Real-Life Activity Recognition

Kai Kunze

Robust Activity Recognition

Recognizing Reading Activities

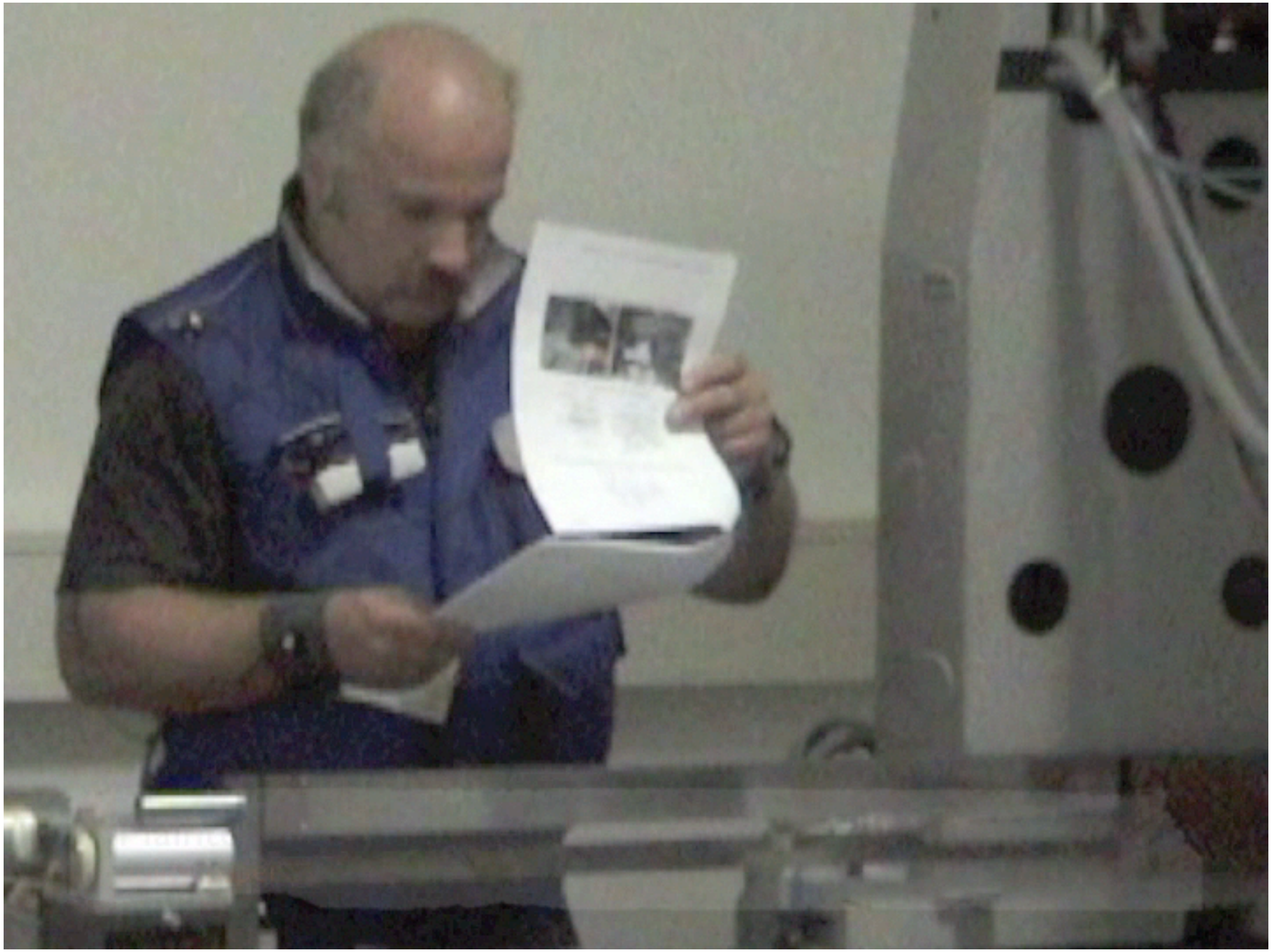
Compensating for On-Body Placement Effects in Activity Recognition

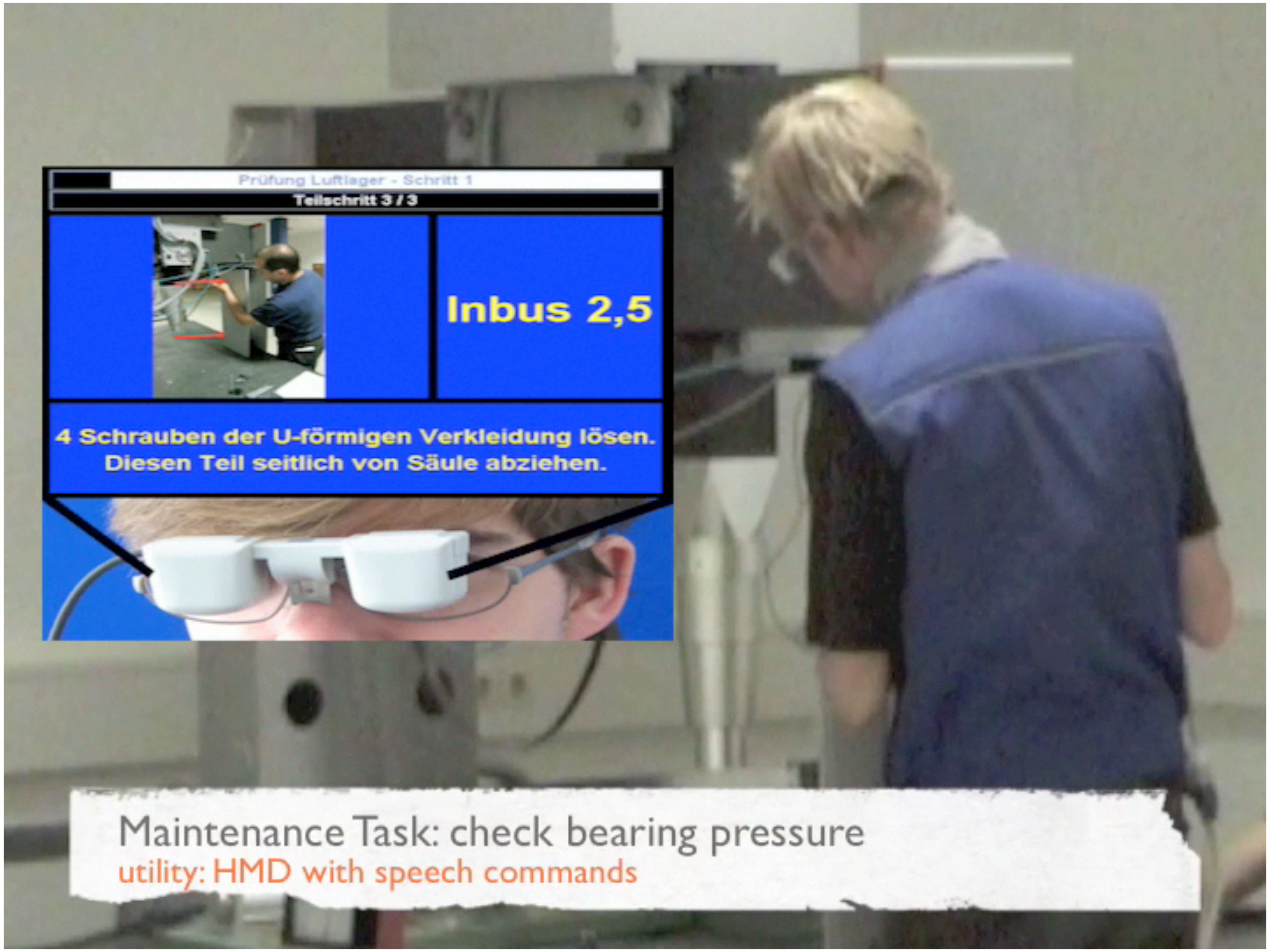
Kai Kunze

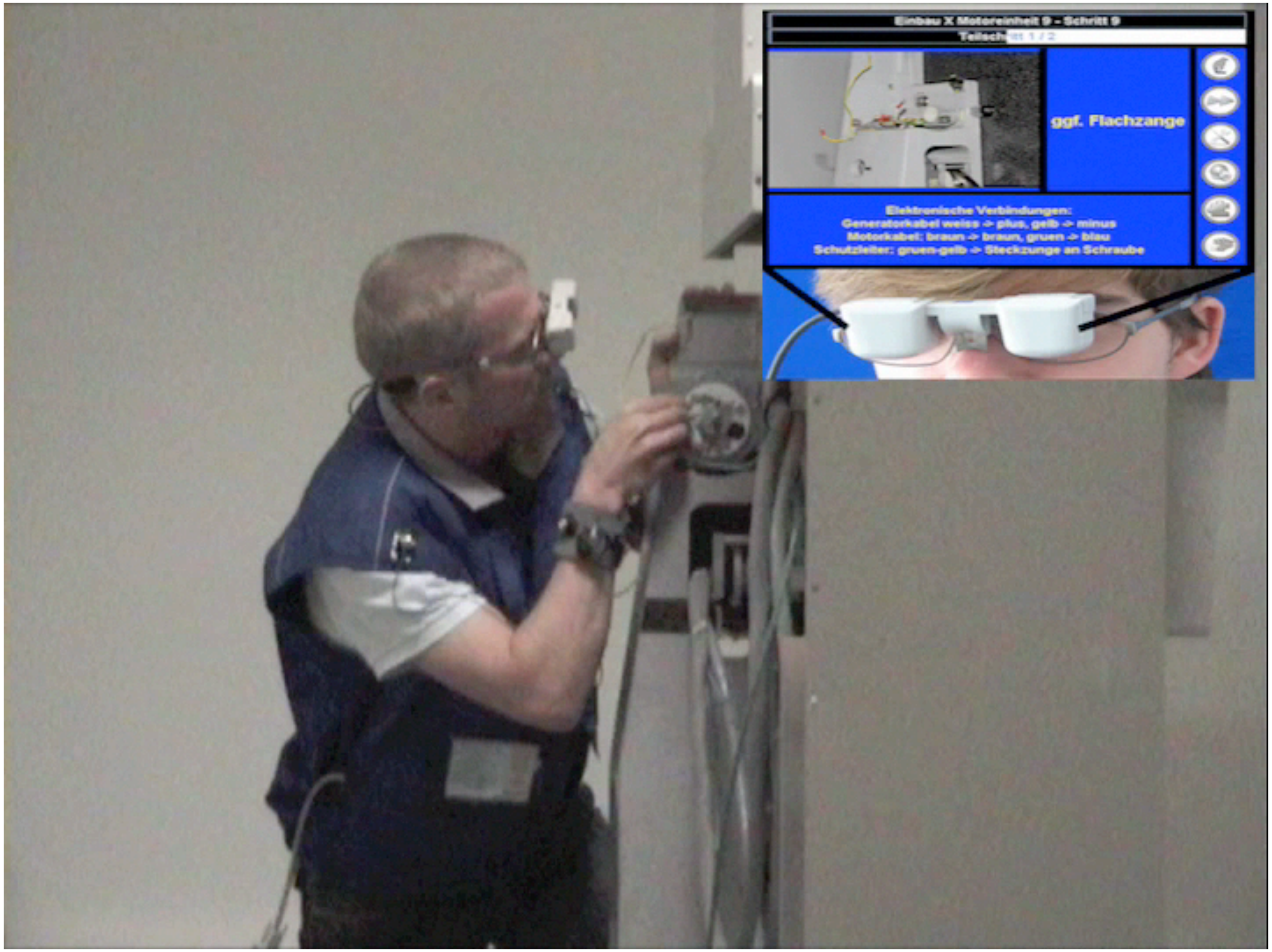
Compensating for On-Body Placement Effects in Activity Recognition

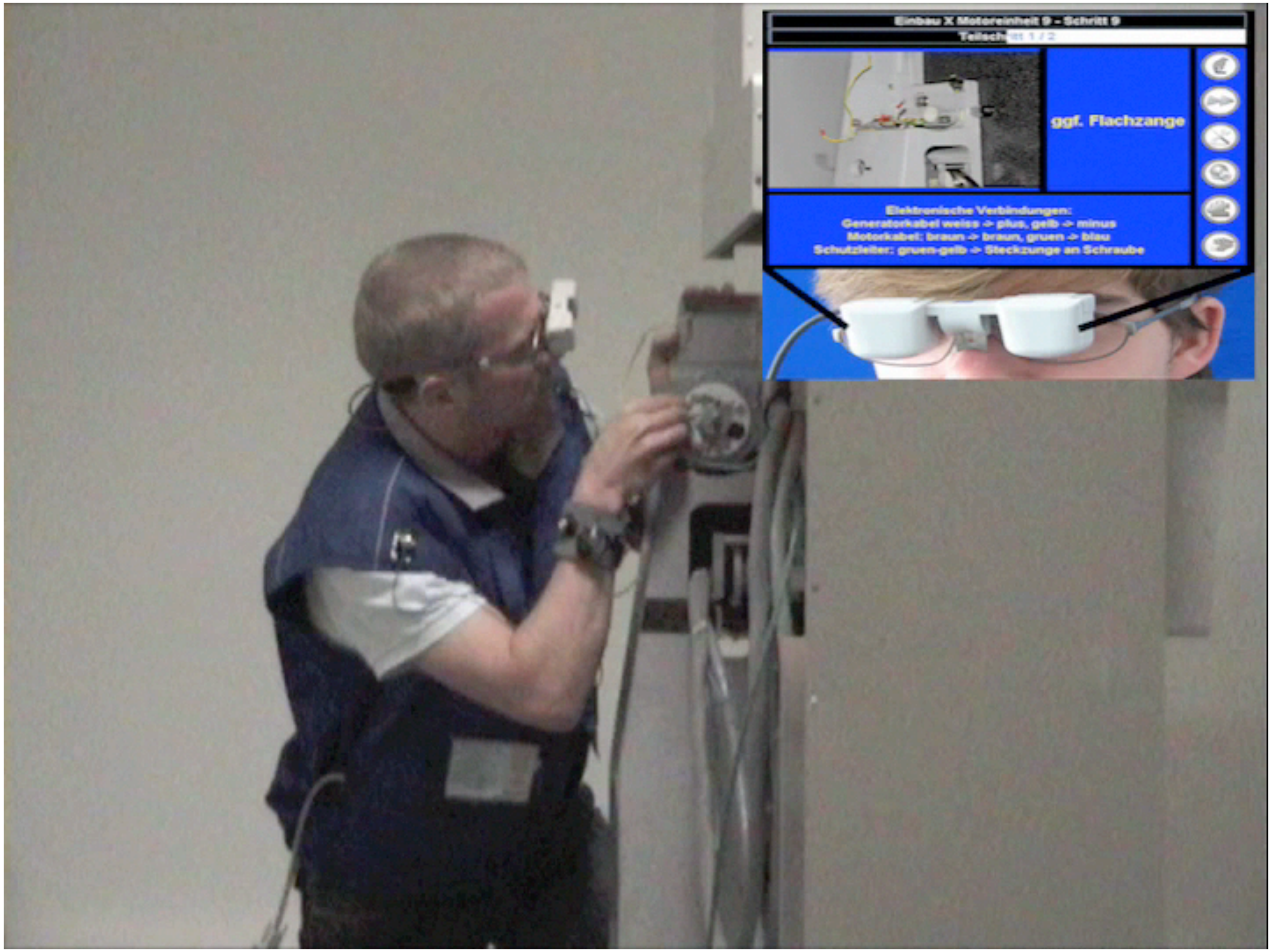
Kai Kunze

公立大学法人
大阪府立大学
OSAKA PREFECTURE UNIVERSITY



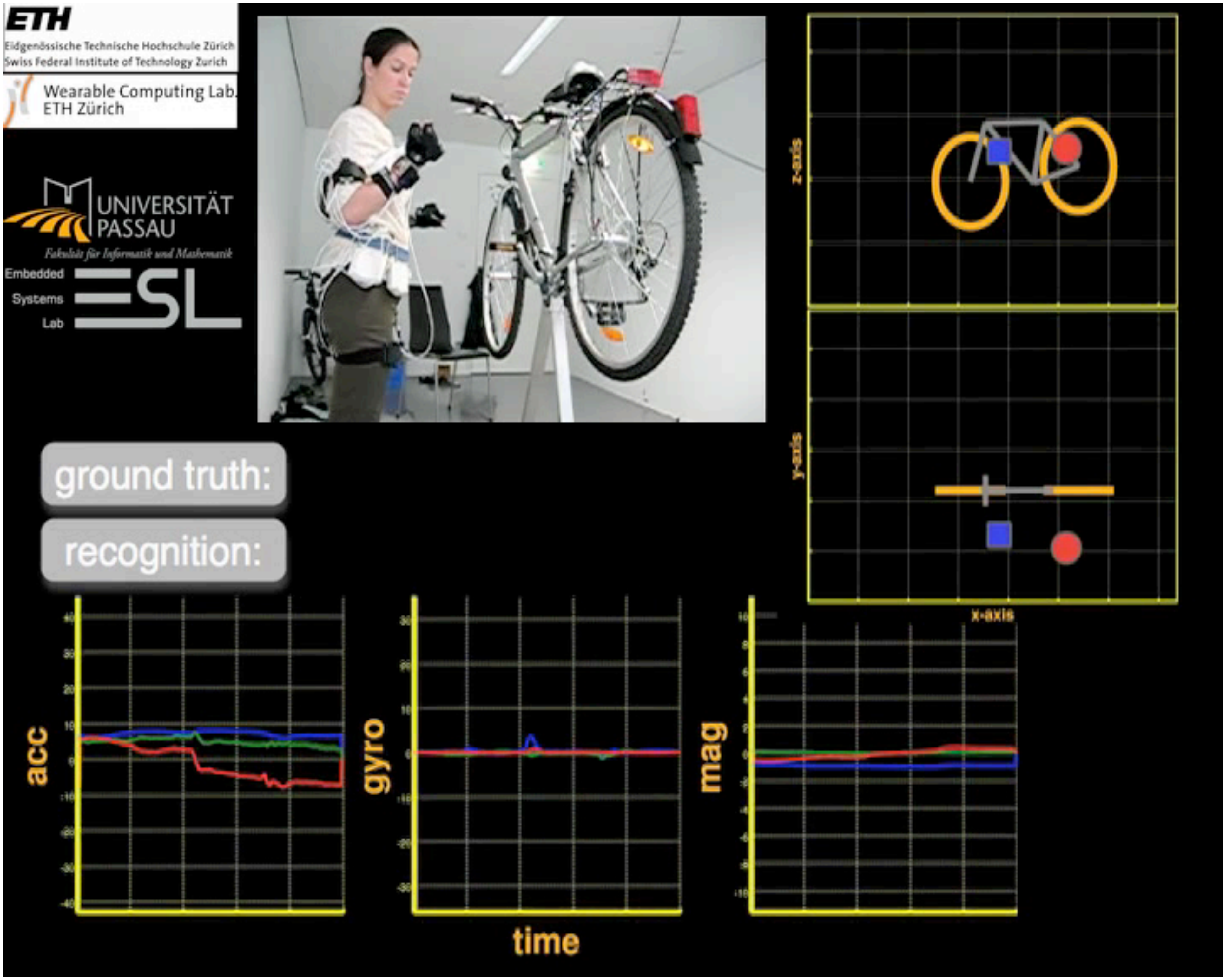

Prüfung Luftlager - Schritt 1
Teilschritt 3 / 3
Inbus 2,5
4 Schrauben der U-förmigen Verkleidung lösen.
Diesen Teil seitlich von Säule abziehen.
Maintenance Task: check bearing pressure
utility: HMD with speech commands


Einbau X Motoreinheit 9 - Schritt 9
ggf. Flachzange
Elektronische Verbindungen:
Generatorkabel weiss -> plus, gelb -> minus
Motorkabel: braun -> braun, gruen -> blau
Schutzleiter: gruen-gelb -> Steckzunge an Schraube

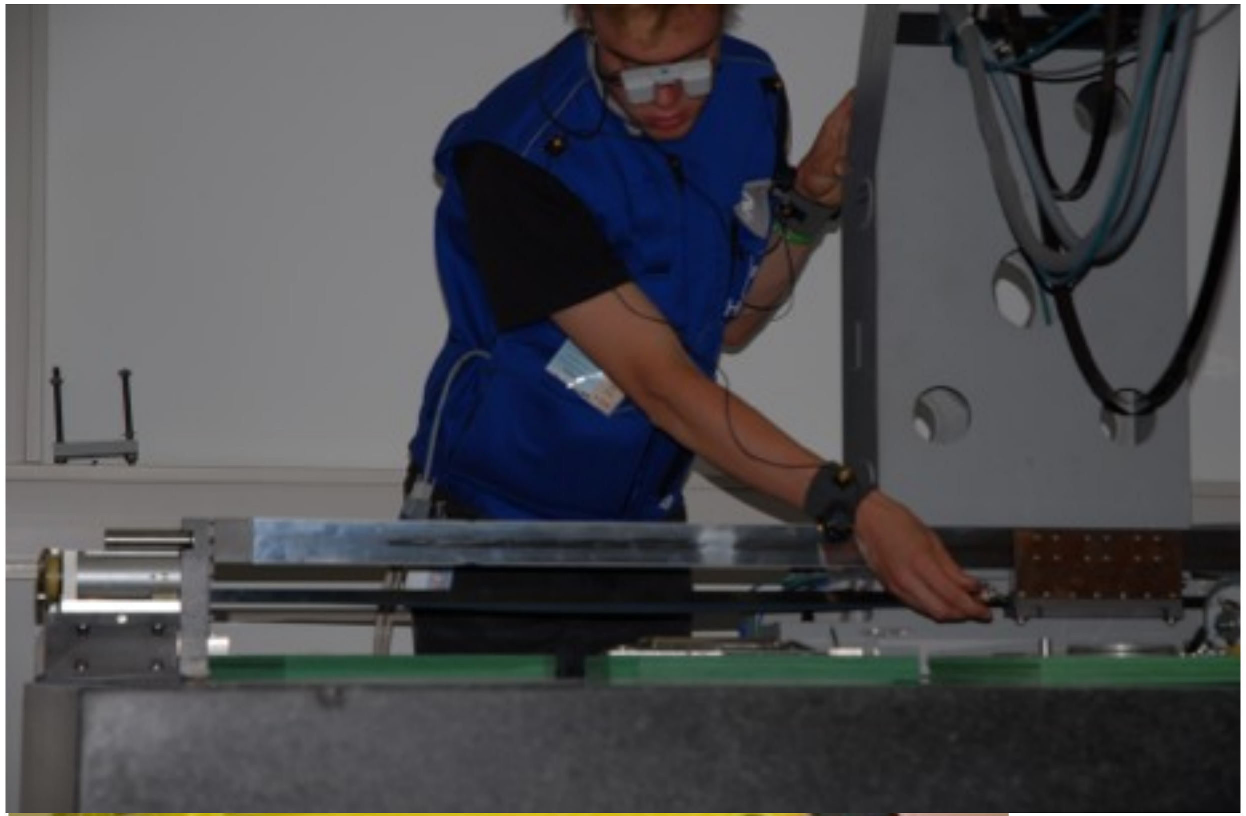


Kunze, K.,Wagner, F., Kartal, E., Morales Kluge, E., and Lukowicz, P. Does Context Matter ? - A Quantitative Evaluation in a Real World Maintenance Scenario. *In Proceedings of the 7th international Conference on Pervasive Computing Nara*, Japan, May 11 - 14, 2009.

