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Real-Life Activity Recognition

from recognizing physical activities towards large scale knowledge logging

Kai Kunze

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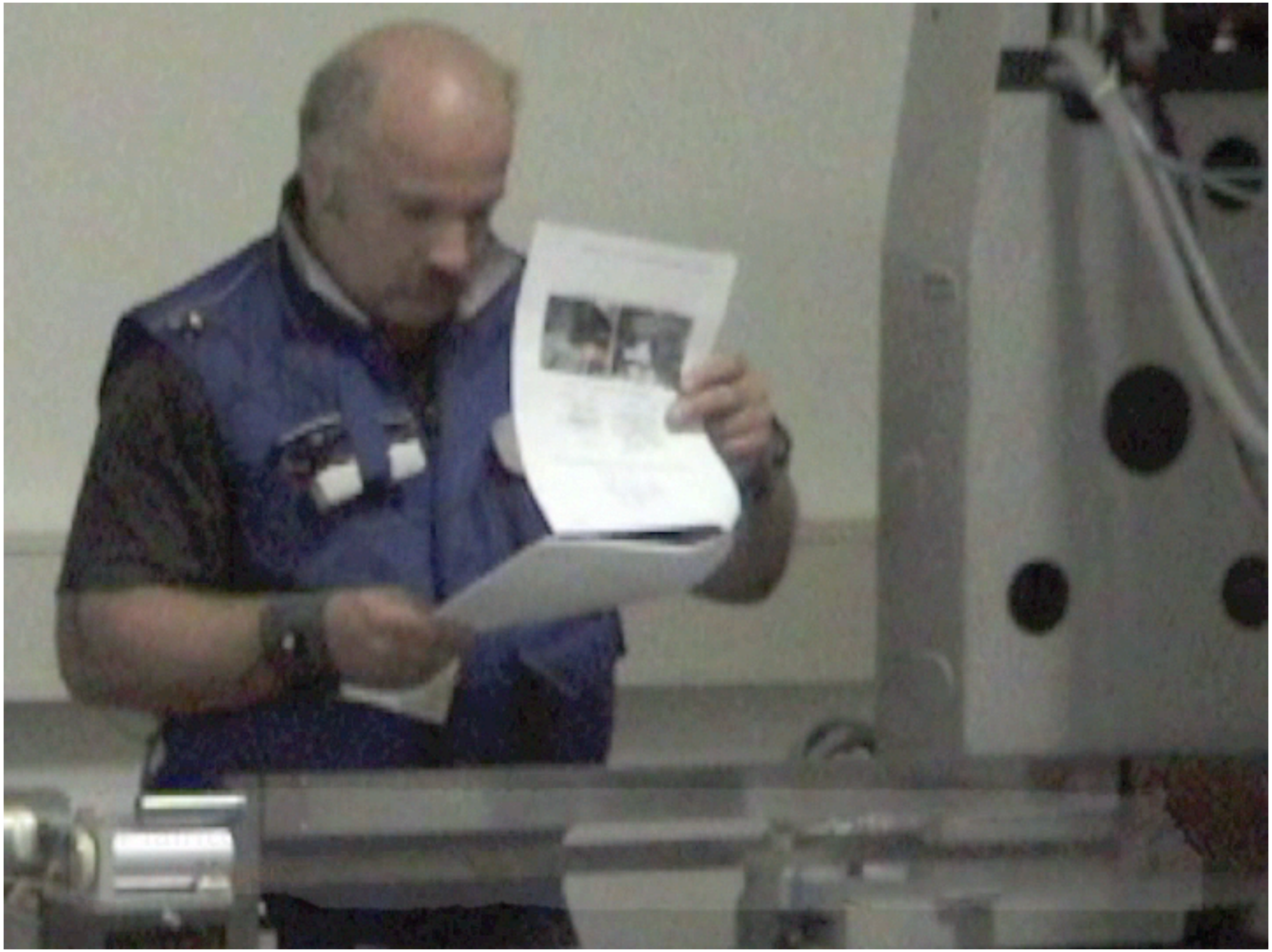
http://kaikunze.de/talks/ai4ie2013.pdf
(14 MB)

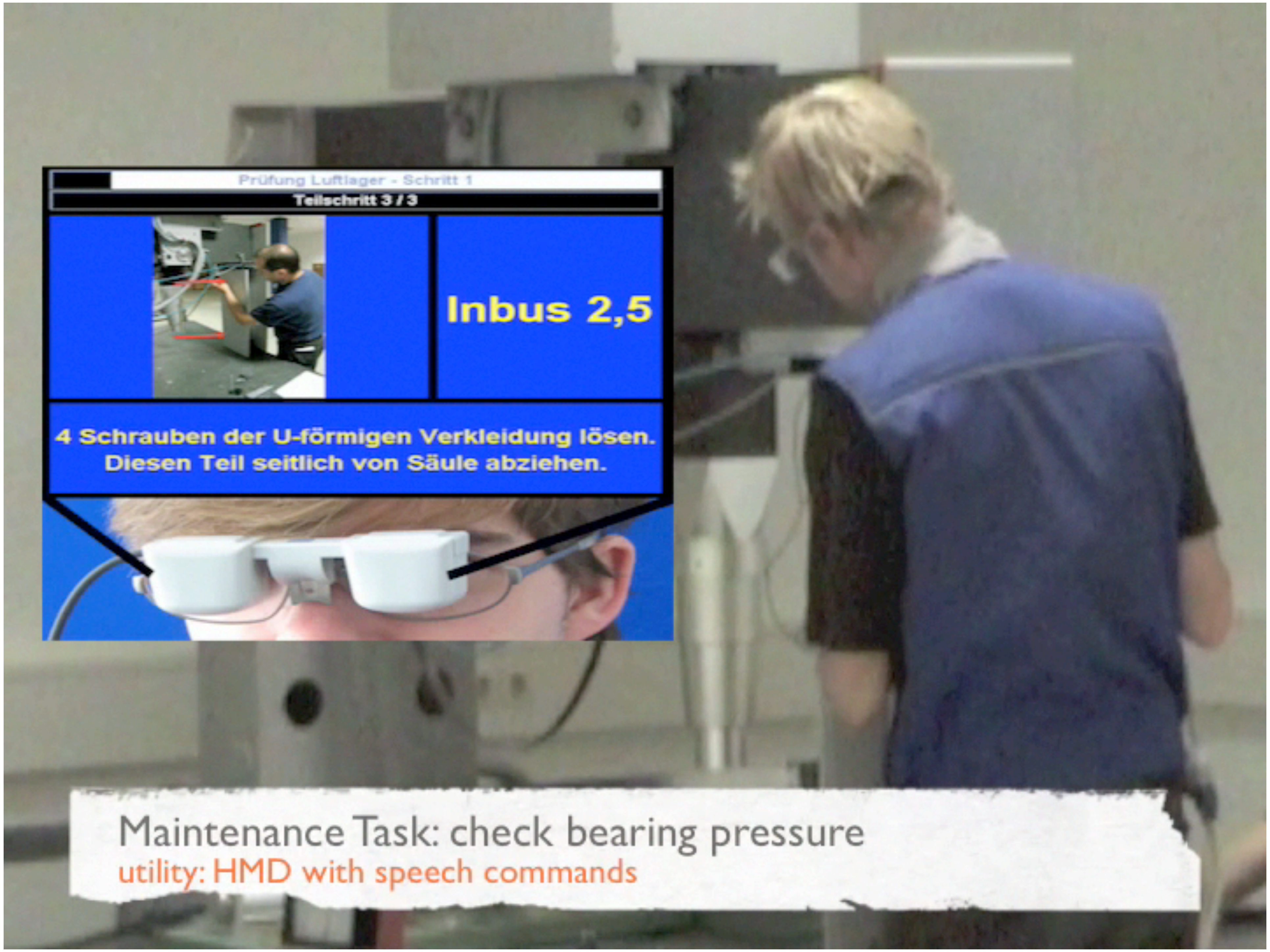
1. state of the art in activity recognition
   on-body sensing
2. special focus: knowledge and reading activities

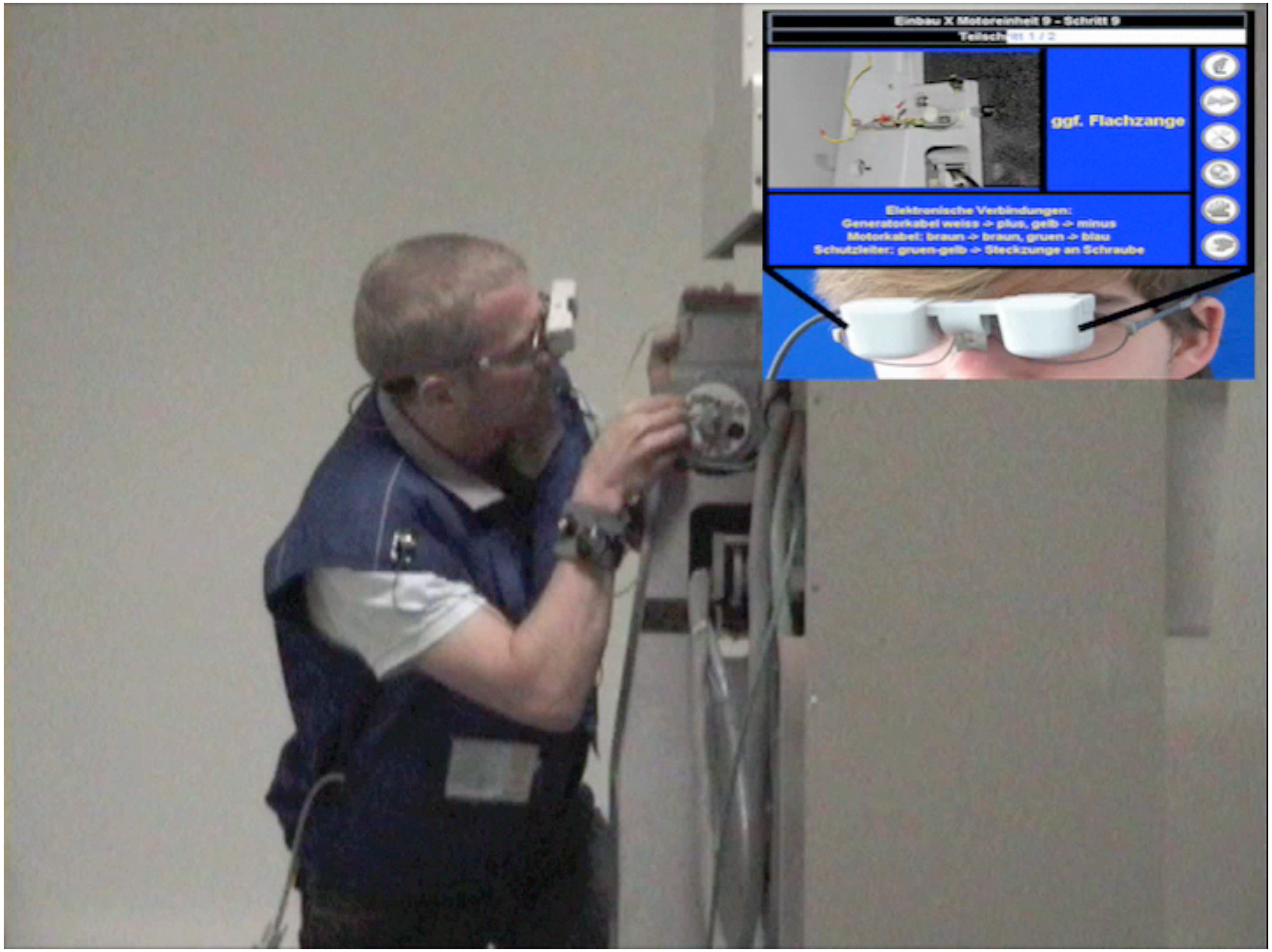
3. challenges
4. demos

why activity recognition?



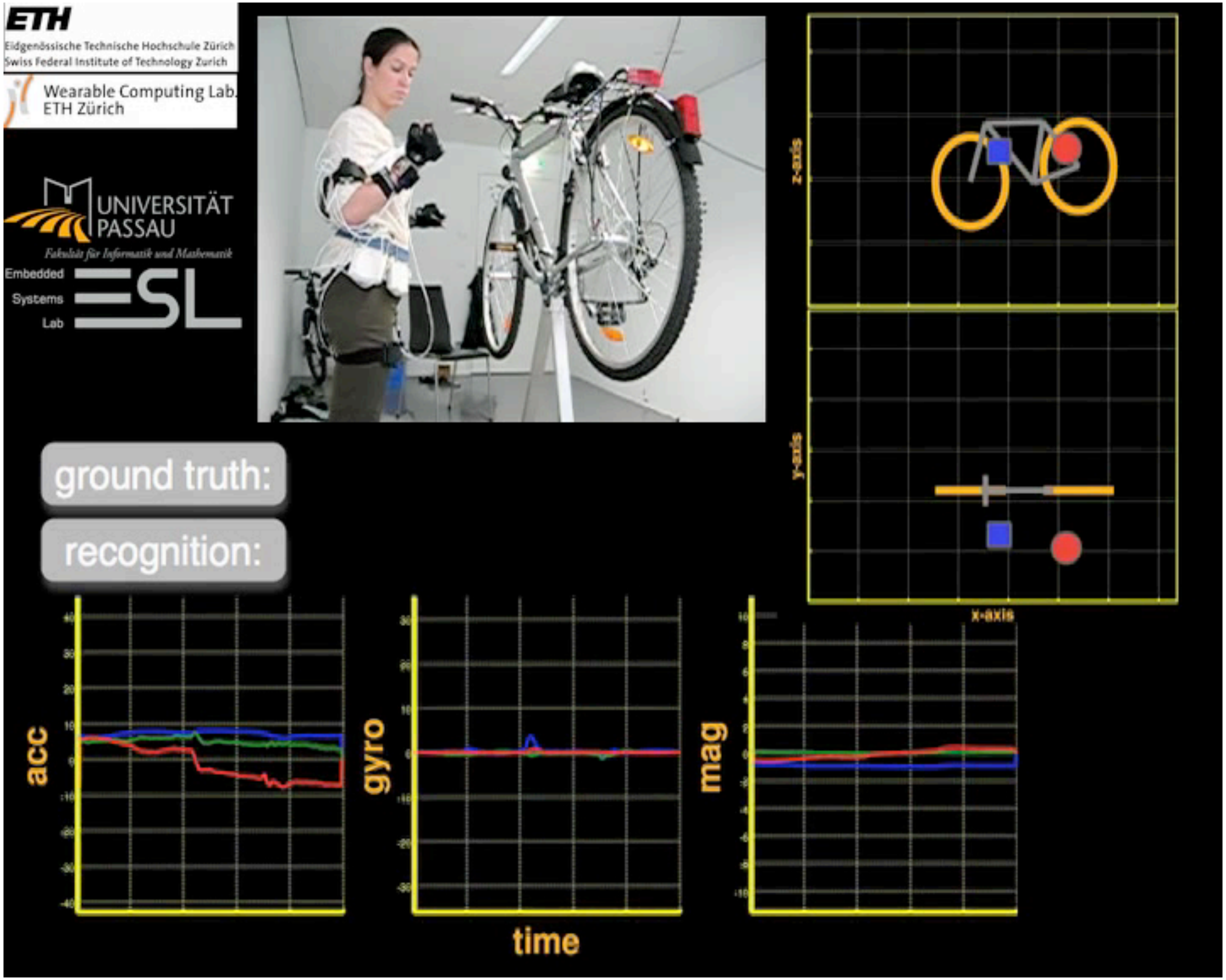
already possible today ...





