, SURF, OpenCV-Tools)
- **Robustness** and **invariance** is of importance
  - variances in illumination, rotation, scaling, moving objects, noise, or others complicate analysis
- Classification via **patterns** or trained **models,** also clustering

Cameras and microphones as mobile sensors

Microphones as a sensor for

- **Synthesis and recognition** of speech or voice commands (see Amazon Alexa, Siri, etc…)
- Context analysis
  - Emotional state of mind (see affective computing)
  - **Recognition** of surroundings or activities
- Others…

amazon echo

Source: http://www.amazon.com/

Possible implementation

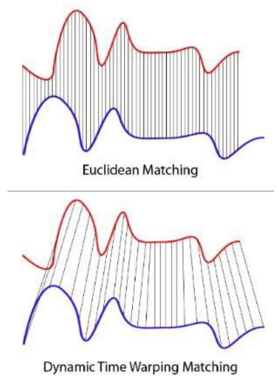
- Smoothing and de-noising
- Sequential **segmentation** (e.g., sliding window, energy based)
- **Feature engineering** is necessery (classification dependent)
- **Comparison of distances** or **model-based approaches** for classification

Example: Speech Recognition

- **Simple classification** approach via time series and **pattern-based** comparison
- General **pipline design**:

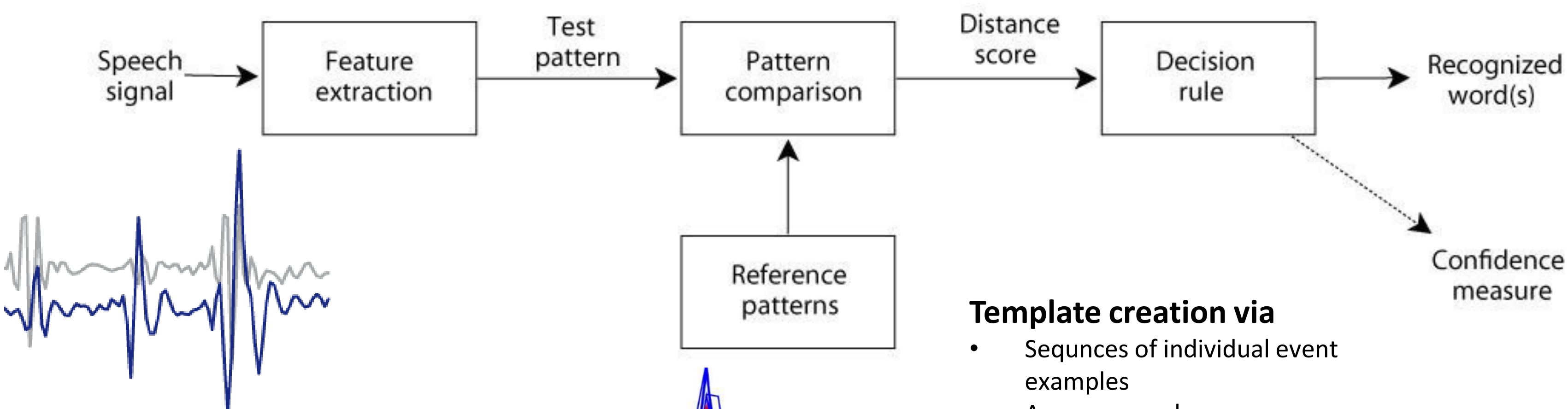
Extraction via

- raw time series
- interpolation
- Principal-Component-Analysis (PCA)



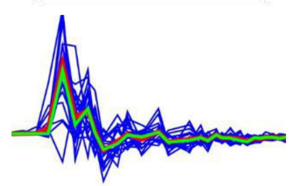
Decisions by using

- thresholds,
- min, max
- Target areas
- etc.



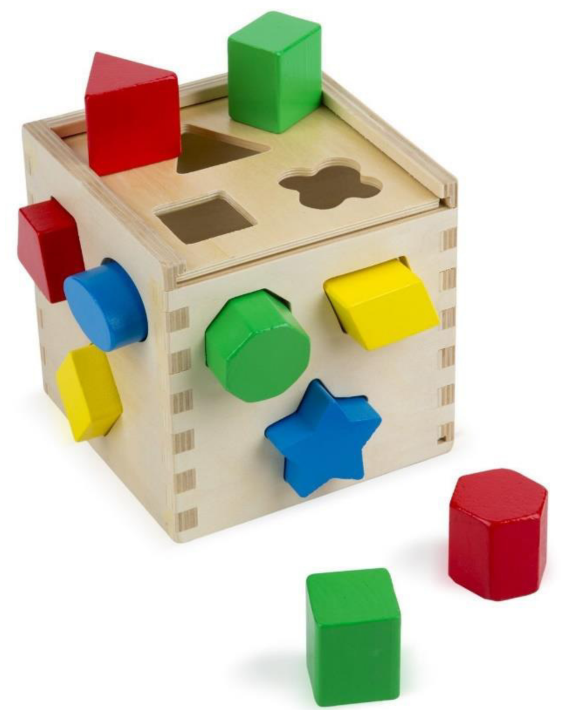
Template creation via

- Sequnces of individual event examples
- Averages, such as mean or median
- Others…



Speech Recognition - Pattern comparison

- Compare incoming signals with a set of **in prior created** templates
- Matching via distance or similarity measures
- **Template creation** on basis of **segmented and preprocessed** temporal events
  - smoothing, interpolation, cropping
  - Usage of **averages** (mean, median, etc.)