Work by Georg Ogris and Thomas Stiefmaier

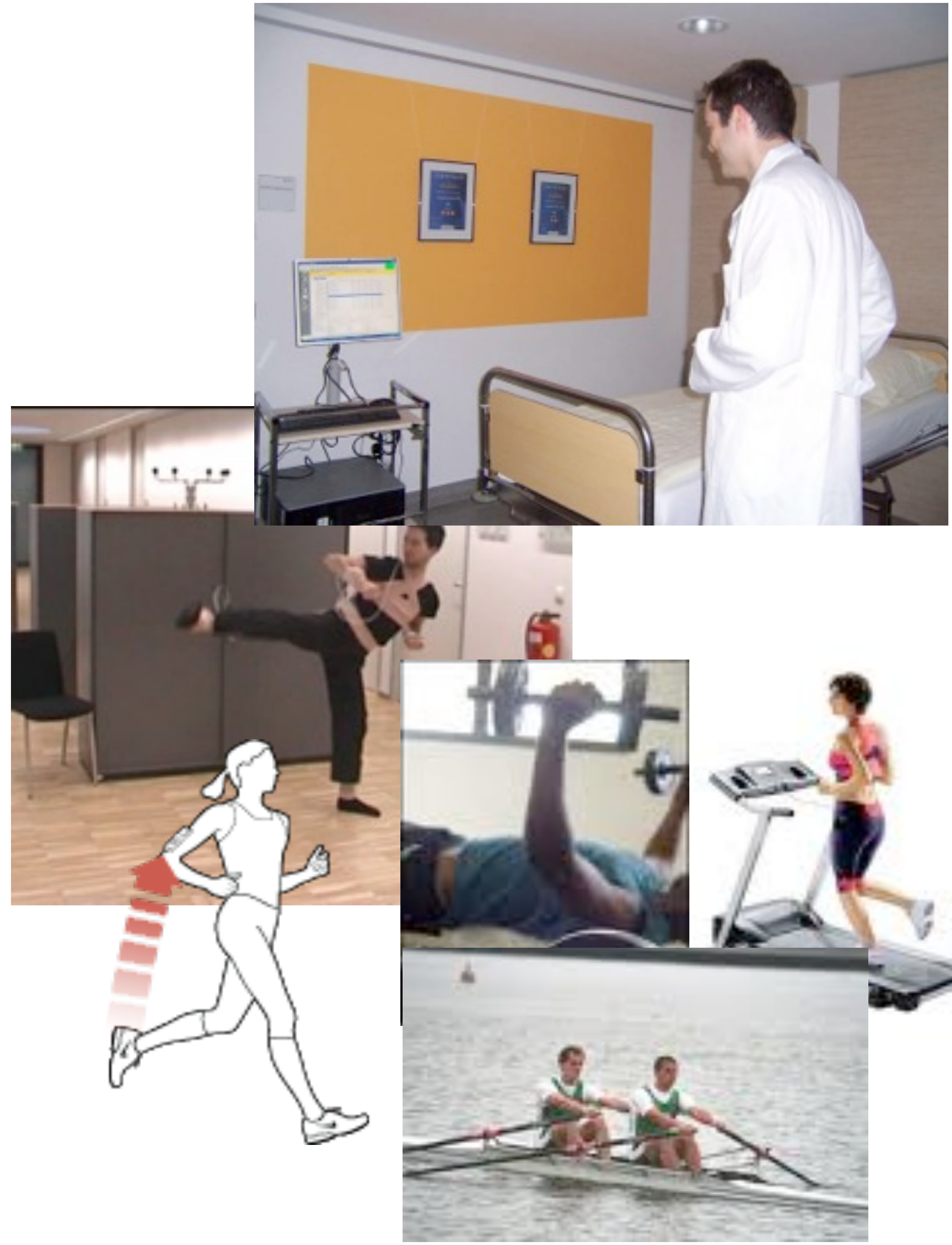


Applications



Applications

Applications



Applications

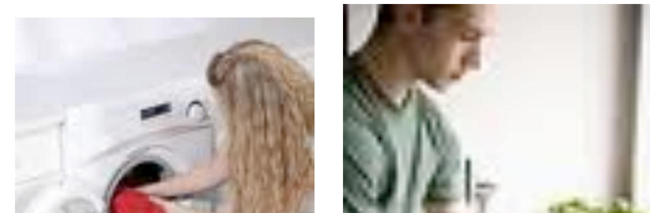
公立大学法人 大阪府立大学
OSAKA PREFECTURE UNIVERSITY

Applications

公立大学法人
大阪府立大学
OSAKA PREFECTURE UNIVERSITY

Applications

Applications



Applications

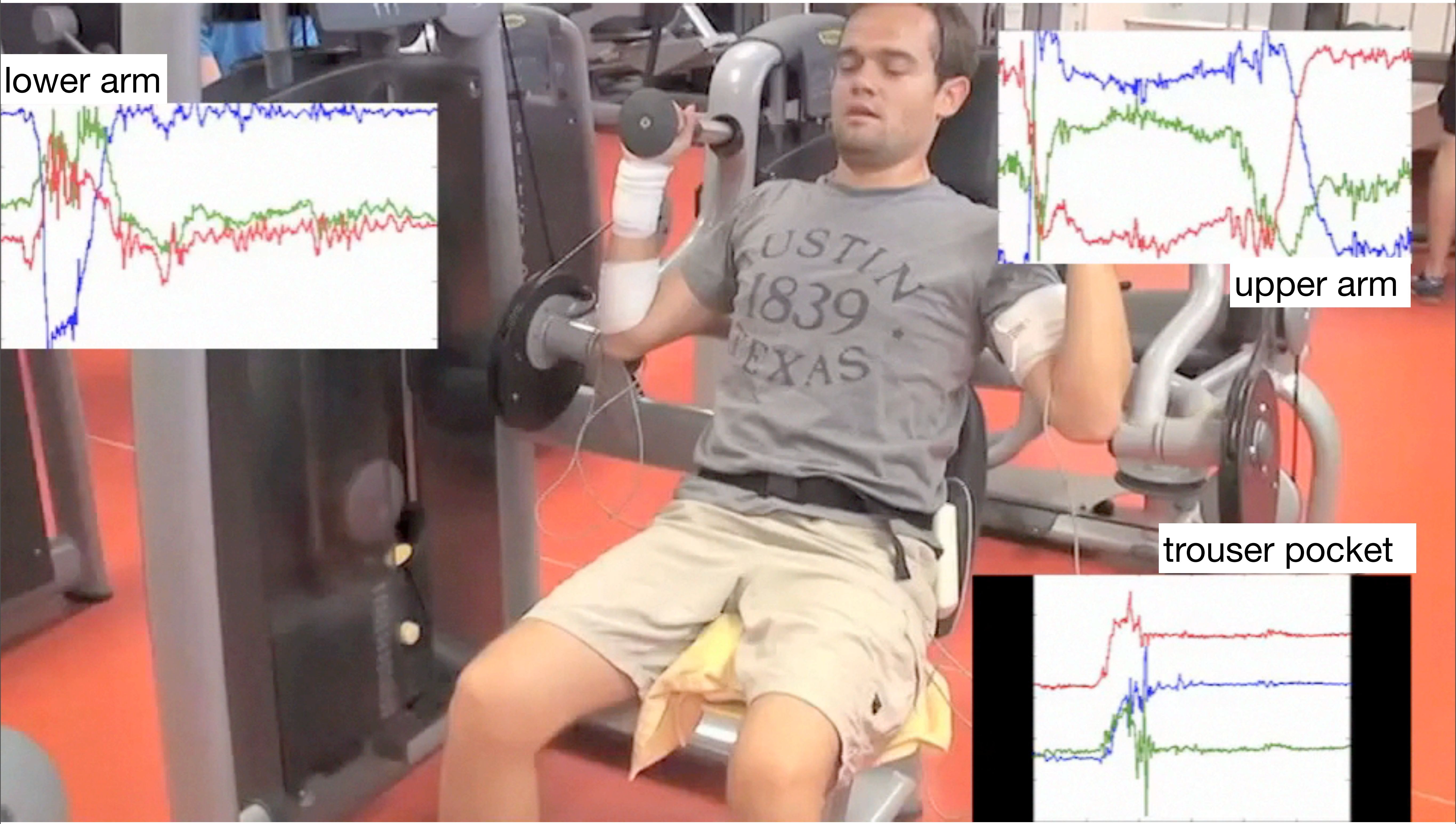
... using environment and onbody sensors

lower arm

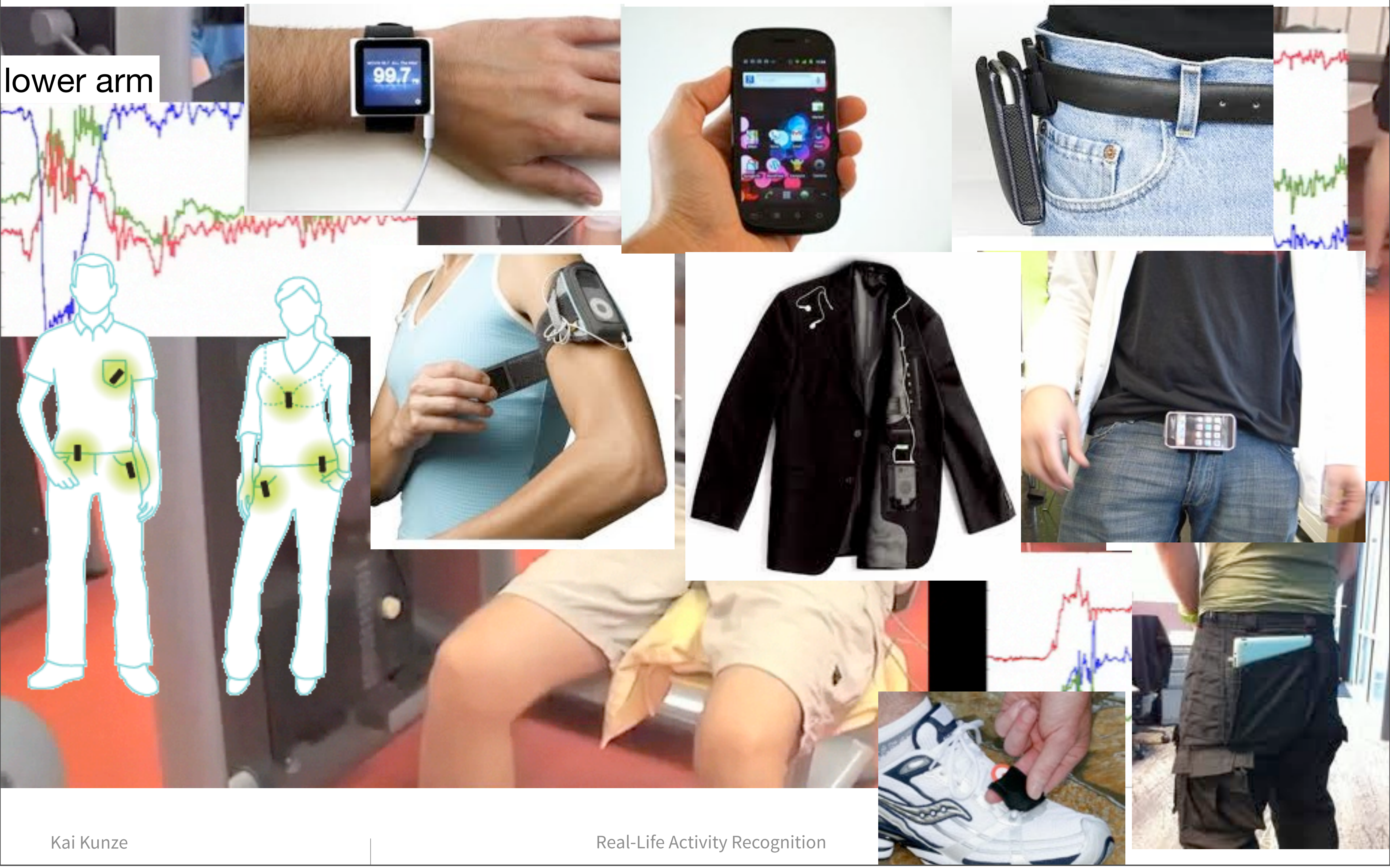
upper arm

trouser pocket

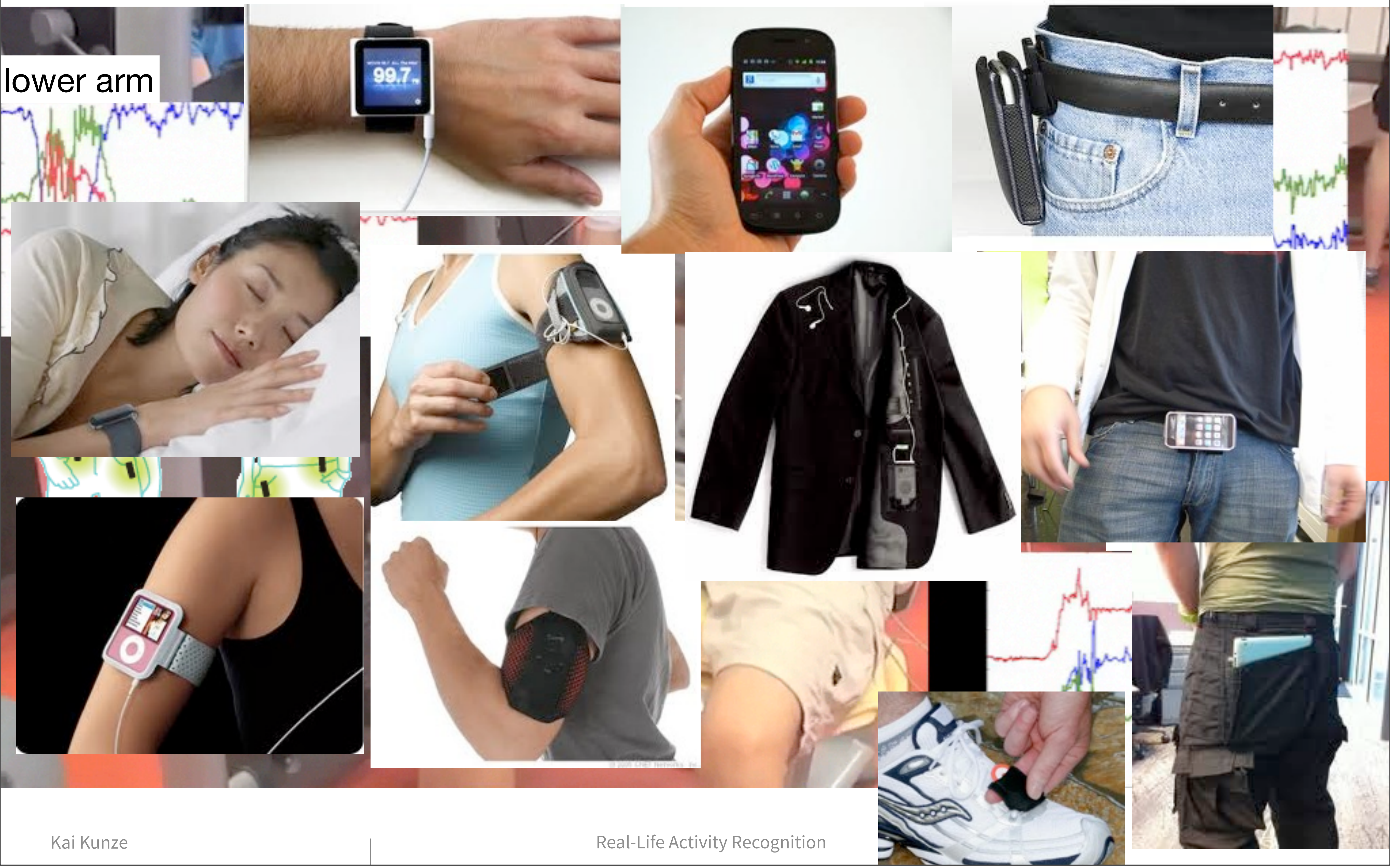
... using environment and onbody sensors



... using environment and onbody sensors



... using environment and onbody sensors



Compensating for On-Body Placement Effects in Activity Recognition

Kai Kunze

Overview and Contributions

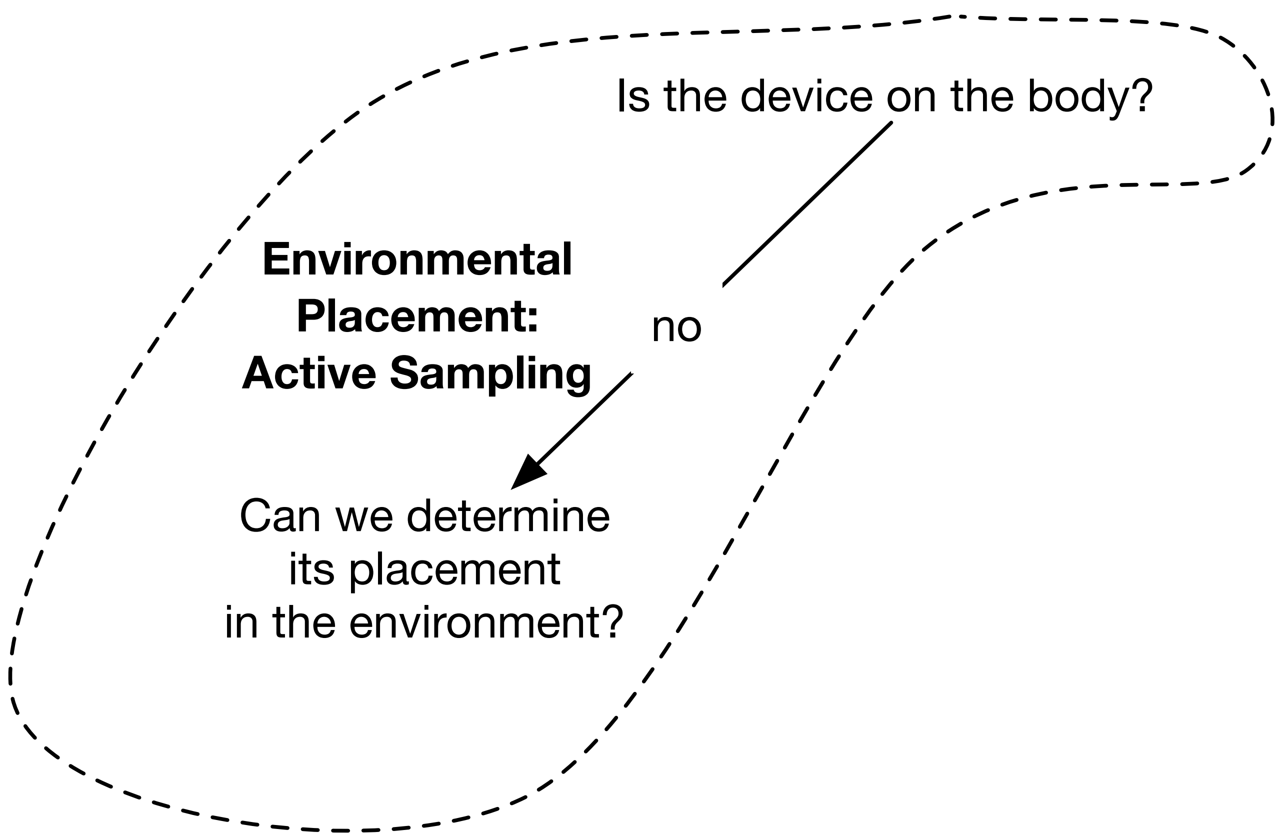
Is the device on the body?

no

Can we determine
its placement
in the environment?