Kunze, K.,Wagner, F., Kartal, E., Morales Kluge, E., and Lukowicz, P. Does Context Matter ? - A Quantitative Evaluation in a Real World Maintenance Scenario. *In Proceedings of the 7th international Conference on Pervasive Computing Nara*, Japan, May 11 - 14, 2009.

Work by Georg Ogris and Thomas Stiefmaier



Sunday, 4 August 13

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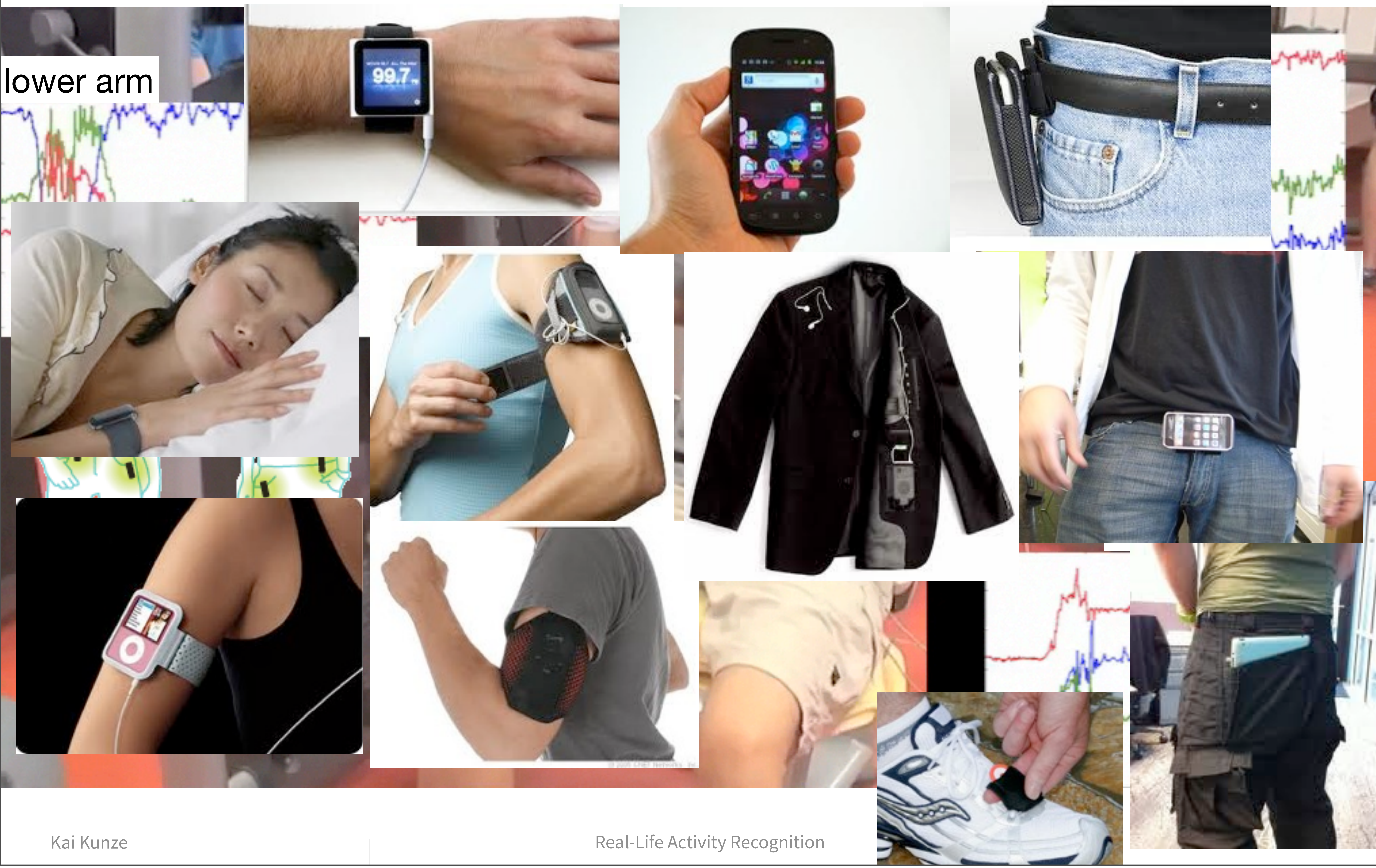
Applications

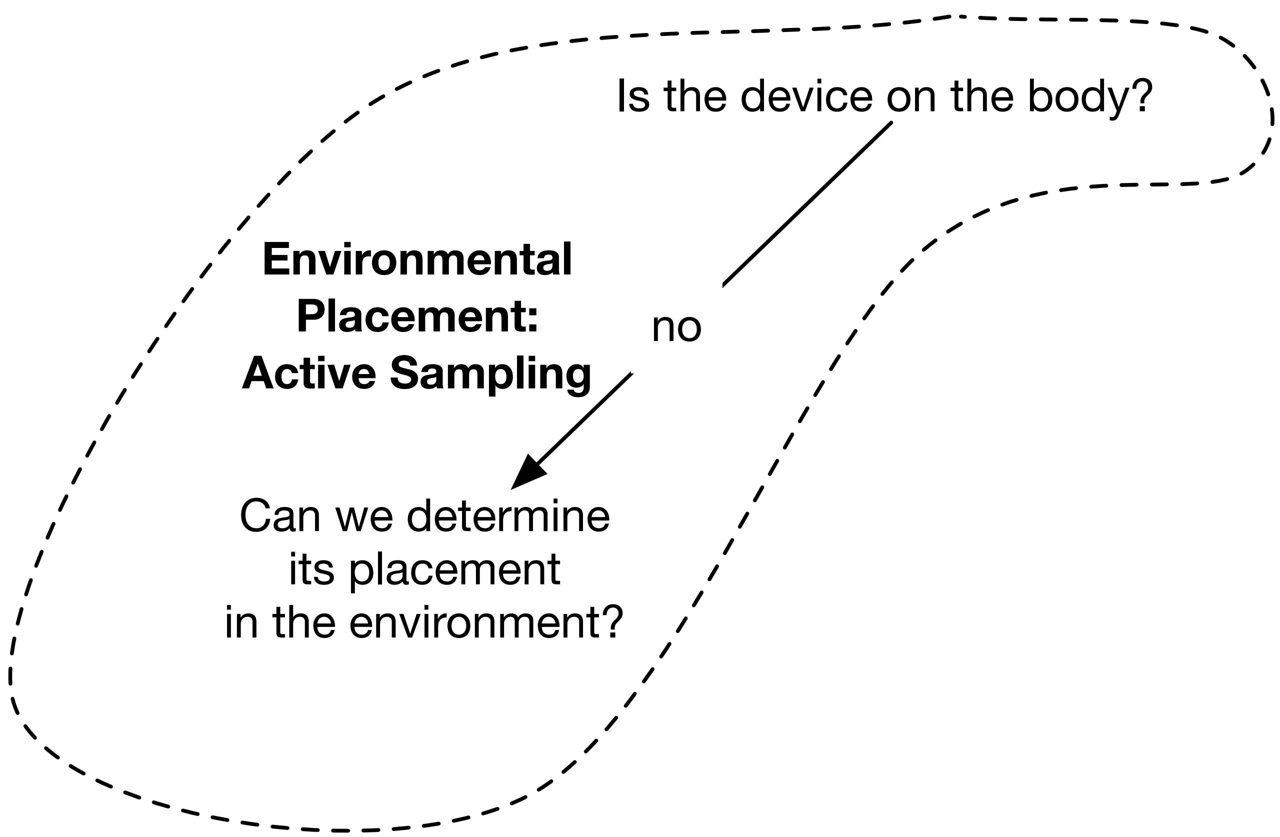
... using environment and onbody sensors



Compensating for On-Body Placement Effects in Activity Recognition

Kai Kunze

How to make activity recognition more robust?



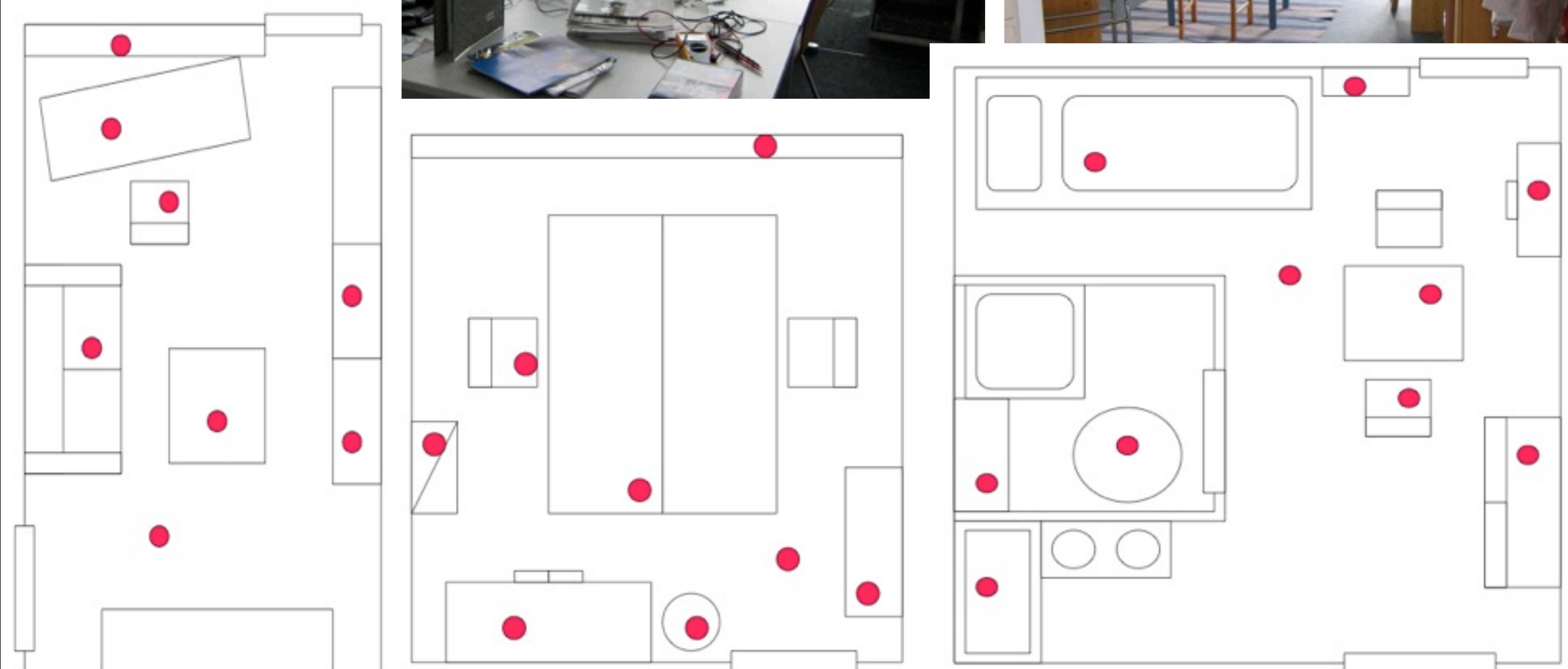
Kunze, K. and Lukowicz, P. *Symbolic object localization through active sampling of acceleration and sound signatures.* In Proceedings of the 9th international Conference on Ubiquitous Computing. Innsbruck, Austria, September 16 - 19, 2007.
nominated for best paper. (Acceptance rate: 14%)

approach

A mobile phone ringing or vibrating sounds differently depending on where it is.

scenarios

30 samples per location
10 for training 20 for testing



living room
9 locations

office
12 locations

apartment
11 locations

abstract classes

surface types:
padding
glass
iron
metal
stone
wood
compartment:
Open/closed (except metal)