Advantages

- Simple to create and use
- Few loss of information (e.g., when using raw time-series)

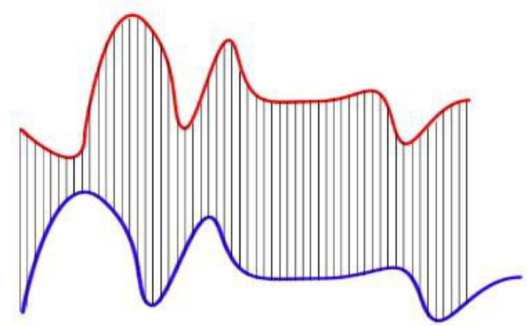
Disadvantages

- Scalability (computation time, integration of new templates)
- Depiction of complex models is difficult, especially for *Big Data*

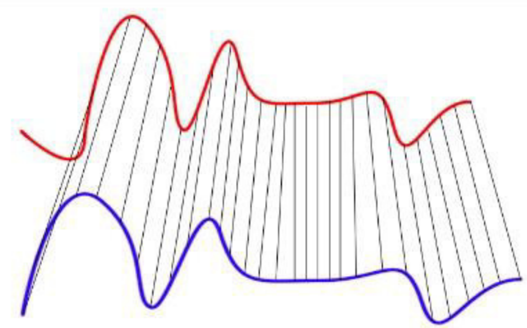
Speech Recognition - Pattern comparison

Simple approach: limited or no feature engineering

1. Static pattern comparison, e.g., euclidian
   - Despite similar shape, due **to different phases, magnitudes and lengths** a signal may not be recognized
   - For the same reasons, static algorithms may not be applicable
2. Dynamic measures, e.g., **Dynamic Time Warping (DTW)**
   - Comparing time-series sequences of **varying length** and **speed**
   - Common for analysis and recognition of **speech**
   - **Retainment of temporal dynamics** by directly modelling time-series
   - Asynchronuous curve mapping



Euclidean Matching



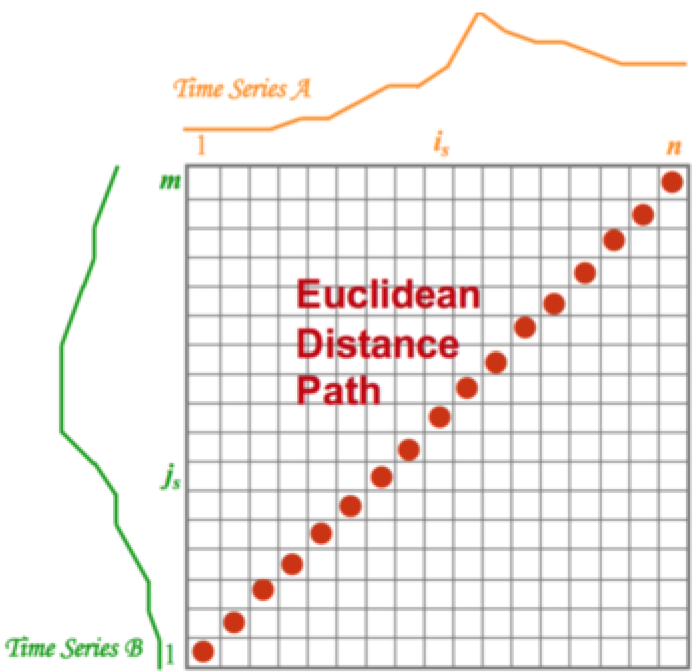
Dynamic Time Warping Matching

Source: https://sflscientific.com/data-science-blog/2016/6/3/dynamic-time-warping-time-series-analysis-ii

Speech Recognition - Dynamic-Time-Warping (DTW)

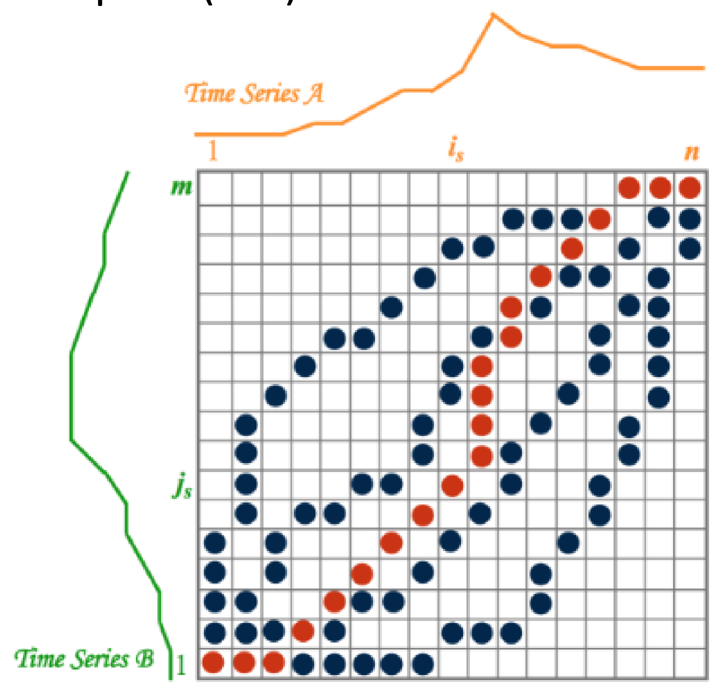
Euclidean Distance

- Sequential, linear comparison
- 1^{st} to 1^{st}, 2^{nd} to 2^{nd}, etc.