Wednesday, 26 June 13

Overview and Contributions



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.

approach

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

approach

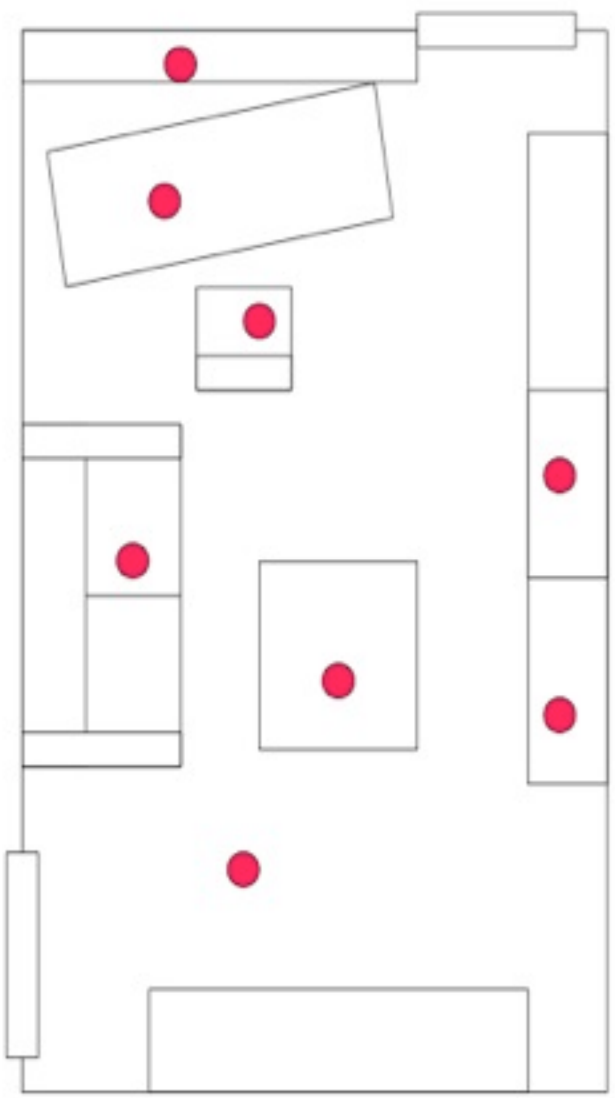
A mobile phone ringing or vibrating sounds differently depending on where it is.

approach

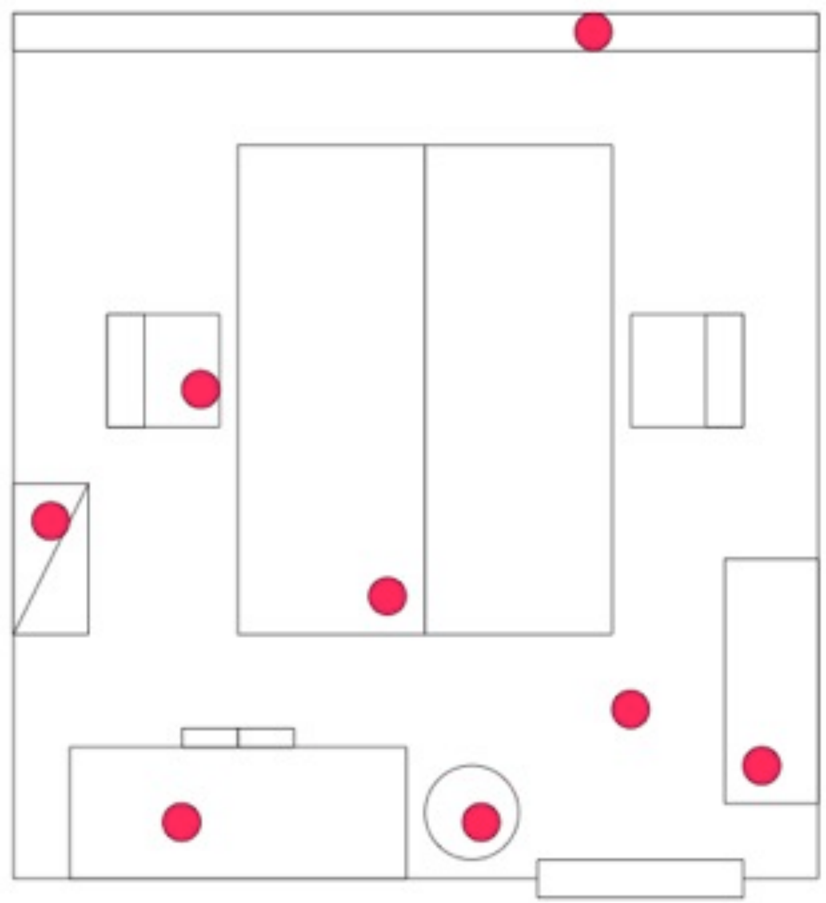
A mobile phone ringing or vibrating sounds differently depending on where it is.

scenarios

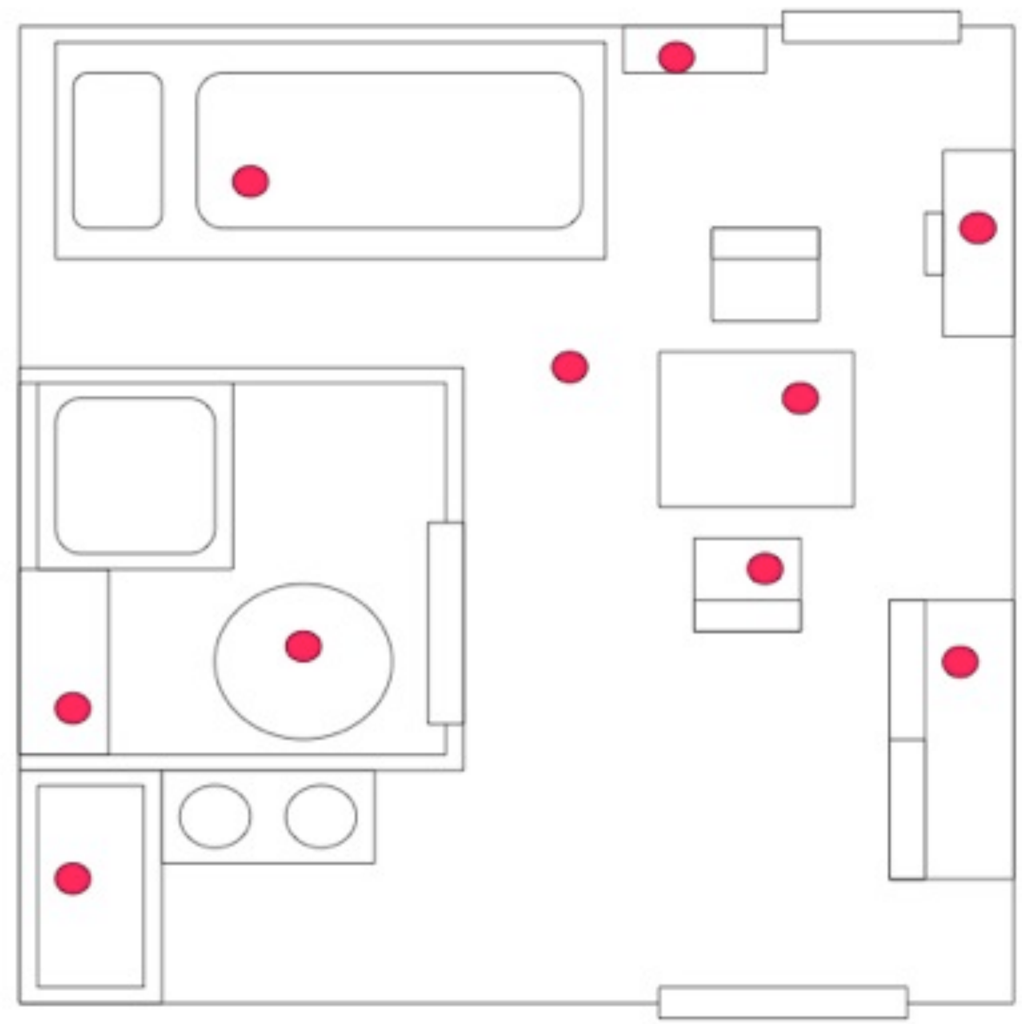
30 samples per location
10 for training 20 for testing



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

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

abstract classes

surface types:

padding

glass

iron

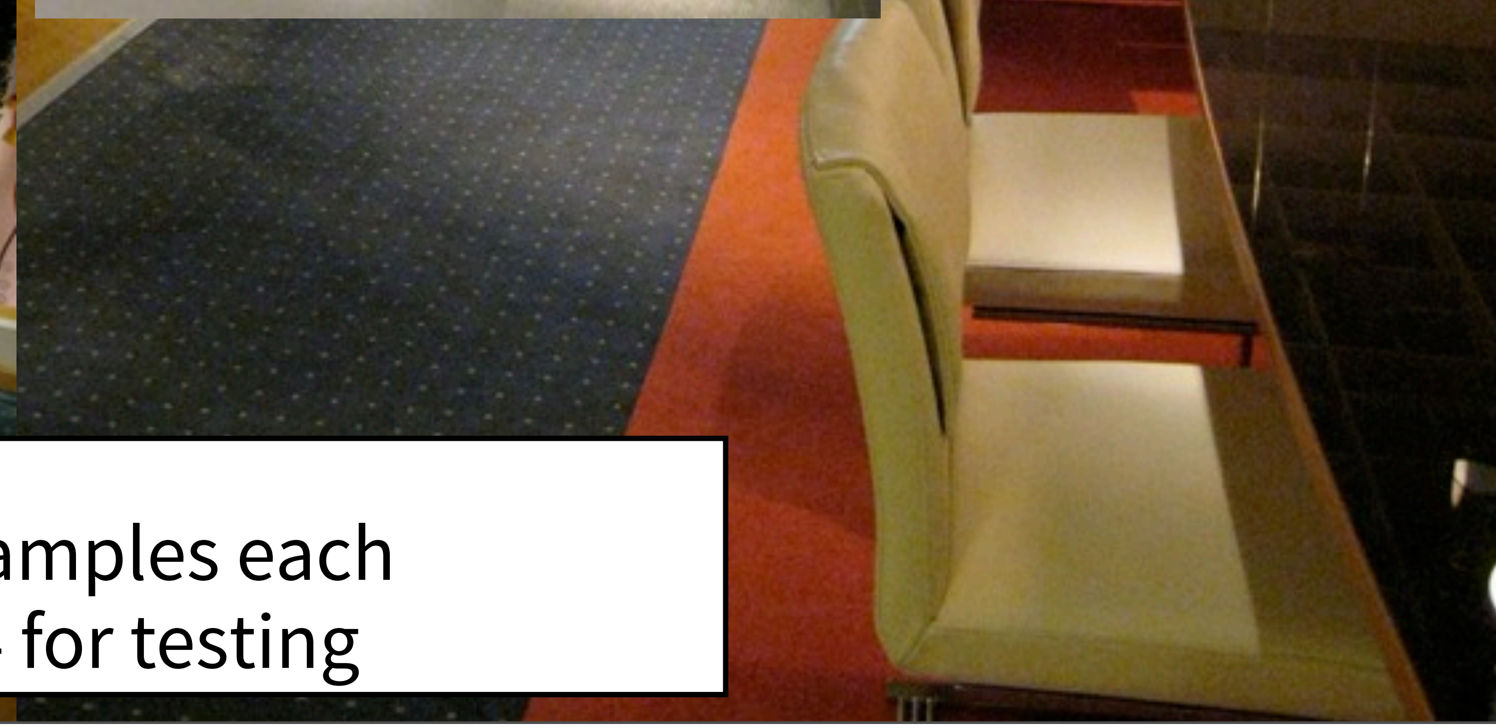
metal

stone

wood

compartment:

Open/closed (except metal)



For each type and compartment:

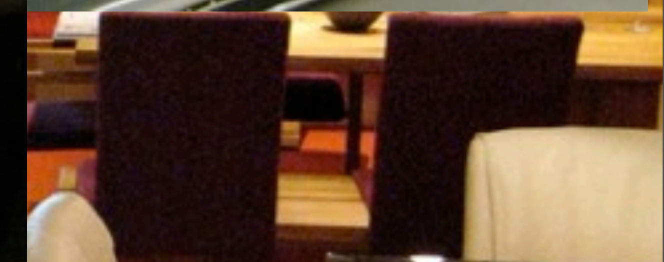
6 different kinds of furniture 12 samples each

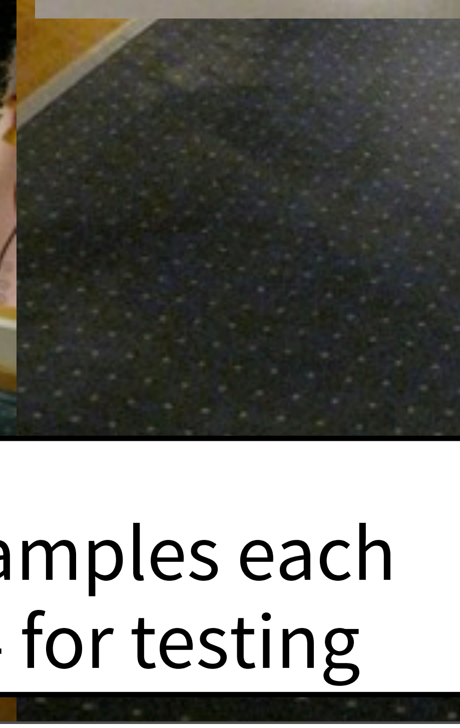
2 pieces of furniture for training, 4 for testing

abstract classes

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





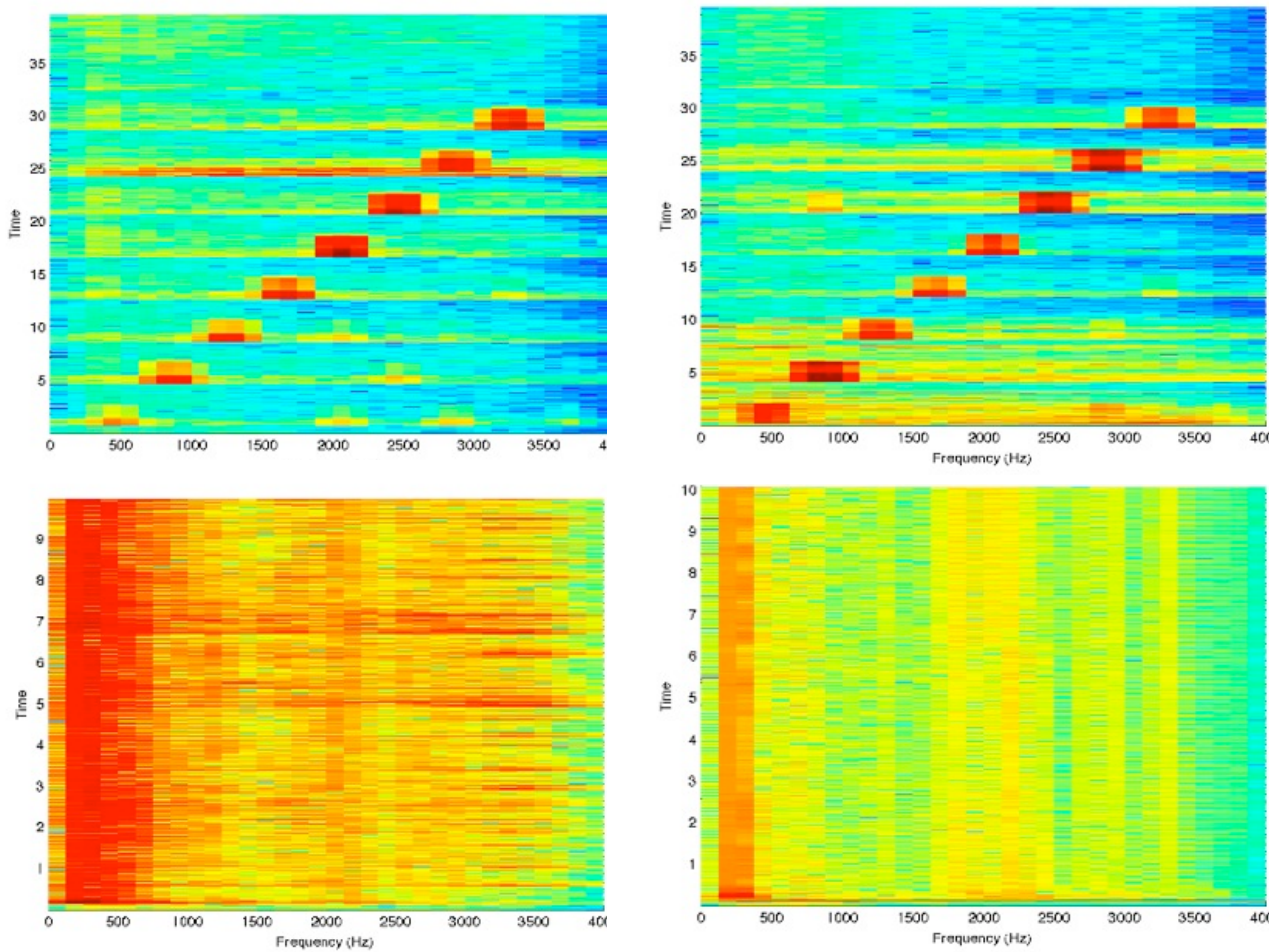

For each type and compartment:
6 different kinds of furniture 12 samples each
2 pieces of furniture for training, 4 for testing

