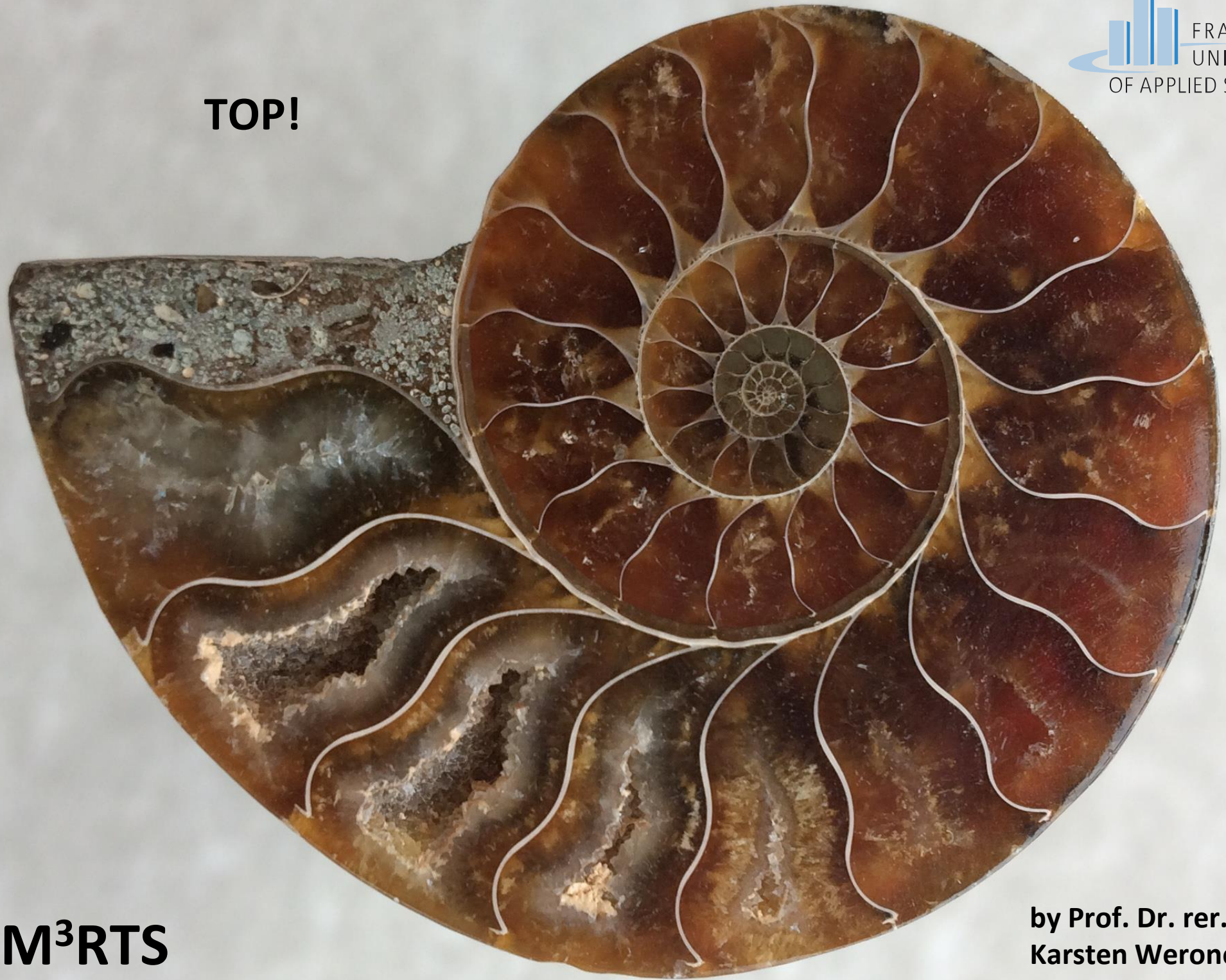


TOP!



M³RTS

by Prof. Dr. rer. nat.
Karsten Weronek

M³Real-Time-Systems

SS 2017

Prof. Dr. rer. nat. Karsten Weronek
Faculty 2
Computer Science and Engineering

[Top!](#)

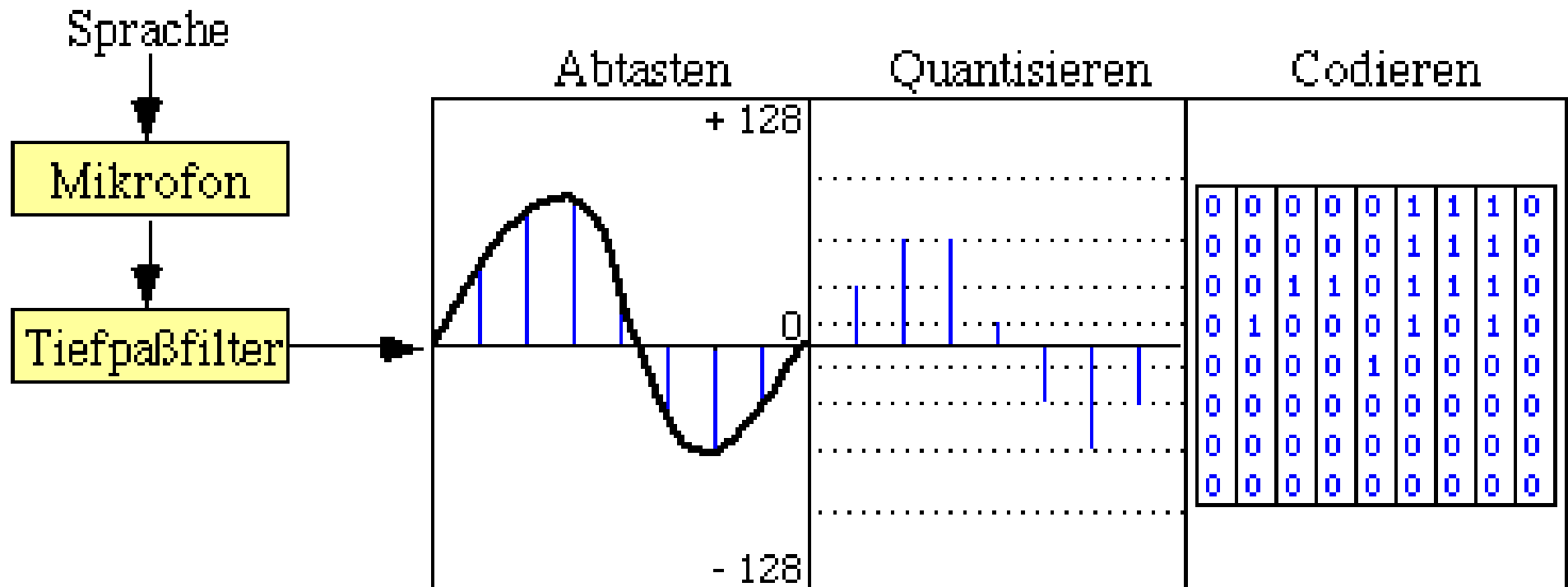
A Sensor converts a physical or chemical measure
into electrical signals.

Example:

A microphone converts an alternating air pressure
into electrical alternating voltage.

An analog/digital-converter (ADC) digitalizes the alternating voltage
to digital Data.

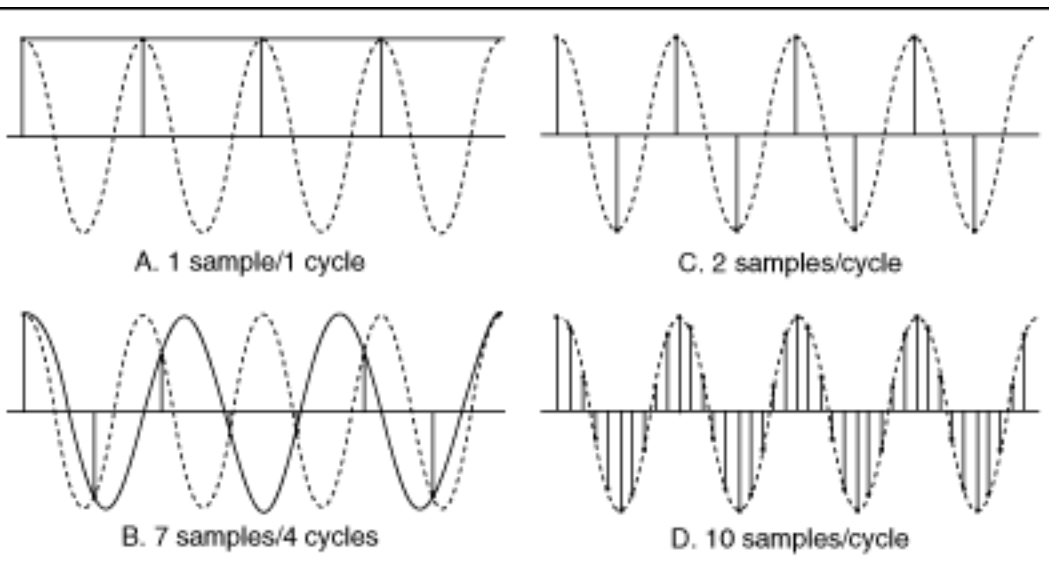
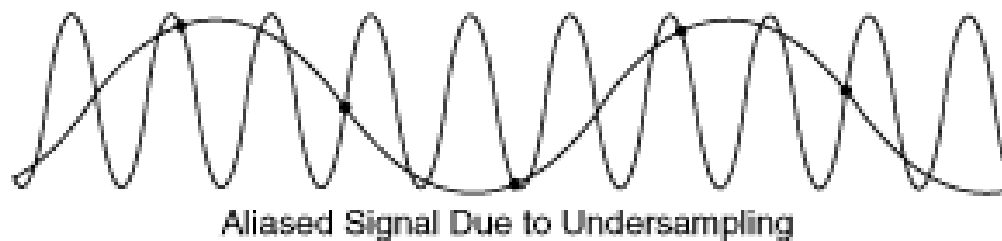
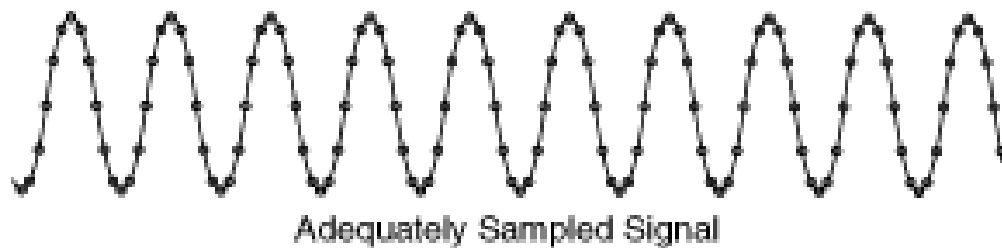
digital data of sensors is called raw-data



Import for DAC:

How many bits need to be used to hit the minimal error?

Sampling frequency: needs to be at least twice the maximum of the recorded signal
(Nyquist Theorem) therefore we need a low pass filter



An aliased signal provides a poor representation of the analog signal. Aliasing causes a false lower frequency component to appear in the sampled data of a signal. The following illustration shows an adequately sampled signal and an inadequately sampled signal. In this illustration, the inadequately sampled signal appears to have a lower frequency than the actual signal—two cycles instead of ten cycles.

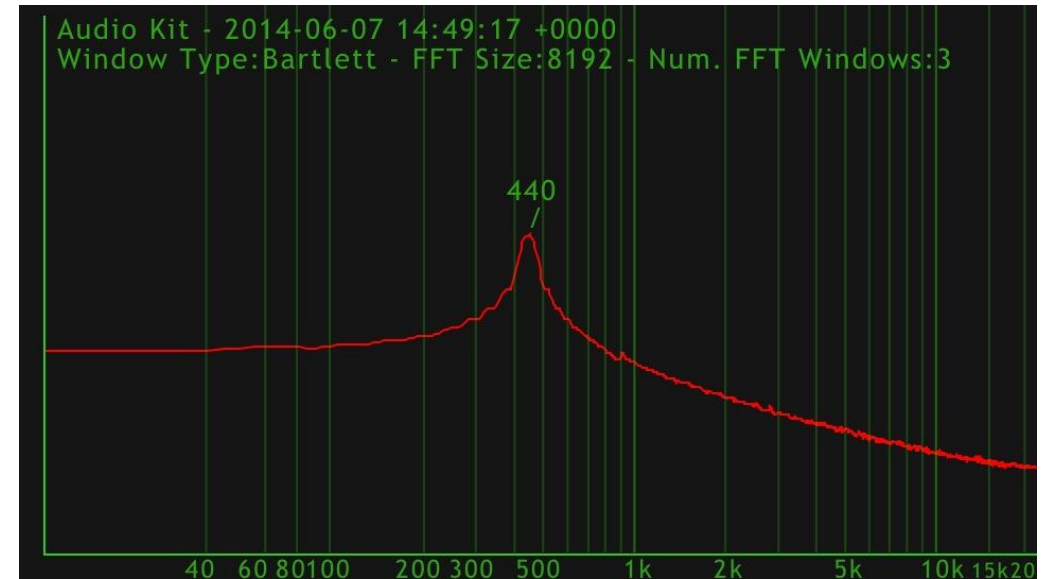
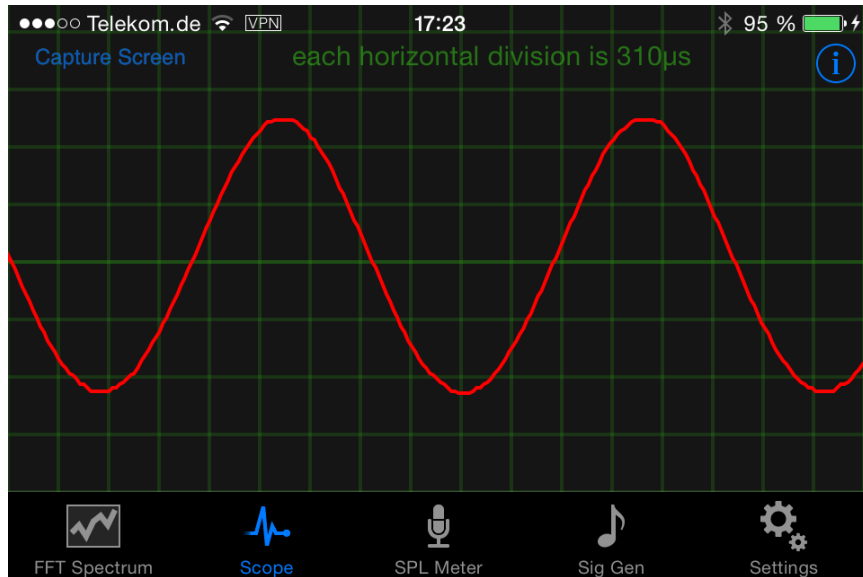
In **case A** of this illustration, the sampling frequency f_s equals the frequency f of the sine wave. f_s is measured in samples/second. f is measured in cycles/second. Therefore, in case A, one sample per cycle is acquired. The reconstructed waveform appears as an alias at DC.