For each type and compartment:
6 different kinds of furniture 12 samples each
2 pieces of furniture for training, 4 for testing

fingerprint and vibration sounds

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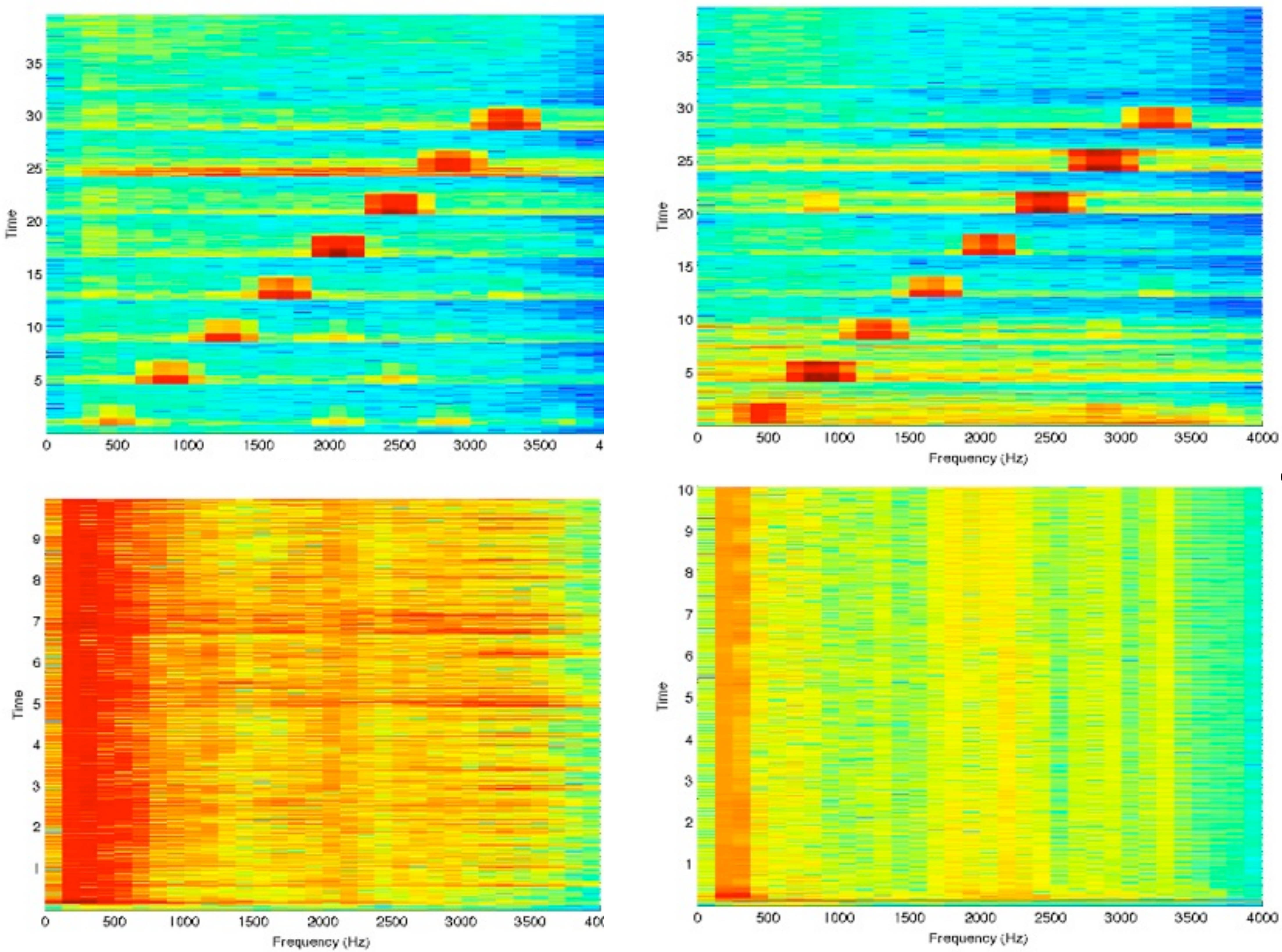
desk

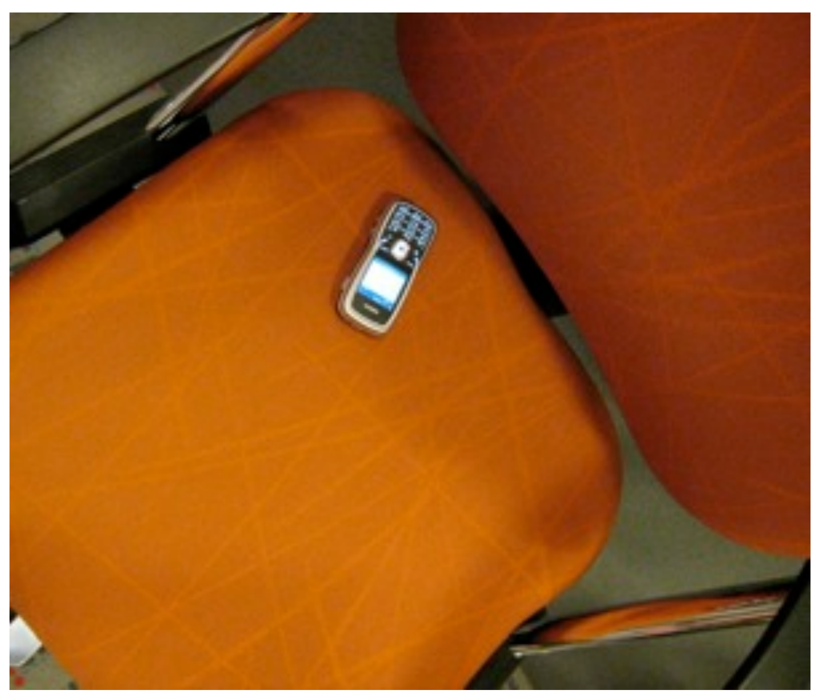
carpet

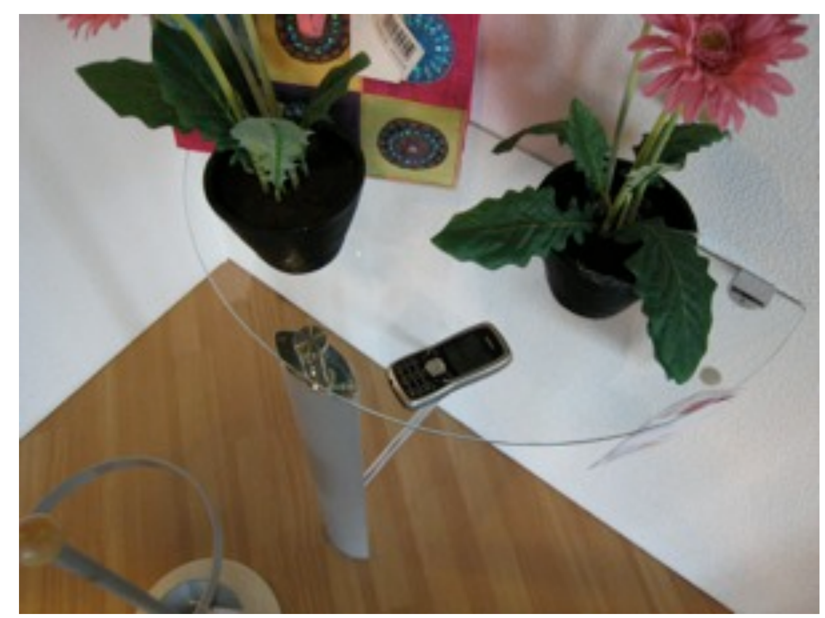


Kai K

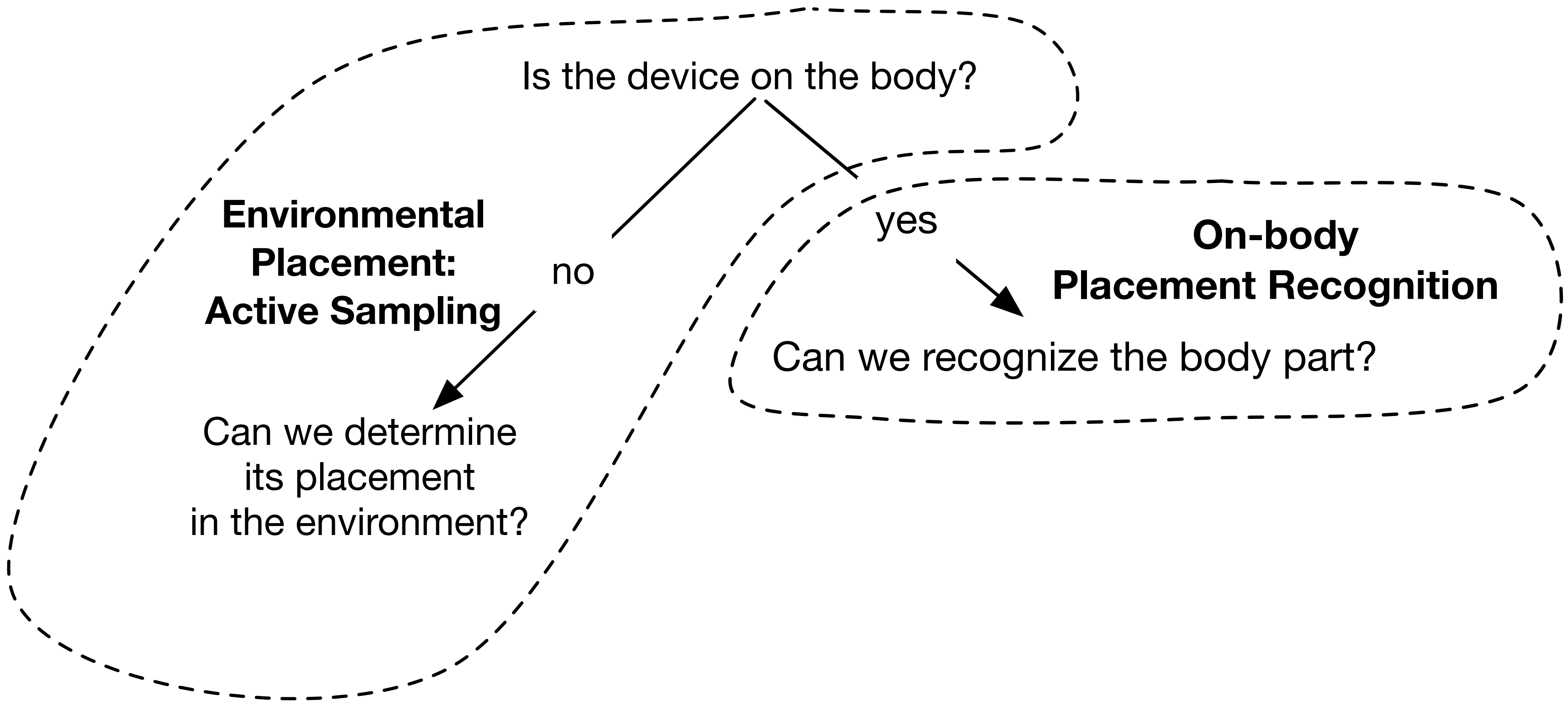
Environmental Placement Detection
-Active Sampling-

- up to 96 % per room
- up to 92 % for abstract classes





How to make activity recognition more robust?



K. Kunze and P. Lukowicz. *Using acceleration signatures from everyday activities for on-body device location.* 11th IEEE International Symposium on Wearable Computers, Sep 2007.

K. Kunze, P. Lukowicz, H. Junker, and G. Troester. *Where am i: Recognizing on- body positions of wearable sensors.* LOCA'04: International Workshop on Location and Context Awareness , Jan 2005.

How to make activity recognition more robust?

Is the device on the body?

no

Environmental Placement: Active Sampling

Can we determine its placement in the environment?

yes

On-body Placement Recognition

Can we recognize the body part?

Is it displaced?

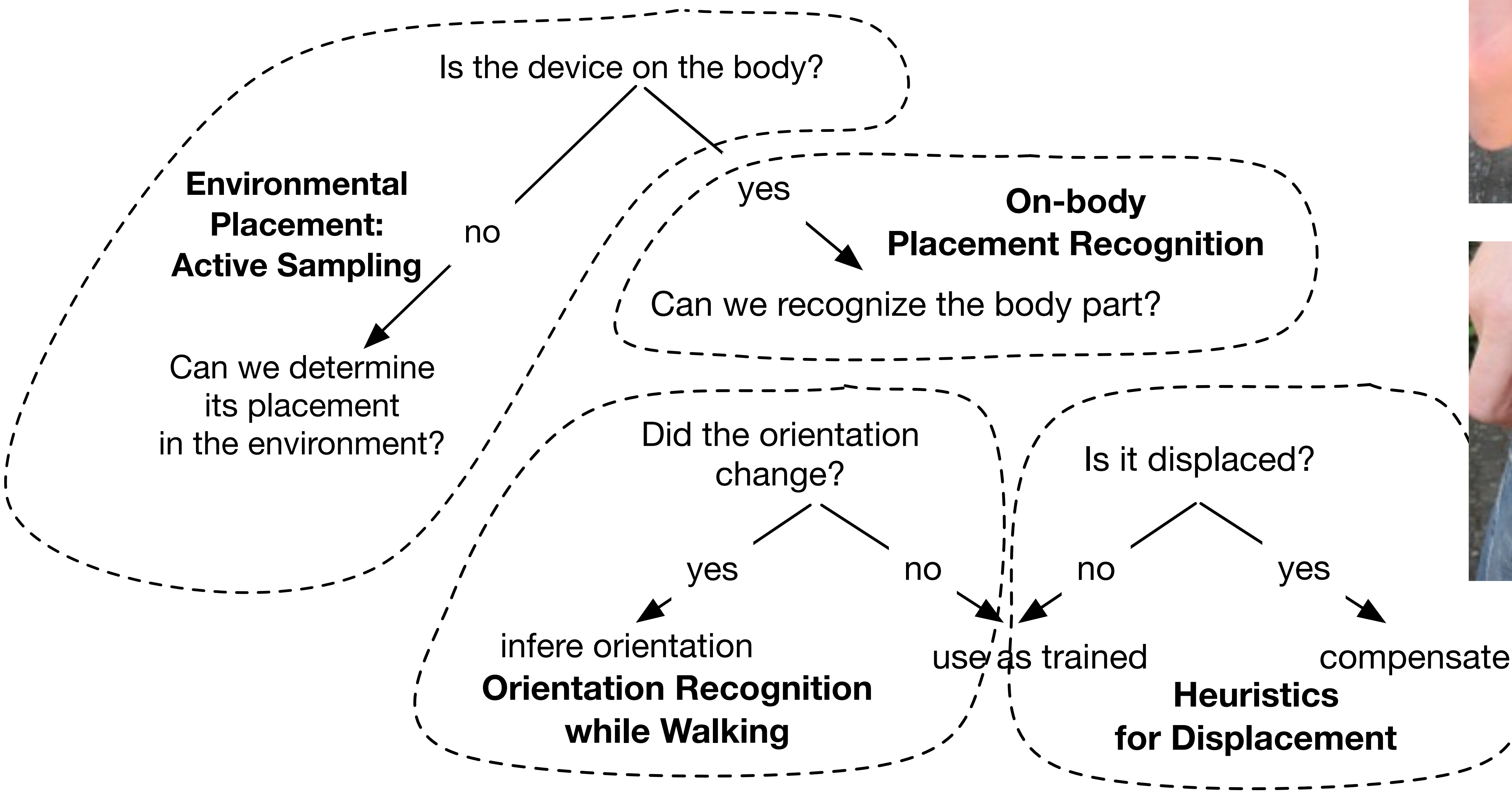
no — use as trained

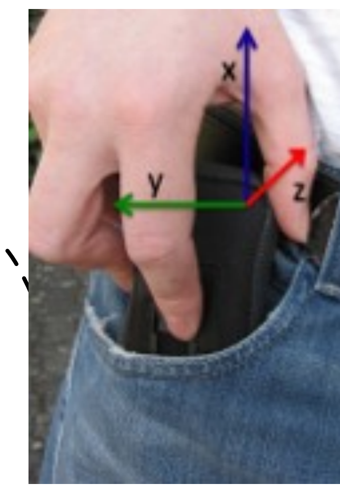
yes — compensate

Heuristics for Displacement

Kunze, K. and Lukowicz, P. *Dealing with sensor displacement in motion-based on-body activity recognition systems.* In Proceedings of the 10th international con- ference on Ubiquitous computing (UbiComp ’08). Seoul, Korea, September, 2008.