DTW

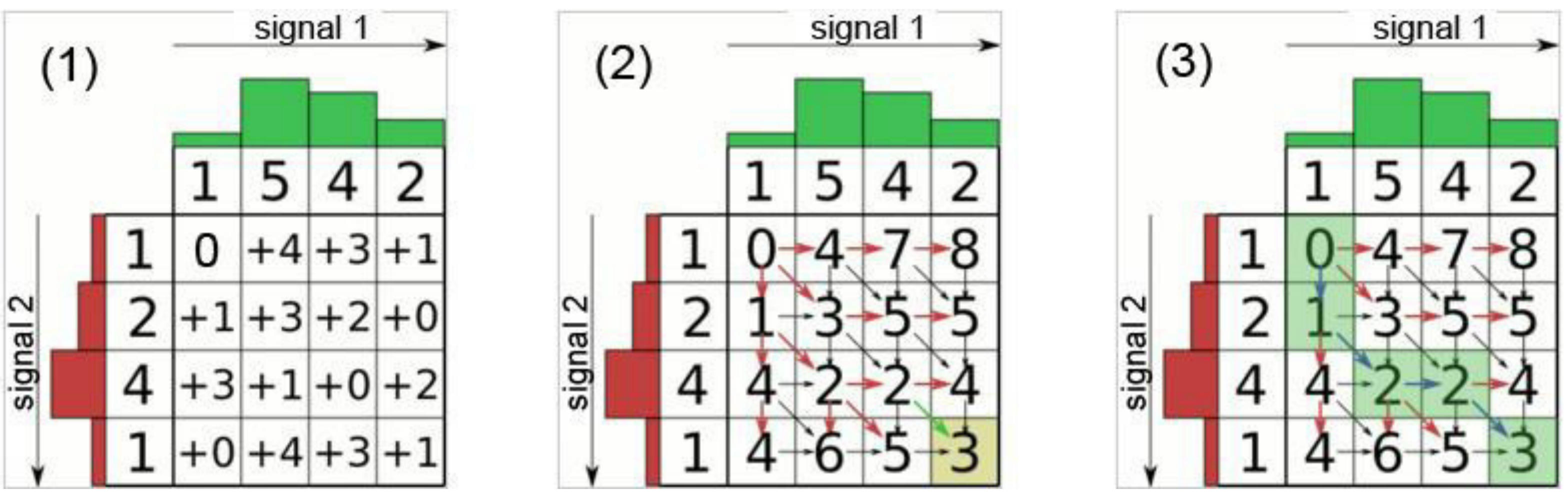
- All possible paths are checked for their warping cost…
- …the path with **the smallest cost function** indicates the optimal path (red)



Source: https://sflscientific.com/data-science-blog/2016/6/3/dynamic-time-warping-time-series-analysis-ii

Speech Recognition - Dynamic-Time-Warping (DTW)

1. **Creation of a matrix** across all points from start till end for both signals, temporal information and signal length are ignored
2. The **optimal** match in between two sequences is called **warping path**
3. The warping path contains the **smallest cost function** from warping one signal into another, it indicates the similarity between two signals



Quelle: Wikipedia // https://de.wikipedia.org/wiki/Dynamic-Time-Warping

Speech Recognition - Dynamic-Time-Warping (DTW)

- **Problem:** exponential search expense
- **Solution**: Imposition of searching constraints
  - *Monotonicity*: path never goes back in time
  - *Continuity*: path must be continuous
  - *Boundary condition*: path must cover the full sequences
  - *Warping windows*: path does not wander to far from diagonal
  - *Slop constraint*: path cannot be too steep or too shallow (see Warping Windows)

DTW is…

- …great for **flexible** comparison of time-series of different length, magnitude or phase
- …an **algorithm** for **supervised classification** which requires a template series
- …much more resource efficient when using adjusted apporaches (see **FastDTW**, **constraints** above, etc.)

Connectivity as a sensor

- **proximity detection**
- **indoor positioning** via, e.g., WLAN
  - via Received Signal Strength (RSS)
- Location-based services, e.g., avertisements, product localization by tagging
- others…

Example: Indoor Positioning via WLAN Fingerprinting

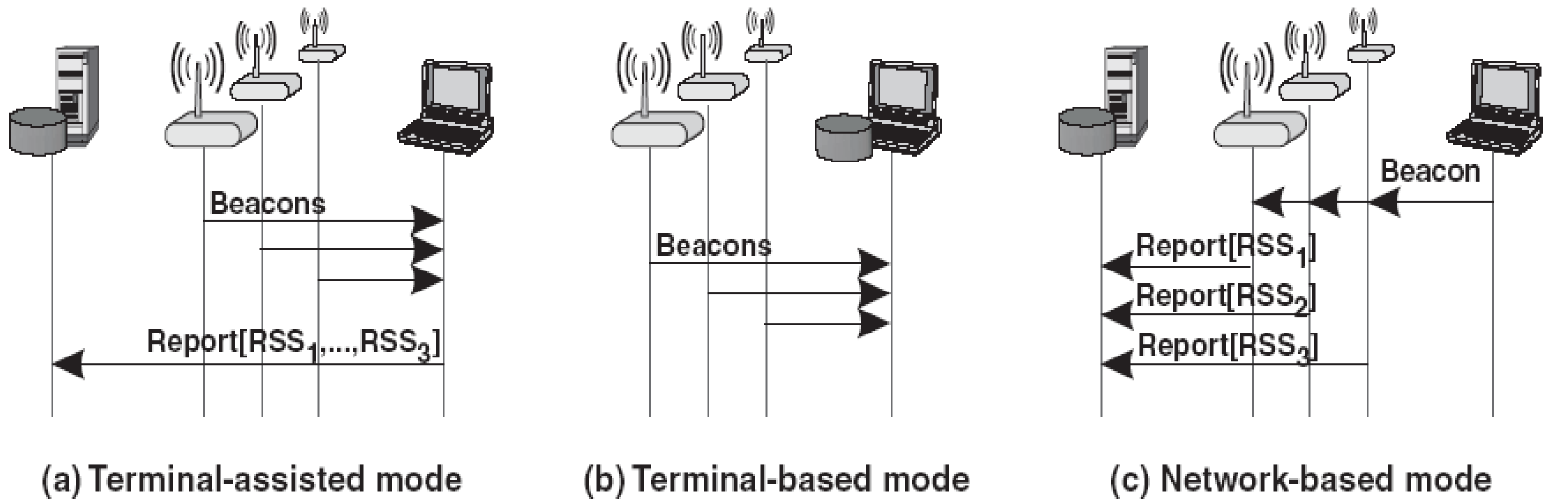
- **why**: access points are widely deployed,
  wall penetrating signals, WLAN ability of smartphones
- creation of **a radio map** by recording samples using modelling approaches (probabilistic vs. deterministic)
- live positioning by **RSS measurements** and mapping to radio map
- matching process: **classification**, **distance measurements**, etc.