In **case B** of the previous illustration, $f_s = 7/4f$, or 7 samples/4 cycles. In case B, increasing the sampling rate increases the frequency of the waveform. However, the signal aliases to a frequency less than the original signal—three cycles instead of four.

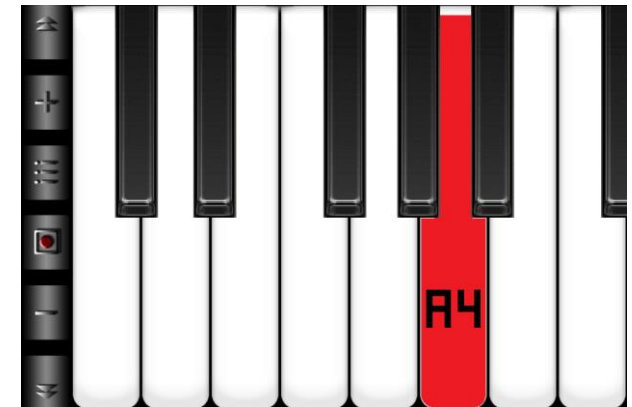
In **case C** of the previous illustration, increasing the sampling rate to $f_s = 2f$ results in the digitized waveform having the correct frequency or the same number of cycles as the original signal. In case C, the reconstructed waveform more accurately represents the original sinusoidal wave than case A or case B. By increasing the sampling rate to well above f , for example, $f_s = 10f = 10$ samples/cycle, you can accurately reproduce the waveform.

Case D of the previous illustration shows the result of increasing the sampling rate to $f_s = 10f$.

Tuning Fork (Stimmgabel)



The sound waves of the Tuning Fork are being transformed into electrical alternating voltage by the microphone (see upper image). By doing a Fast-Fourier-Transformation (FFT) it is indicated that the maximum frequency spectrum is at 440Hz. This results in „A4” on the piano with semantic annotation.