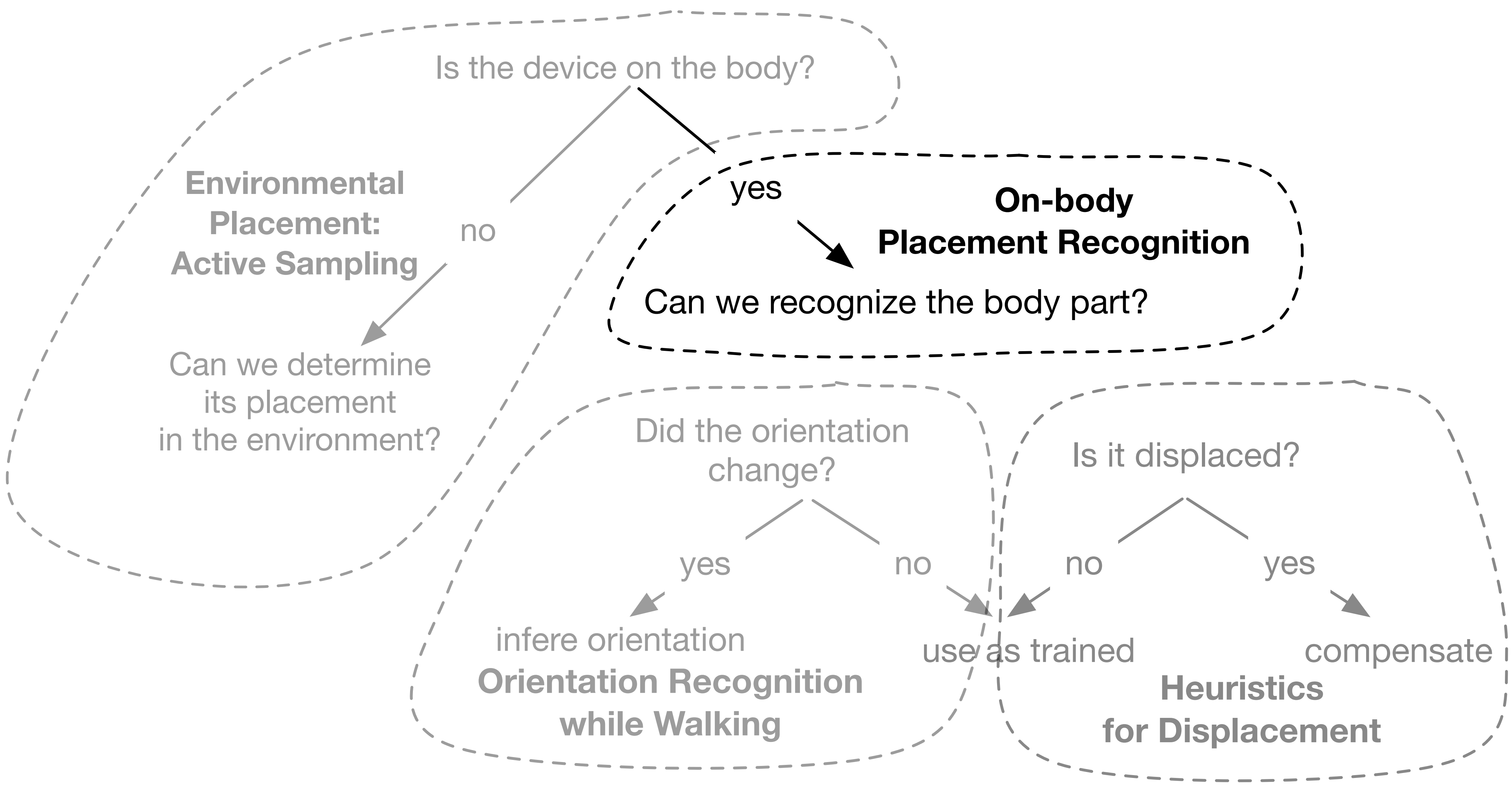
How to make activity recognition more robust?



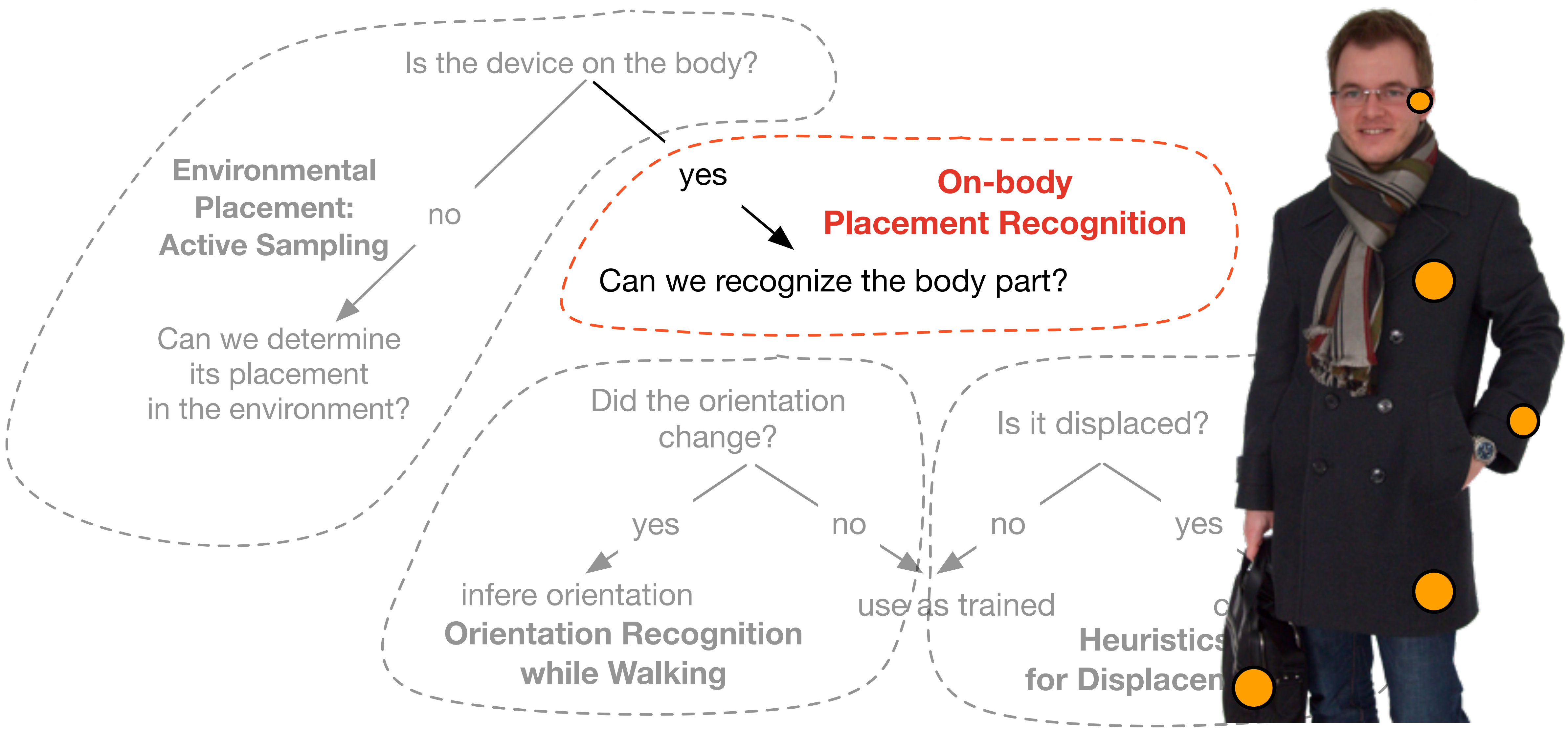


Kai Kunze, Paul Lukowicz, Kurt Partridge, Bo Begole, *Which Way Am I Facing: Inferring Horizontal Device Orientation from an Accelerometer Signal*, 13th IEEE International Symposium on Wearable Computers. Linz, Austria, 2009.

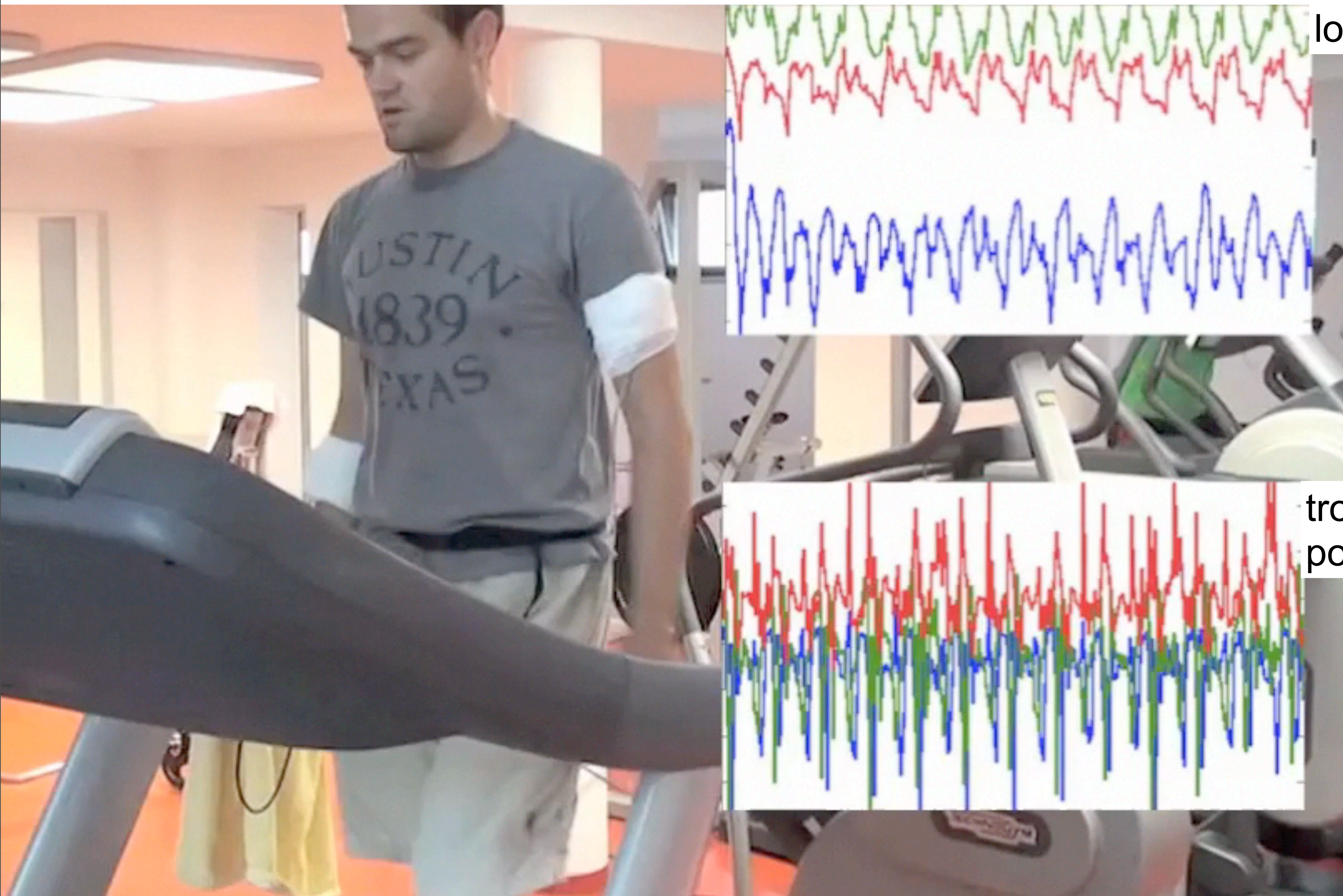
How to make activity recognition more robust?



Overview and Contributions



Walking

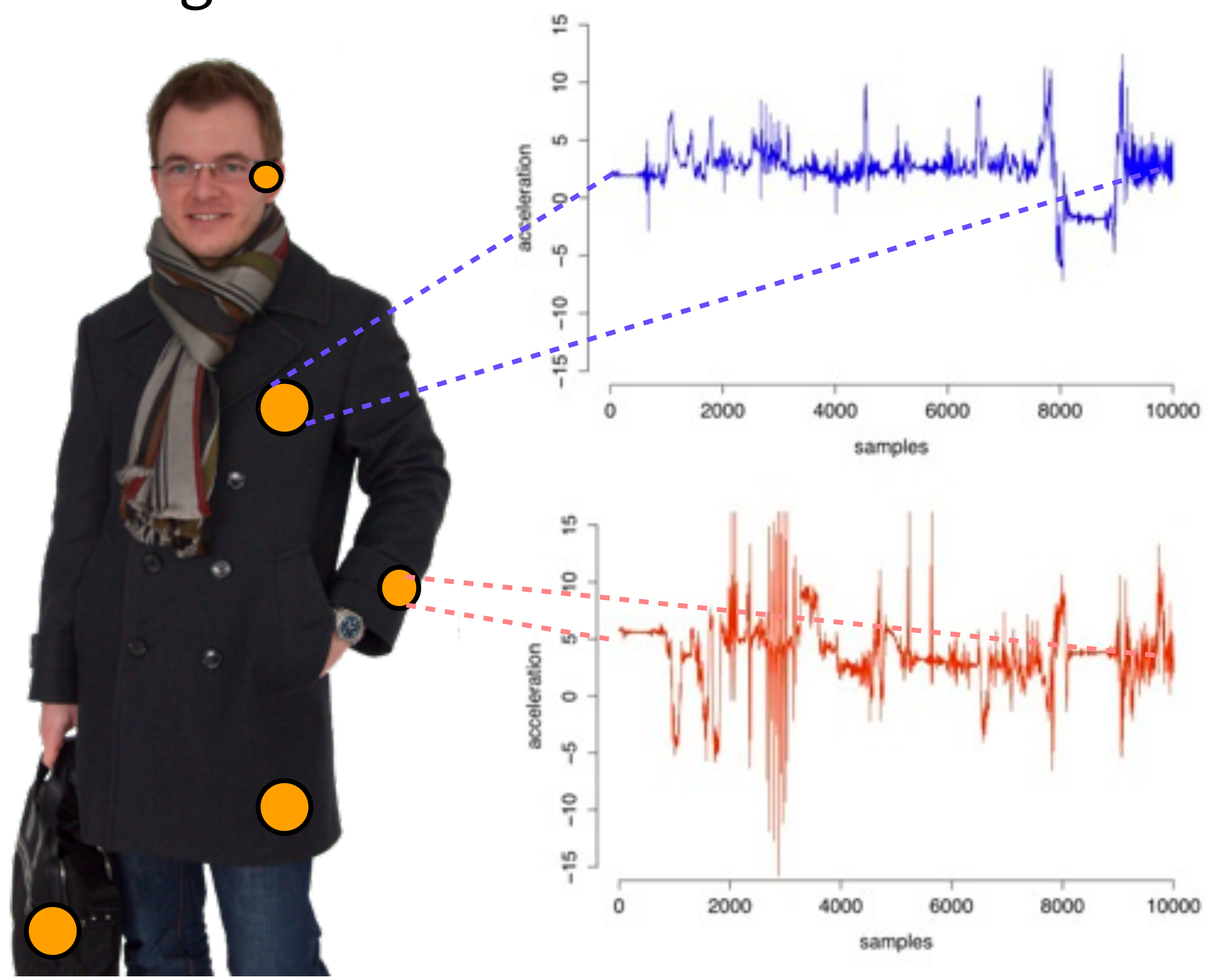



Right wrist
Left wrist
Right arm down
Left arm down
Right arm up
Left arm up
Right knee up
Right hip
Right knee down
Back