fingerprint and vibration sounds

公立大学法人
大阪府立大学
OSAKA PREFECTURE UNIVERSITY

desk

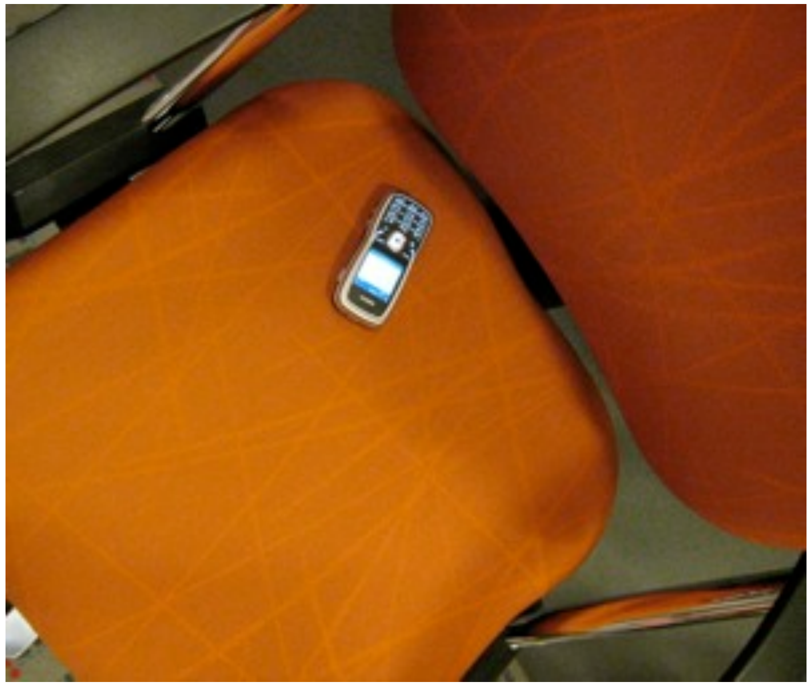
carpet



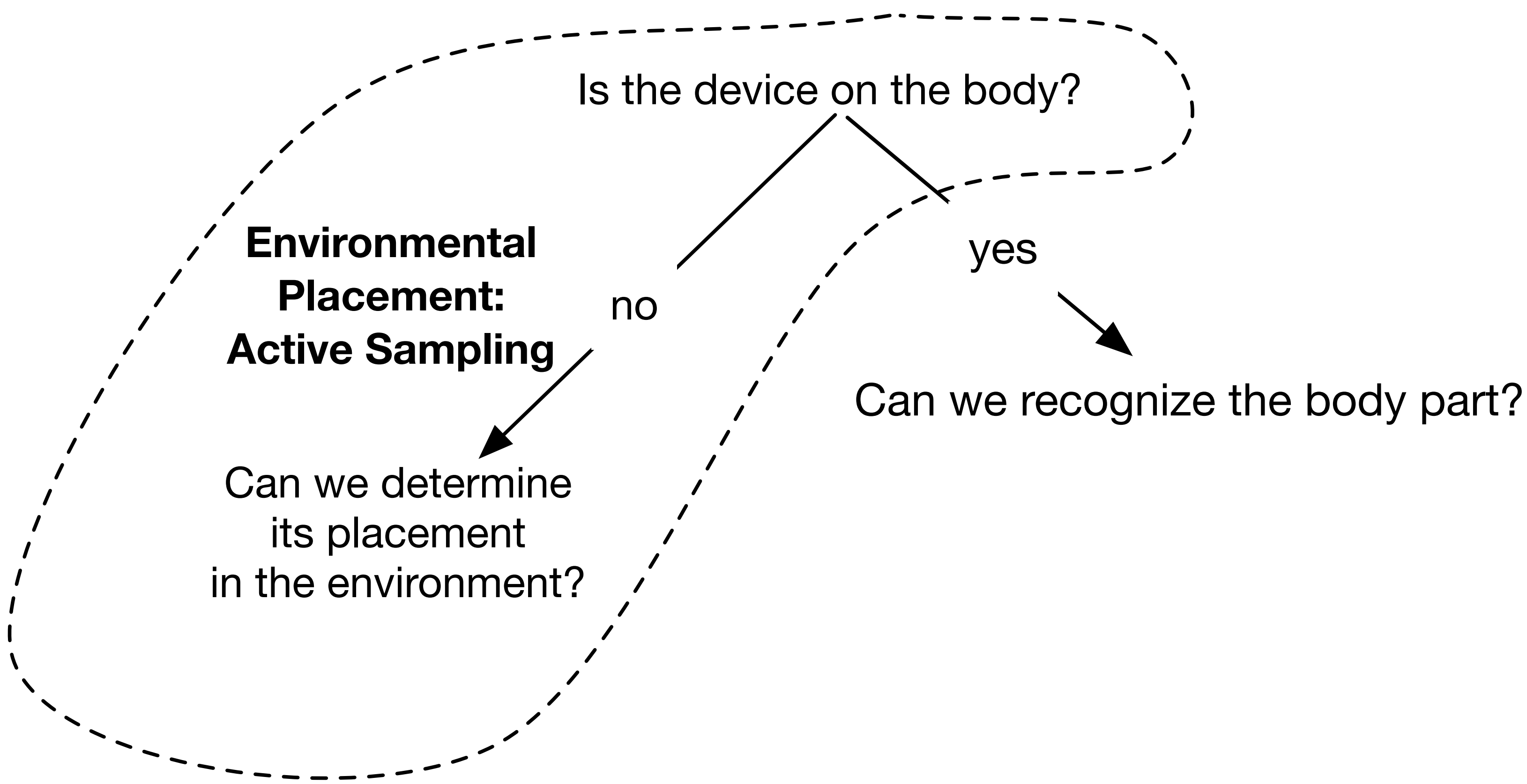
Environmental Placement Detection
-Active Sampling-



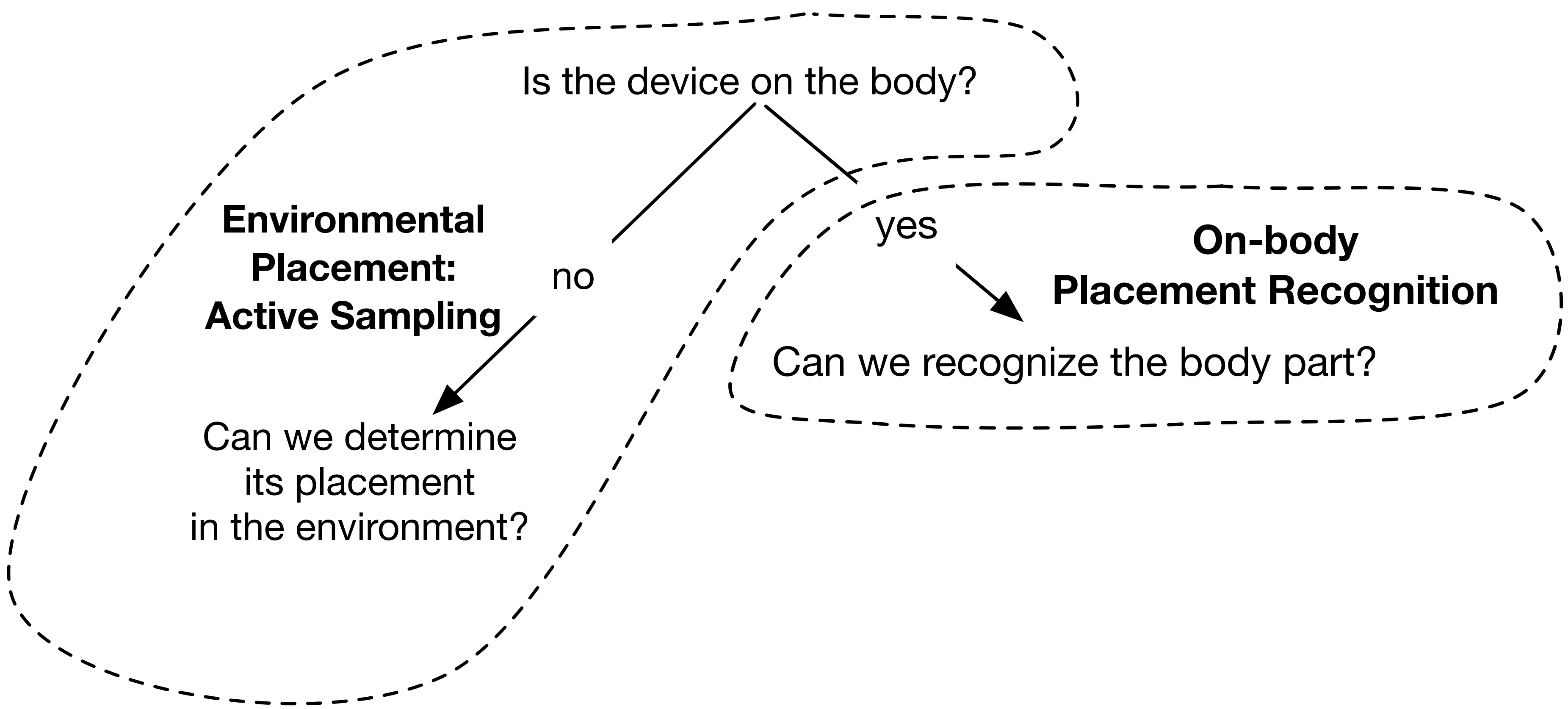
- up to 96 % per room
- up to 92 % for abstract classes




Overview and Contributions



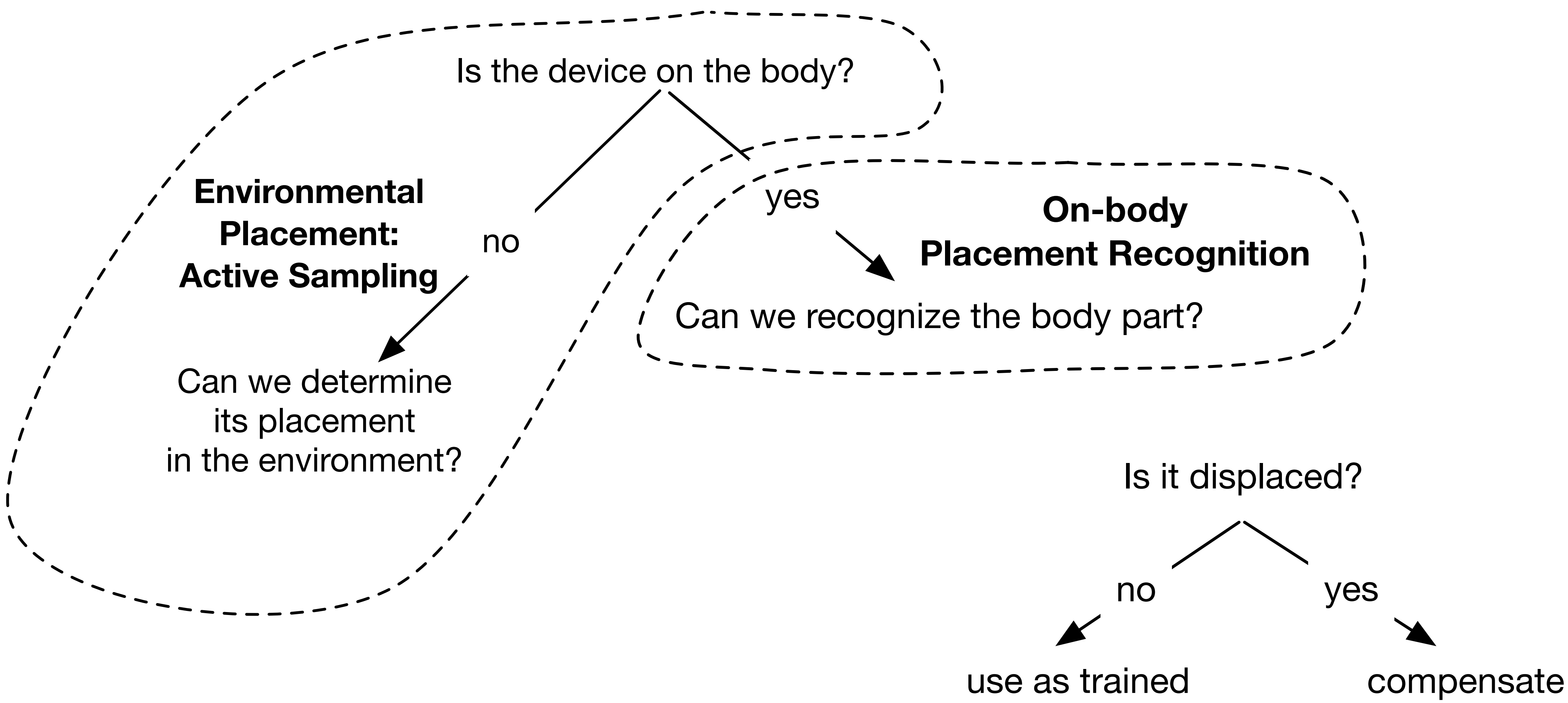
Overview and Contributions



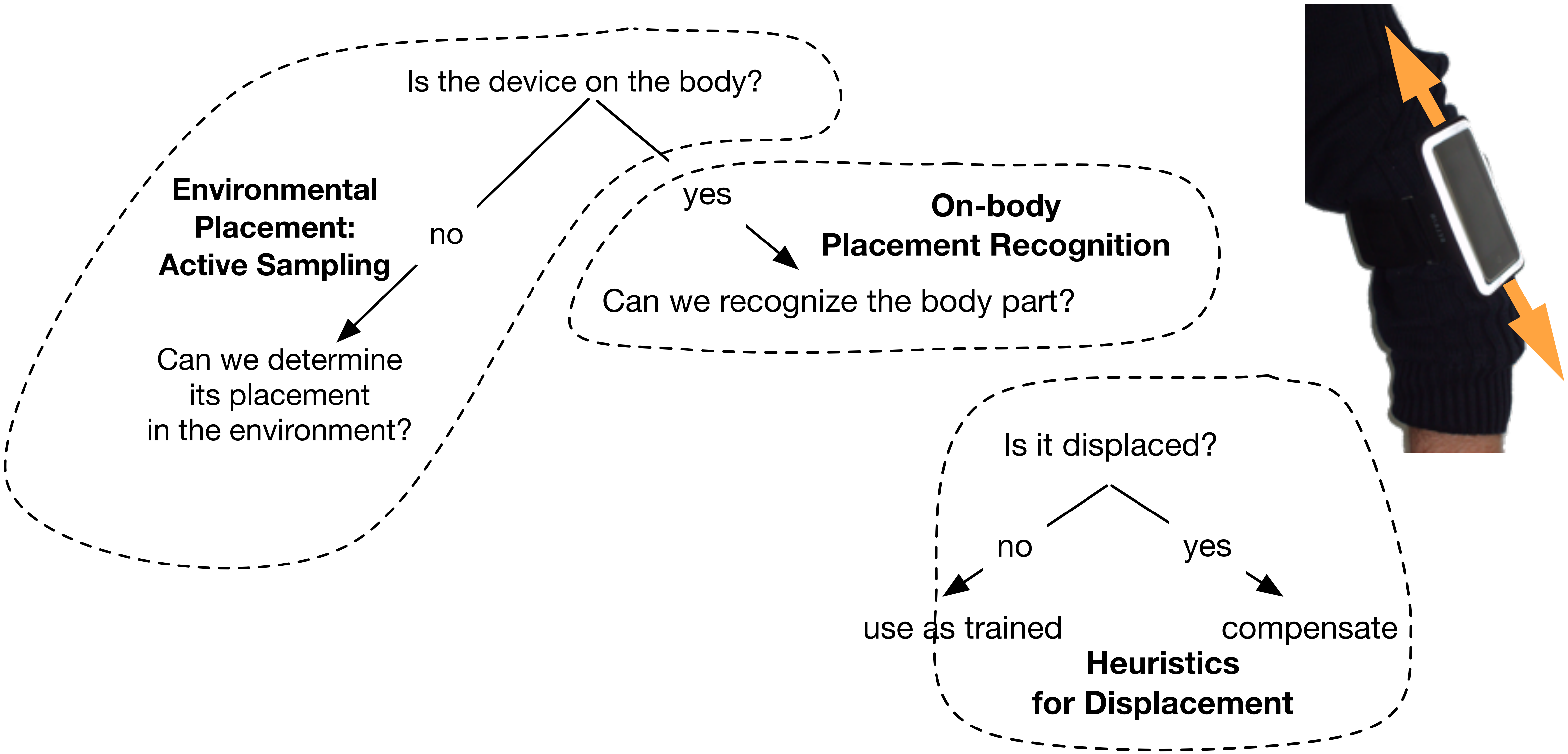
K. Kunze and P. Lukowicz. *Using acceleration signatures from everyday activities for on-body device location.* 11th IEEE International Symposium on Wearable Computers, Sep 2007.

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.