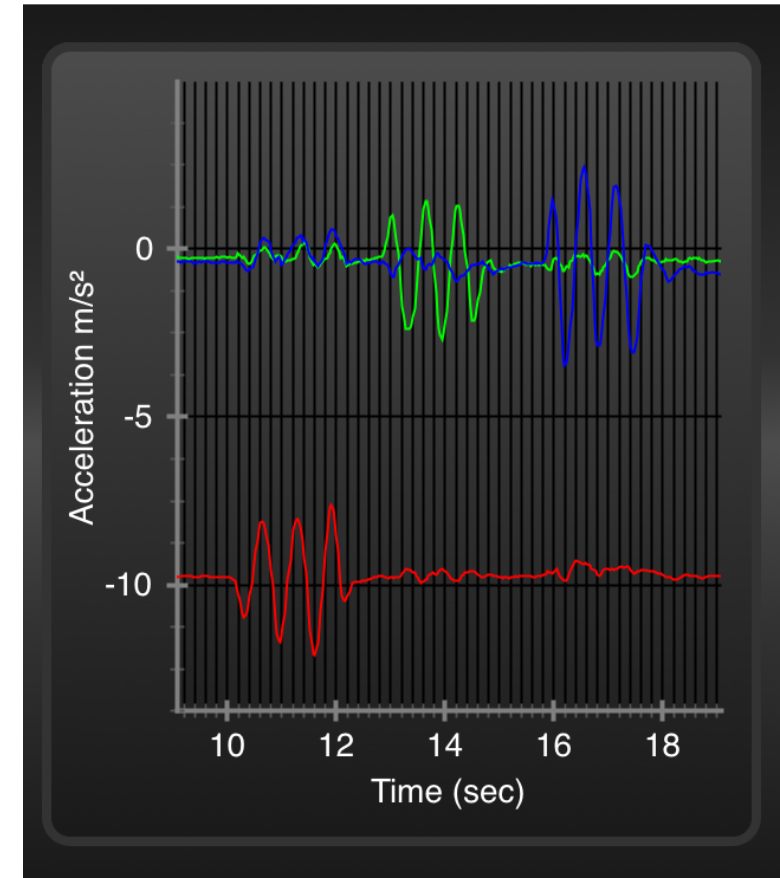


1.2.2 Accelerometer/Der Beschleunigungssensor

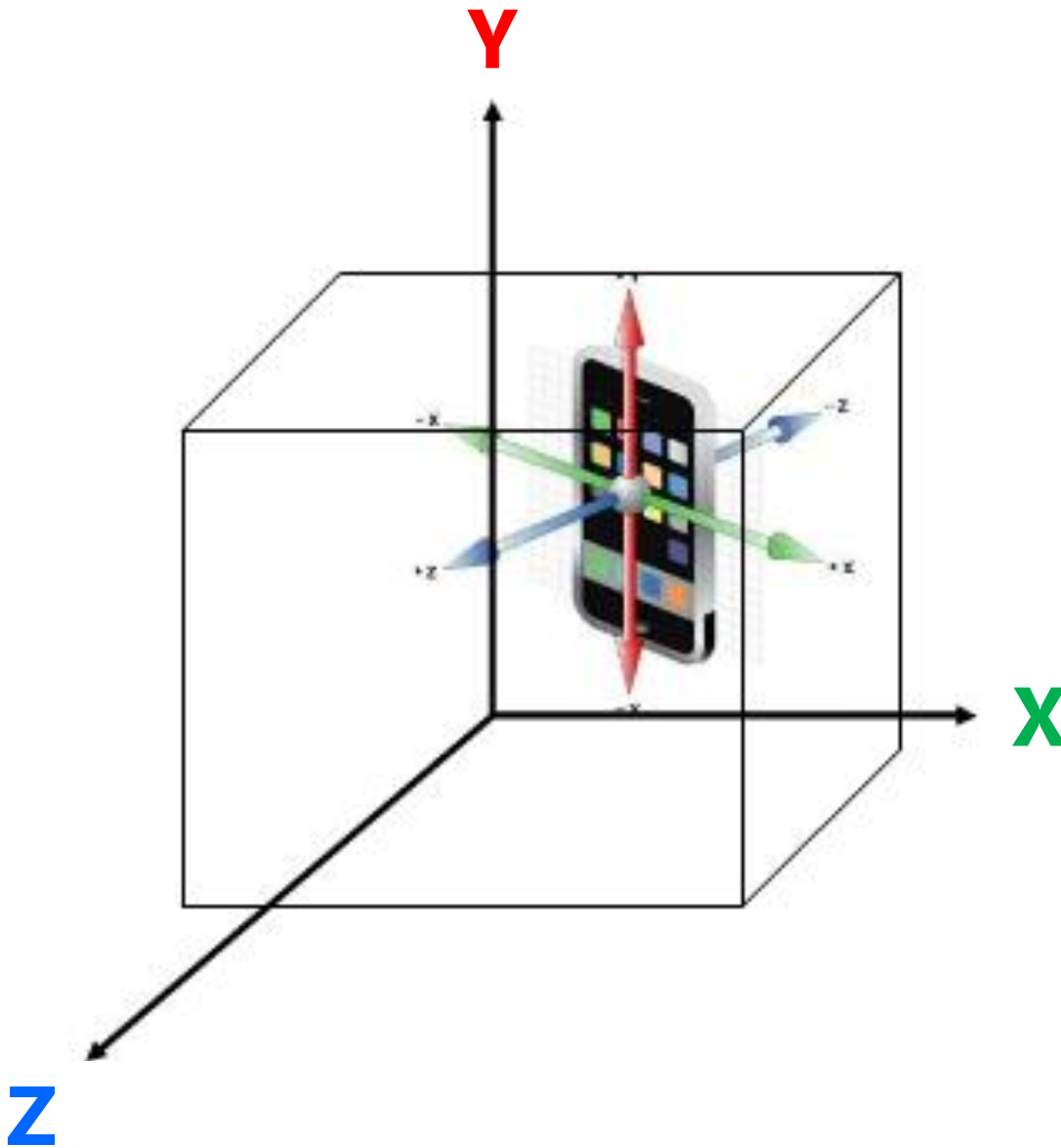
●●●○ Telekom.de 23:29 VPN 15 %

Back

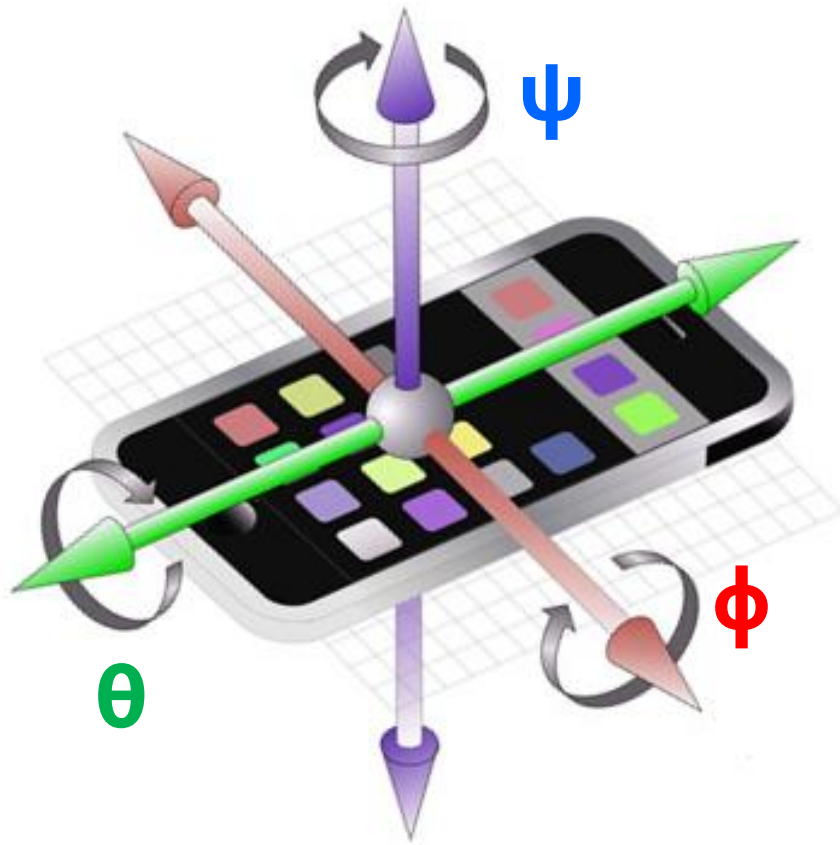
Accelerometer



Start Clear Zoom X,Y,Z F Legend



1.2.3 Gyroscope/Gyroskop-Sensor

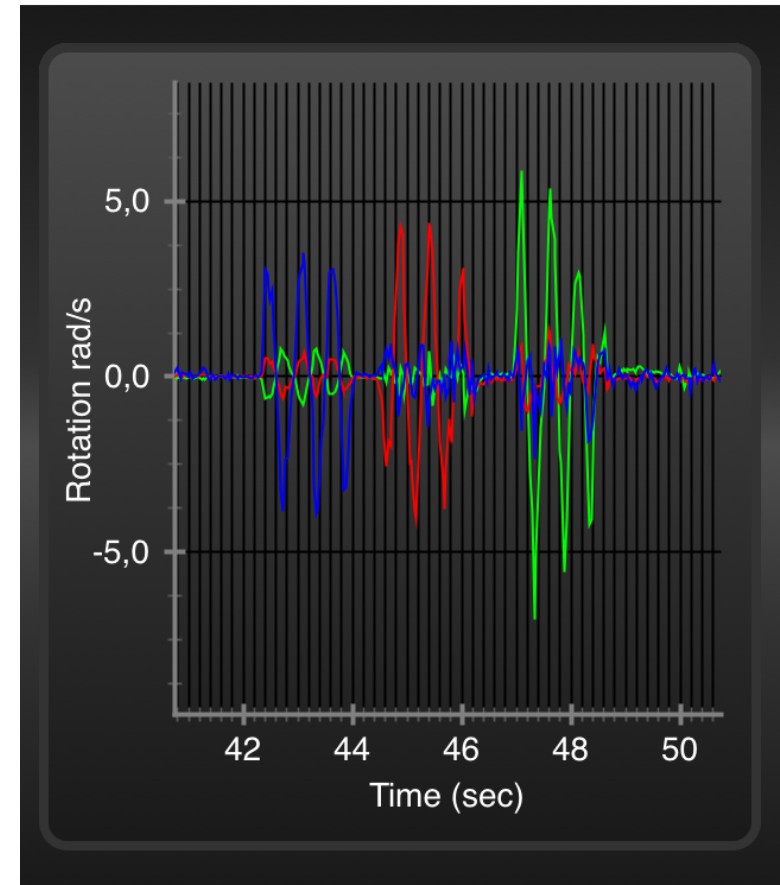


θ : roll/Rollwinkel
 ϕ : nick/Nickwinkel
 ψ : yaw/Gierwinkel

Telekom.de 23:30 VPN 15 %

Back

Gyroscope



Start

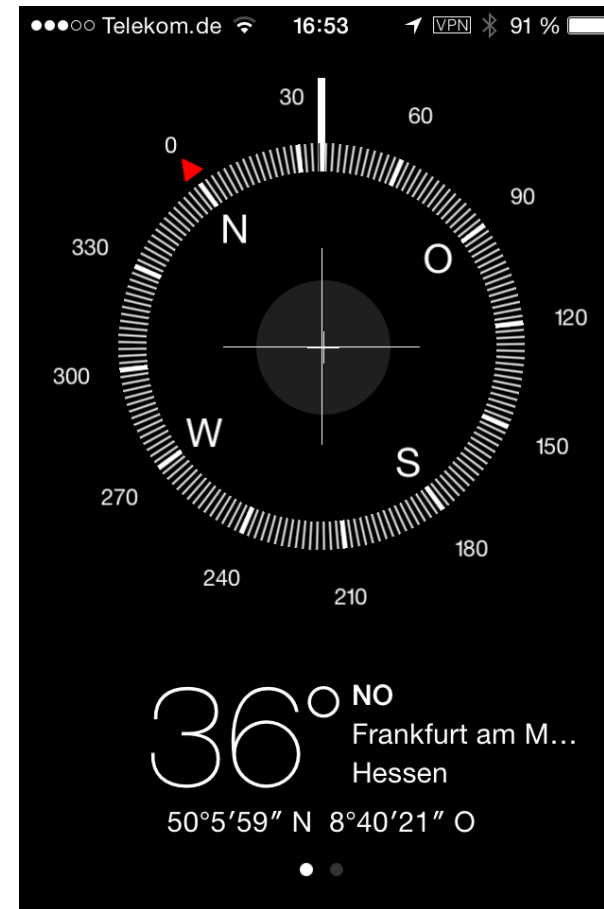
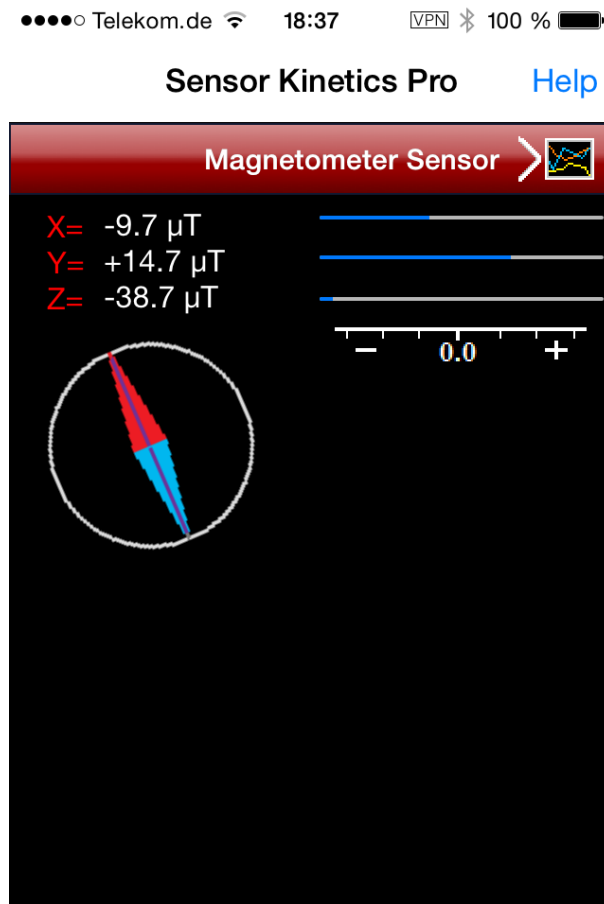
Clear

Zoom

F

Legend

1.2.4 Magnetometer/Kompass, GPS

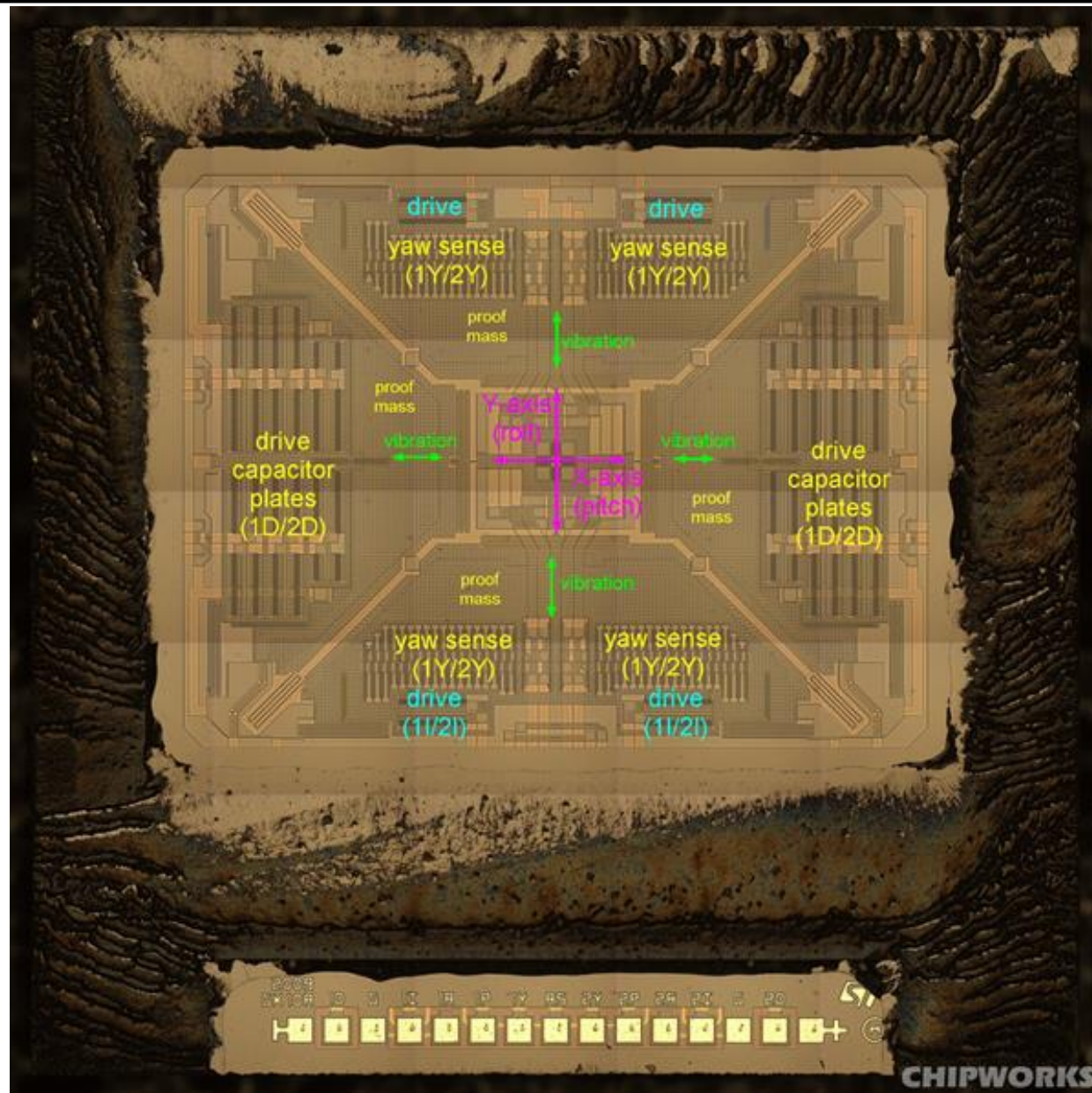


← GPS-Data:
geographical
width & length

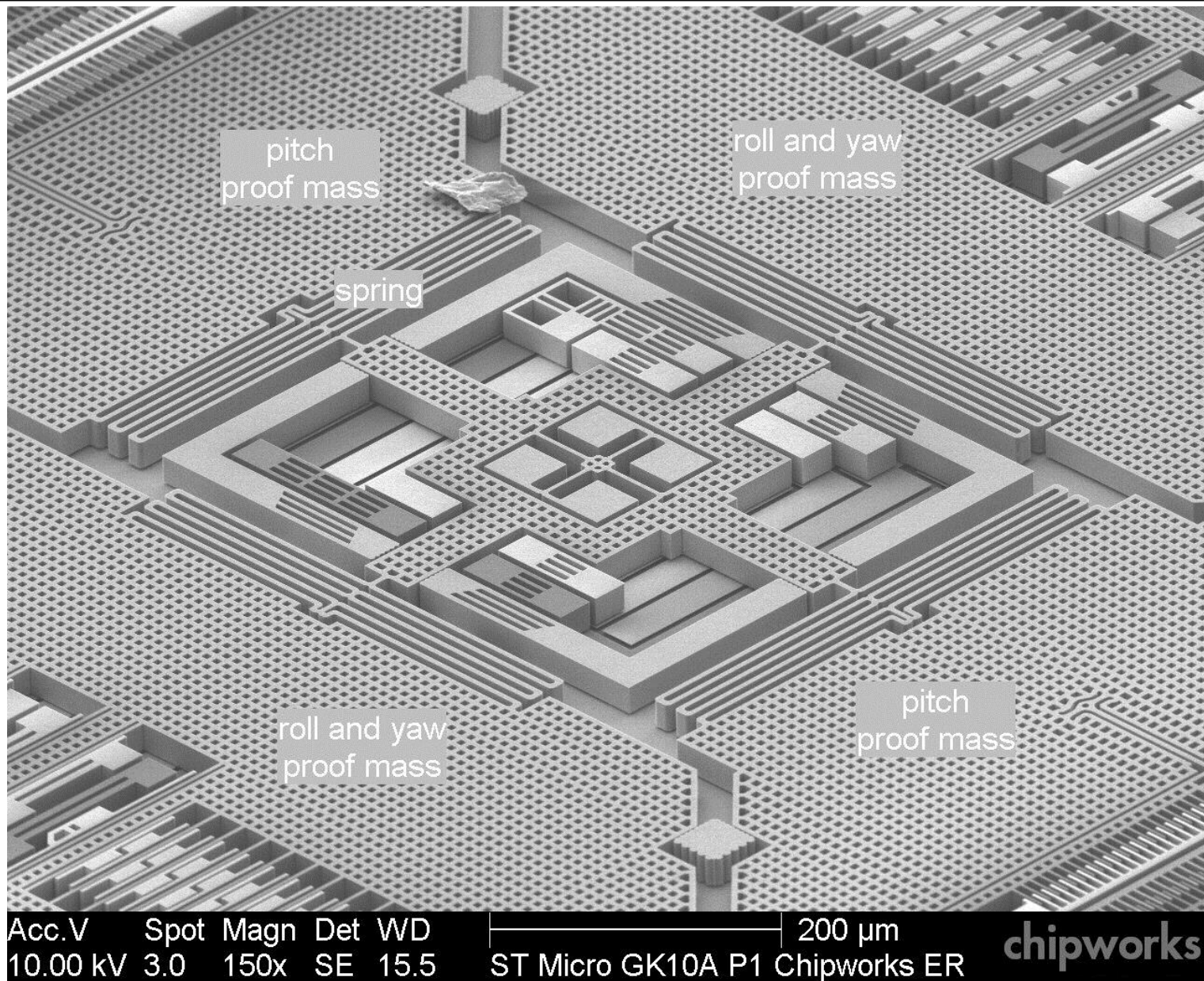
By projecting and correcting an angle of 36° towards the geographical north, we get $(x,y,z)=(-9,7\mu T, +14,7\mu T, -38,7\mu T)$ from the magnetic field strength.

The direction of north-east is derived by semantically annotating the 36° .

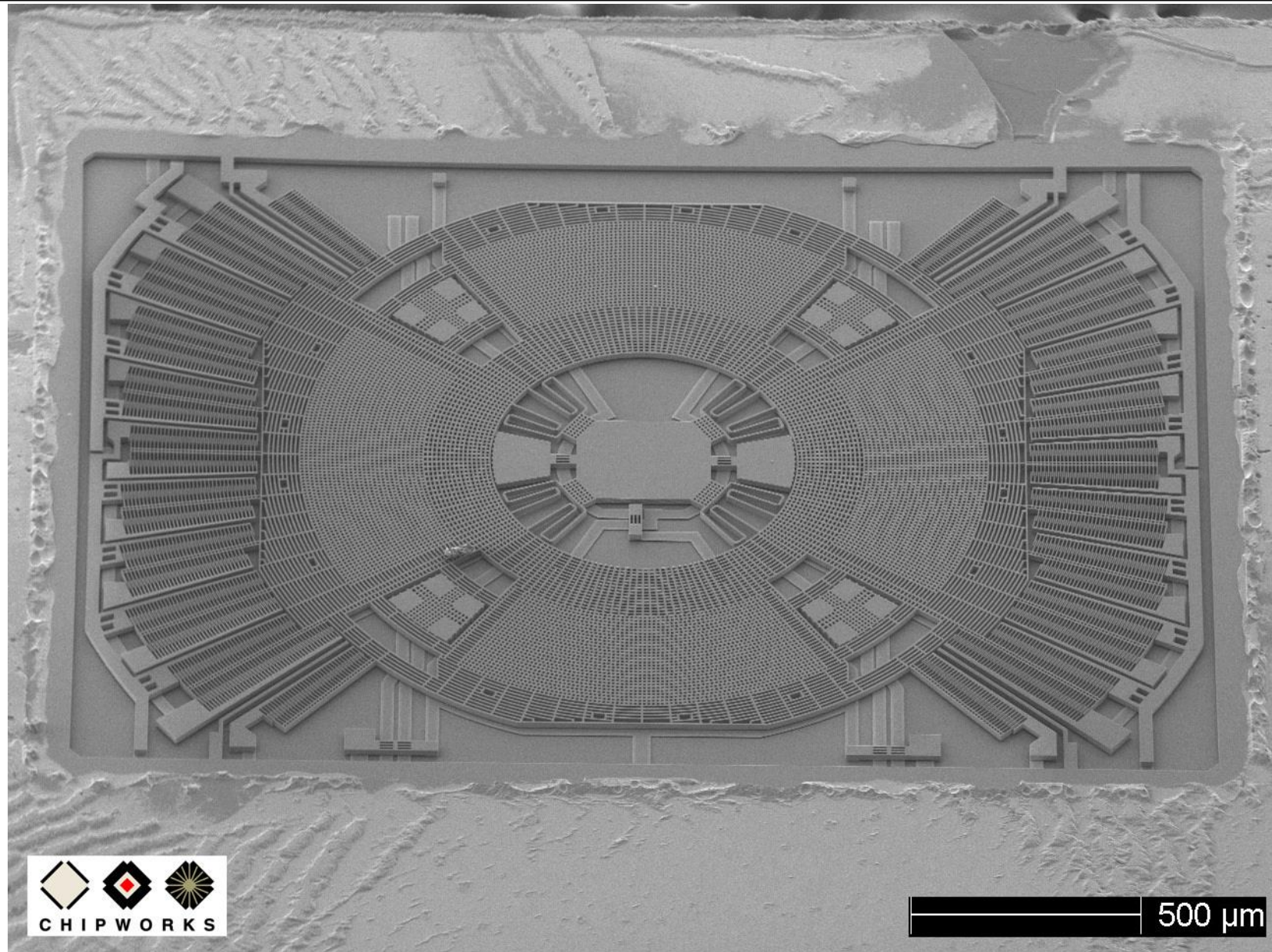
1.2.5 MEMS: Micro Electronic Mechanical Systems