Example: WLAN-Positioning via Fingerprints

Why use IEEE 802.11 components for indoor positioning?

- **Widely deployed** infrastructure
- Available on many mobile platforms
- 2,4 GHz → **signal penetrates walls** → no line-of-sight necessary
- A standard WLAN access point deployment is often already sufficient to achieve at least room-level **accuracy**

WLAN Positioning – TA, TB, NB



Terminal assisted (TA)

- Measurements are made at the terminal
- Position calculation happens at the server

Terminal based (TB)

- Measurements and position calculation are made at the terminal

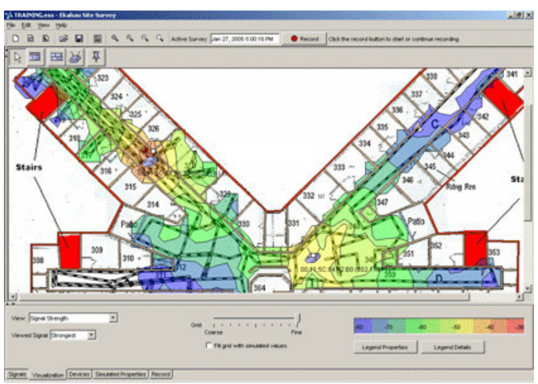
Network based (NB)

- Beacons are emitted by terminal
- Measurements and calculation are done at the server

WLAN Fingerprinting – Idea

WLAN Fingerprinting

- Derive position from **patterns of signals** received from/at several WLAN access points
- Observable: **received signal strength** (RSS)
- **Offline phase**
  - **Record** well-defined RSS **patterns** for **well-defined reference positions** and store them in a radio map
  - Due to **line-of-sight conditions** on the spot, it might be necessary to observe RSS patterns from **several directions** for **each position**
- **Online phase**
  - **RSS patterns** related to the target are recorded and **compared** with the RSS fields of the entries stored in the **radio map**
  - **Position** of the target is extracted from the reference position with the **closest match**



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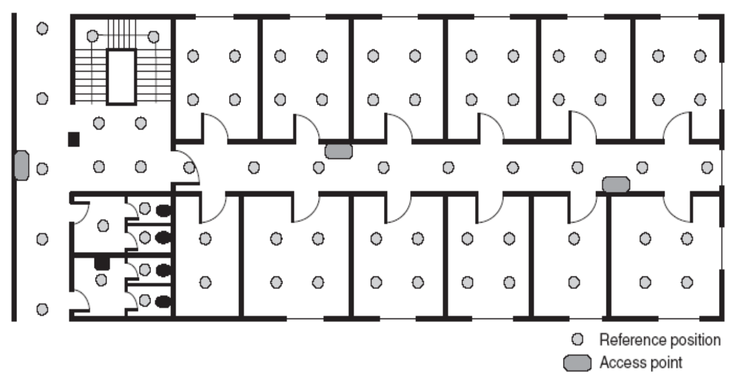


WLAN Fingerprinting – Example of a Radio Map

Position	Direction	RSS / [dBm] from 00:02:2D:51:BD:1F	RSS / [dBm] from 00:02:2D:51:BC:78	RSS / [dBm] from 00:02:2D:65:96:92
Pos. 1	0°	-59	-75	-71
	90°	-54	-73	-67
	180°	-49	-72	-69
	270°	-55	-73	-65
Pos. 2	0°	-35	-64	-50
	90°	-27	-64	-43
	180°	-40	-65	-52
	270°	-30	-60	-64
Pos. 3	0°	-69	-66	-73
	90°	-65	-60	-68
	180°	-63	-66	-70
	270°	-68	-62	-76

$$m = \begin{pmatrix} -65 \\ -57 \\ -71 \end{pmatrix} \; ? \longrightarrow \text{Pos. 3, 0°}$$

$$\arg\min_i \left(\left| m - f_i \right| \right)$$

WLAN Fingerprinting – Empirical vs. Modeling Approach

Empirical approach for measuring signal distribution

- Create radio maps **from measurements**
- Disadvantages
  - **Time consuming**
  - Measurements must be **repeated whenever the configuration** of access points **changes**

Modeling approach for determining signal distribution

- Create radio maps **from** a **mathematical model**
  - **Calculate the radio propagation** conditions taking into account the positions of access points, transmitted signal strengths, free-space path loss, obstacles reflecting or scattering signals, …
- Disadvantages
  - **No measurement** of signal strenghs **by hand**
  - **Complexity** and accuracy of mathematical models

WLAN Fingerprinting – Deterministic vs. Probabilistic Approach

Deterministic Approach

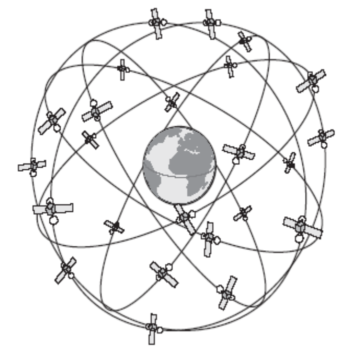
- Record several RSS samples for each reference position and direction
- Create **radio map** from **mean values** of these samples
- **Online phase**: match observed and recorded sample according to Euclidian distance and adopt the reference position with the smallest distance as the current position of the terminal