Overview and Contributions

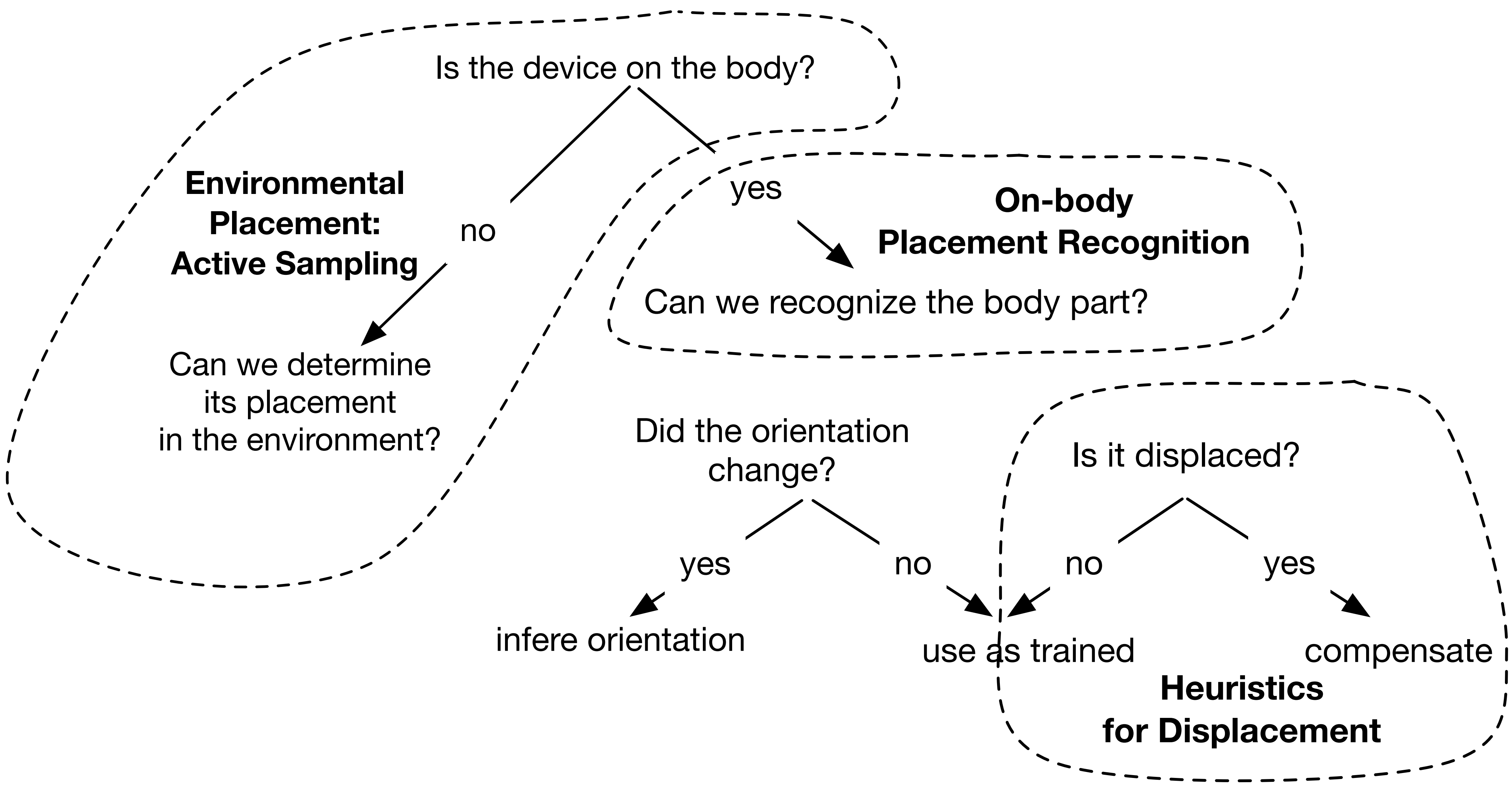


Overview and Contributions

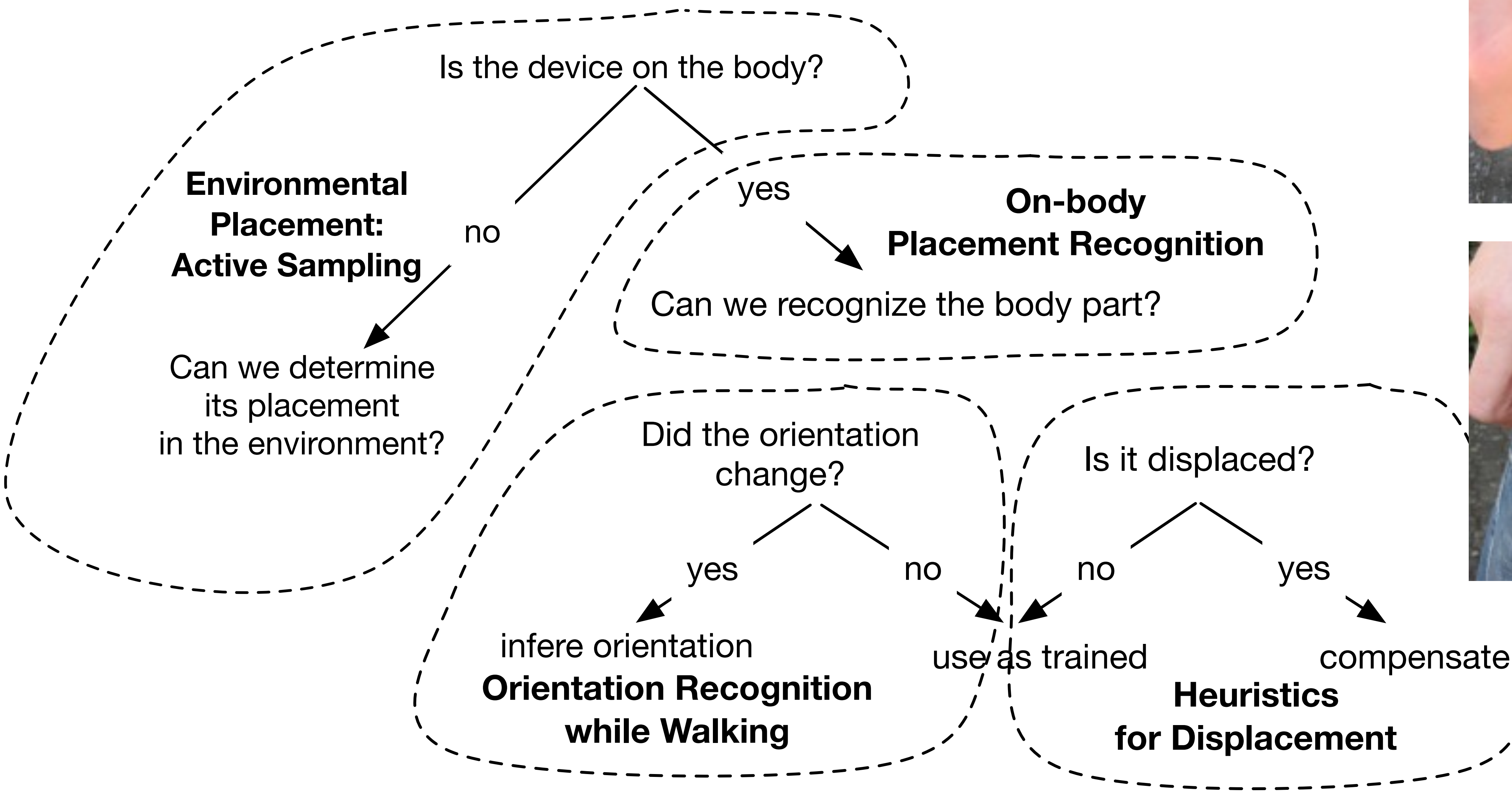


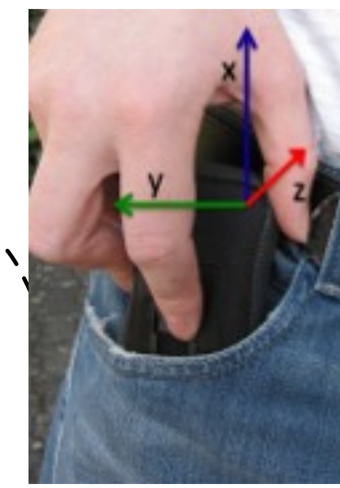
Kunze, K. and Lukowicz, P. *Dealing with sensor displacement in motion-based on-body activity recognition systems.* In Proceedings of the 10th international con- ference on Ubiquitous computing (UbiComp ’08). Seoul, Korea, September, 2008.

Overview and Contributions



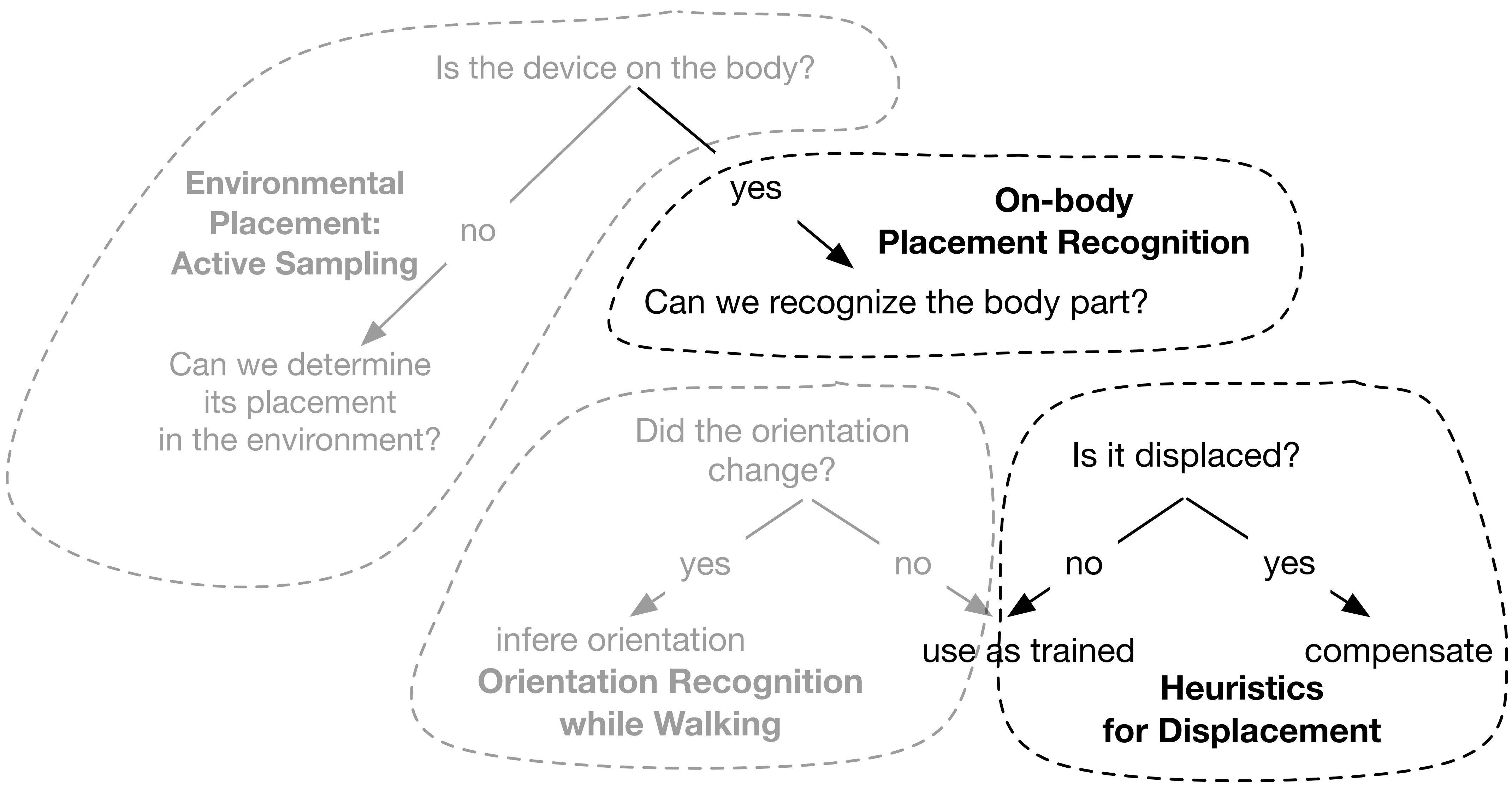
Overview and Contributions



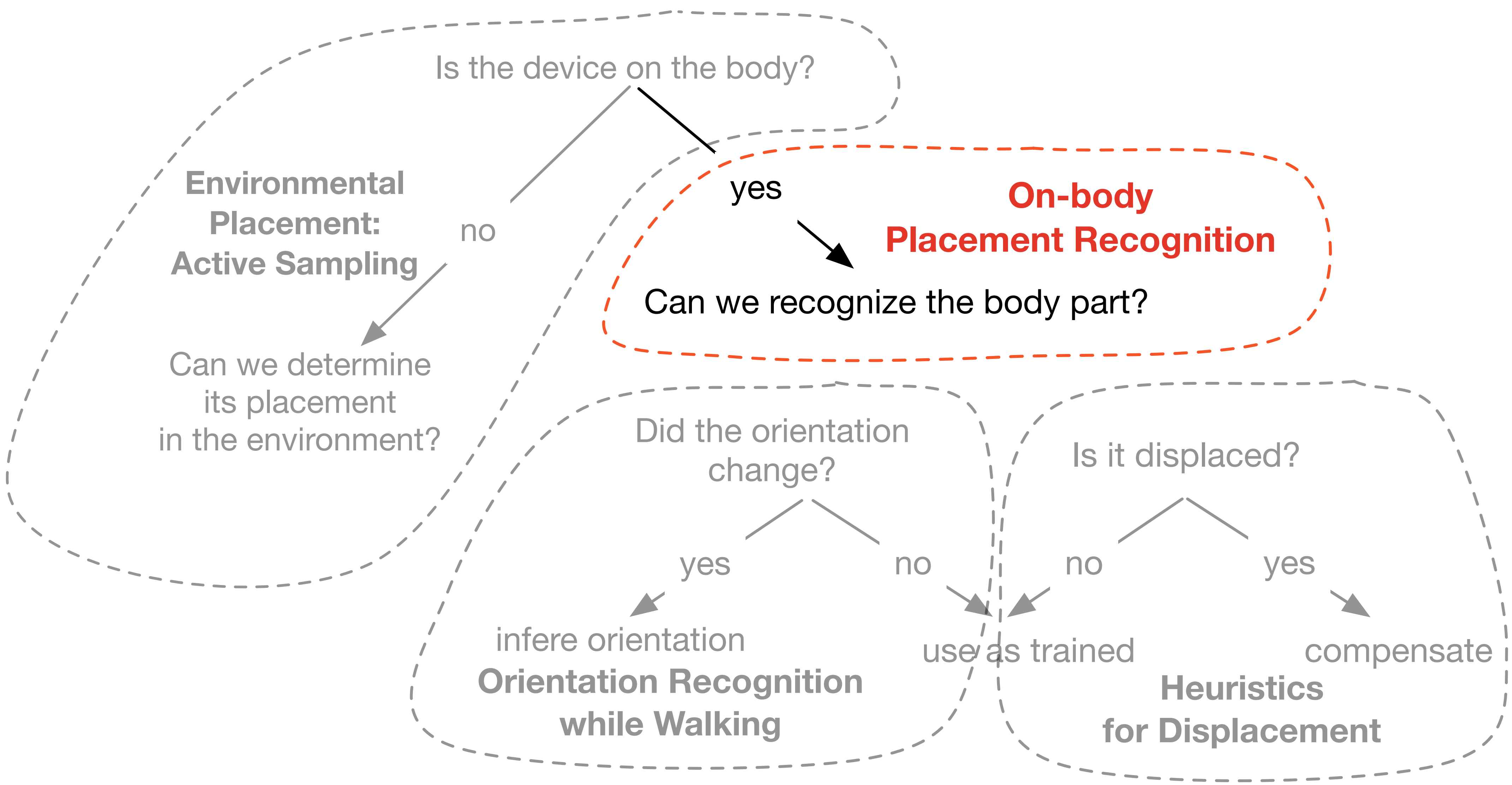


Kai Kunze, Paul Lukowicz, Kurt Partridge, Bo Begole, *Which Way Am I Facing: Inferring Horizontal Device Orientation from an Accelerometer Signal*, 13th IEEE International Symposium on Wearable Computers. Linz, Austria, 2009.