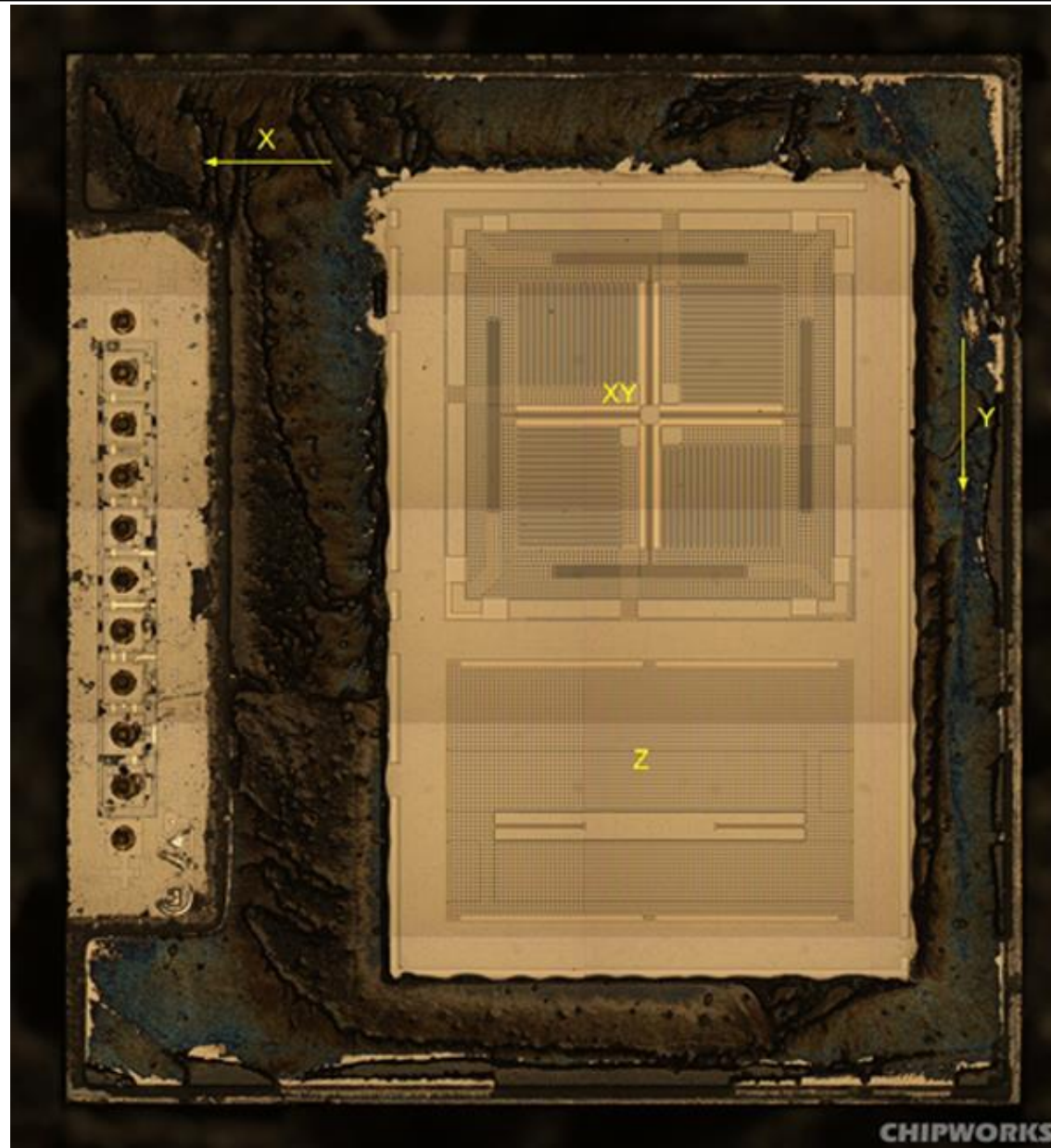
MEMS: Accelerometer iPhone4



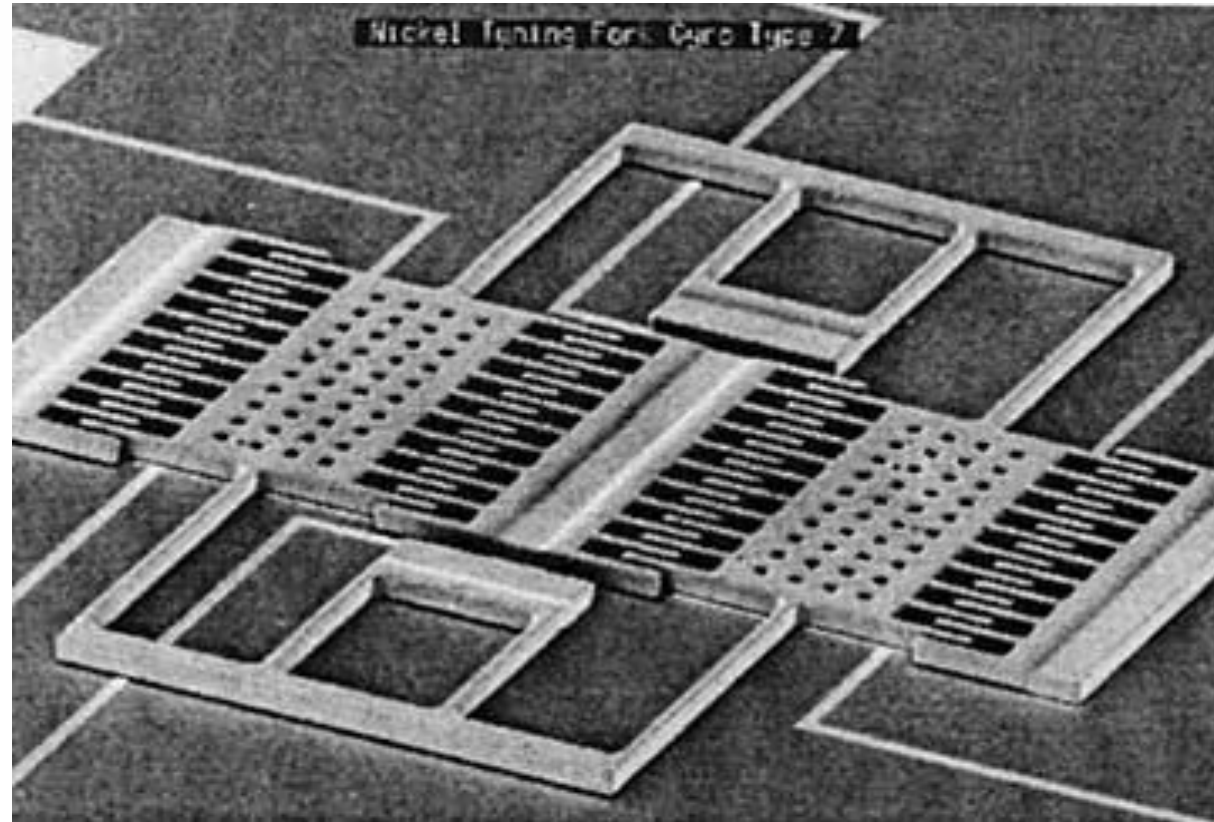
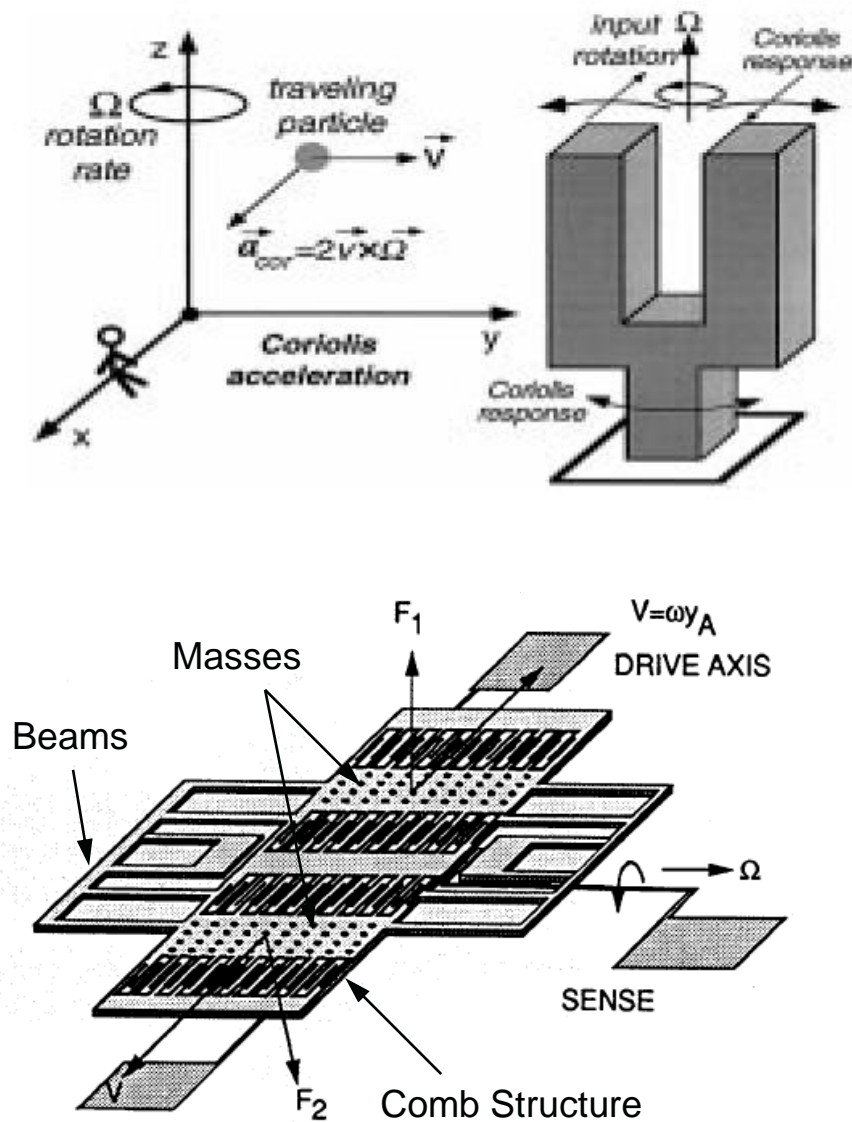
1.2.6 MEMS: Gyroscope



1.2.6 MEMS: Accelerometer



Charles Stark Draper Laboratory: Tuning Fork



Overview

1 Technology: Sensors used in Smartphones

1.1 Sensors and how they work

1.2 Data Capturing with Sensors

1.3 Mobile Transmission of Sensor Data

2 Application: Meaningful Analysis of Location and Movement Data

3 Research, Development & Expectations

Summary and your Questions!

1.3.1 Data Transmission

| | Cable | Bluetooth | NFC | WLAN | 2G/3G/4G |
|-----------------------------------|-------|-----------|-----|------|----------|
| Sensor → Mobile-Phone | ✓ | ✓ | ✓ | ✓ | (✓) |
| Mobile-Phone → Mobile-Phone | — | — | — | ✓ | ✓ |
| Mobile-Phone → Internet | — | — | — | ✓ | ✓ |

NFC: Near Field Communication

2G: **GSM** (Global System für Mobile Communication), **EDGE**

3G: **UMTS** (Univ. Mob. Telecomm. System), **HSDPA**, (Non-Europa: auch CDMA2000)

4G: **LTE** (Long Term Evolution)

1.3.2 Examples of Data Transmission

Examples:

Bluetooth Head-set

WLAN

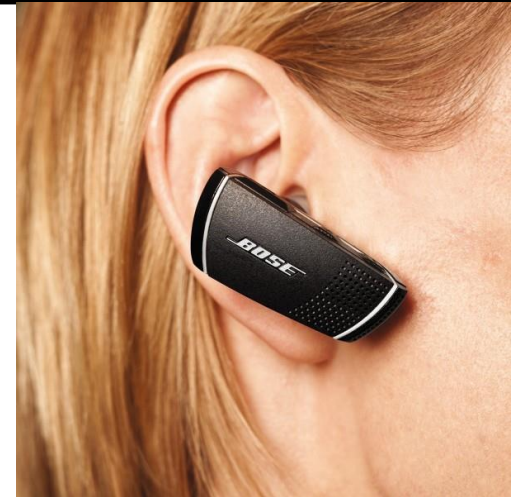
WLAN-Camera

NFC

„girogo“ using RMV

UMTS

Mobile Identification reader at the Frankfurt airport



2. Meaning analysis of location and movement data

Semantic-Trajectory Modeling

Overview

1 Technology: Sensores used in Smartphones

2 Semantic Trajectories from Position Sensor Data

2.1 Semantic-Trajectory Modeling

2.2 Structured-Trajectory Computation

2.3 Semantic Trajectory-Annotation

2 Application: Meaningful Analysis of Location and Movement Data

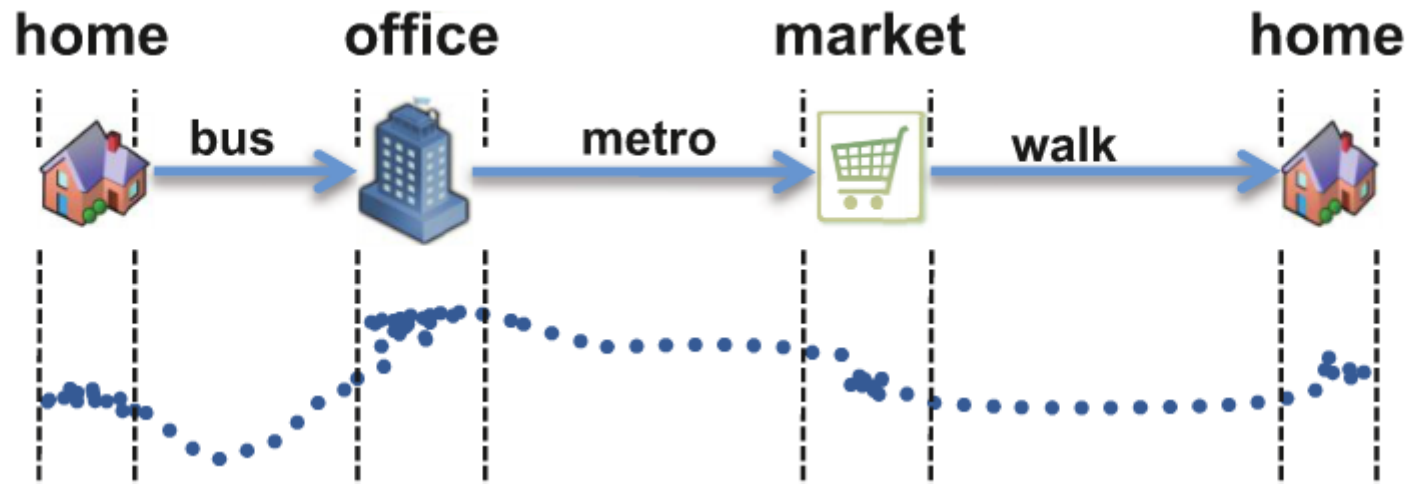
3 Research, Development & Expectations

Summary and your Questions!

