Real-Life Activity Recognition

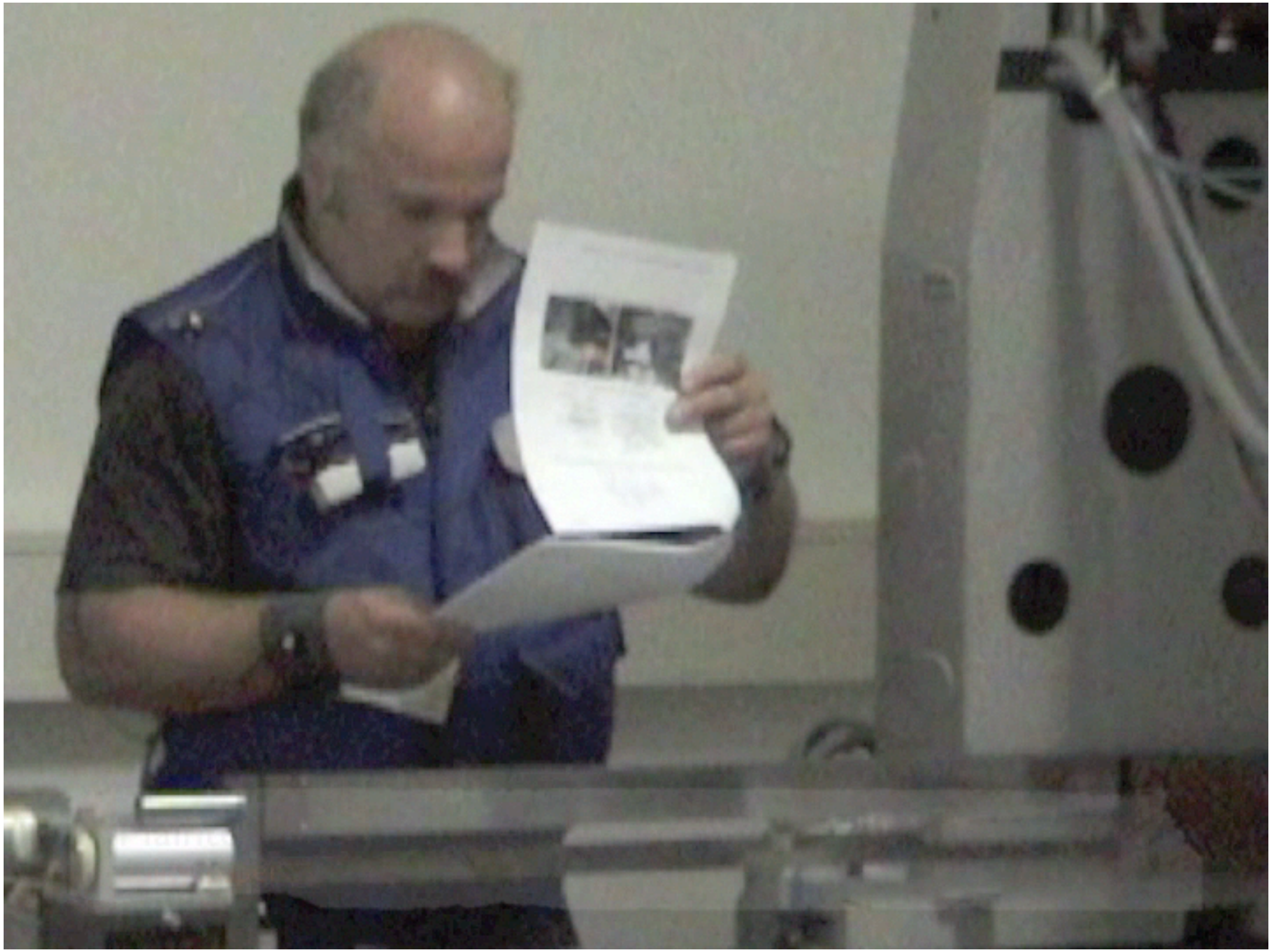
Kai Kunze