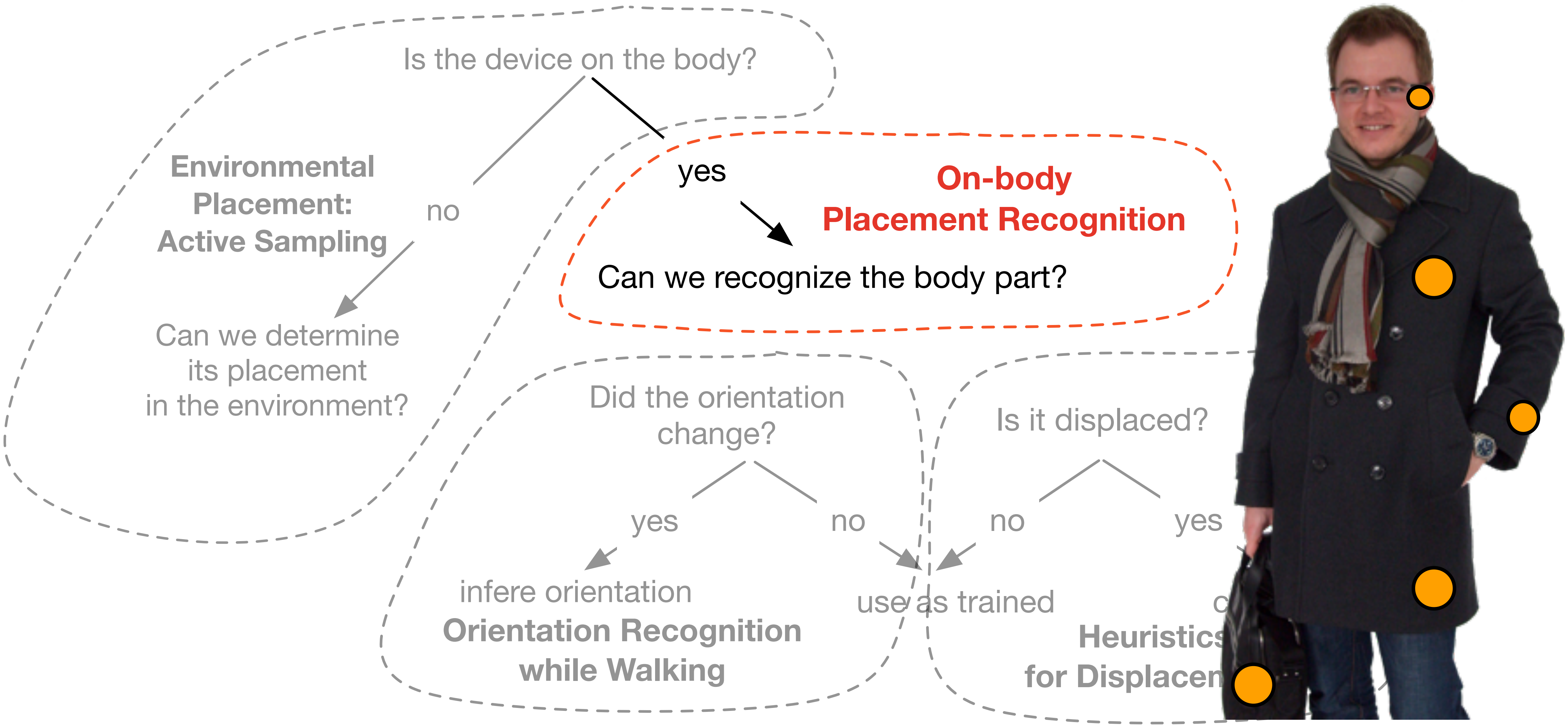
Overview and Contributions



Overview and Contributions



Overview and Contributions

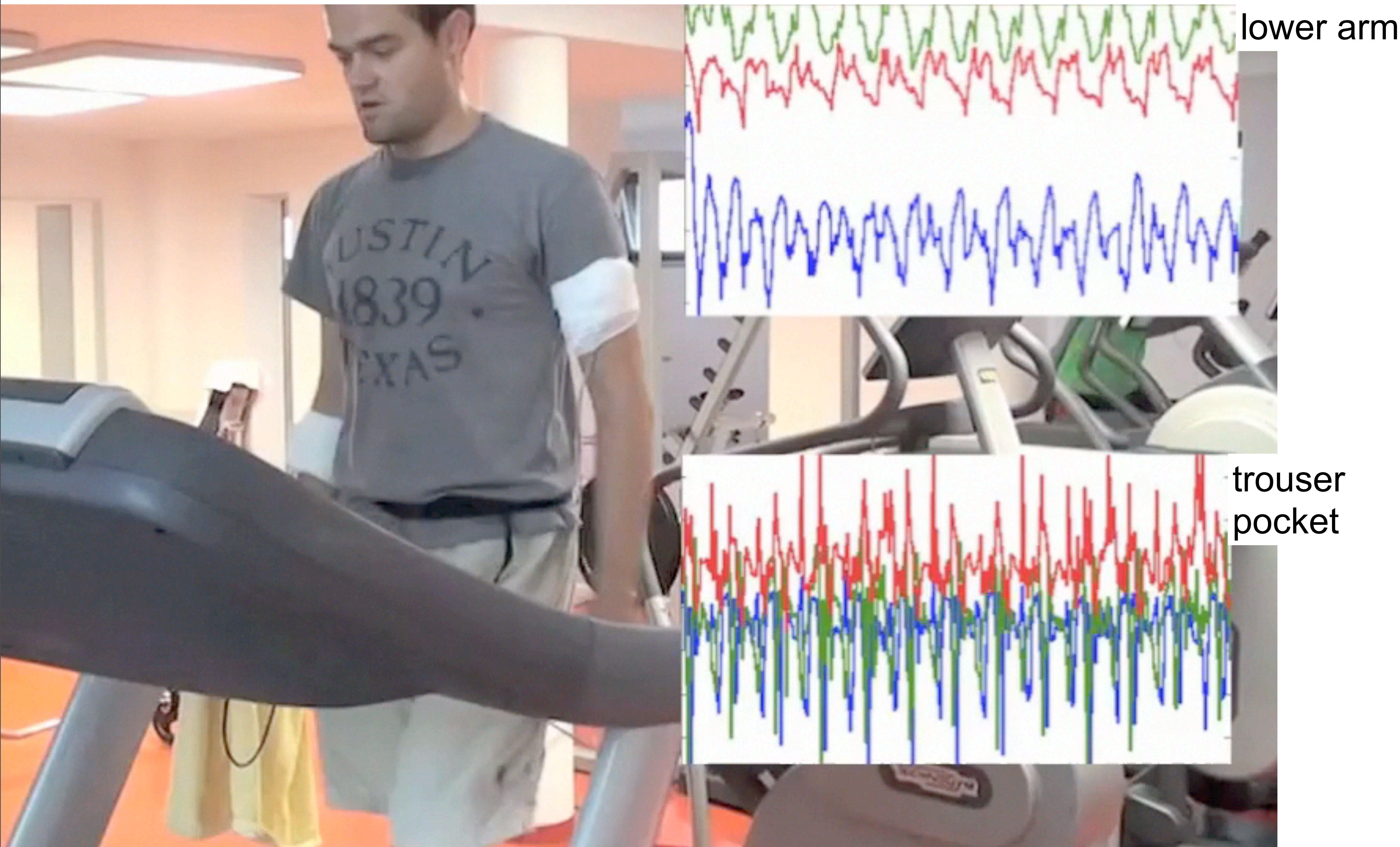


Walking

lower arm

trouser
pocket

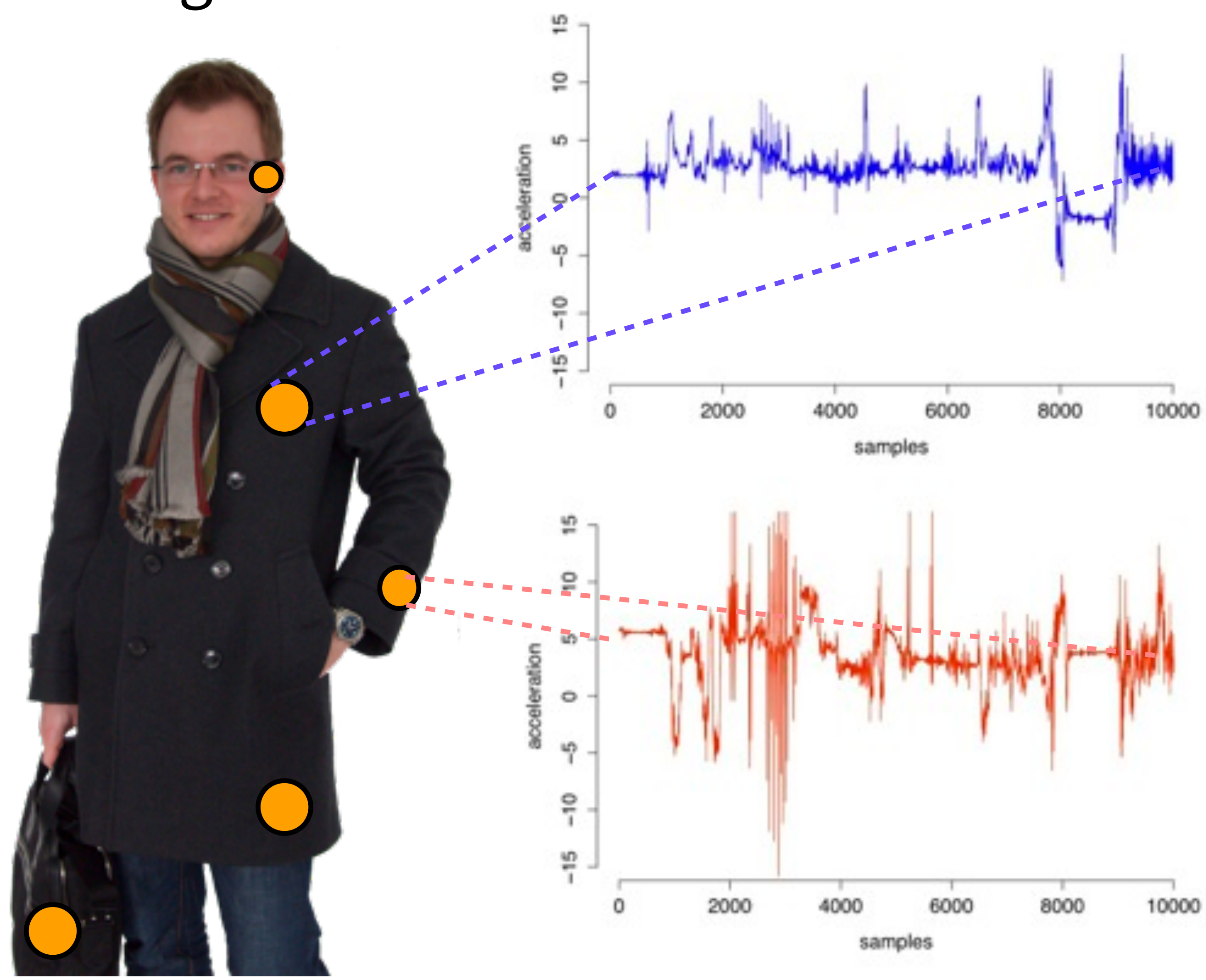
Walking



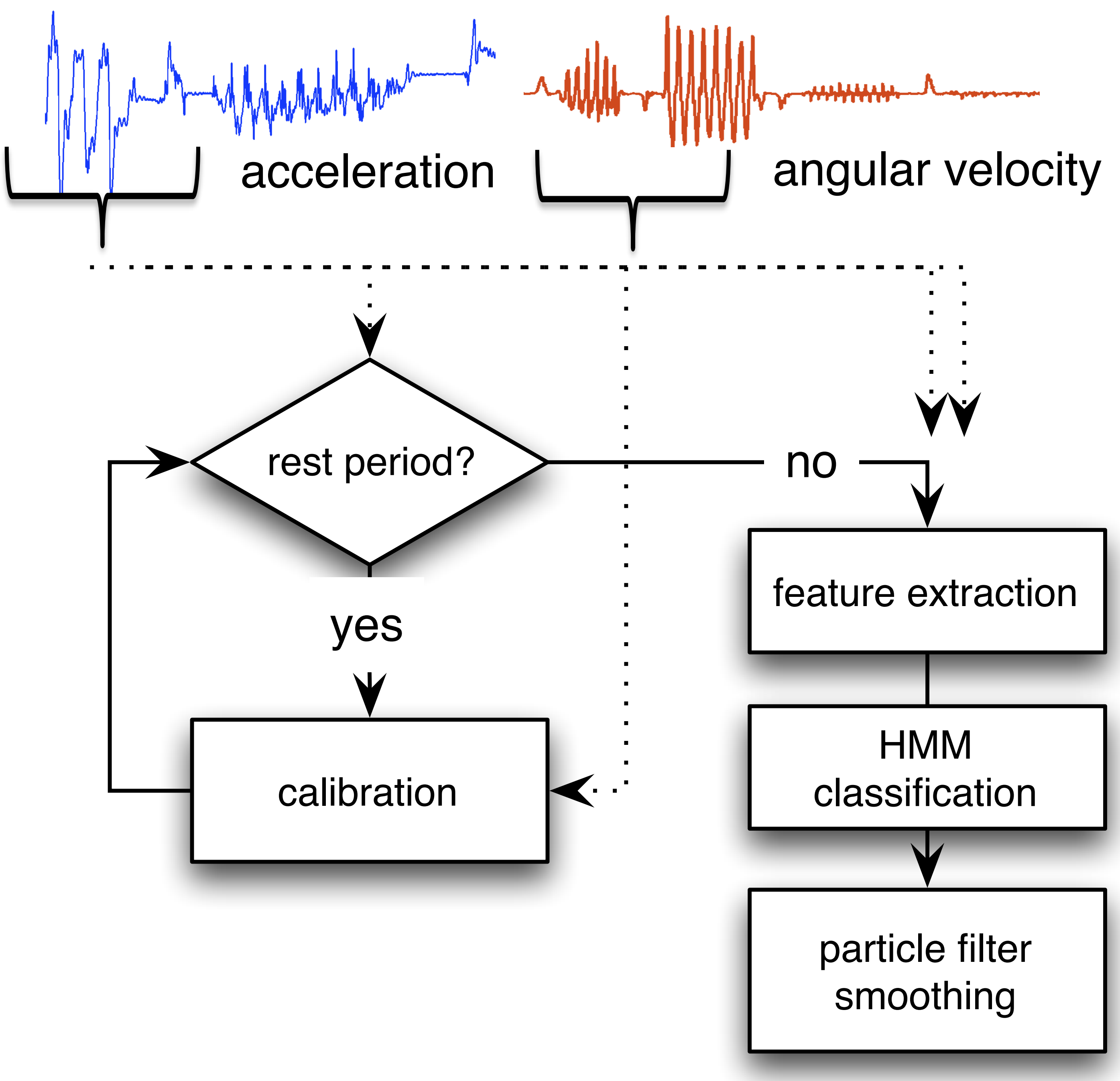
Unconstraint Onbody Placement Recognition

- 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



Unconstrained Method



- acceleration features:
  - std, mean, fft center of mass, duration of rest period
- gyro features:
  - pca angle, frequency range power
- both:
  - sum of the differences in variance per axis

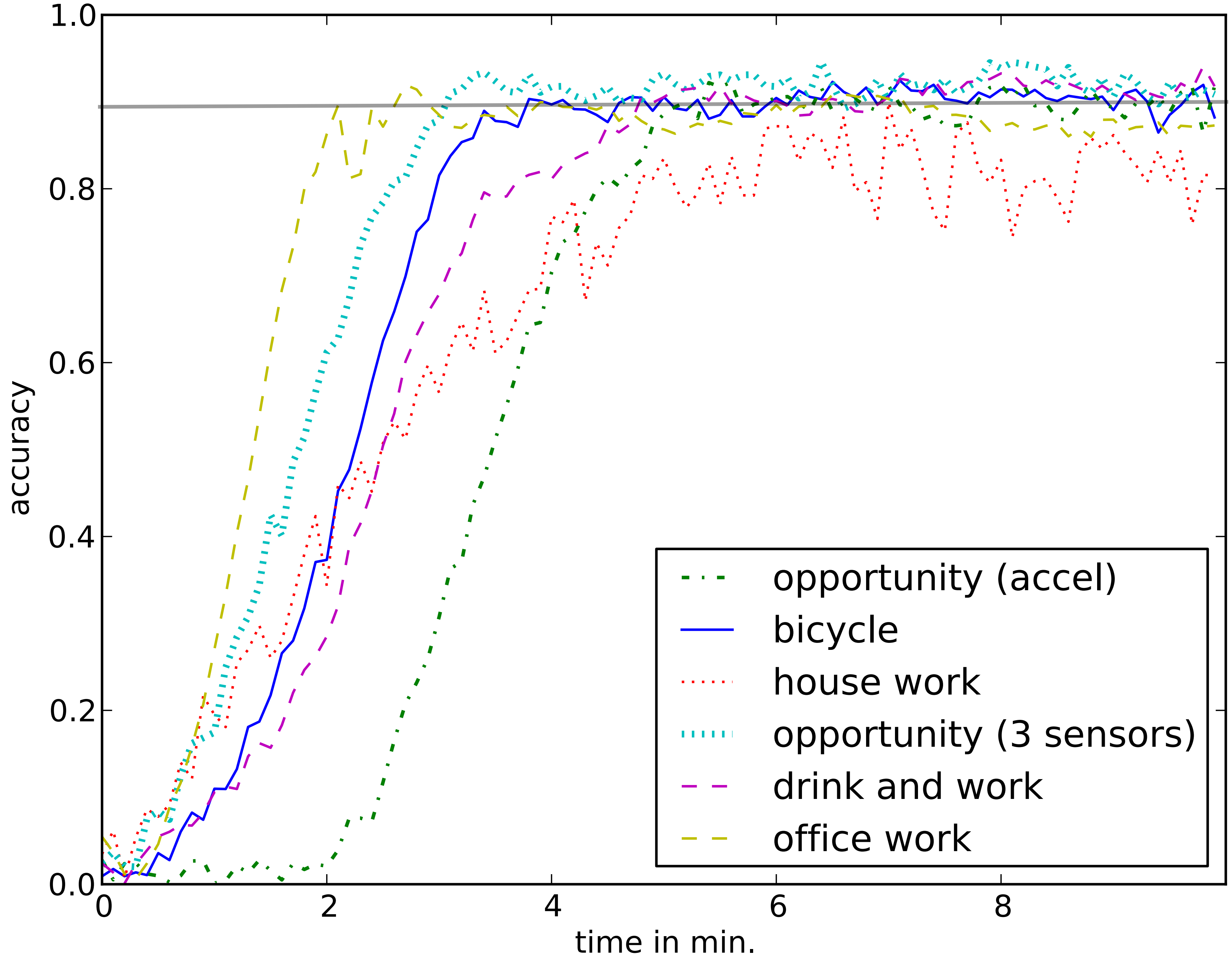
$$\frac{1/2 \sum_{i=1}^{n} \sum_{j=1, j<i}^{n} \mid var(a_i) - var(a_j) \mid}{var(norm)}$$

Experimental Evaluation

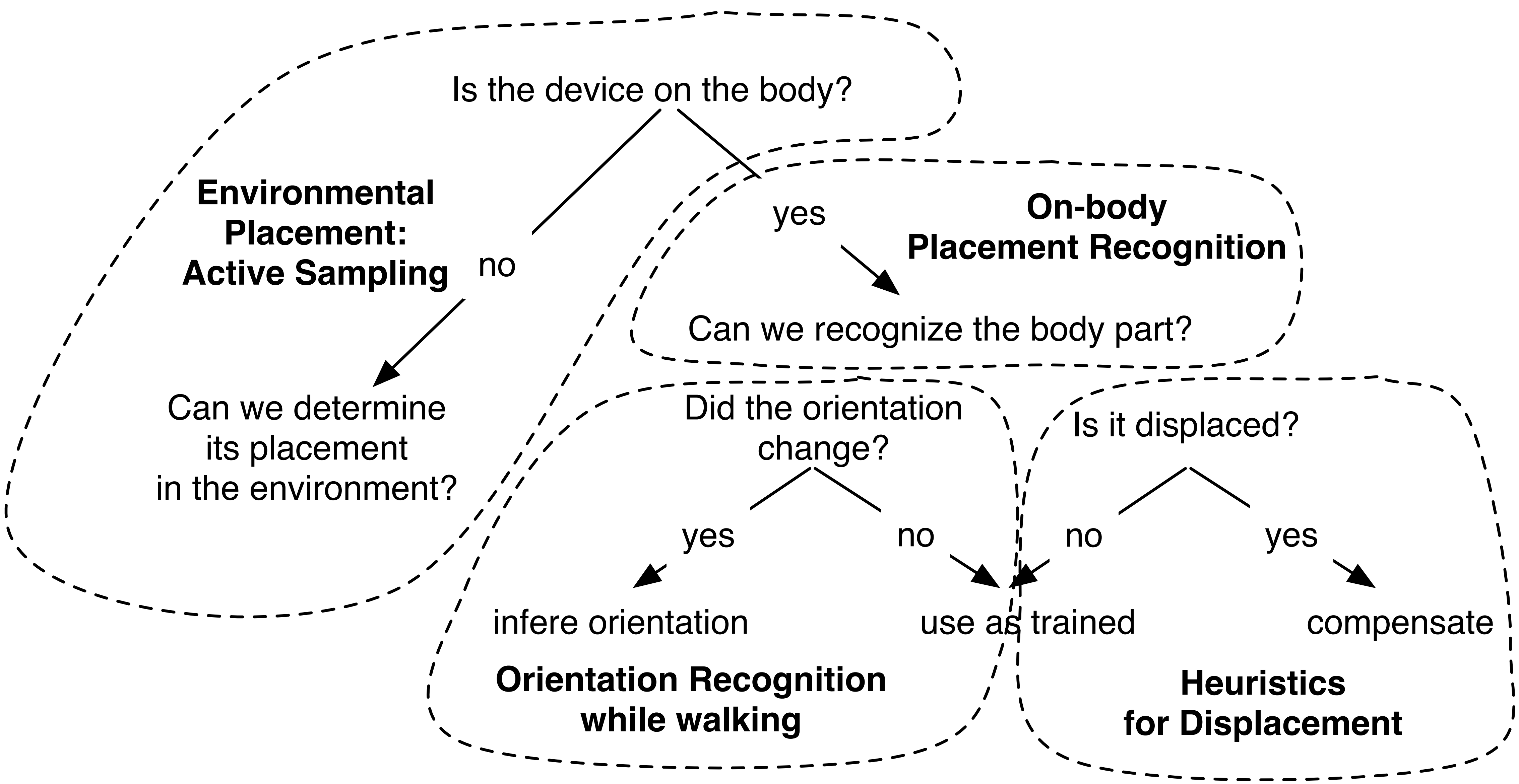
- 5 data sets
- house work to bicycle repair
- 3 to 7 participants per data set
- 1 real life data set
- age range 17 - over 60
- 4-5 on-body placements

around 30 hours of sensor data

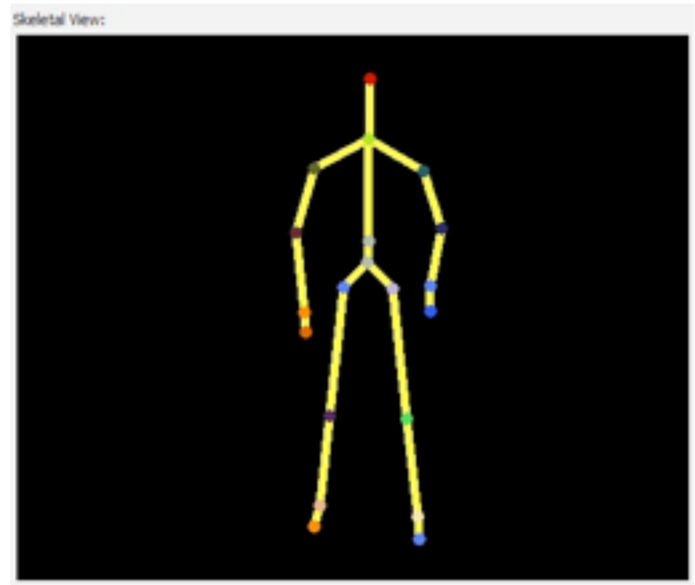
Results: Particle Filtering

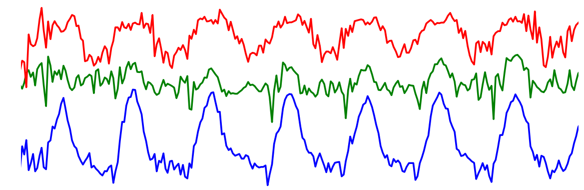


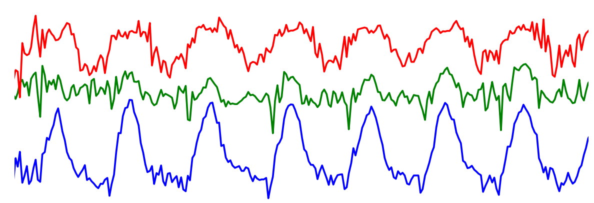
Summary


Is the device on the body?
Environmental Placement: Active Sampling
no
Can we determine its placement in the environment?
yes
On-body Placement Recognition
Can we recognize the body part?
Did the orientation change?
yes
no
infere orientation
use as trained
Orientation Recognition while walking
Is it displaced?
no
yes
compensate
Heuristics for Displacement

incorporating environmental sensors







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.

… shifting to mobile phone sensing (Tobias Franke and Martin Wirz)

Robust Activity Recognition

Recognizing Reading Activities

公立大学法人 大阪府立大学 OSAKA PREFECTURE UNIVERSITY

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” 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 activities

Tracking reading habits

Everyday

On digital devices

Current focus:

How much? (quantity)

What? (types of documents)

How? (skill level)

Current focus:

(in addition to the offline cases)

Explore reading habits

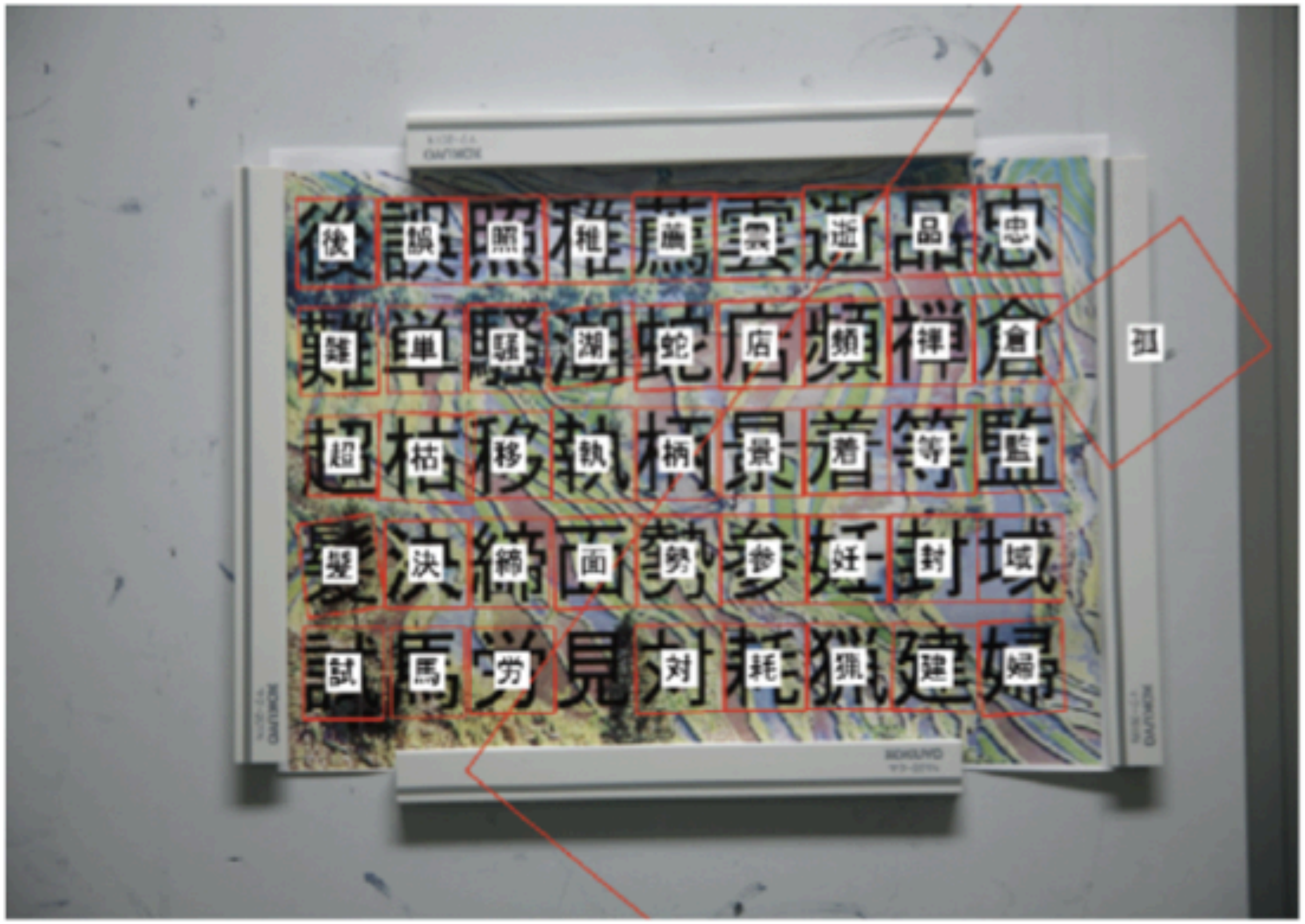
(when, where and how are digital devices used)

Improve reading experience

Provide tools to reflect on ones reading habits

Detect: Is a user really reading?