2. Semantic Trajectories from Position Sensors Bedeutungspfade aus Ortsmessungen

Semantic Trajectory / Bedeutungspfad

Sequence of episodes with meaningful identification



Sequenz von GPS-Punkten (x, y, [z], t)

The target is to determine how the person moved around
or to find out where the person stayed
for longer periods of time.

2.1 Meaning analysis of location and movement data

Semantic-Trajectory Modeling

Semantic-Trajectory Modeling

Translation „**Semantic Trajectory Modeling**“:

Semantic: Semantisch, Bedeutung

Trajectory: Trajektorie, Bewegungsverlauf, Bewegungspfad

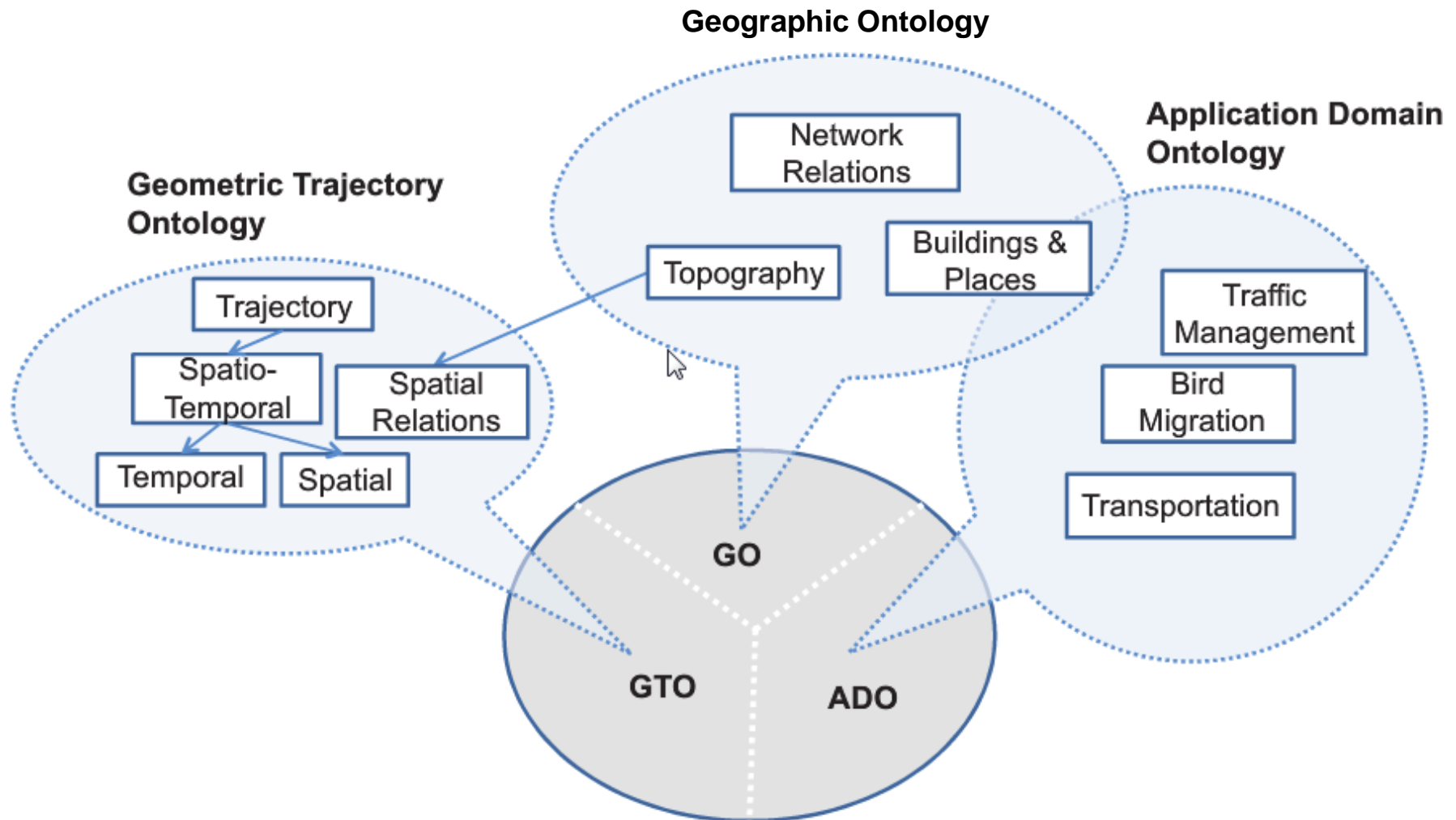
Modeling: Modellierung, Erschaffung, Gestaltung, Erzeugung (Inf.)

Modellierung von semantischen Trajektorien

Erzeugen von Bedeutungspfaden (bedeutungsbehaftete Bewegungspfade)

Darstellung von sinnhaften Bewegungsverläufen

2.1.1 Semantic Trajectory Ontology Ontologie für Bedeutungspfade

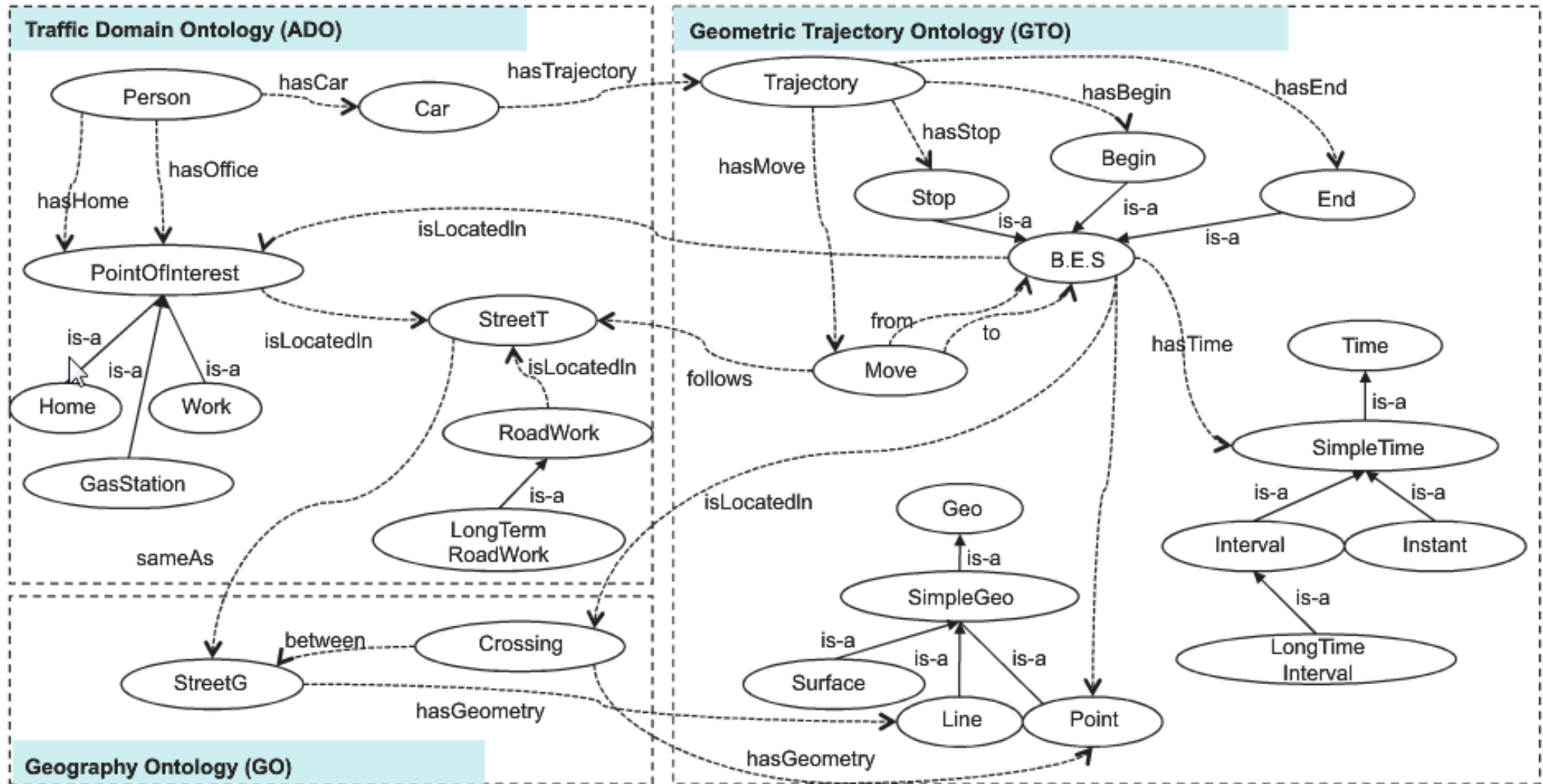


Ontologie: Darstellung einer Menge von Begrifflichkeiten und der zwischen ihnen bestehenden Beziehungen in einem bestimmten Gegenstandsbereich

Ontology: Portrayal of a set of terminology and the relationship between them within a certain subject area.

2.1.1 Example: Semantic Trajectory Ontology for Traffic Management

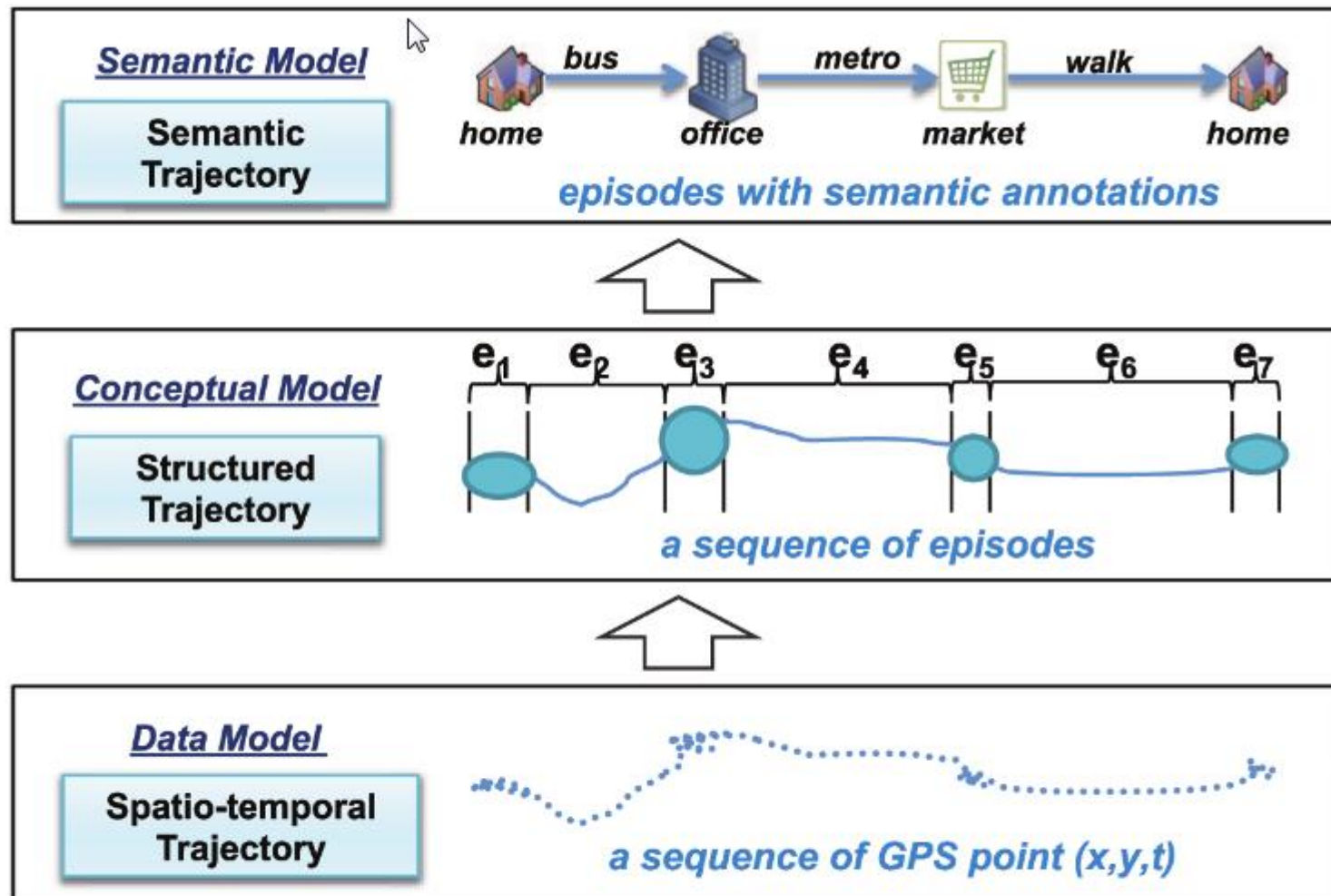
Ontologie für Bedeutungspfade im Verkehrsmanagement



„Gib den Dingen einen Namen, dann weißt Du, worüber Du sprichst!“

„Give the things a name and then you will know what you are talking about!“

2.1.2 The Hybrid Spatio-Semantic Trajectory Model „Das duale Raum-Bedeutungspfad-Modell“



The model subsumes 3 partial models all connected to one another:

Spacetime-path → A Structured path (locations and paths) → Meaning afflicted path

2 Semantic Trajectories from Position Sensor Data: Model

2.1 Semantic-Trajectory Modeling

2.2 Structured-Trajectory Computation

2.2.1 Data Preprocessing/Rohdatenaufbereitung

2.2.2 Stop Identification/Identifizierung von Verweilorten

2.2.3 Episode Identification/Identifizierung von Wegabschnitten

2.3 Semantic Trajectory-Annotation

Raw data from moved objects is flawed. The flaw/The variation is not constant. So for us to be able to make sensible use of the data we must eliminate the variation, as best as possible, by:

- Outlier-/Peek-elimination (i.e. Sensor-overload, malfunction)
- Data gap-Elimination (Interpolation, Extrapolation, Spline)
- Static reduction (highpass, lowpass, bandpass, median)
- Constraint correction (Humans can't go through walls; Cars drive on streets)

But also

- Data compression
- Data conversion, i.e. $(r, \varphi, \theta) \rightarrow (x, y, z)$