Unconstraint Onbody Placement Recognition

- rest periods need to be filtered out
- "carrier" frequency is gone (compared to walking)
- probabilities of distinct movements for a given body part differ greatly
- time-series approach necessary

- smoothing
  - majority decision too crude
  - stochastic filtering needed

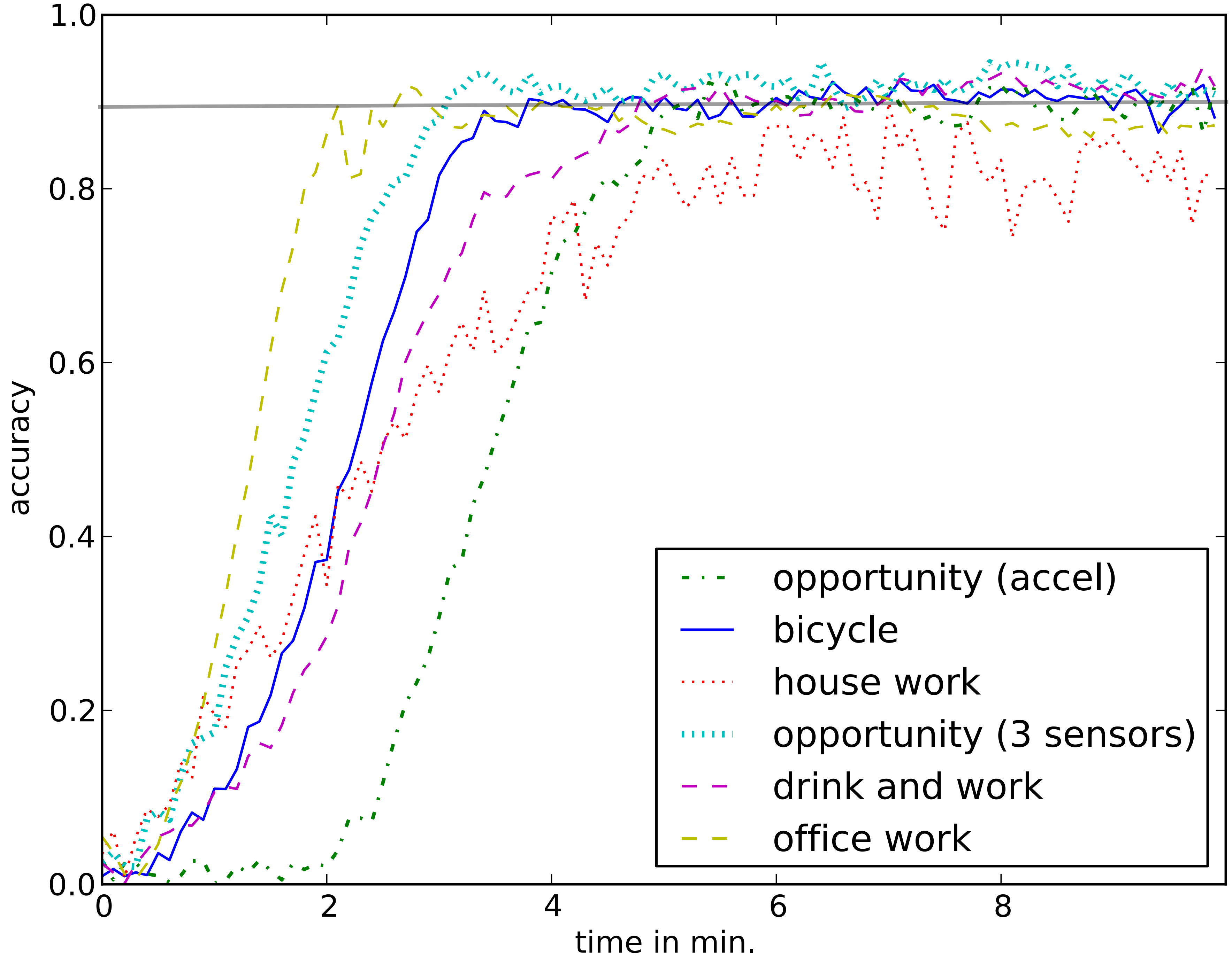


Experimental Evaluation

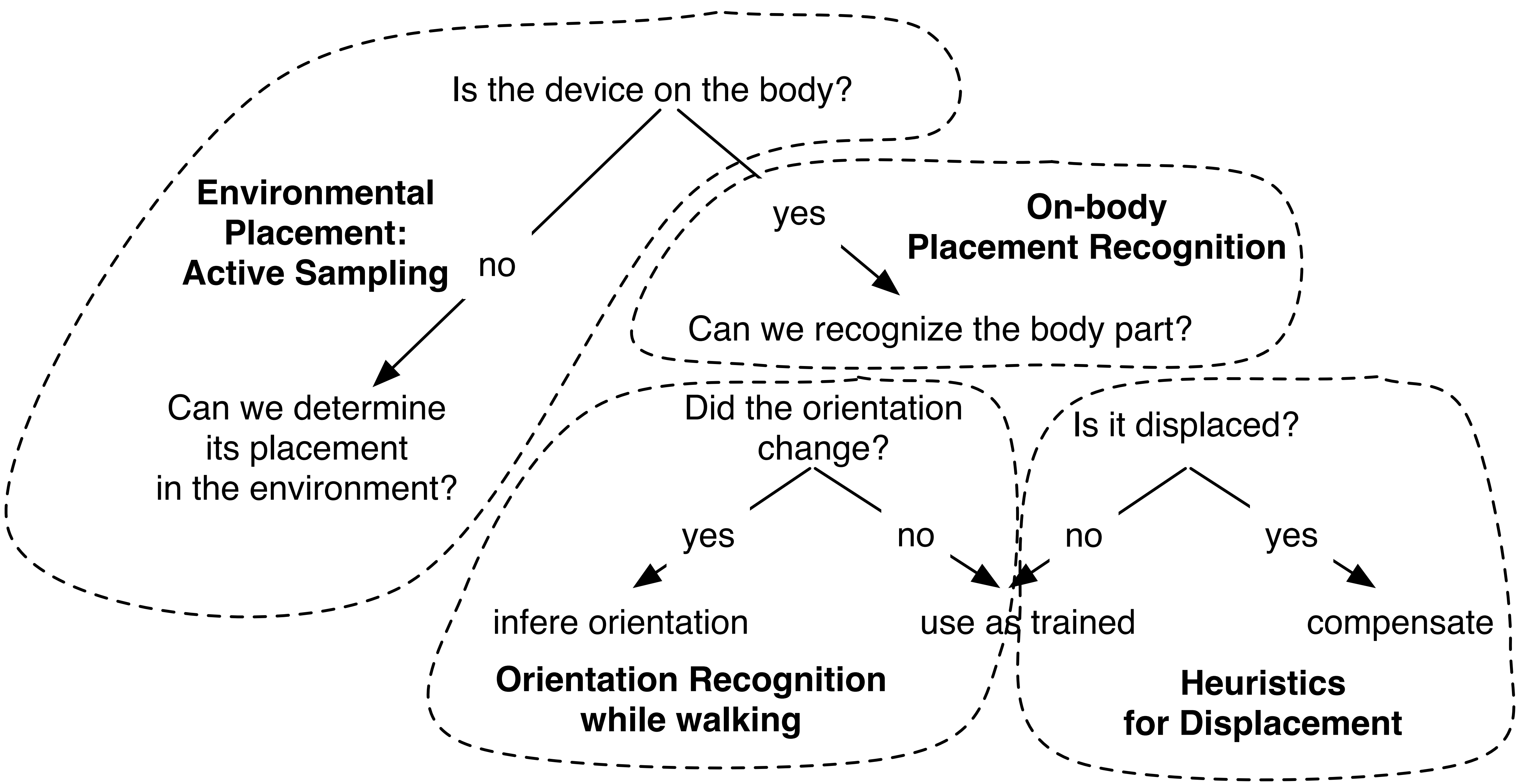
- 5 data sets
- house work to bicycle repair
- 3 to 7 participants per data set
- 1 real life data set
- age range 17 - over 60
- 4-5 on-body placements

around 30 hours of sensor data

Results: Particle Filtering

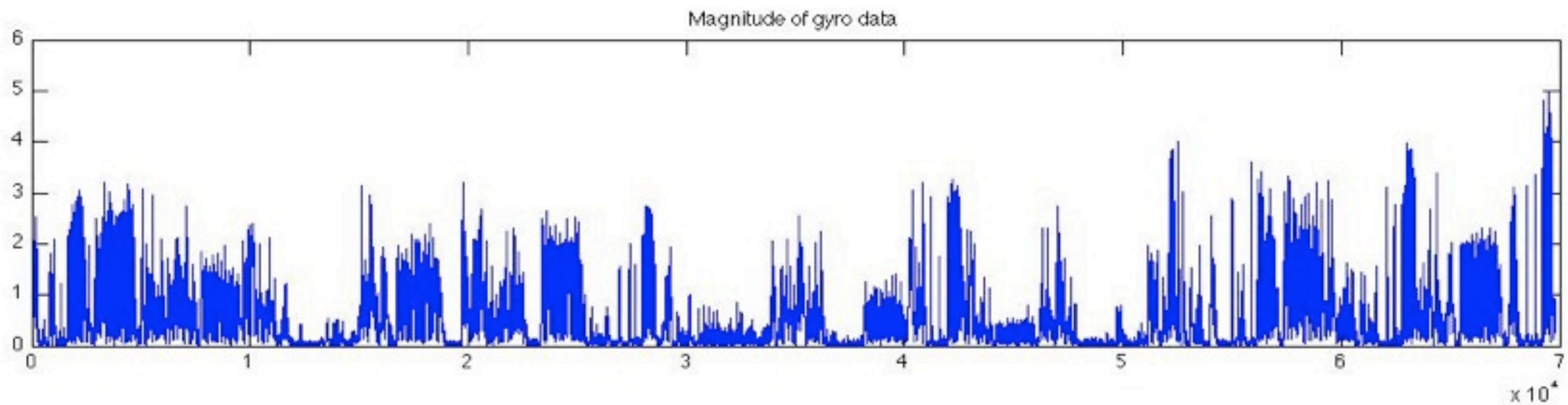


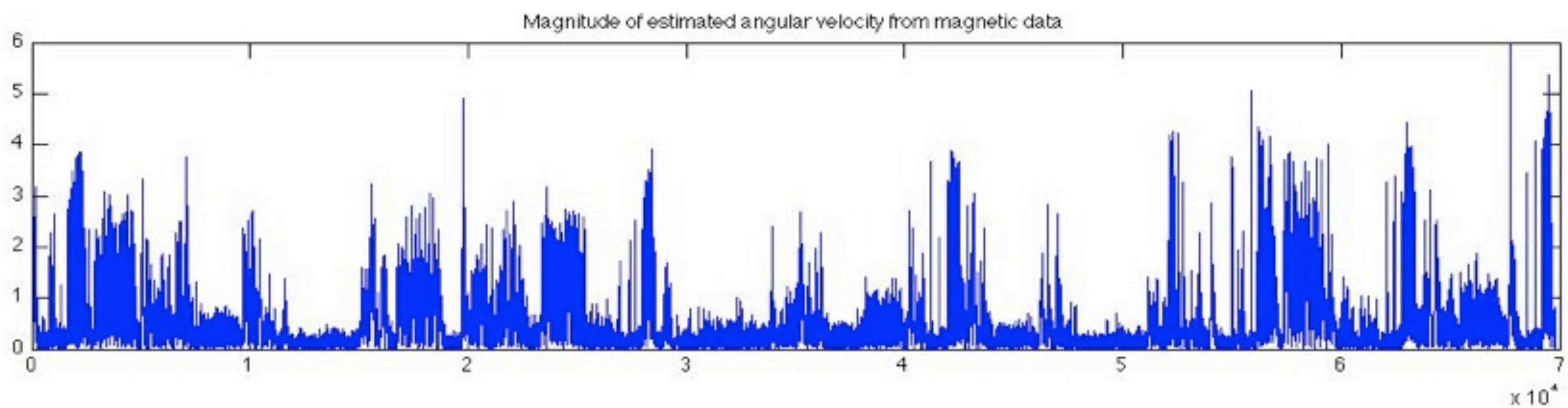
Robust Onbody Activity Recognition



What about new sensors?