Probabilistic Approach

- Describe **variations** of signal strengths experienced during the offline phase by **probability distribution**
- Probability distributions of various access points are applied to the observed RSS pattern to **find the most probable position**
- **Accuracy can be significantly refined** compared to the deterministic approach

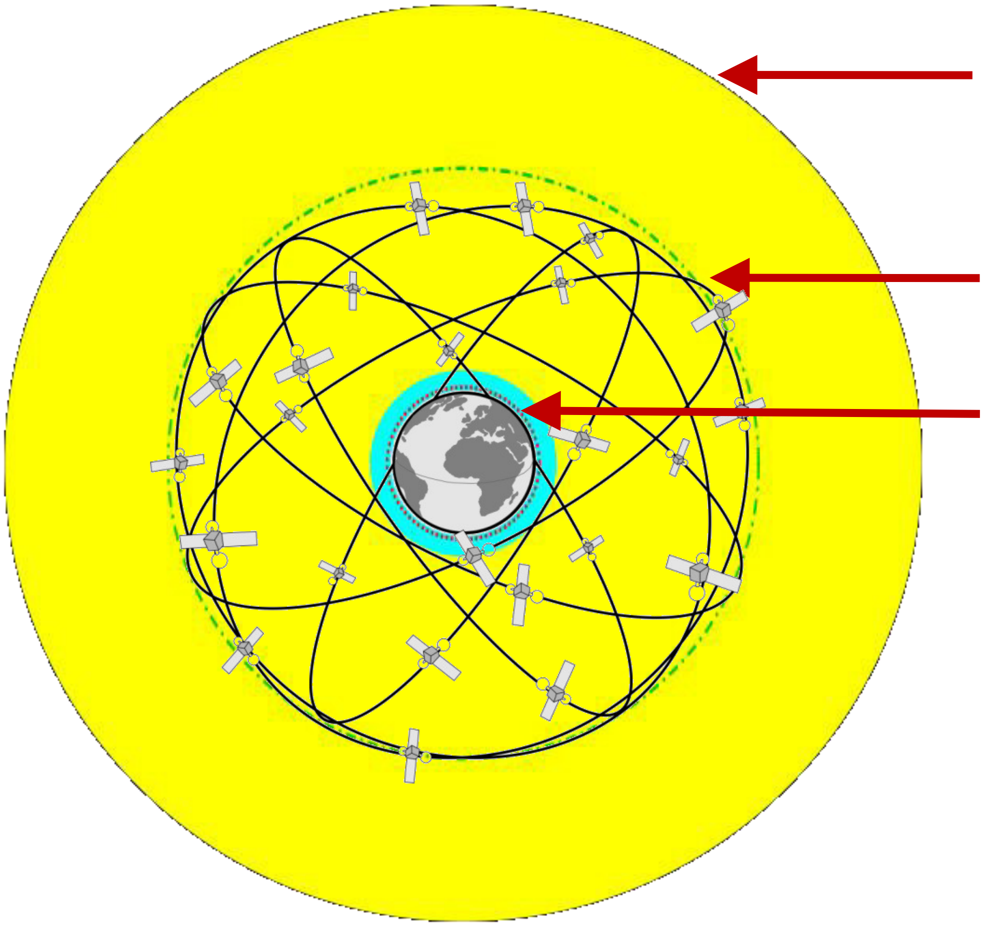
Outdoor positioning

- Goal of positioning: derive the geographic position of a target with respect to a spatial reference system
- Spatial reference system
  – Coordinate system (Ellipsoidal/Cartesian)
  – Projection (if location is to be represented on a map)



- Satellites are generally located within the Medium Earth Orbit (MEO)
- Positioning via **circular trilateration**, needs 3 satellites within 2D- and 4 within 3D-space localization
- Generally used satellite systems: **GPS, Beidou / Beidou 2, Galileo, GLONASS**

Outdoor positioning – GPS



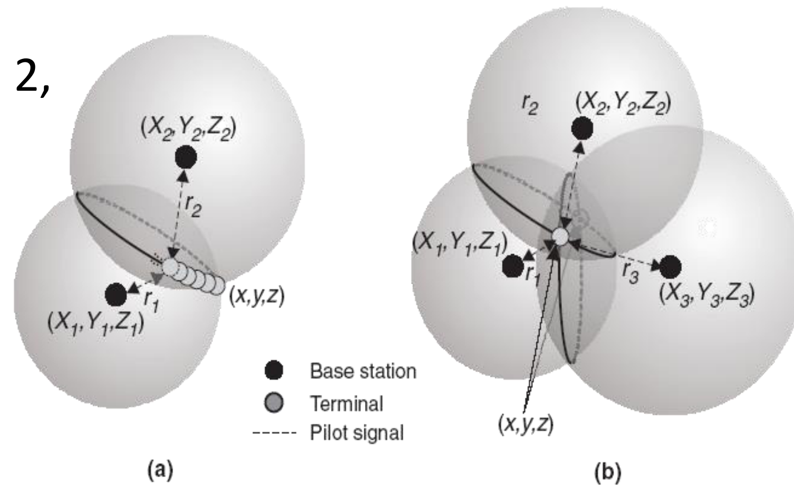
Geostationary Orbit, e.g., Communication, TV, Meteorologie (ca. 36.000 km)