2.2.2 Stop Identification Identifizierung von Verweilorten

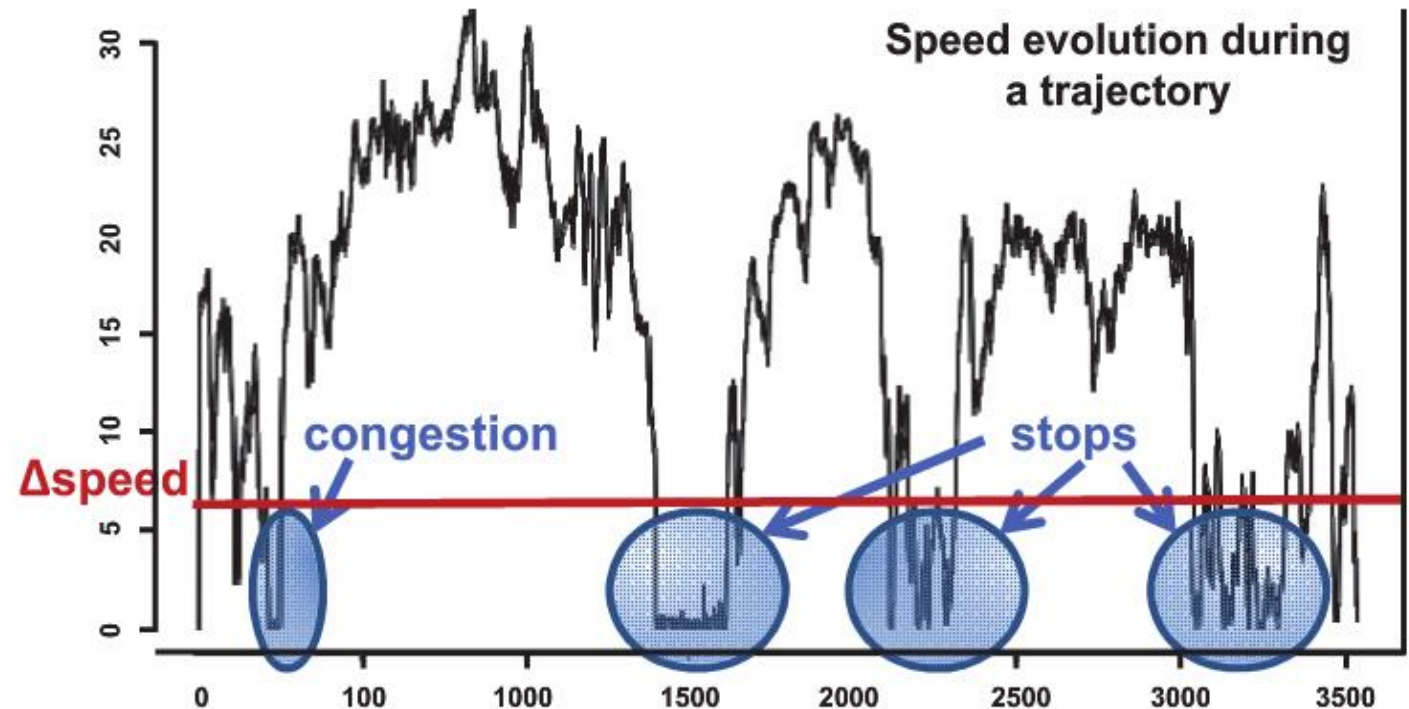


Figure 2.14: Velocity-based stop identification.

Identification of stops by analyzing the speed.

Elimination of overloads and congestions

2.2.2 Stop Identification Identifizierung von Verweilorten

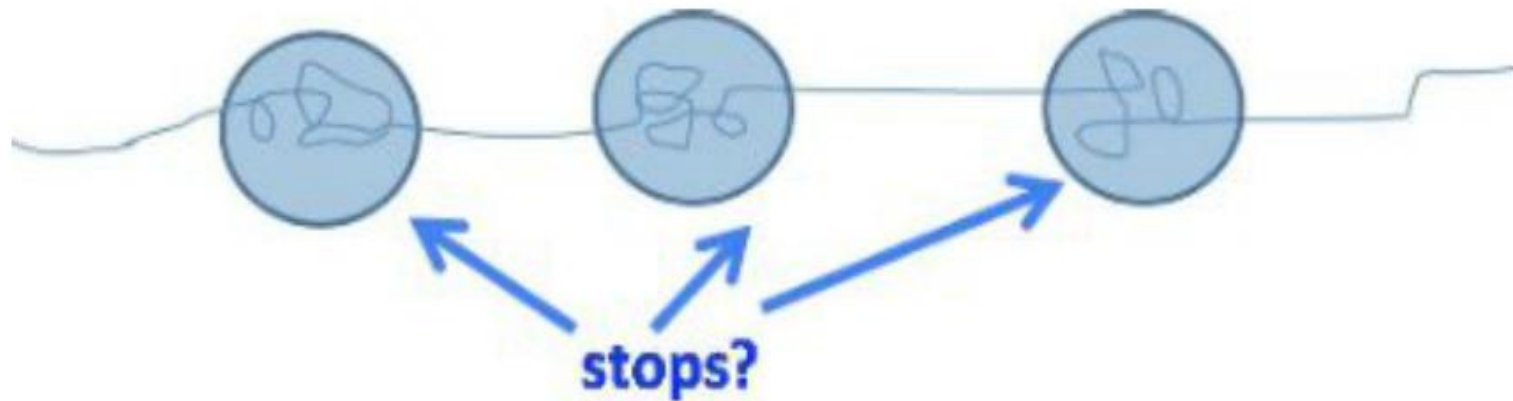


Figure 2.15: Density-based stop identification.

Identification of stops by analyzing the density of movement paths

2.2.3 Trajectory Identification Identifizierung von Wegabschnitten

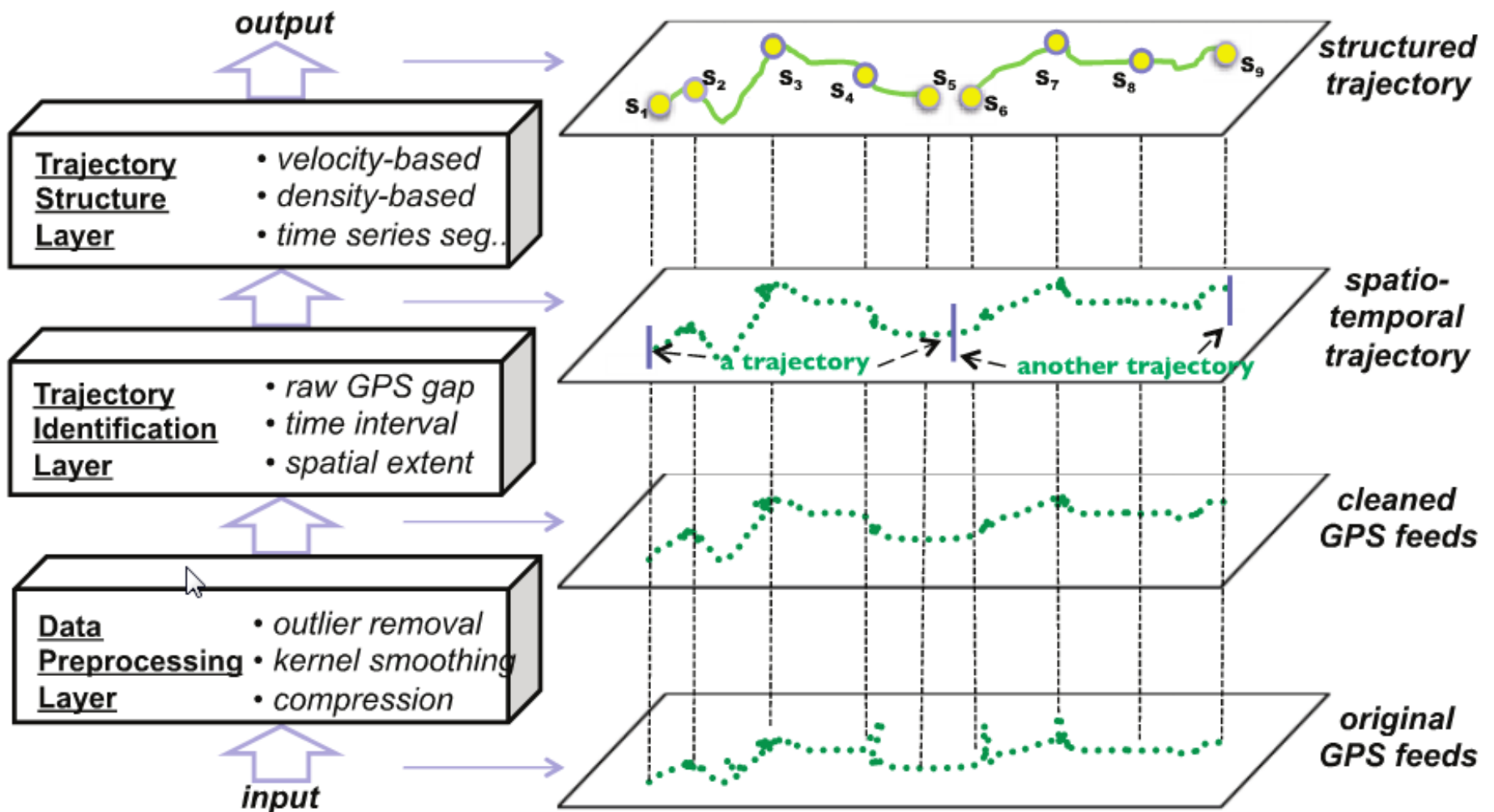


Figure 2.7: Trajectory computing platform.

2 Semantic Trajectories from Position Sensor Data

2.1 Semantic Trajectory Modeling

2.2 Structured-Trajectory Computation

2.3 Semantic Trajectory-Annotation

2.3.1 Annotation of Path Segments

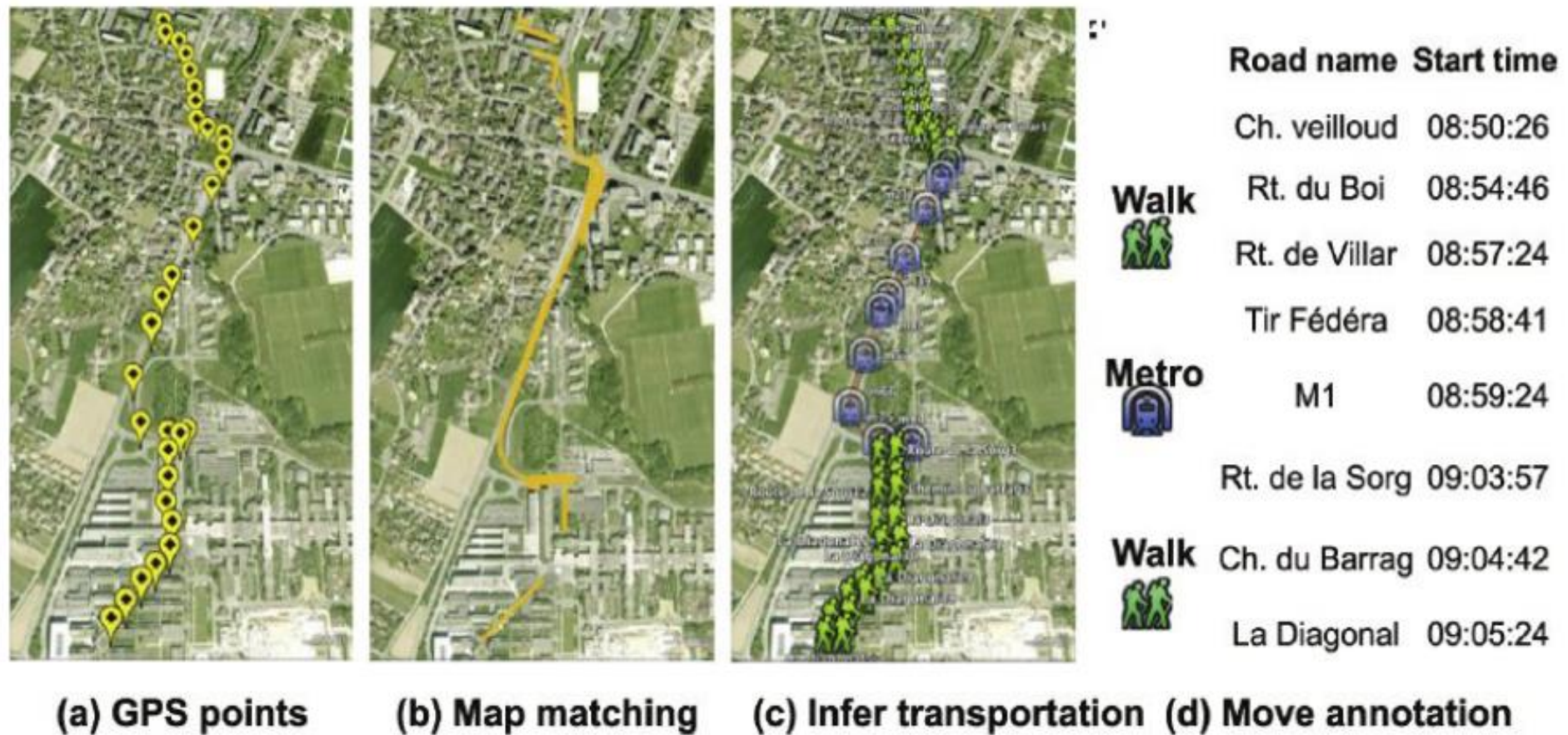
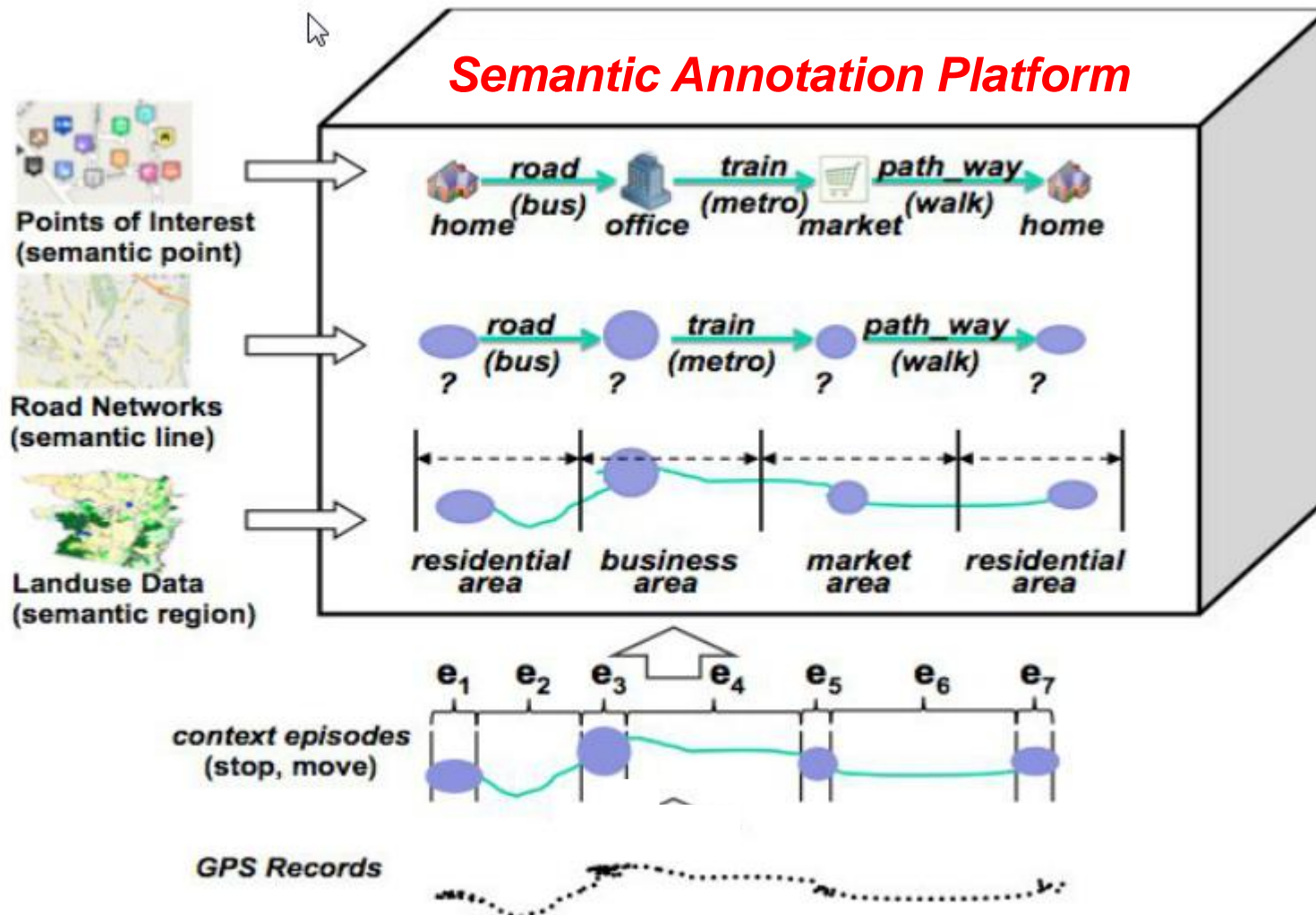