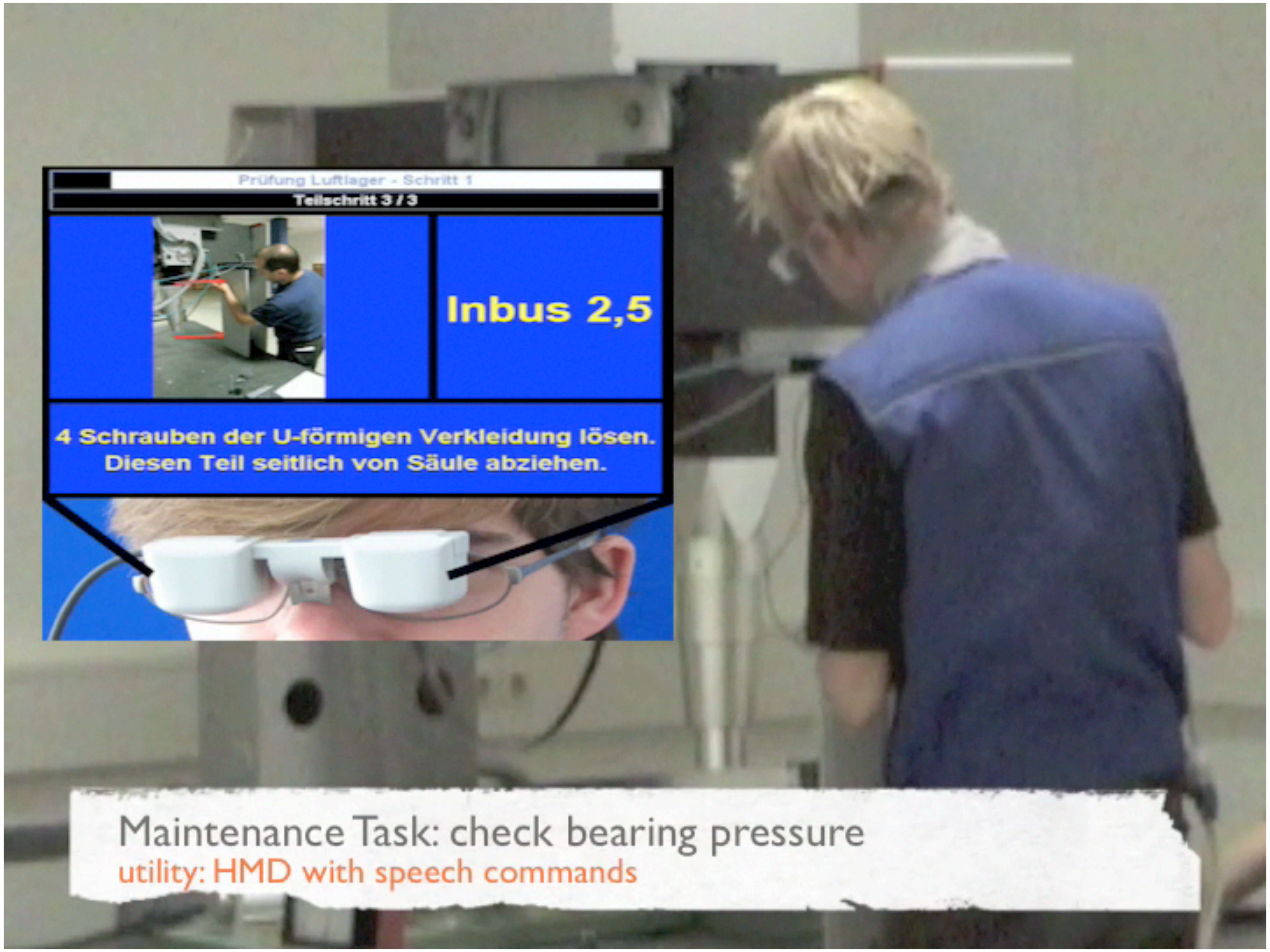
Compensating for On-Body Placement Effects in Activity Recognition