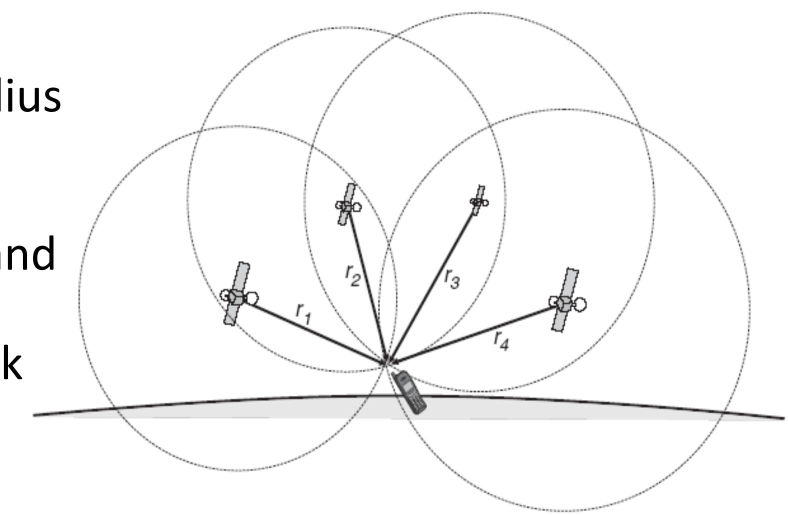
MEO: Medium Earth Orbit, e.g., **GPS satellites** (ca. 20.200 km)

LEO: Low Earth Orbit, e.g., ISS (ca. 700 km)

Outdoor positioning – circular trilateration

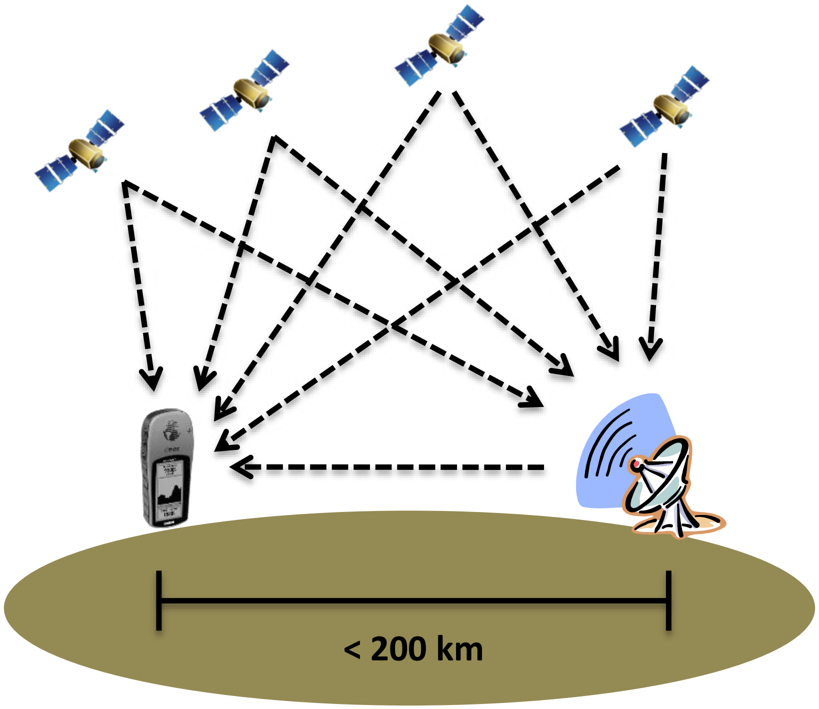
- **Known:**
  - Position $p_i = (x_i, y_i, z_i)$ for satellites i ϵ {1, 2, 3, 4} at time t_i
  - Inaccurate reception time tr_i
  - Speed of light c
- **Unknown:**
  - Position p
- **Calculation:**
  - $r_i = (tr_i – t_i)*c$ for i = **1,2,3**
  - Estimate position p_{est} : intersection of spheres (centered on satellite i with radius $r_{i)}$
  - P_{est} contains the coordinates (x,y,z), determined on basis of the signals 1,2 and 3
  - P_{est} is **not accurate** due to different clock times at the satellites and the receiver
  - Signal 4 is now used to determine the corrected reception time ***t***





Outdoor positioning – differential GPS (DGPS)

- Reference station (RS) located at a known and accurately surveyed point
- RS determines its GPS position using four or more satellites
- Deviation of the measured position to the actual position can be calculated
- Variations are valid for all the GPS receivers around the RS
- Corrections are transmitted by radio



Motion sensing

Source: http://www.biomech-solutions.com/images/sensores-biomecanicos-2.jpg

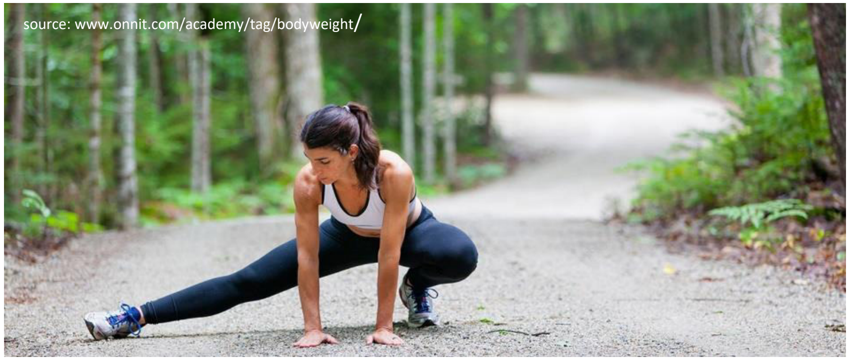
Use within

- Medical applications
- Vehicles, Traffic and Driving behaviour
- Physical activities and fitness
- Gesture recognition and control

Activity Recognition on basis of human motion

- **Offline** or **online** tracking of motion data (acceleration, rotation, etc.)
- Preprocessing, interpolation, smoothing, and segmentation
- Template creation or selection of expressive feature sets
- Classification via **pattern matching**, **distance measurement**, **clustering (unsupervised)** or **supervised approaches**