Figure 2.22: Move annotation: a home-office move via taking metro and walking.

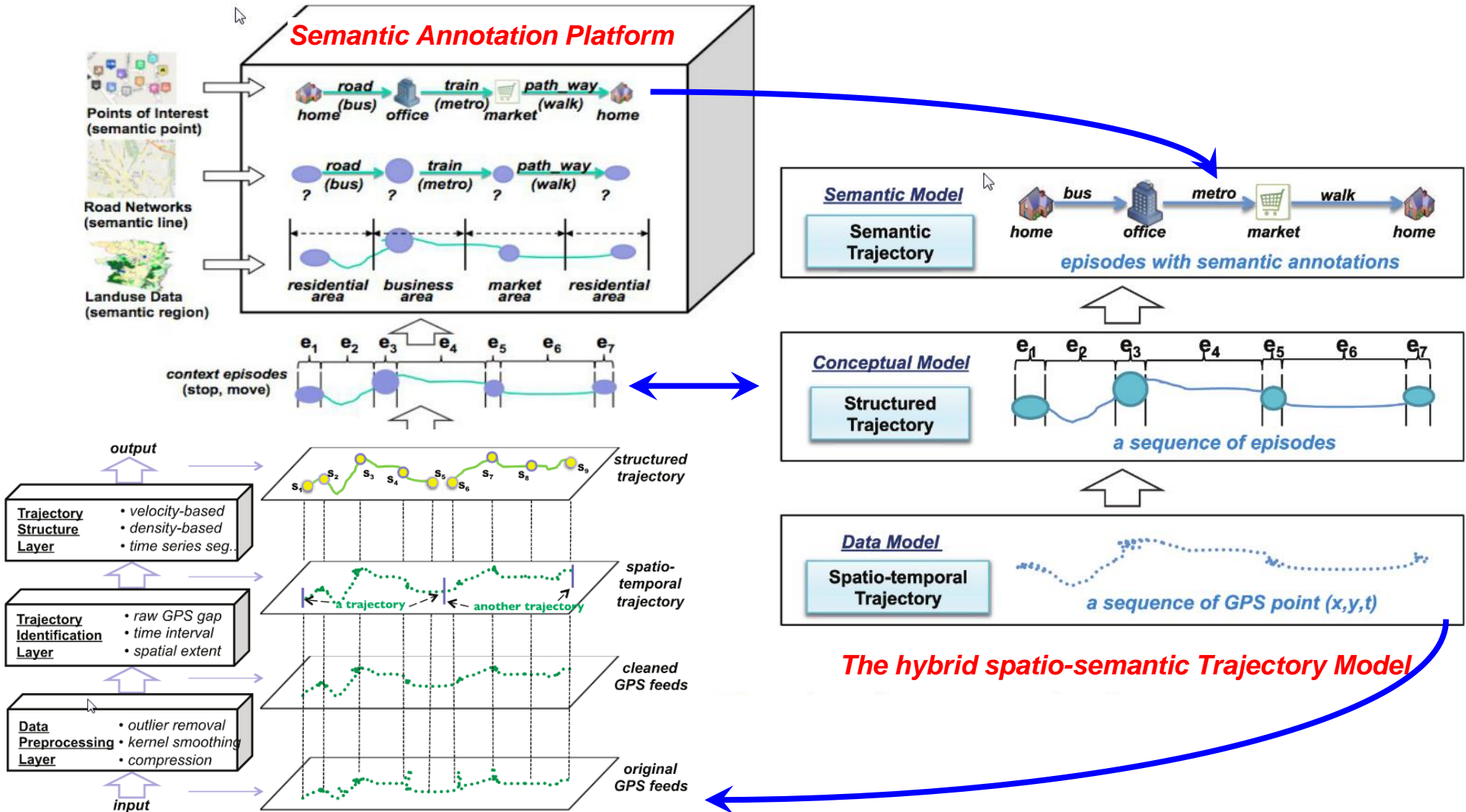
We can find paths and means of transportation by
comparing or correlating Geodata

2.3.2 Annotation of Stopping Places



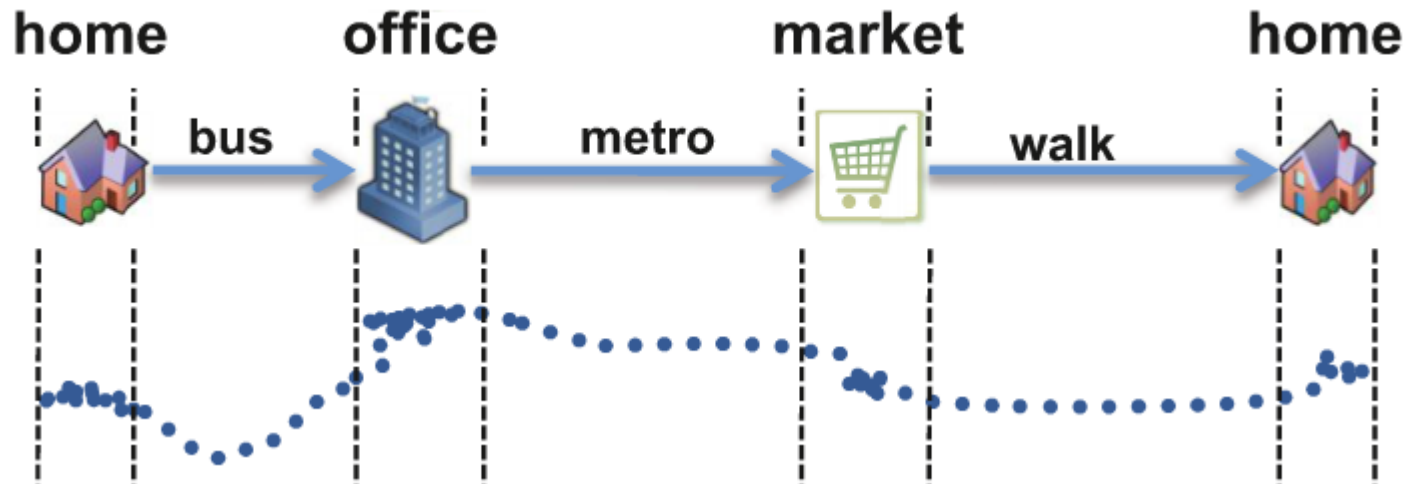
The meaning of the individual episodes are assigned/annotated by correlating external semantic data.

2.3.3 The Entire Model



2.3.3 Destination Reached!

Semantic Trajectory



Sequence of GPS-points (x, y, [z,] t)

Overview

1. Technology: Sensors used in Smartphones
2. Application: Meaningful Analysis of Location and Movement Data
3. Research, Development & Expectations
 - 3.1 Analysis of POIs (Sehenswürdigkeiten)
 - 3.2 Semantic Activity of Motion Sensors
 - 3.3 Downscaling/Internet of Things

Summary and your questions!

3.1 Analysis of POIs

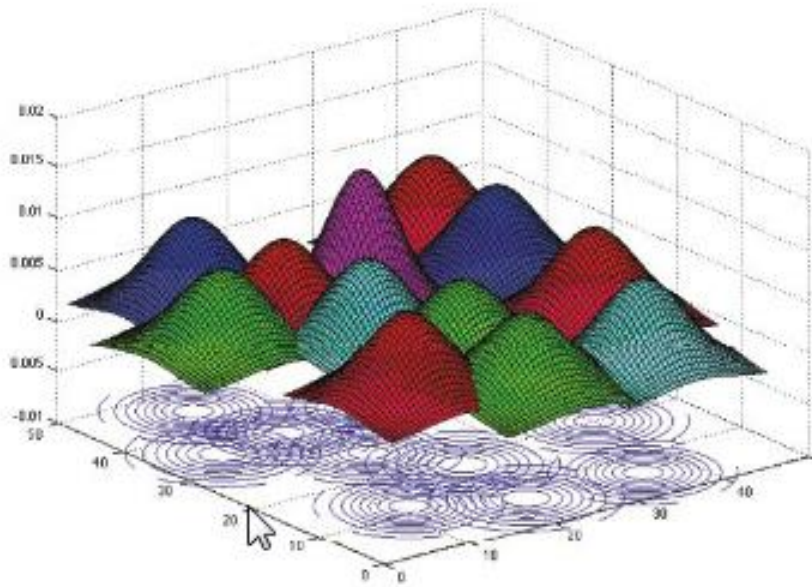


Figure 2.25: POI densities.

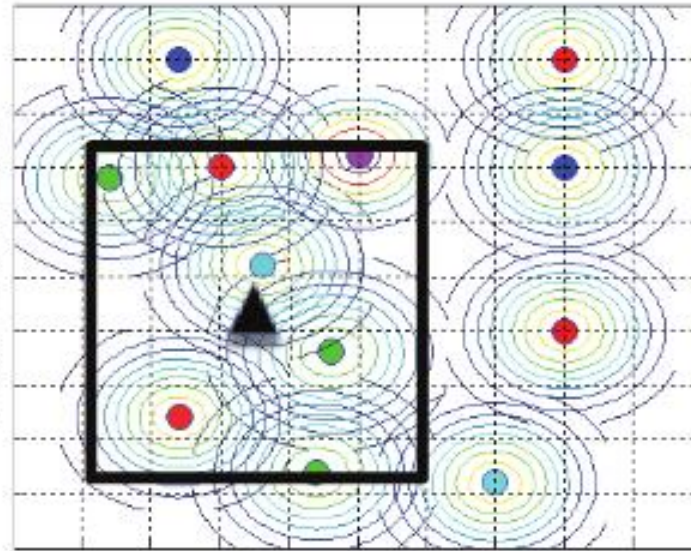


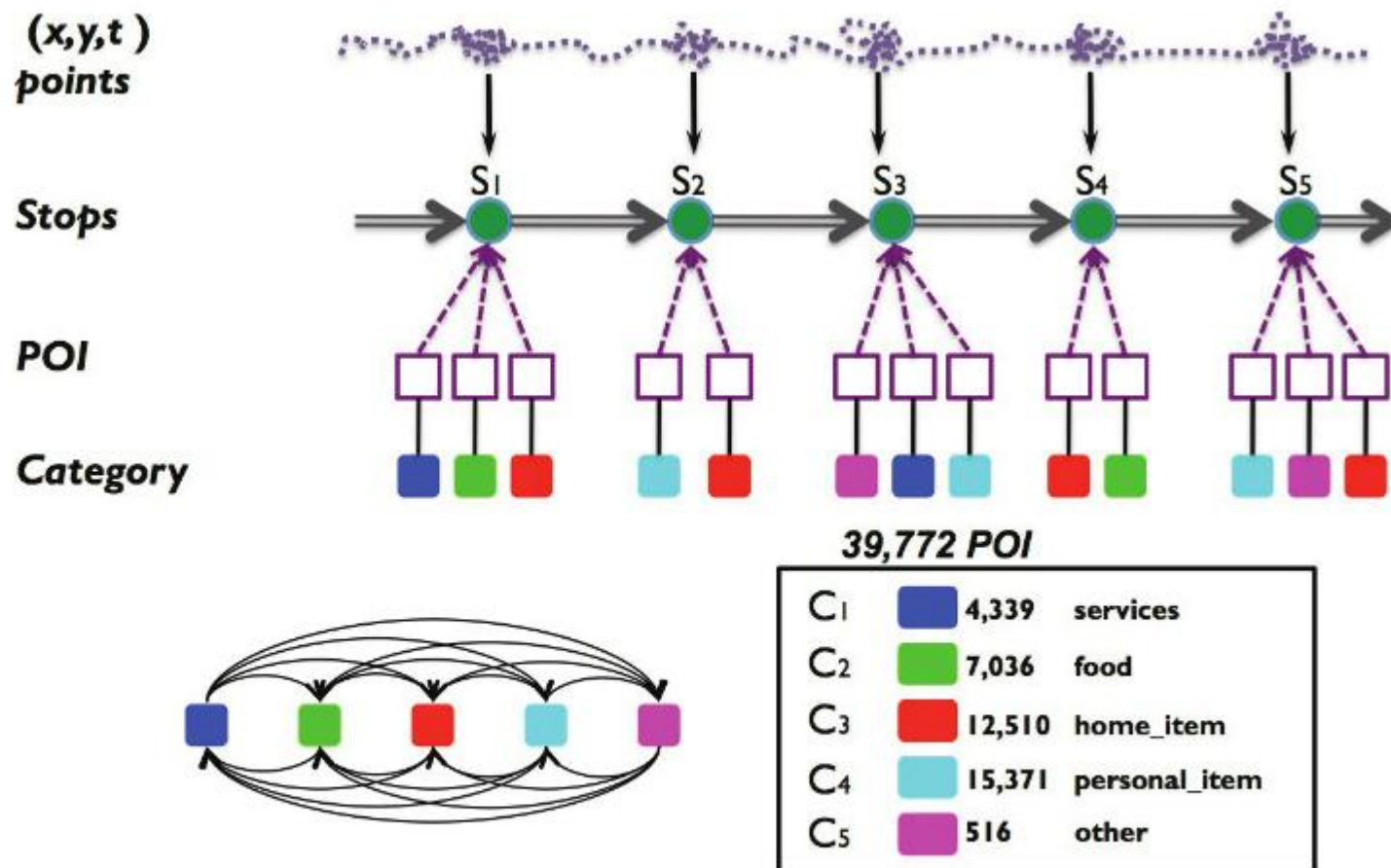
Figure 2.26: POI discretization.