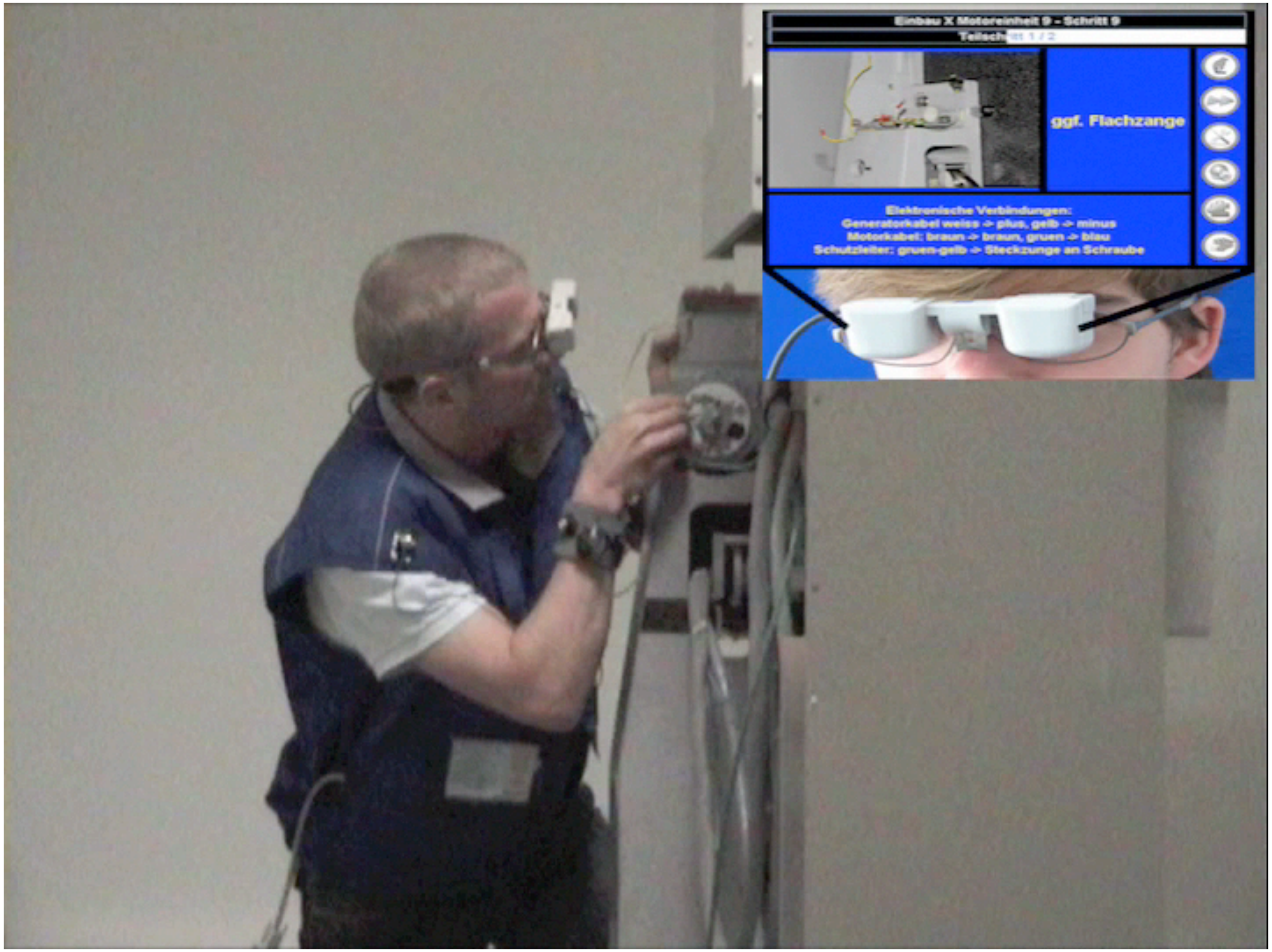
Recognizing Reading Activities

Compensating for On-Body Placement Effects in Activity Recognition

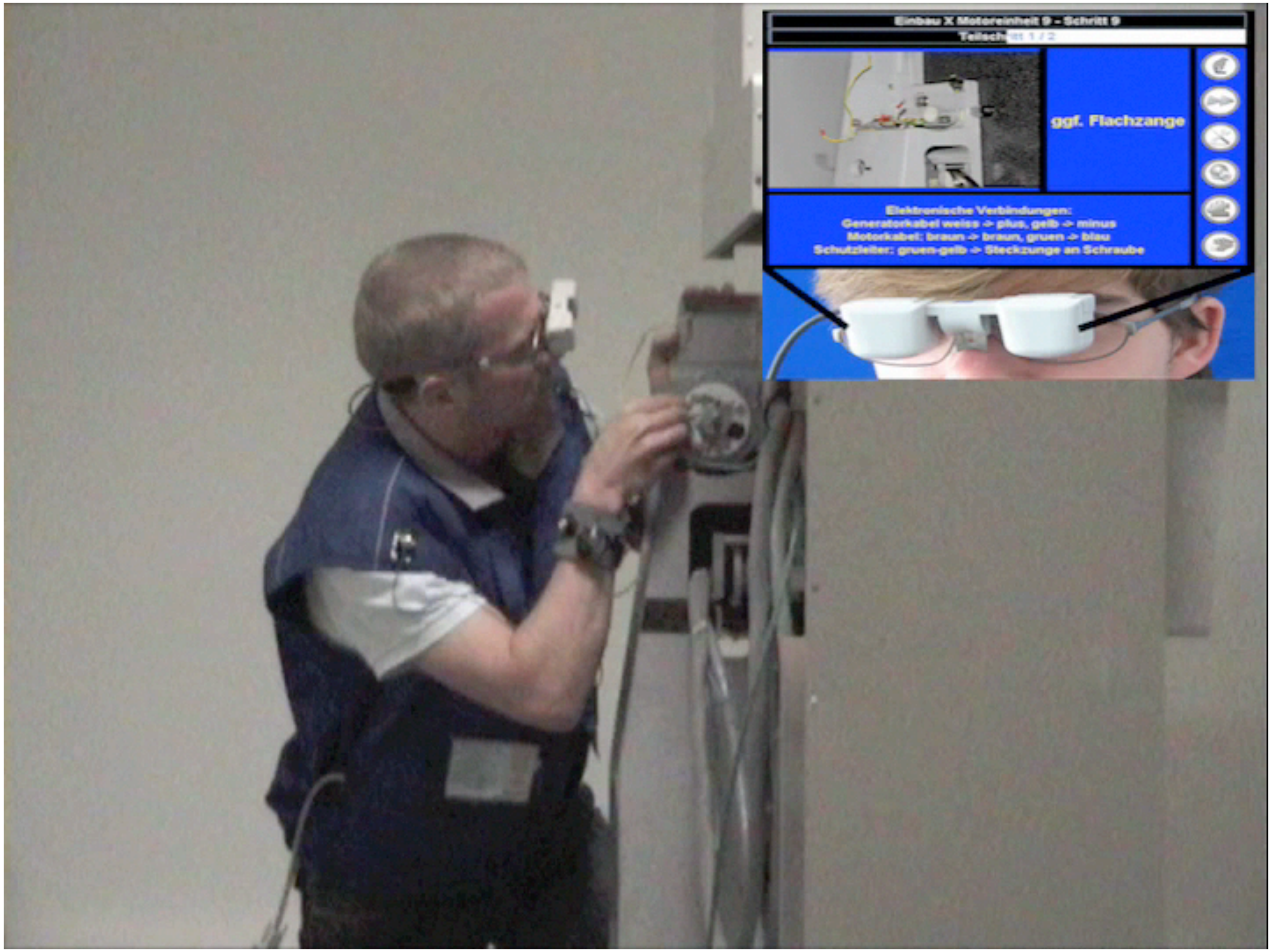