Motion sensing - human activity



Category 1: predictable motion	**Category 2: unpredictable motion**
Predicable motion patterns and events	No patterns are or predictable events
Mostly symmetric	No symmetries
Segments of defined temporal duration	No in prior defined motion segments

Recognition and **assessment** on basis of

- Ideal motion motion curves of **defined events** with a **similar, determinable length**
- Template matching
- Examination of energy potentials and variances
- Temporal features

Analysis and **Assessment** on basis of

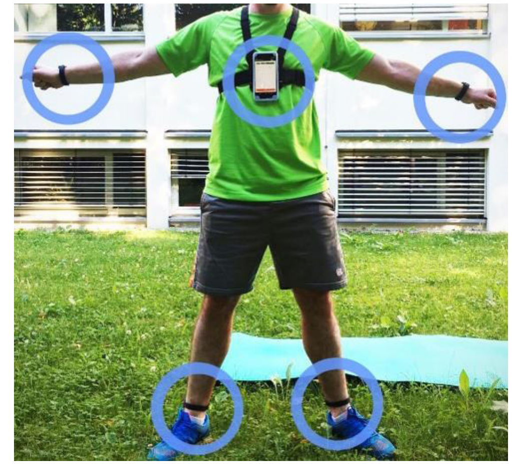
- Examination of motion segments with significant characteristics and **variable length**
- Mapping of physical skills to numerical features
- Identification and extraction of features from segment characteristics

Motion sensing - tracking human activity

- **Tracking with wearables**
  - accelerometer & gyroscope
  - light sensor
  - thermometer
  - barometer
- In general, sample rates in between **40 Hz -100 Hz** are sufficient

- Numerous solutions are commercially and open source available by now:
  - XSENS - http://www.biomech-solutions.com/
  - EnFlux - https://enflux.com/
  - MbientLab - https://mbientlab.com/
  - SensX

- Commonly access to **raw data** and realtime visualization (Unity, Blender, etc.)
- Usage also for **motion captureing**

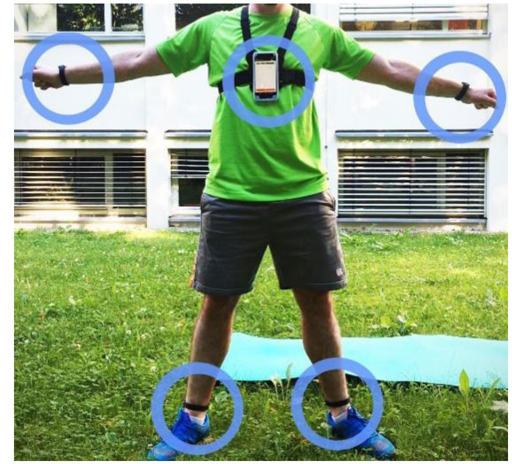


Motion sensing - data input

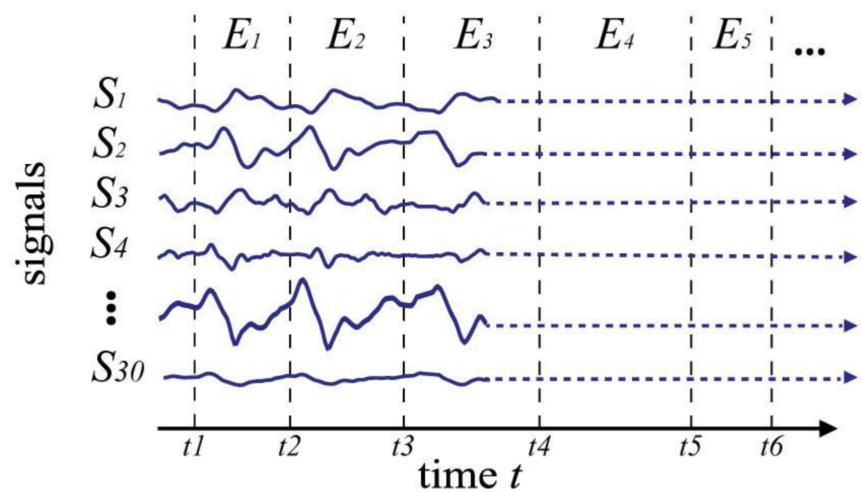
A distributed sensor system provides:

- **Continuos**, **multi-dimensional** data stream
- **Sequential** series of **events** with **individual length**
- Commonly, each sensor covers the 3 dimensions into **X-, Y-, and Z-direction**
- Signals have an individual sampling rate and may be delayed
  - different **sensor hardware**
  - transportation issues
  - Interface dependent

  → **synchronization** is needed at a central location

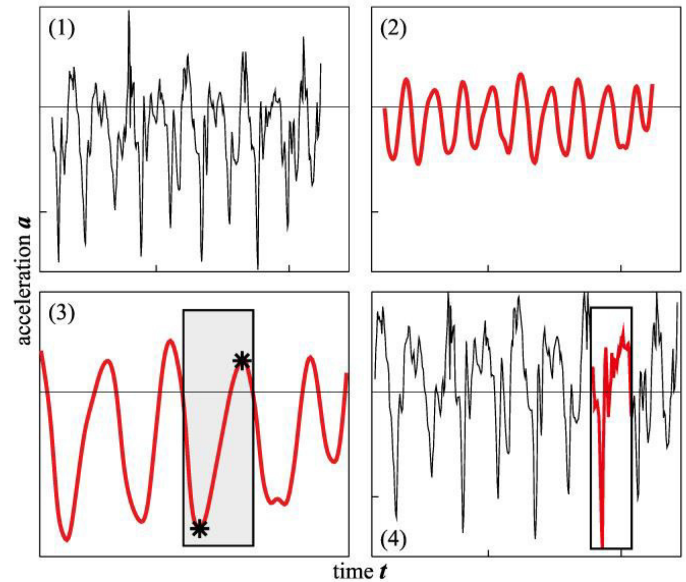


Above, the applied SensX sensor system is depicted. Below, a scheme of its data input tracking a sequential event series is shown.