Path Densities (time-space)

Discretisation of the statistical maxima

Mapping of the POI(people stand around the fountain, not in it)

3.1 Analysis of POIs



Hidden Markov Model (HMM) used for telling the statistical relationships to the POIs identification of interests

3.2 Semantic Activity from Motion Sensors

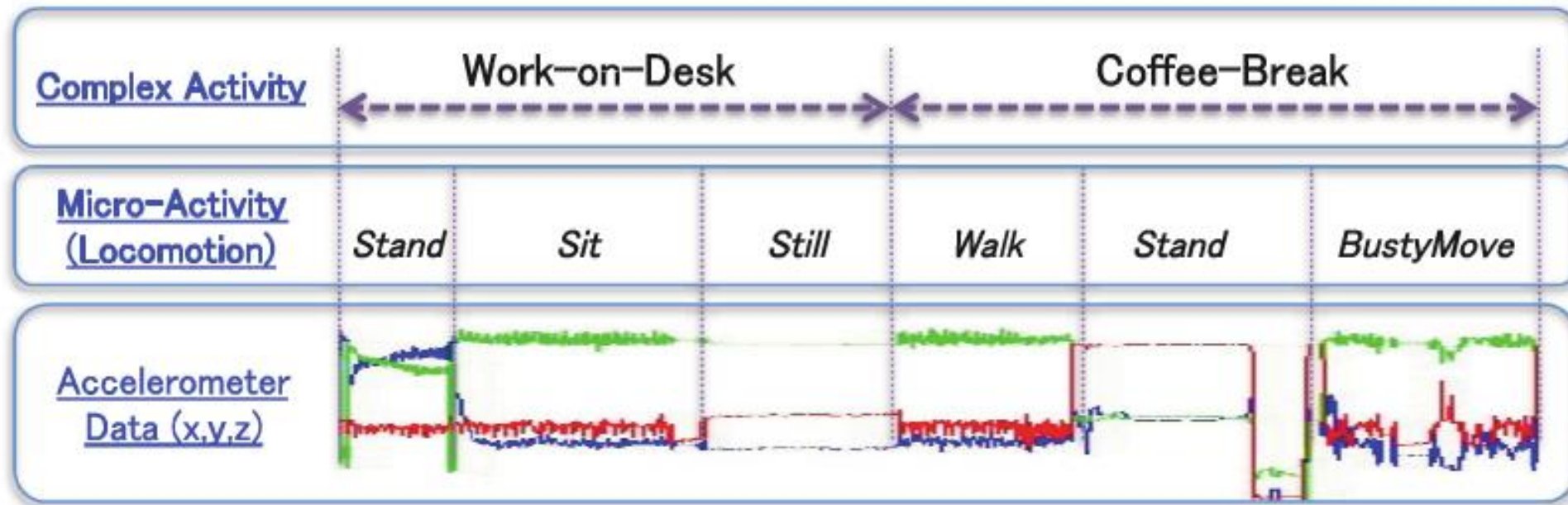


Figure 3.2: From accelerometer to semantic activities.

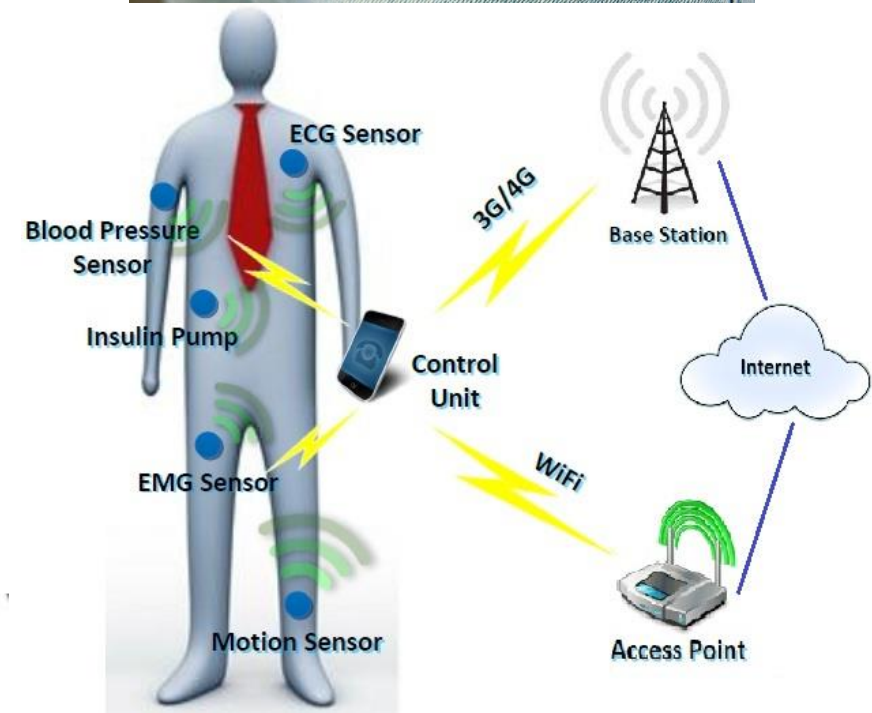
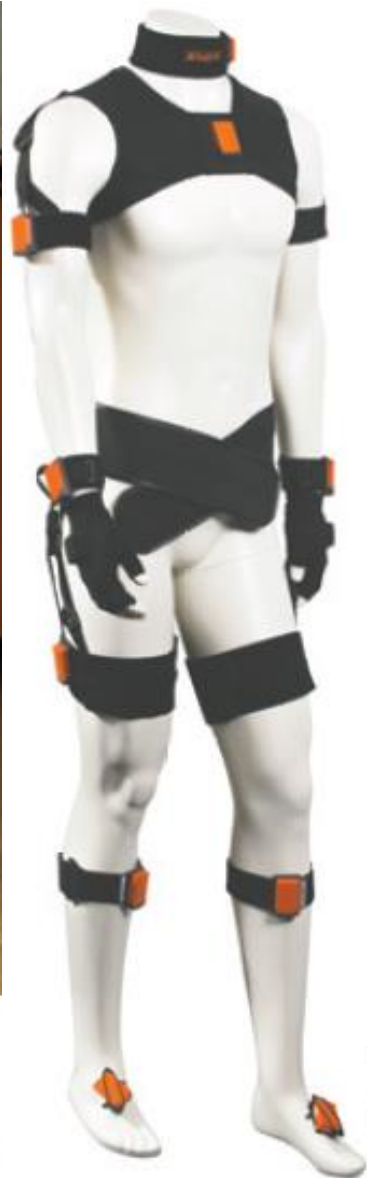
Determining activities from data from accelerometers.

3.3.1 „Wearables“ for Sport, Fitness, Medication, etc.



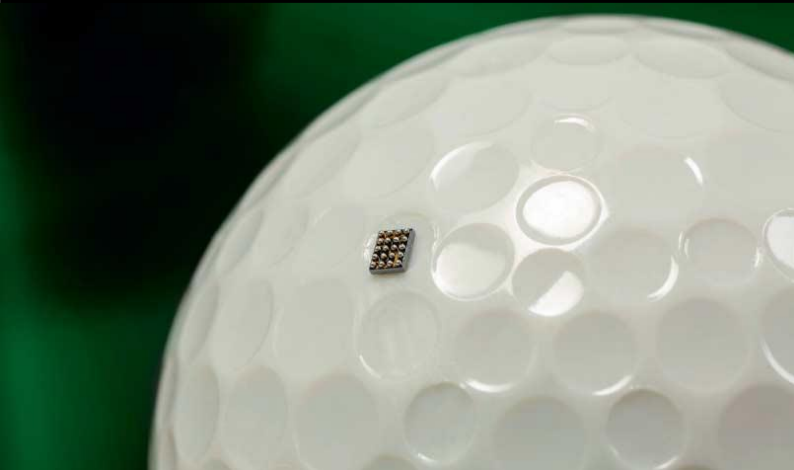
www.xsens.de

MVN Awinda
Completely Wireless Motion Capture



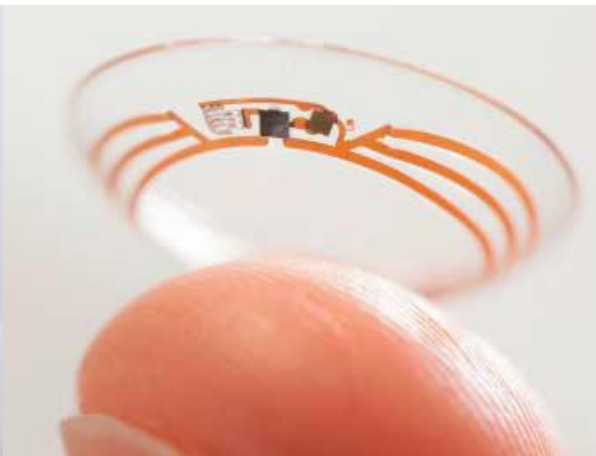
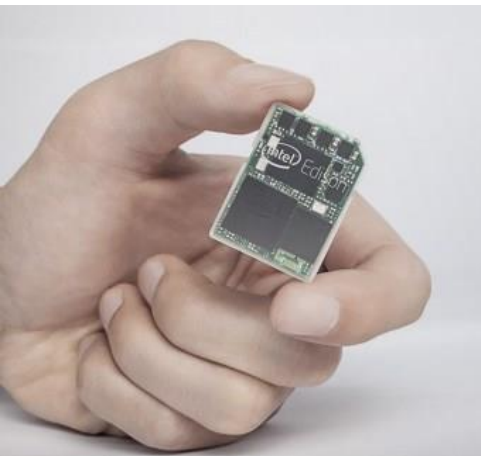
Personal Area Network (PAN)

3.3.2 Downscaling: Pervasive/Ubiquitous Computing



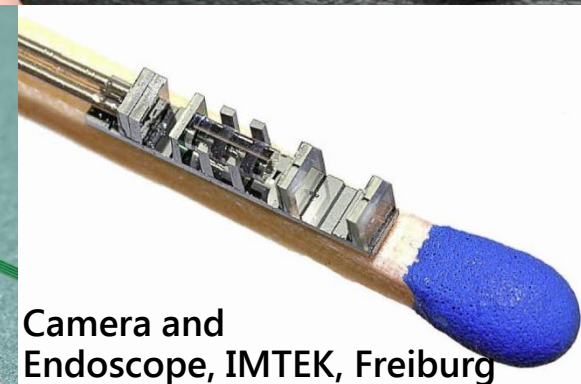
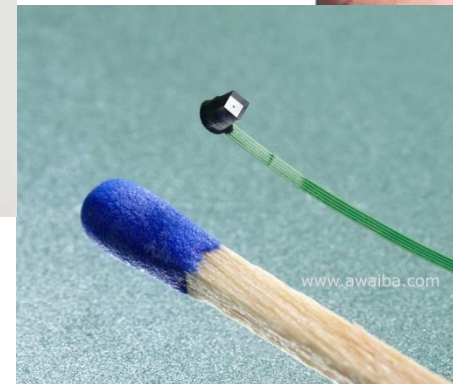
The smallest ARM-Processor in the world –
The Kinetis KL03; c't 07/14, S. 54

Microsystem made by
Fraun-hofer Instituts IZM,
Berlin



Intel Edison, Pentium Class
PC with WiFi and BT

Google Smartlens
Measures bloodsugar



Camera and
Endoscope, IMTEK, Freiburg

Books for lecture follow-up:

Randy Frank, **Understanding Smart Sensors**,
ISBN-13: 978-1-60807-507-2, Third Edition,
ARTECH HOUSE, Boston/London, 2013

Zhixian Yan; Dipanjan Chakraborty, **Semantics in Mobile Sensing**,
Synthesis Lectures on The Semantic Web: Theory and Technology #8,
James Hendler and YinDing, series editors,
ISBN-13: 978-1-62705-390-7, Morgan & Claypool Publishers, May 1, 2014
Online mit preview auf <http://safaribooksonline.com>

Dan Chalmers, **Sensing and Systems in Pervasive Computing**,
Undergraduate Topics in Computer Science, Ian Mackie, series editor
ISBN 978-0-85729-840-9, Springer Verlag, London, 2011

Some articles to go deeper into the materia:

Christine Parent et. al., **Semantic Strjectories Modeling and Analysis**, in
Journal ACM Computing Surveys (CSUR) Vol. 34 Issue 4, ACM New York, August 2013; Fundstelle:
<http://www.uhasselt.be/Documents/datasim/Papers/Semantic-Trajectories-Modeling-and-Analysis.pdf>

Mani Srivastava, Rarek Abdelzaher, and Boleslaw Szymanski, **Human-centric Sensing**
Philosophical Transactions of Royal Society, 370 ser. A (1958), 2012, pp 176-197

Furthermore, some youtube videos fitting to the subject:

<http://www.youtube.com/watch?v=A03AENwOVNY> (STMicroelectronics: MEMS gyrosopes)

<http://www.youtube.com/watch?v=-QKaPXBWILs> (Dr. Niki Trigoni: Indoor Navigation)

http://www.youtube.com/watch?v=R62uwR6_YhQ (Prof. Marta Kwiatkowska (Ubiquitous Computing))

You have seen which sensors
are available in smartphones
and how they work.

You have seen and heard how you can make
Semantic Trajectories (Bedeutungspfade)
out of GPS-Data.

You have noticed the connections and found examples,
that "mobile sensing" is an exciting future market for
Computer Science.

Overview

- 1 Technology: Sensors used in Smartphones
- 2 Application: Meaningful Analysis of Location and Movement Data
- 3 Research, Development & Expectations

Thank you very much for your attention

Your questions and discussions.....