Kai Kunze




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

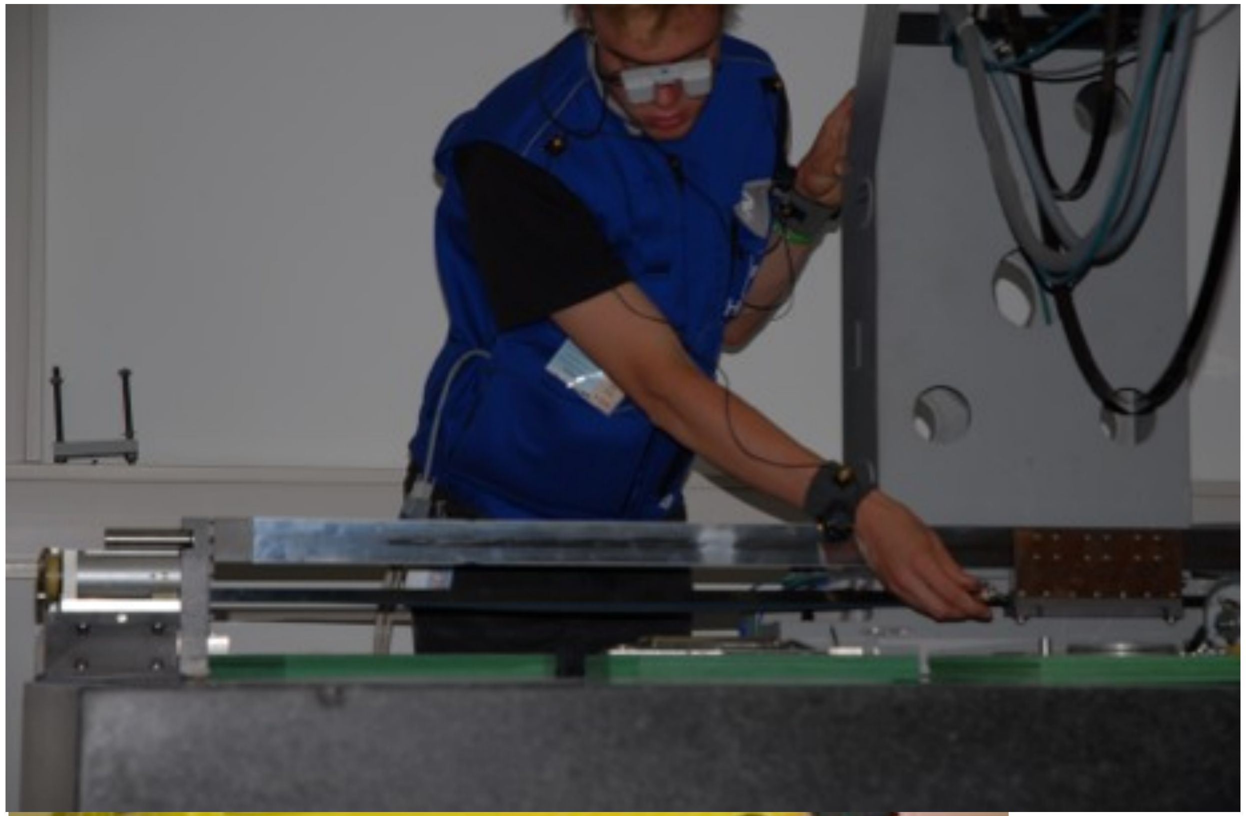


Einbau X Motoreinheit 9 - Schritt 9
ggf. Flachzange
Elektronische Verbindungen:
Generatorkabel weiss -> plus, gelb -> minus
Motorkabel: braun -> braun, gruen -> blau
Schutzleiter: gruen-gelb -> Steckzunge an Schraube