Motion sensing - segmentation of predictable motion

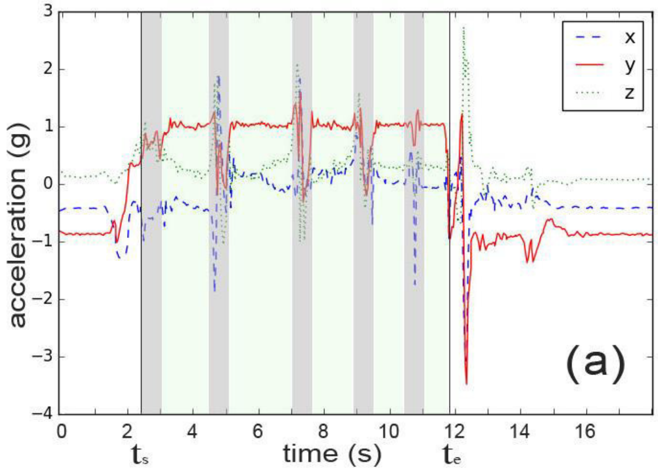
- Event length is **similar but not equivalent**
- Adaptive segmentation process in order to
  - Avoid noise within individual segments
  - Increase the classification success
- General segmentation process:
  1. Identify the **most meaningful signal** within the signal set
  2. **Harsh smoothing** (Savitzky-Golay, low pass filters (e.g., Butterworth), etc.)
  3. Sequential detection of periodic events on basis **local extrema fingerprints**, storing of start and end timestamps
  4. **Extract each event** out of all parallel tracked signals based on the noted start and end timestamps
- Each event is described by a signal set of the size *S*, whereby *S* is dependent on the number of used sensor platforms *p*, sensors *s*, and covered dimensions *d: S = p*s*d*



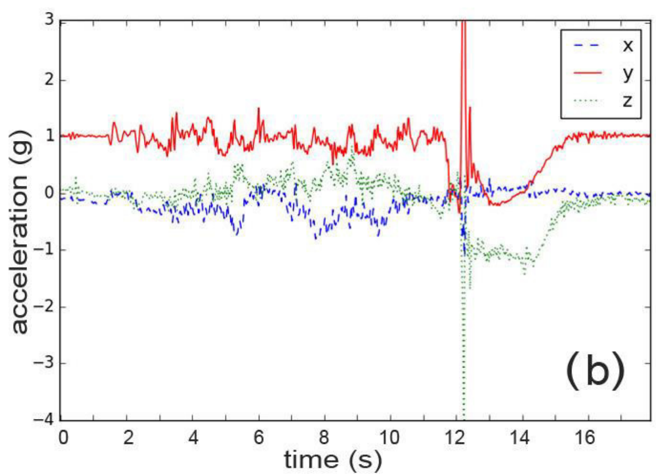
The **Most-Meaningful-Sign**al is determined by facilitating the standard deviation:

$$\sigma = \sqrt{Var(X)} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}}$$

Motion sensing - How to segment unpredictable motion



(a) Left hand acceleration during climbing



(b) Chest acceleration during the same route as (a)

Example: Segmentation of climbing activity

1. Initial **smooting** (Butterworth, Savitzky-Golay, etc.)
2. Segmentation of **climbing** activities from **noise** activities for a specific climbing route
   - **750ms sliding window**, applied sequentially
   - Identification of a climbing activitie's start and end (t_s and t_e) on basis of the athlete's **hands positions**
   - An active climbing phase starts, if both hands are positioned upwards
3. Segmentation of **active climbing** from **rest phases**
   - Released energy potentials are depicted by the sum of the mean deviations of all dimensions ***(X,Y,Z):***

     $\boldsymbol{S = S_X + S_Y + S_Z}$
   - Empirical determination of threshold ***T***
     - if $S < T \rightarrow$ rest phase
     - if $S > T \rightarrow$ active climbing phase
4. **PCA:** Chest sensor provides no distinctive pattern for segementing rest and active climbing phases:
   - no segmentation for the chest sensor data

Motion sensing - feature extraction

- Description of **real world features** with **numerical values**
- Features for human motion description may be
  - **used energy potentials**
  - **Runtime**
  - **Stability**
  - **Exhaustion**
  - **Strength**
  - **Speed**
  - **Others…**
- Organization of features within vectors
- Each vector describes one **event instance**
- Lists of instances function as a basis for the **following classification**, e.g., by supervised learning algorithms

Environmental sensors

Device orientation and proximity sensing

- Navigation (e.g., compass, dead reckoning, etc.)
- Control of applications (e.g., video games)
- Device and software adaption to the user‘s context

Source: http://www.bergfreunde.de

Environmental sensing

- **Temperature** measurement
- **Screen control** via ambient light
- **Context creation** via humidity or height detection
- …one discrete, single value (set) is sufficient for most applications

Further information

- Control of smartphone sensors on Android devices
  - https://developer.android.com/guide/topics/sensors/sensors_overview.html
  - https://developer.android.com/guide/topics/media/index.html
  - https://developer.android.com/reference/android/media/AudioRecord.html

- Environments for data processing, classification and clustering
  - https://www.scipy.org/, http://www.numpy.org/
  - https://www.gnu.org/software/octave/
  - https://www.cs.waikato.ac.nz/ml/weka/