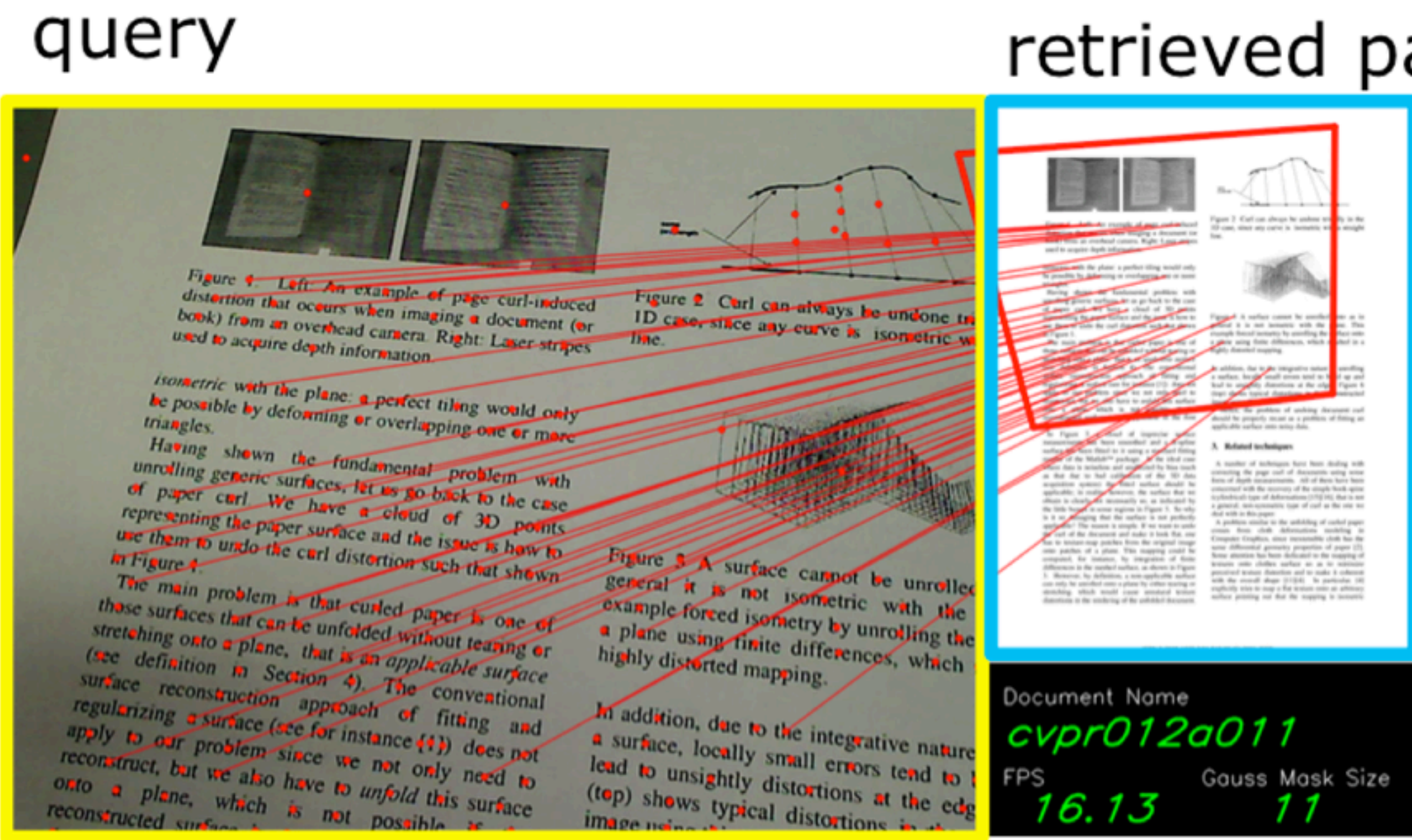
Character Recognition



Kanji under background clutter

公立大学法人 大阪府立大学 OSAKA PREFECTURE UNIVERSITY

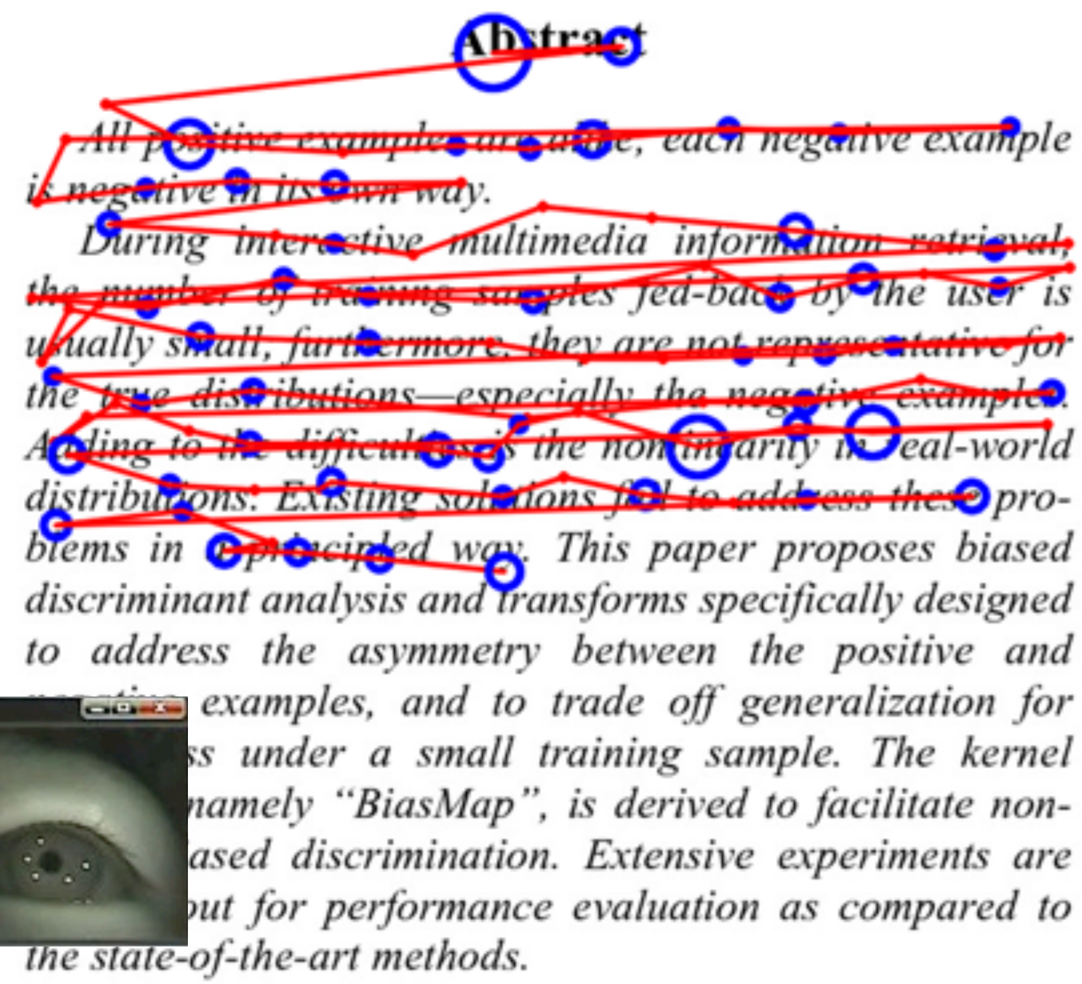
Document Image Retrieval



Wordometer

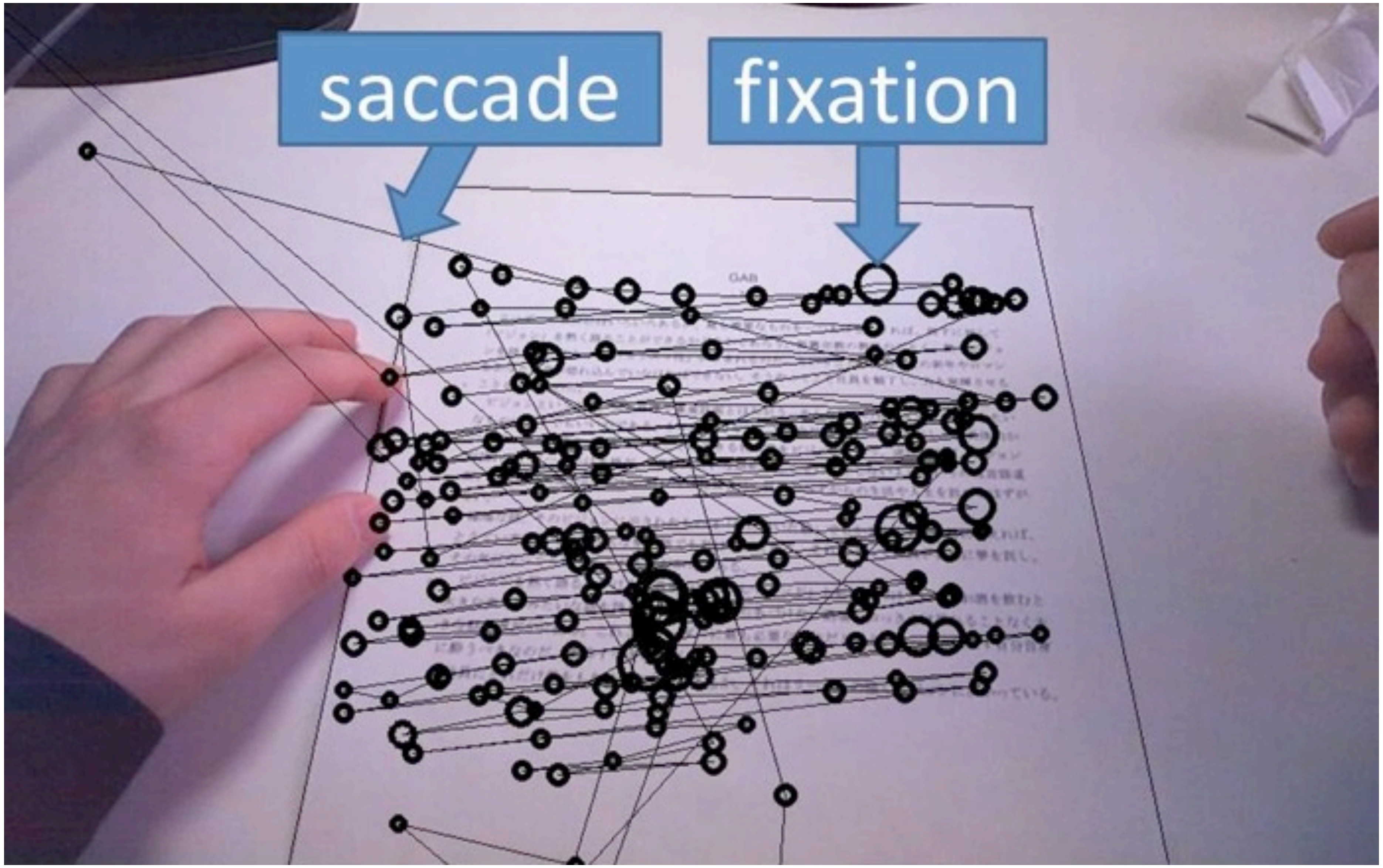
Experimental setup

Gaze overlaid on the document using Document image retrieval

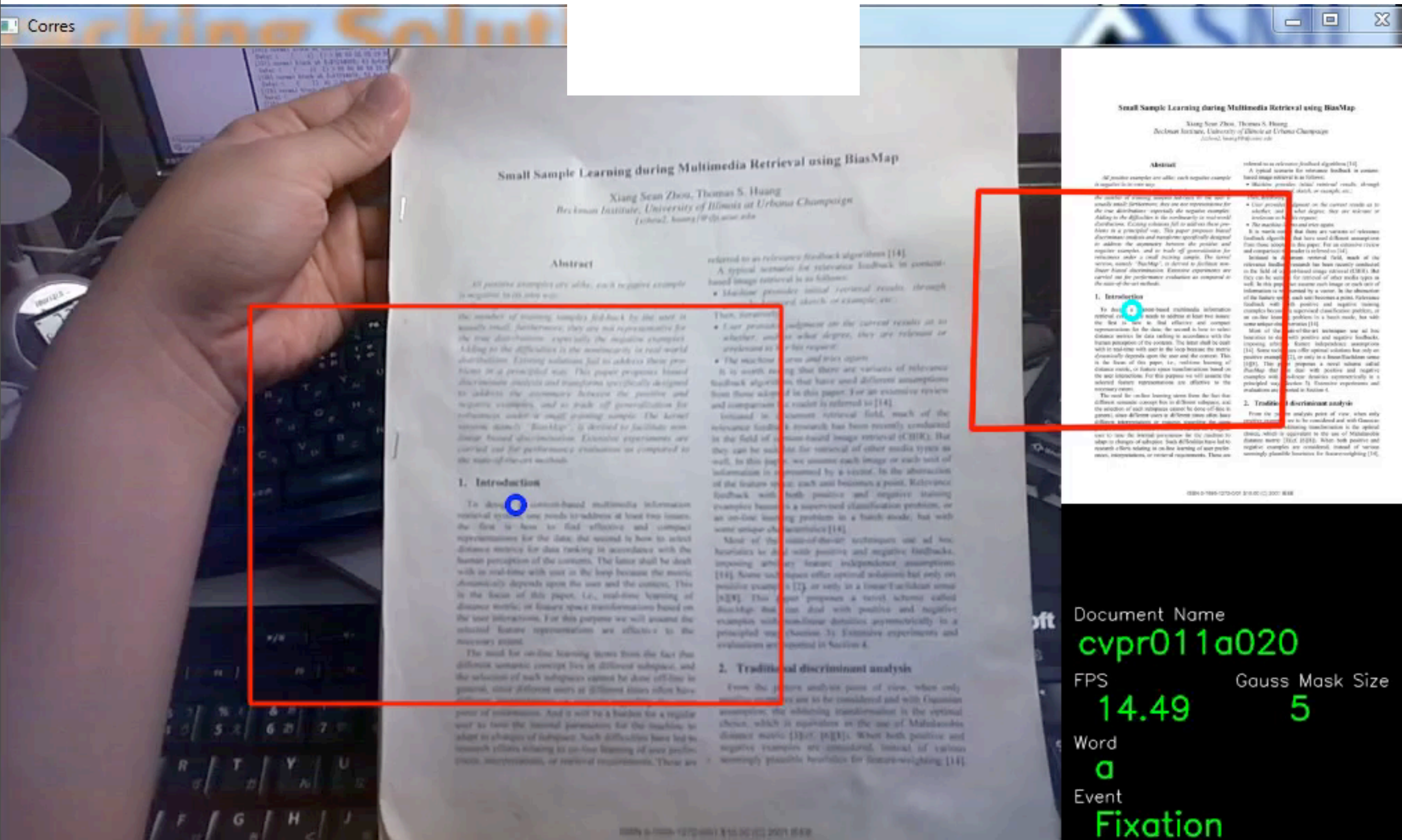

Abstract

All positive examples are alike, each negative example is negative in its own way.
During interactive multimedia information retrieval, the number of training samples fed-back by the user is usually small, furthermore, they are not representative for the true distributions—especially the negative examples. Adding to the difficulties is the nonlinearity in real-world distributions. Existing solutions fail to address these problems in a principled way. This paper proposes biased discriminant analysis and transforms specifically designed to address the asymmetry between the positive and ... examples, and to trade off generalization for ...ss under a small training sample. The kernel ... namely "BiasMap", is derived to facilitate non-...ased discrimination. Extensive experiments are ...out for performance evaluation as compared to the state-of-the-art methods.

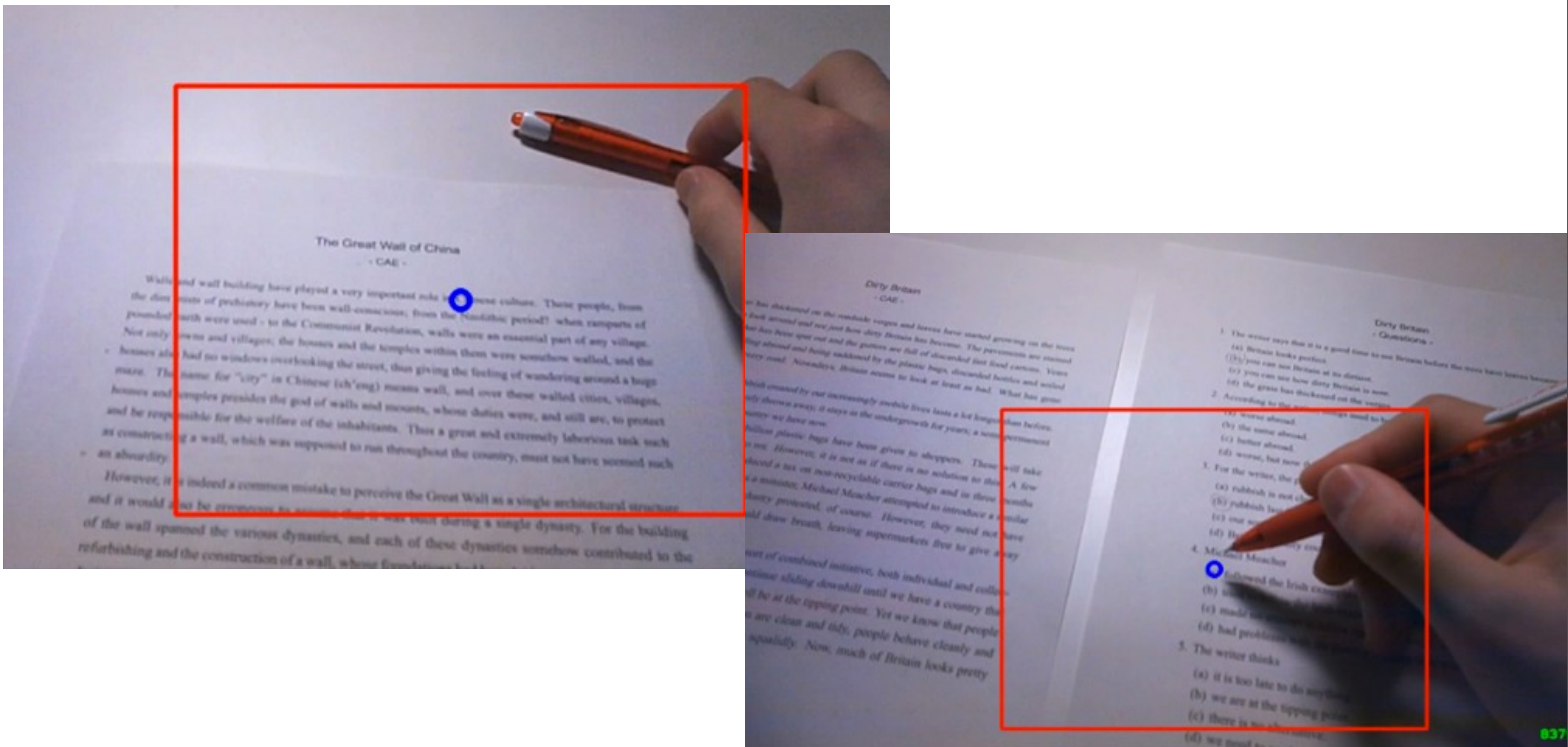
K. Kunze, H. Kawaichi, K. Yoshimura, K. Kise. **The Wordometer – Estimating the Number of Words Read Using Document Image Retrieval and Mobile Eye Tracking** ICDAR 2013.


saccade
fixation

Eye-tracking with Document Image Retrieval

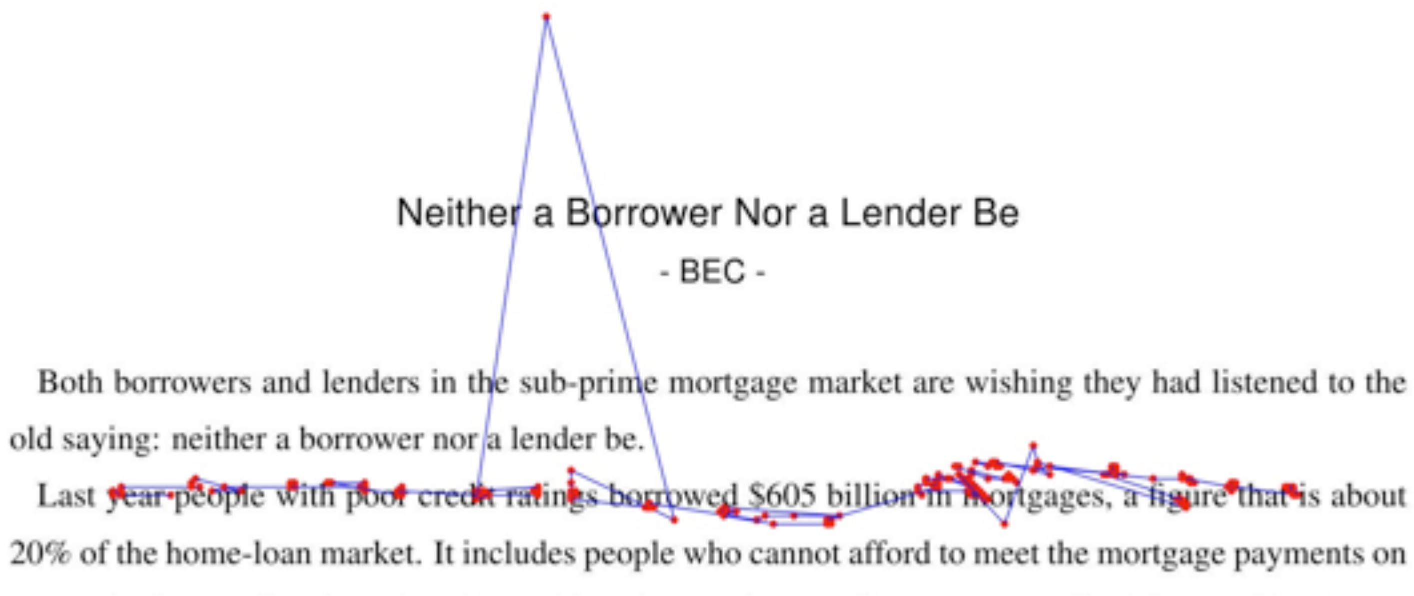


Inferring Language Expertise

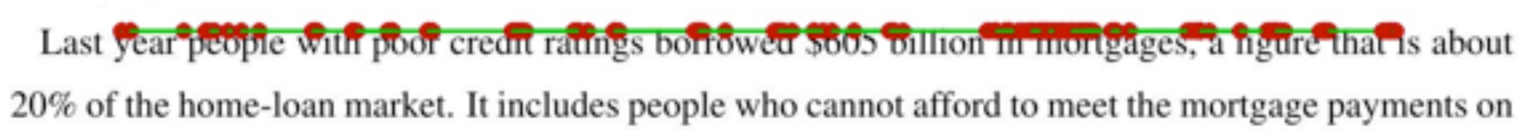


K. Kunze, H. Kawaichi, K. Yoshimura, K. Kise. **Towards inferring language expertise using eye tracking**. accepted as Work in Progress at *ACM SIGCHI Conference on Human Factors in Computing Systems*, Paris, France 2013.