Abstract Features

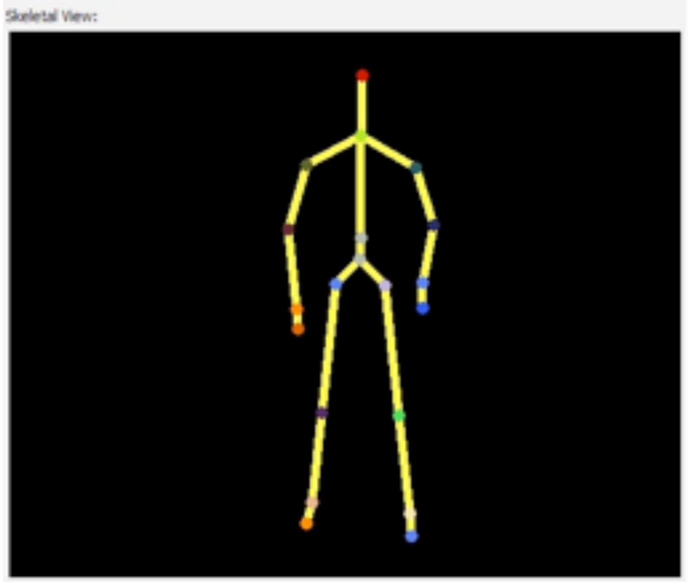


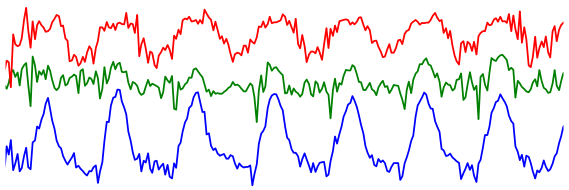


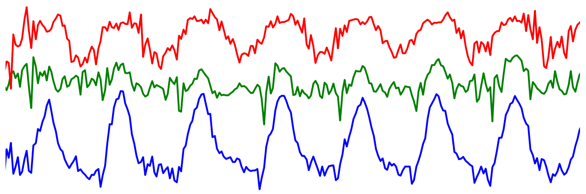
Example: rate of rotation can be derived from gyros as well as from magnetic field sensors

Bahle, Kunze ISWC 10

incorporating environmental sensors







correlation between signals:

highest match wins

Gernot Bahle, Paul Lukowicz, Kai Kunze, Koichi Kise, *I see you: How to improve wearable activity recognition by leveraging information from environmental cameras*

Percom, San Diego, 2013.

Best Work in Progress Paper

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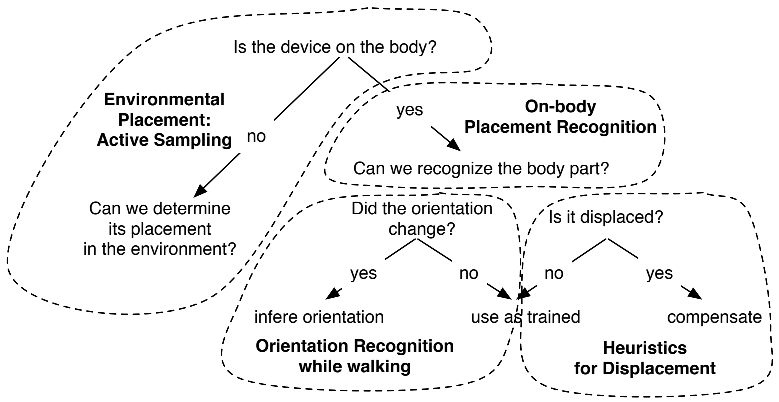
2015-2020



1. complex activities
2. accuracy well over 95%
3. real people in real environments

not students in the lab !

Key Requirements

The field needs to mature

- Established problem definitions and experimental standards
- Established evaluation methodologies
- Standard data sets for objective comparison between methods
- Recognition of incremental but solid and well proven improvements as scientific contributions
- higher level abstractions needed

Use synergy effects from other fields.

Don’t reinvent the wheel!

1. state of the art in activity recognition
   on-body sensing
2. special focus: knowledge and reading activities

3. challenges
4. demos

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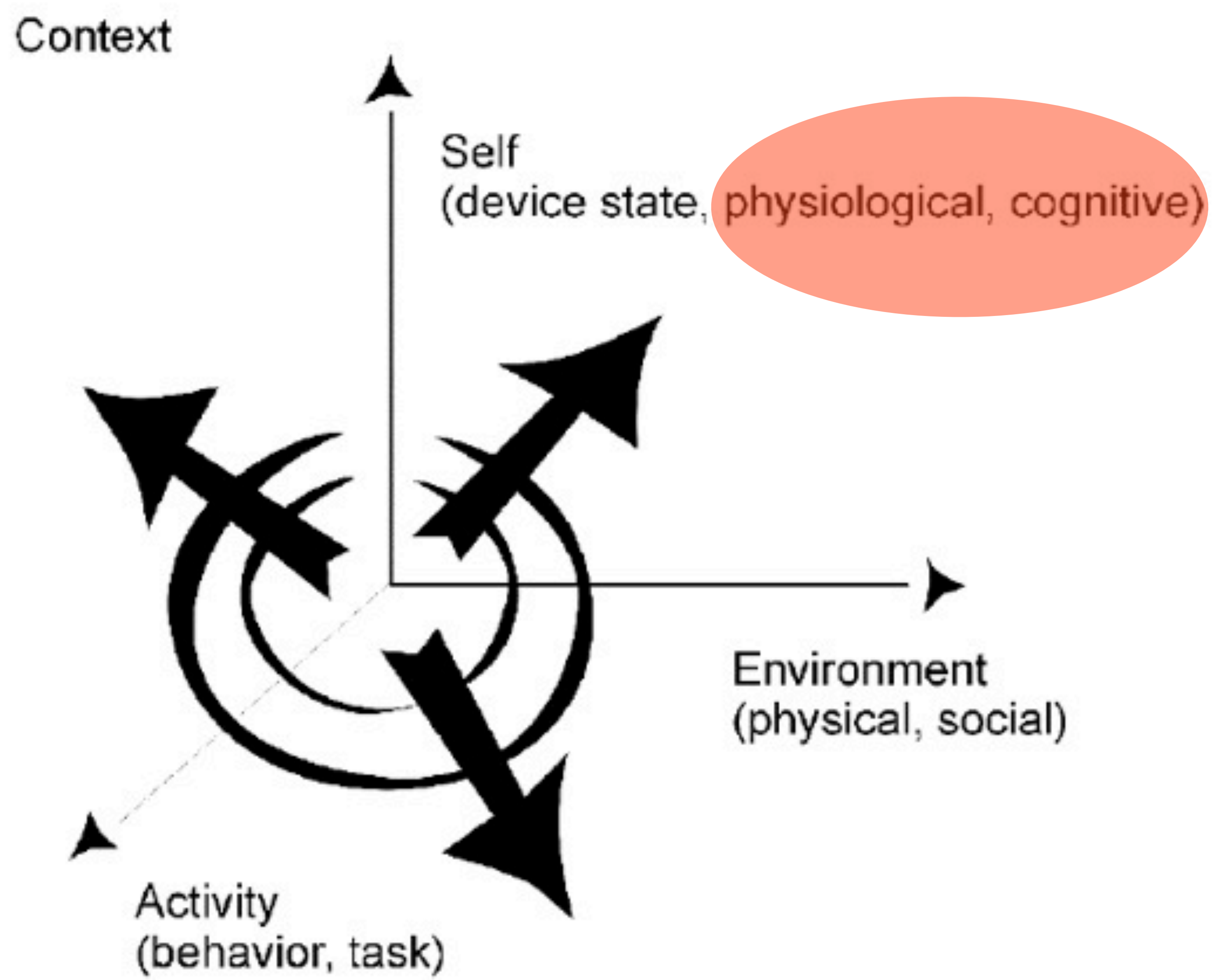
Context Aware Systems 2000

acceleration, sound, light...



Gellersen, Schmidt, Beigl 1999, from the SmartIts project

also Day, Abowd, Pentland, Starner, Schiele,... around 2000

knowledge acquisition

- very few in-situ studies concerning reading activities
- utilizing pervasive sensing and computer vision to recognize:
  - what you read
  - how you read it
- “Reading-life” /Knowledge Log

Why do we track reading habits?

- Quantified approach to reading (knowledge acquisition)
- People who read more
  - higher vocabulary skill
  - **higher general knowledge [1]**
- Give people tools to measure the quantity, quality and type of reading they do
- Similar to tracking applications for fitness and health
  - They have been shown to improve physical fitness
  - We want to improve the **fitness of the mind**

[1] A. Cunningham and K. Stanovich. What reading does for the mind. Journal of Direct Instruction, 1(2):137–149, 2001.

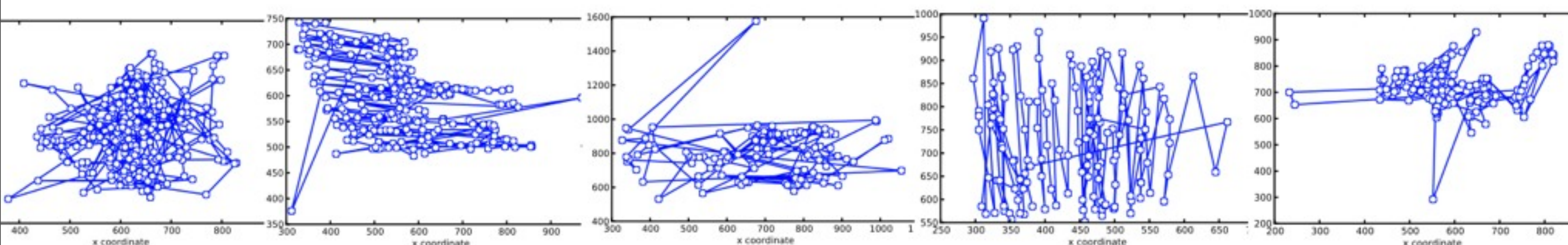
Reading recognition – What are you reading?

Modalities:

- Eyetracking
- EEG

Document type recognition

Using eygaze to distinguish document types

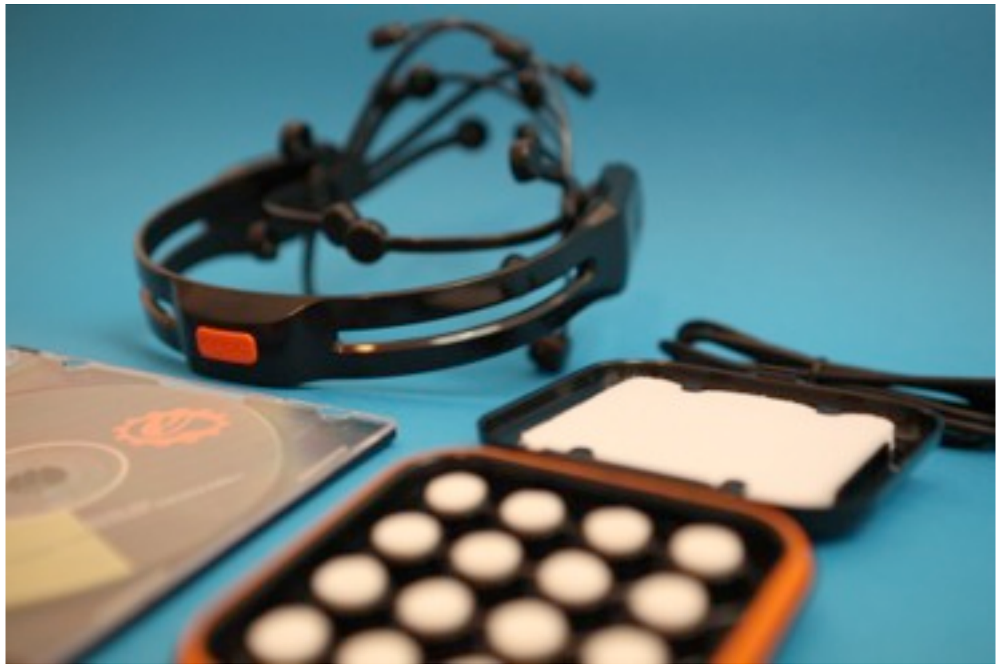


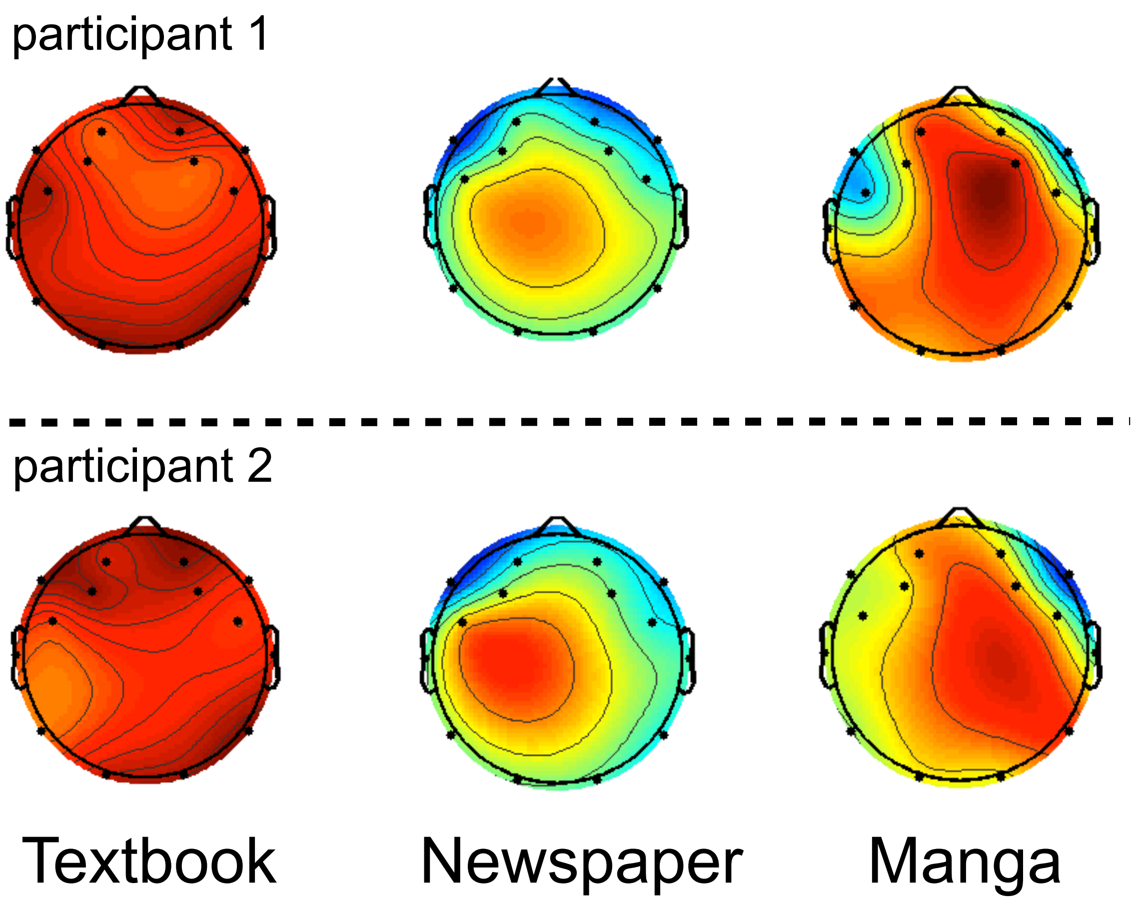
72 % user independent recognition (10 users,
5 document types, 5 environments)

Kai Kunze, Andreas Bulling, Yuzuko Utsumi,Koichi Kise. **I know what you are reading – Recognition of document types using mobile eye tracking**, ISWC 2013, Zurich.