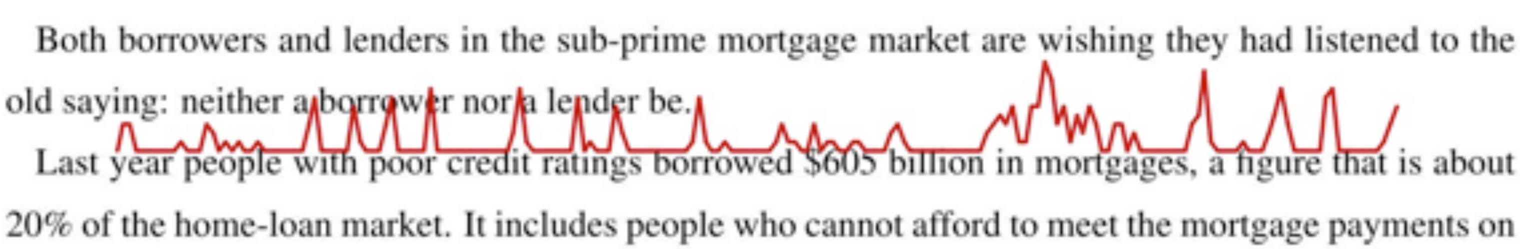
Difficult word detection



Eye-gaze translated to Document coordinate System using LLAH



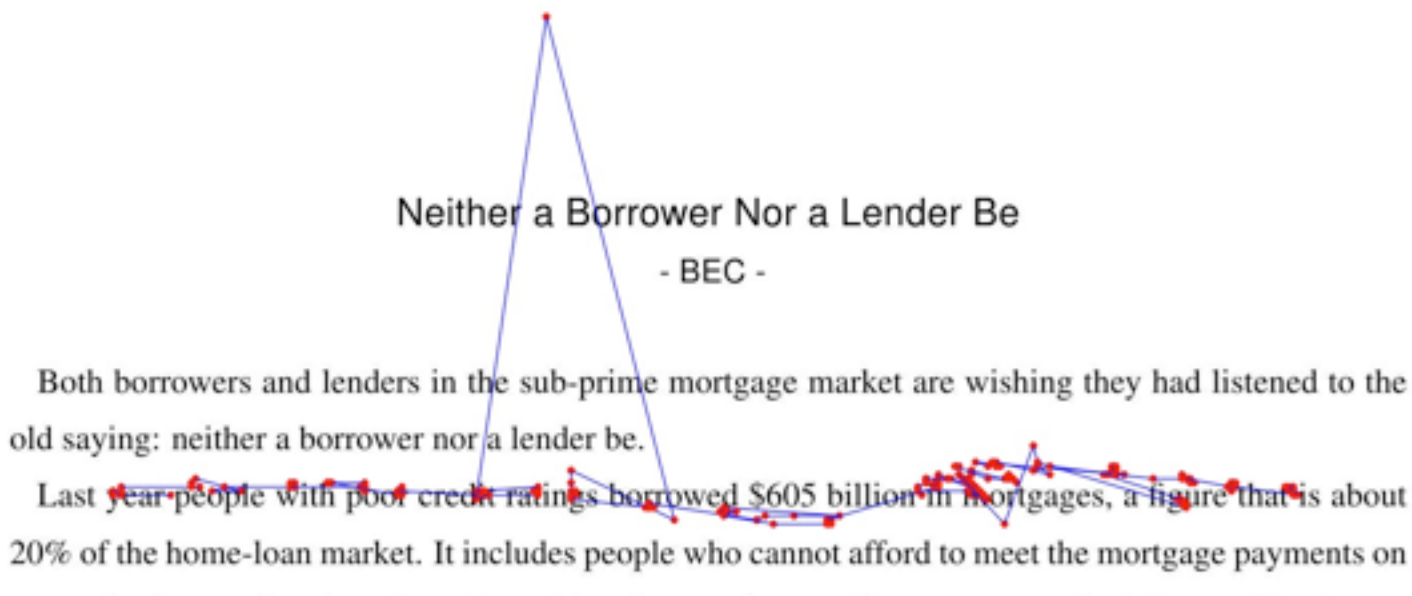
Horizontal projection To a line



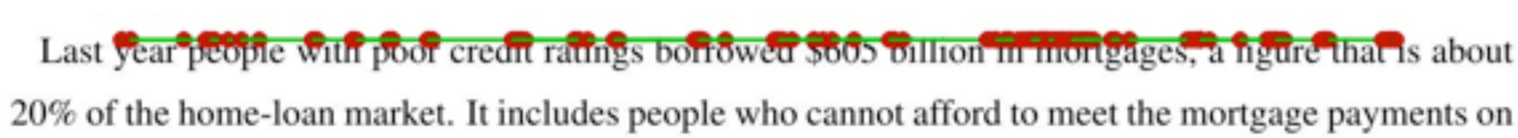
histogram

公立大学法人 大阪府立大学 OSAKA PREFECTURE UNIVERSITY

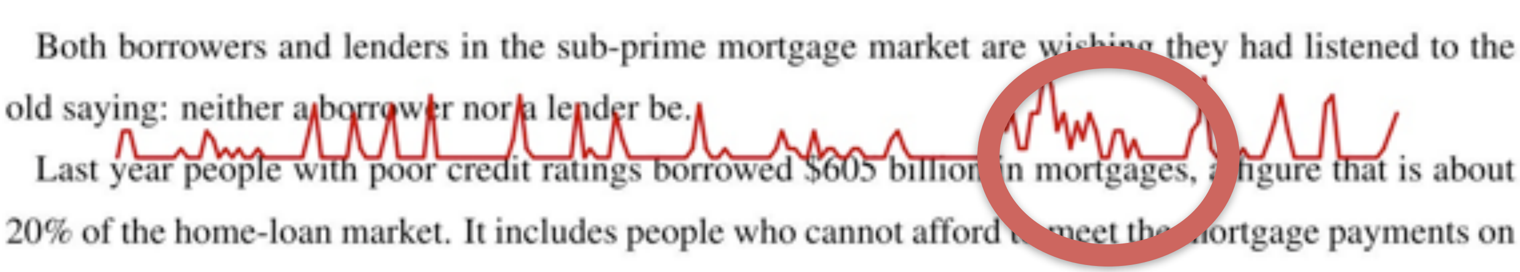
Difficult word detection



Eye-gaze translated to Document coordinate System using LLAH



Horizontal projection To a line



histogram

Reading recognition – What are you reading?

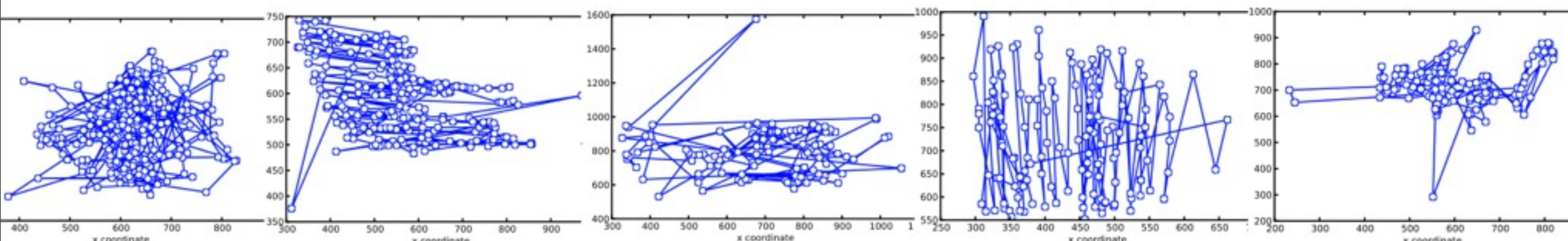
Modalities:

- Eyetracking
- EEG

Document type recognition

公立大学法人 大阪府立大学
OSAKA PREFECTURE UNIVERSITY

Using eygaze to distinguish document types

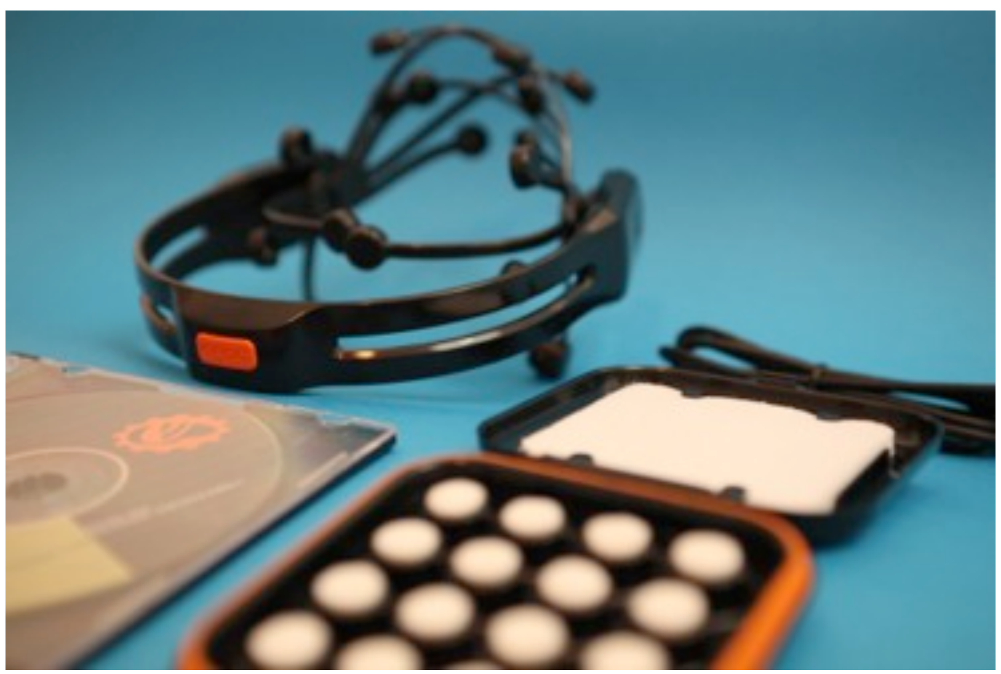


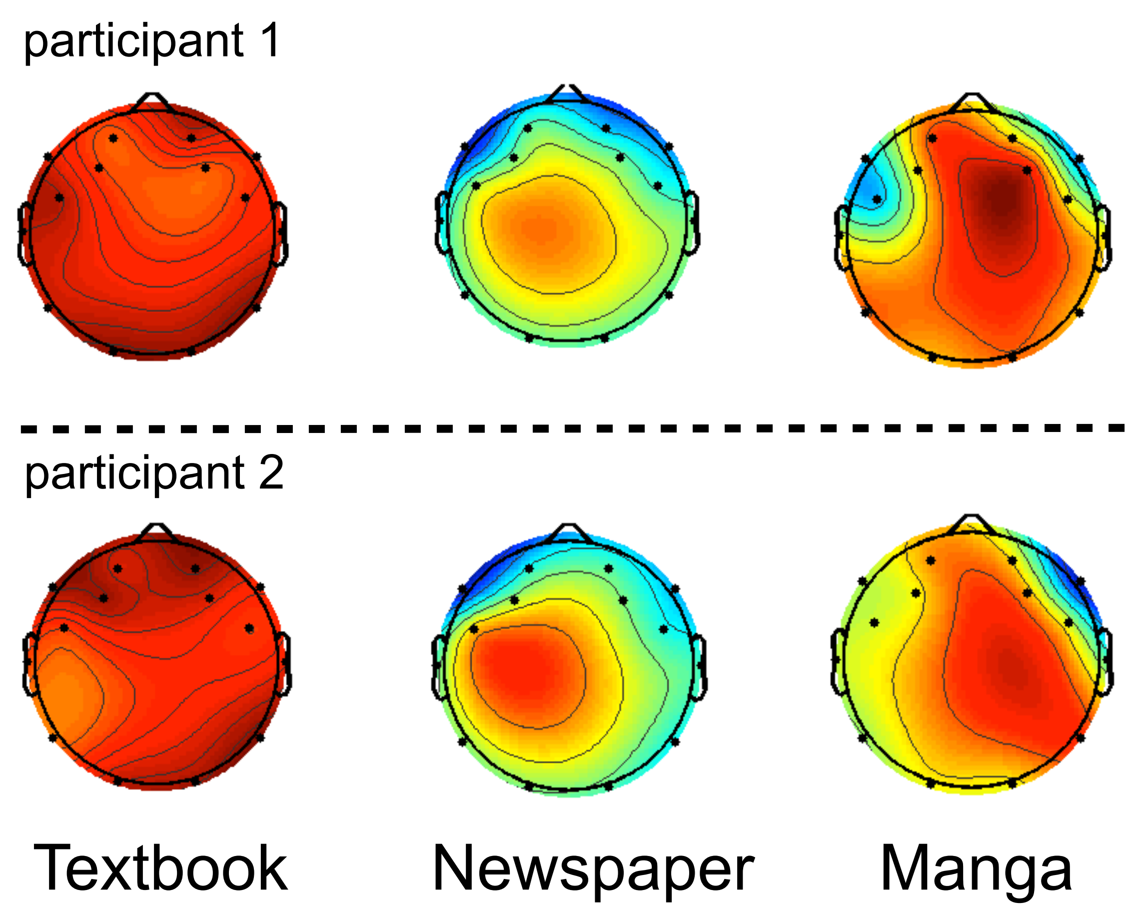
72 % user independent recognition (10 users, 5 document types, 5 environments)

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

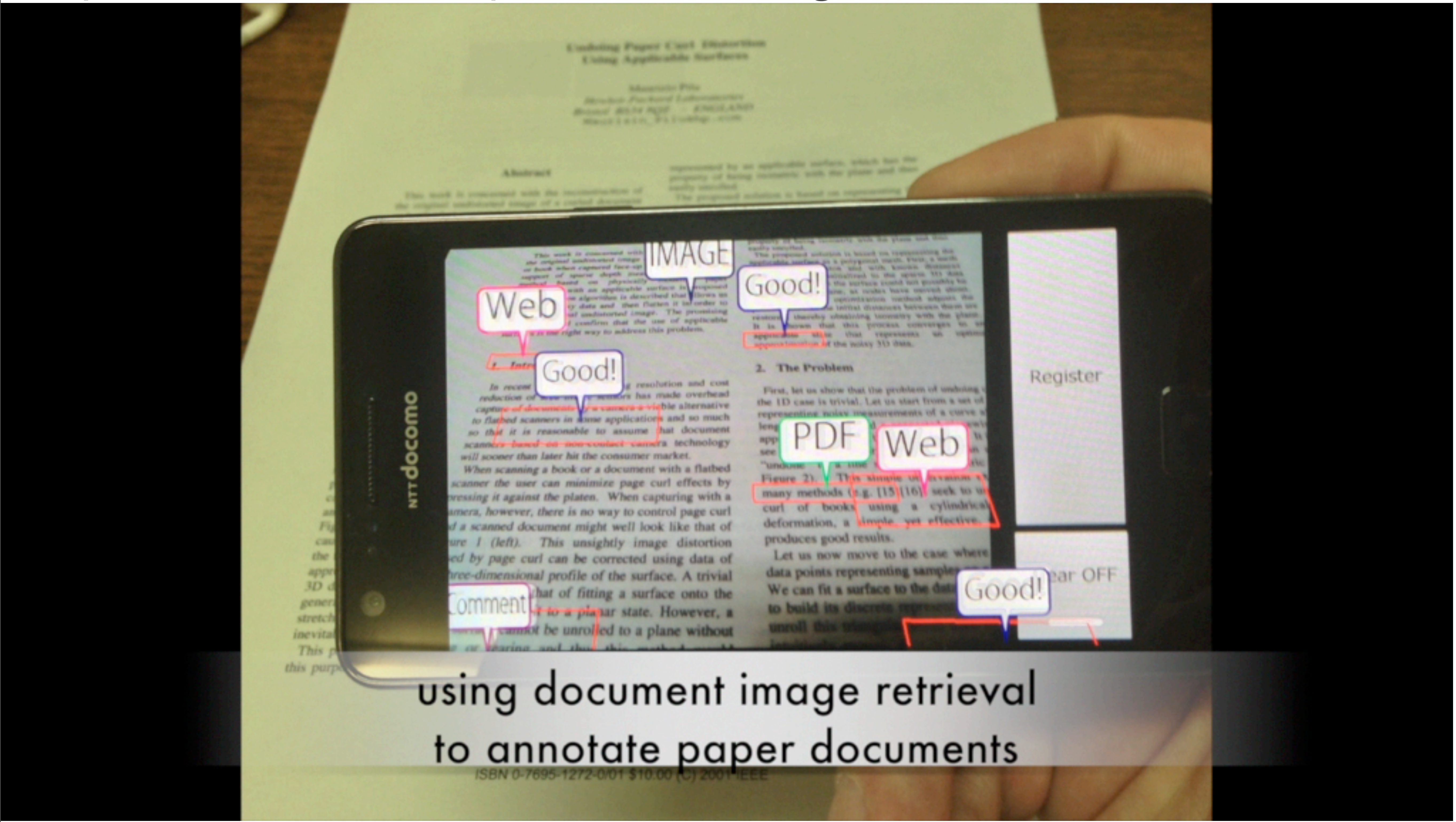




K. Kunze, Y. Shiga, S. Ishimaru, Y. Utsumi, K. Kise. Reading activity recognition using an off-the-shelf EEG — detecting reading activities and distinguishing genres of documents accepted at ICDAR, Washington D.C., 2013.

公立大学法人 大阪府立大学 OSAKA PREFECTURE UNIVERSITY

can we use special devices to help us with reading?



Questions, remarks, violent dissent?

Contact:

kaikunze.de
kai.kunze@gmail.com
Twitter: @k_garten
Facebook: kai.kunze
App.net: @kkai