... using EEG

- detecting different document types is difficult ...
  - reading detection/ segmentation working for a small set of test users



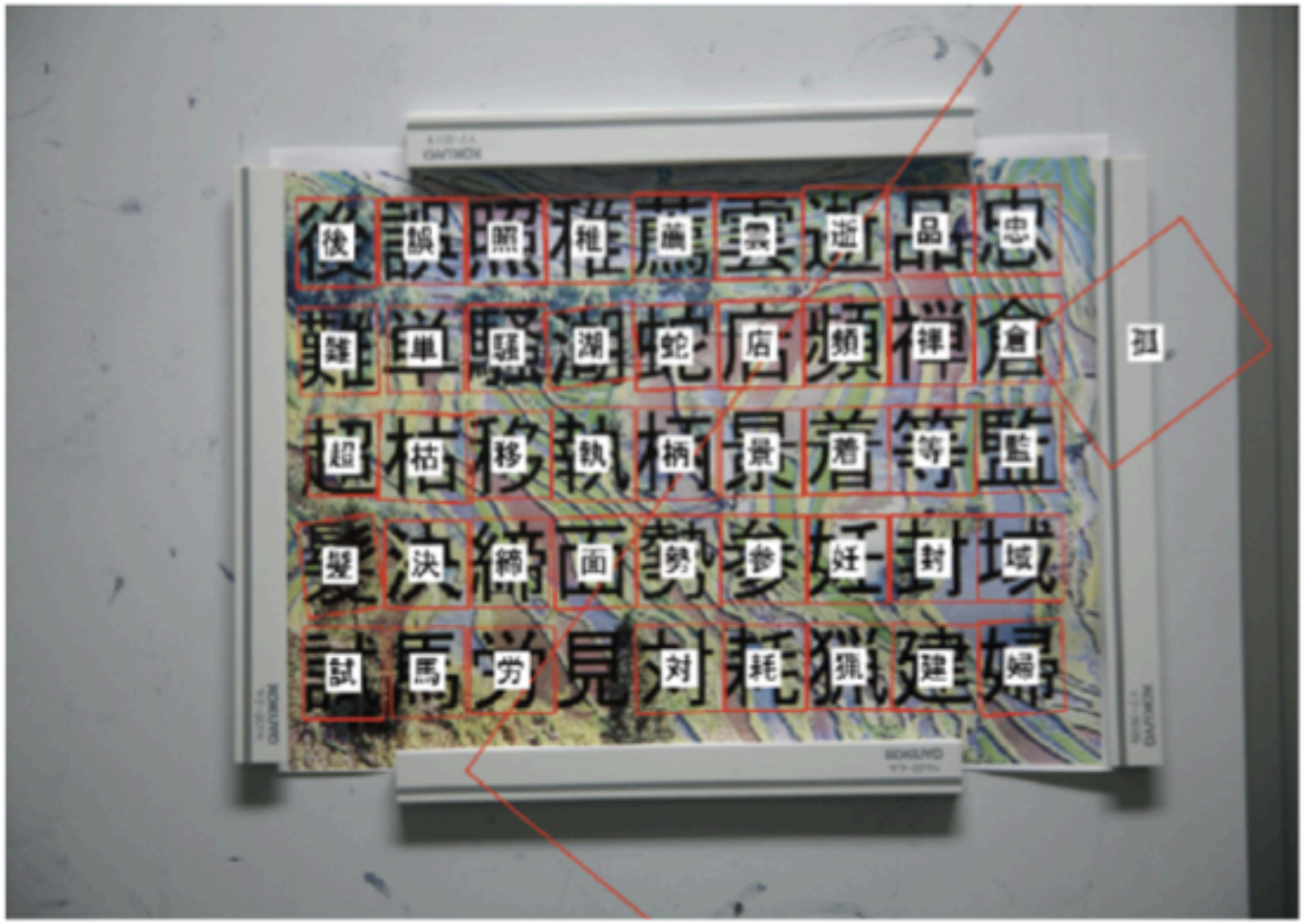


K. Kunze, Y. Shiga, S. Ishimaru, Y. Utsumi, K. Kise. Reading activity recognition using an off-the-shelf EEG — detecting reading activities and distinguishing genres of documents accepted at ICDAR, Washington D.C., 2013.

However, it get’s really interesting ...

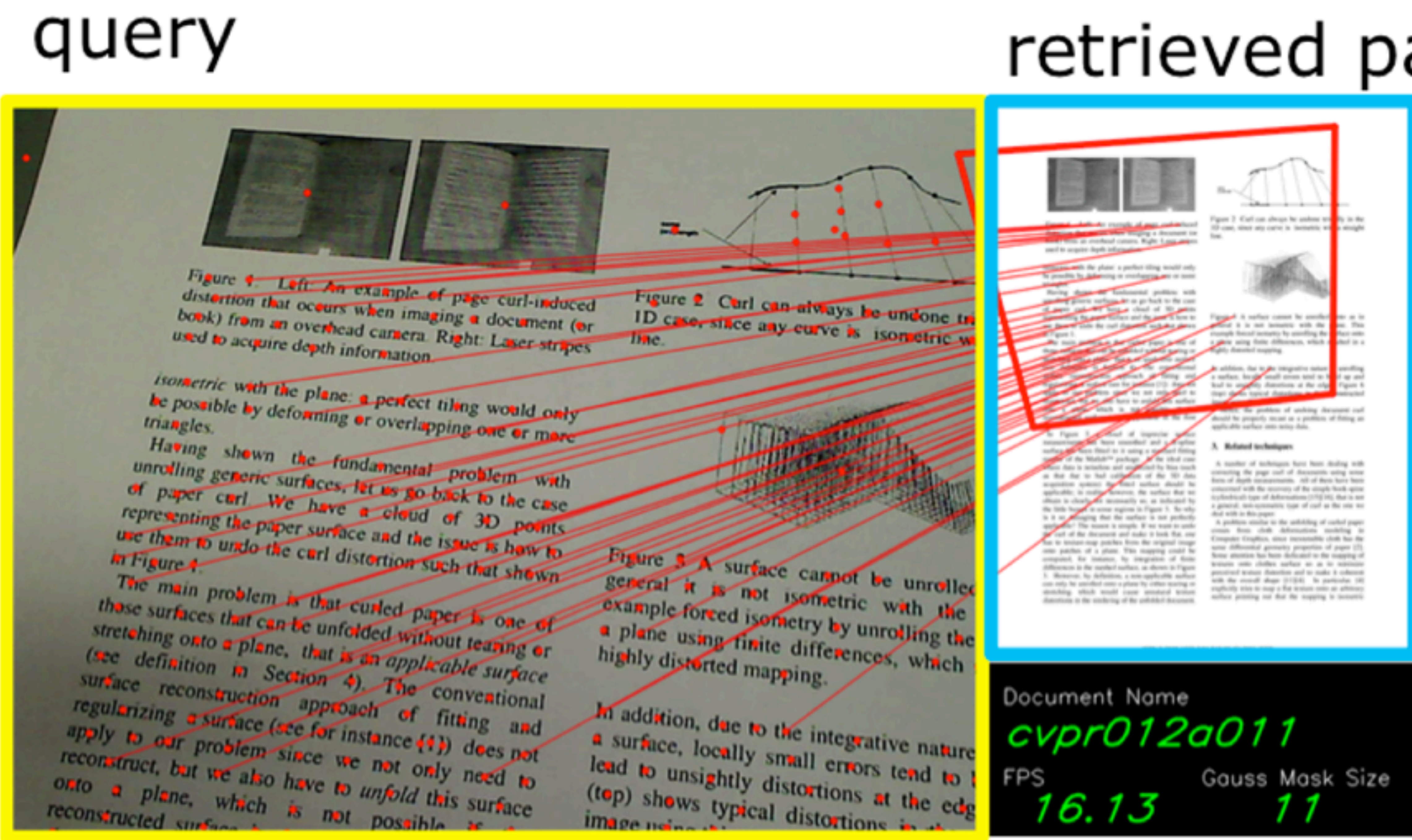
- leveraging other disciplines
  - **computer vision (mature field)**
  - artificial intelligence (higher level reasoning)
  - ...

Character Recognition



Kanji under background clutter

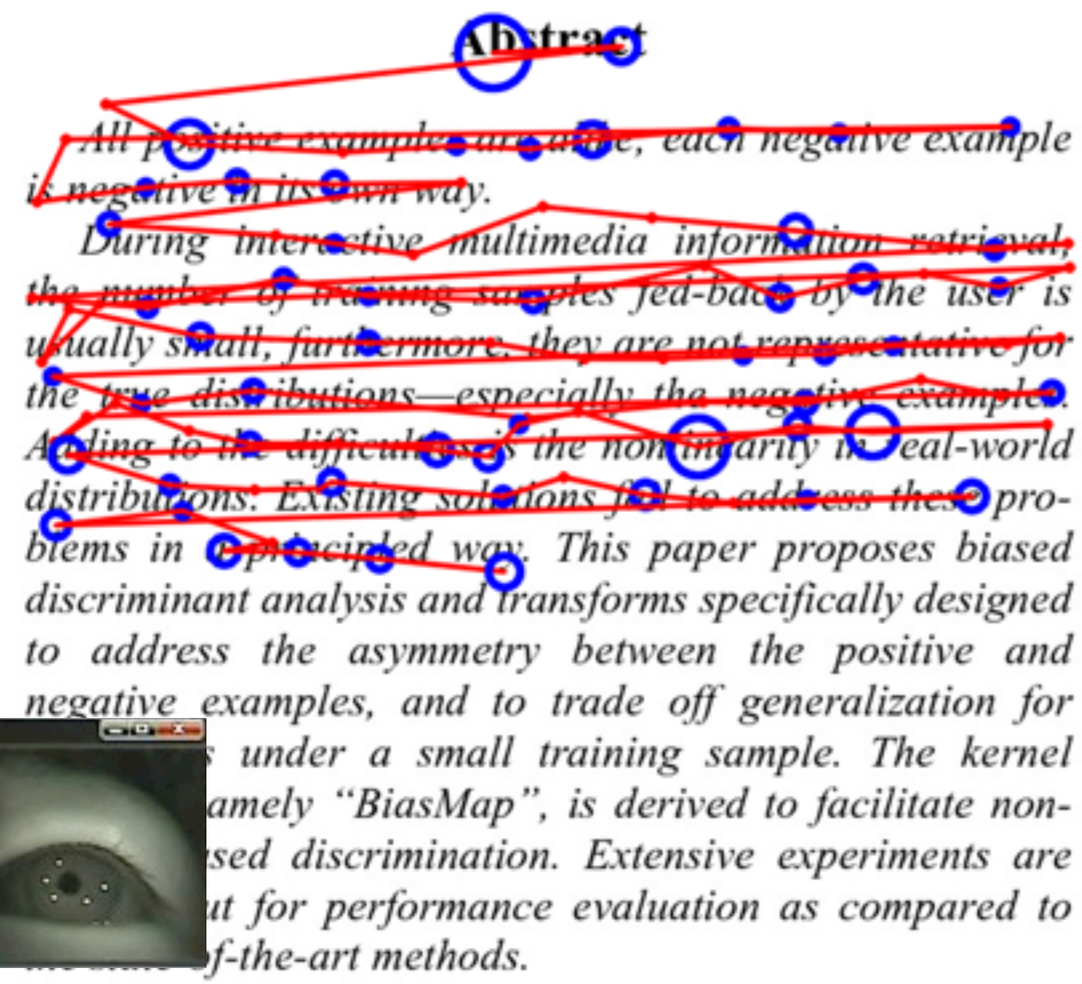
Document Image Retrieval



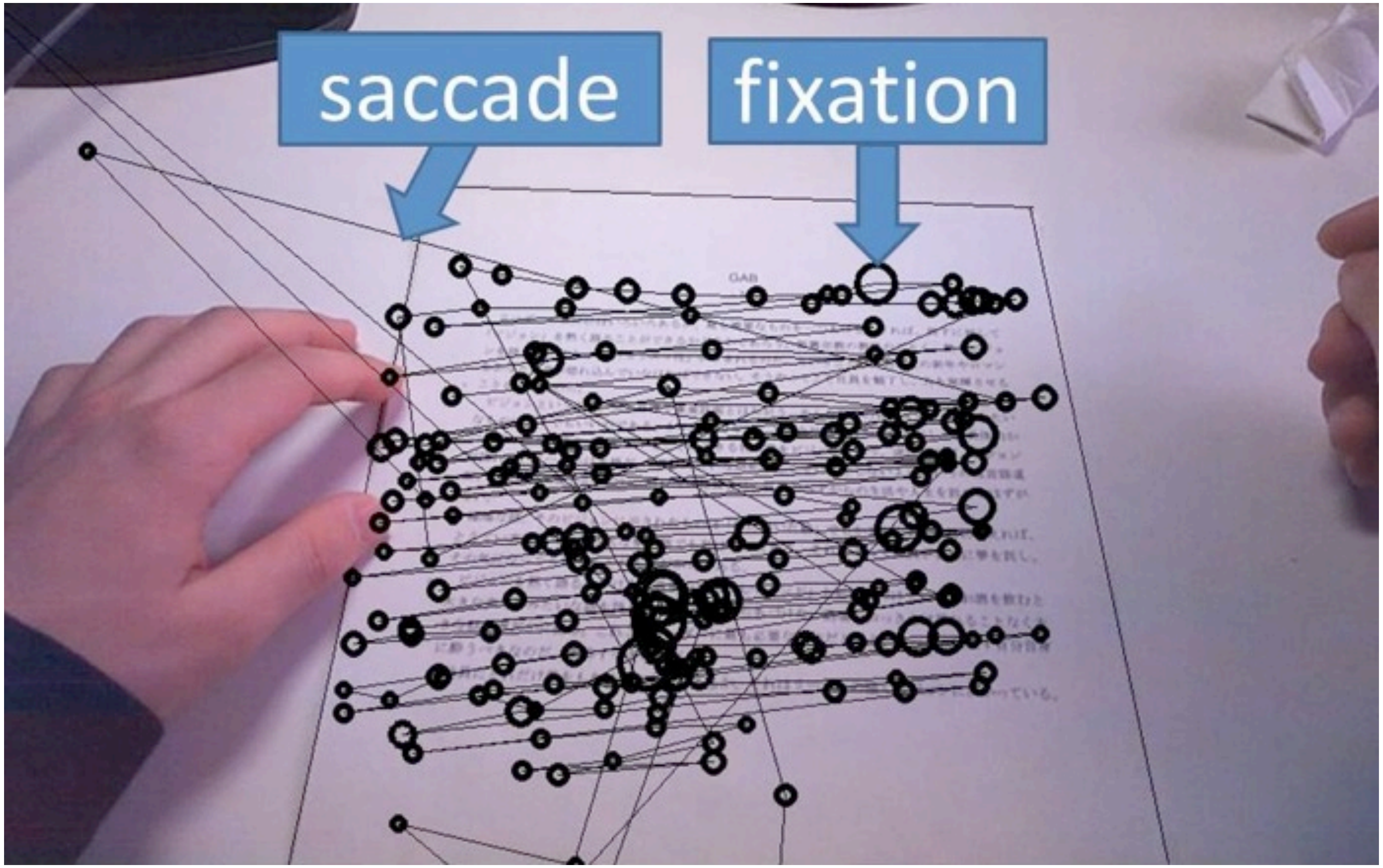
Wordometer

Experimental setup

Gaze overlaid on the document using Document image retrieval



K. Kunze, H. Kawaichi, K. Yoshimura, K. Kise. **The Wordometer – Estimating the Number of Words Read Using Document Image Retrieval and Mobile Eye Tracking** ICDAR 2013.


saccade
fixation

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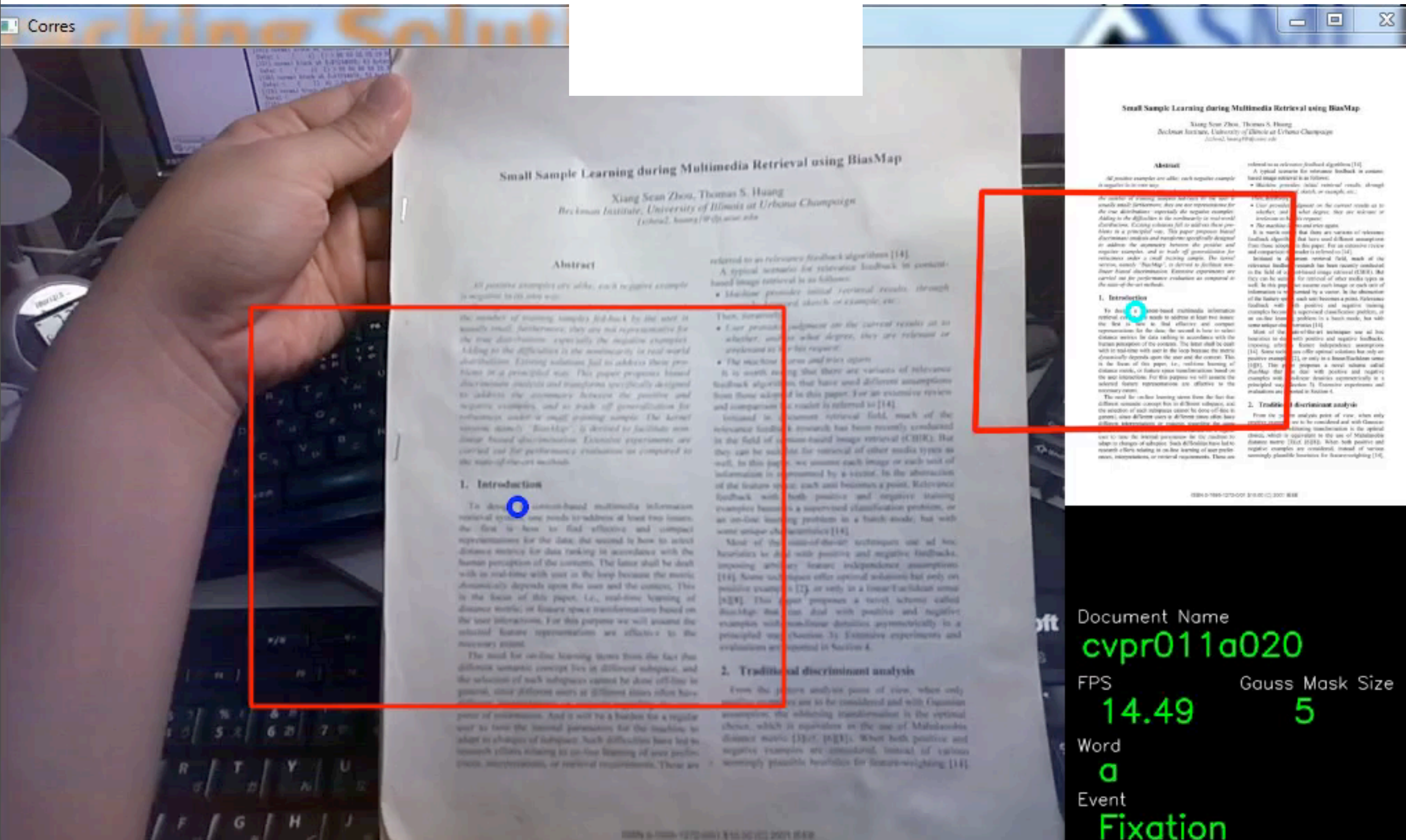
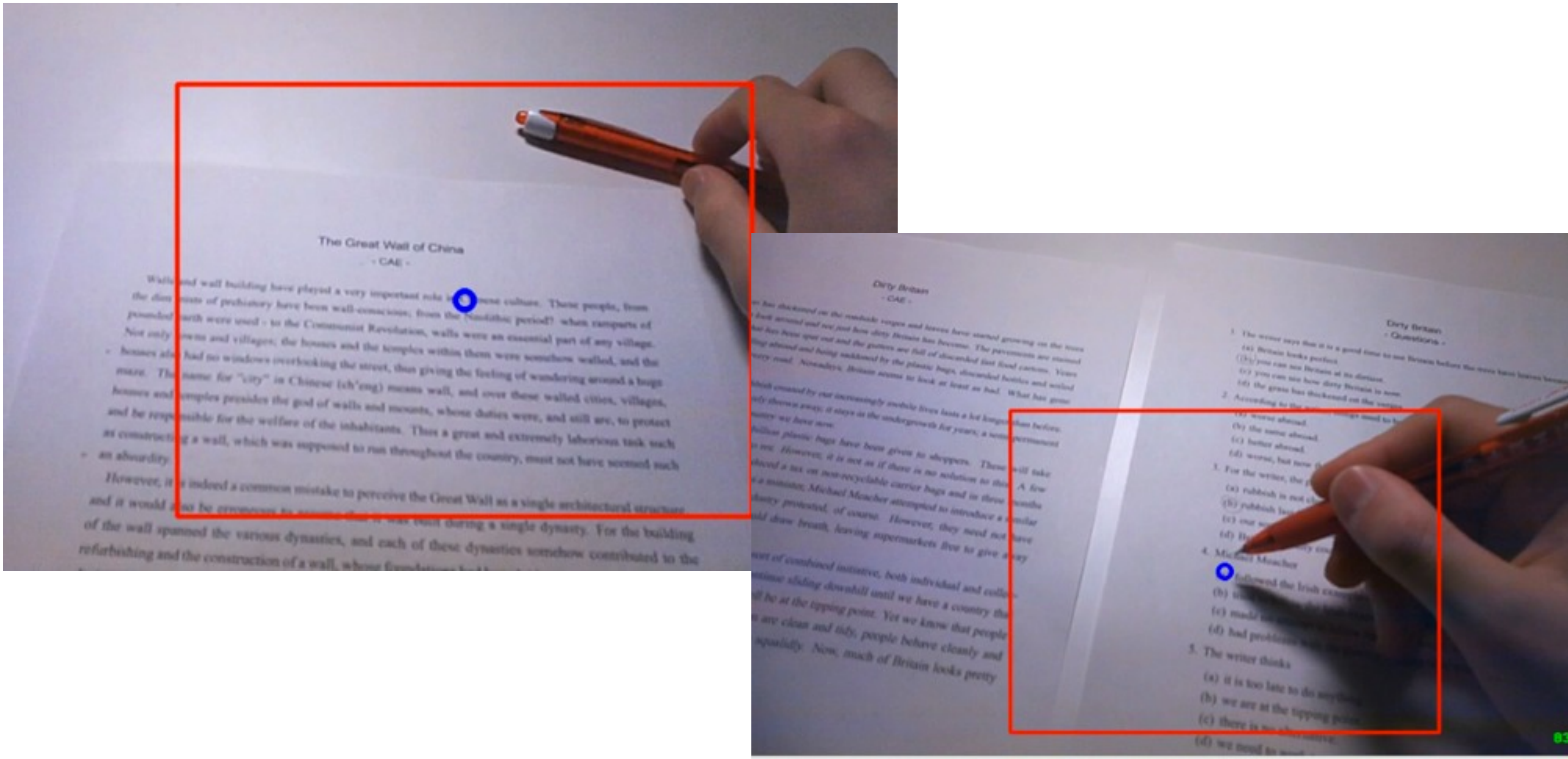
Eye-tracking with Document Image Retrieval

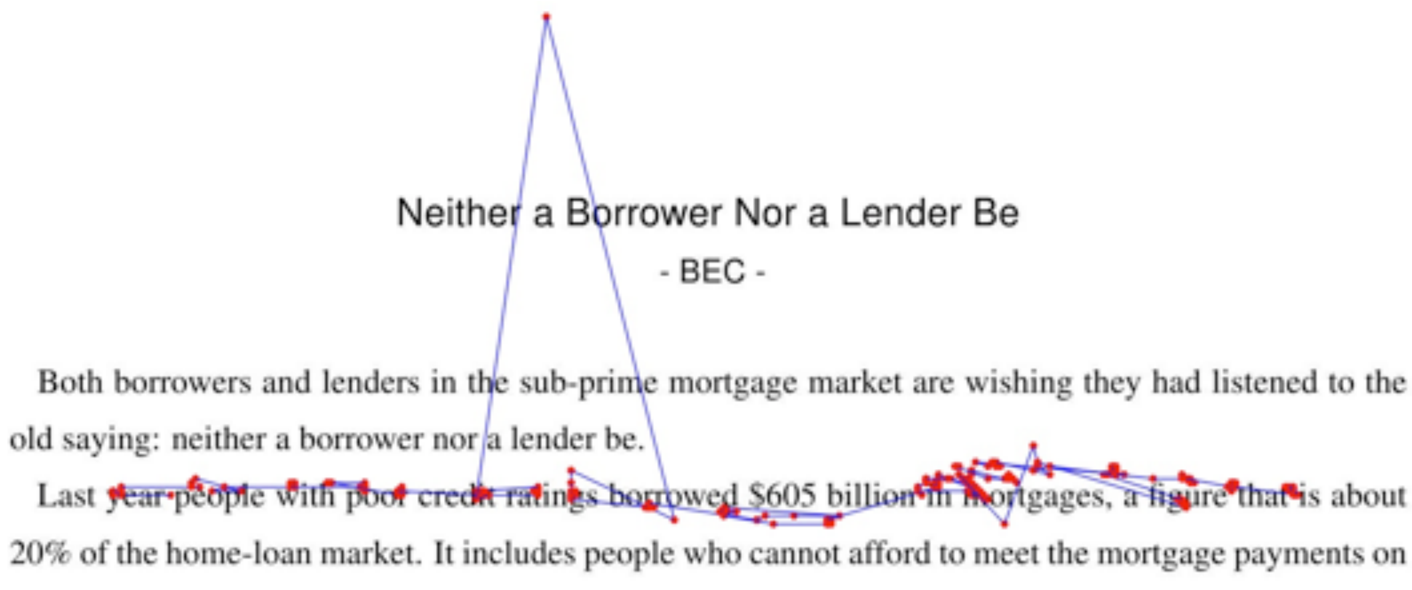


Inferring Language Expertise

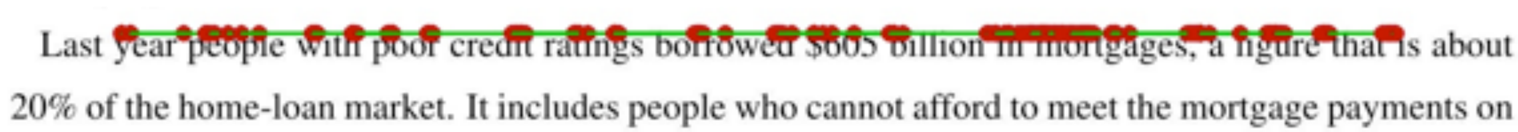


K. Kunze, H. Kawaichi, K. Yoshimura, K. Kise. **Towards inferring language expertise using eye tracking**. accepted as Work in Progress at *ACM SIGCHI Conference on Human Factors in Computing Systems*, Paris, France 2013.

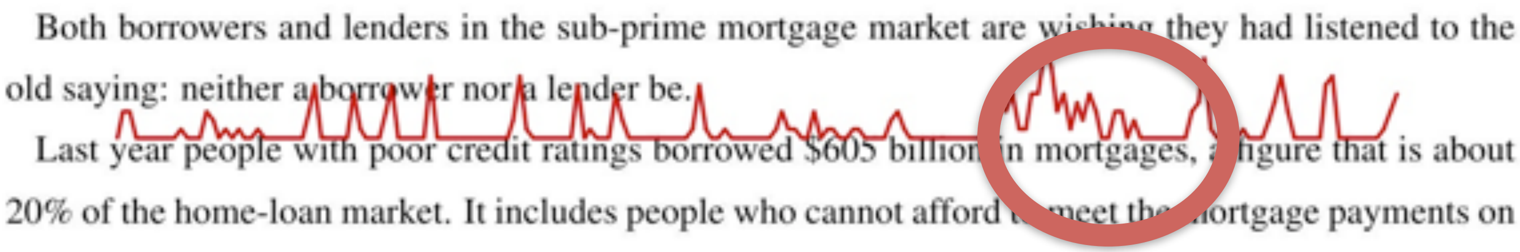
Difficult word detection



Eye-gaze translated to Document coordinate System using LLAH



Horizontal projection To a line



histogram

Challenges

- The field needs to mature
  - Established problem definitions and experimental standards
  - Established evaluation methodologies
  - Standard data sets for objective comparison between methods
  - Recognition of incremental but solid and well proven improvements as scientific contributions

- Sensing in the large ...
  - higher abstraction levels needed
  - how to scale? (e.g. eyetrackers are quite espensive)

Demos

Ubicomp 2013 Demo/Poster

My Reading Life – Towards Utilizing Eyetracking on Unmodified Tablets and Phones

Annotate Me – Supporting Active Reading using Real-Time Document Image Retrieval On Mobile Devices

Questions, remarks, violent dissent?

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