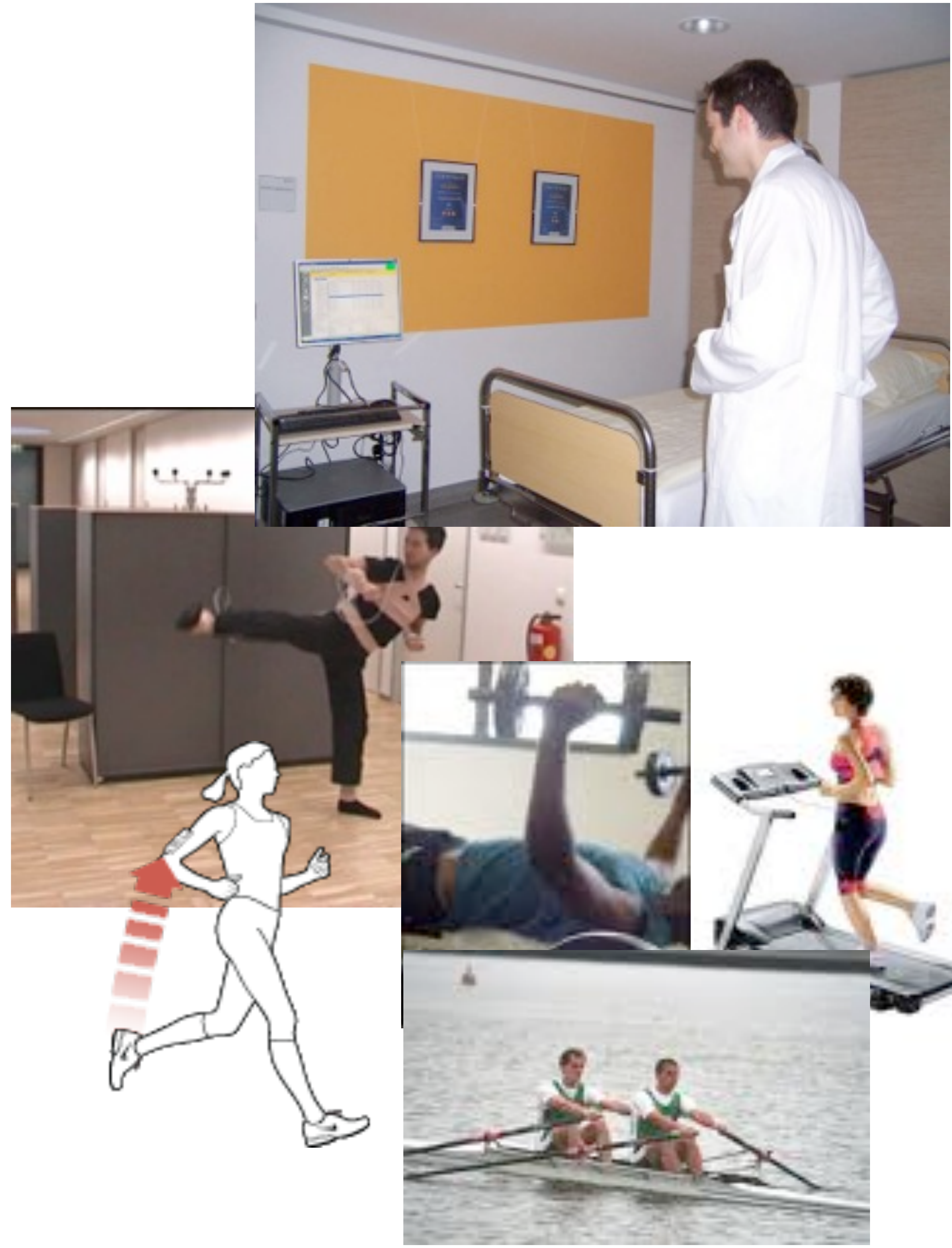
Kunze, K.,Wagner, F., Kartal, E., Morales Kluge, E., and Lukowicz, P. Does Context Matter ? - A Quantitative Evaluation in a Real World Maintenance Scenario. *In Proceedings of the 7th international Conference on Pervasive Computing Nara*, Japan, May 11 - 14, 2009.

Applications



Applications

Applications



Applications

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Applications

Applications

Applications

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Applications

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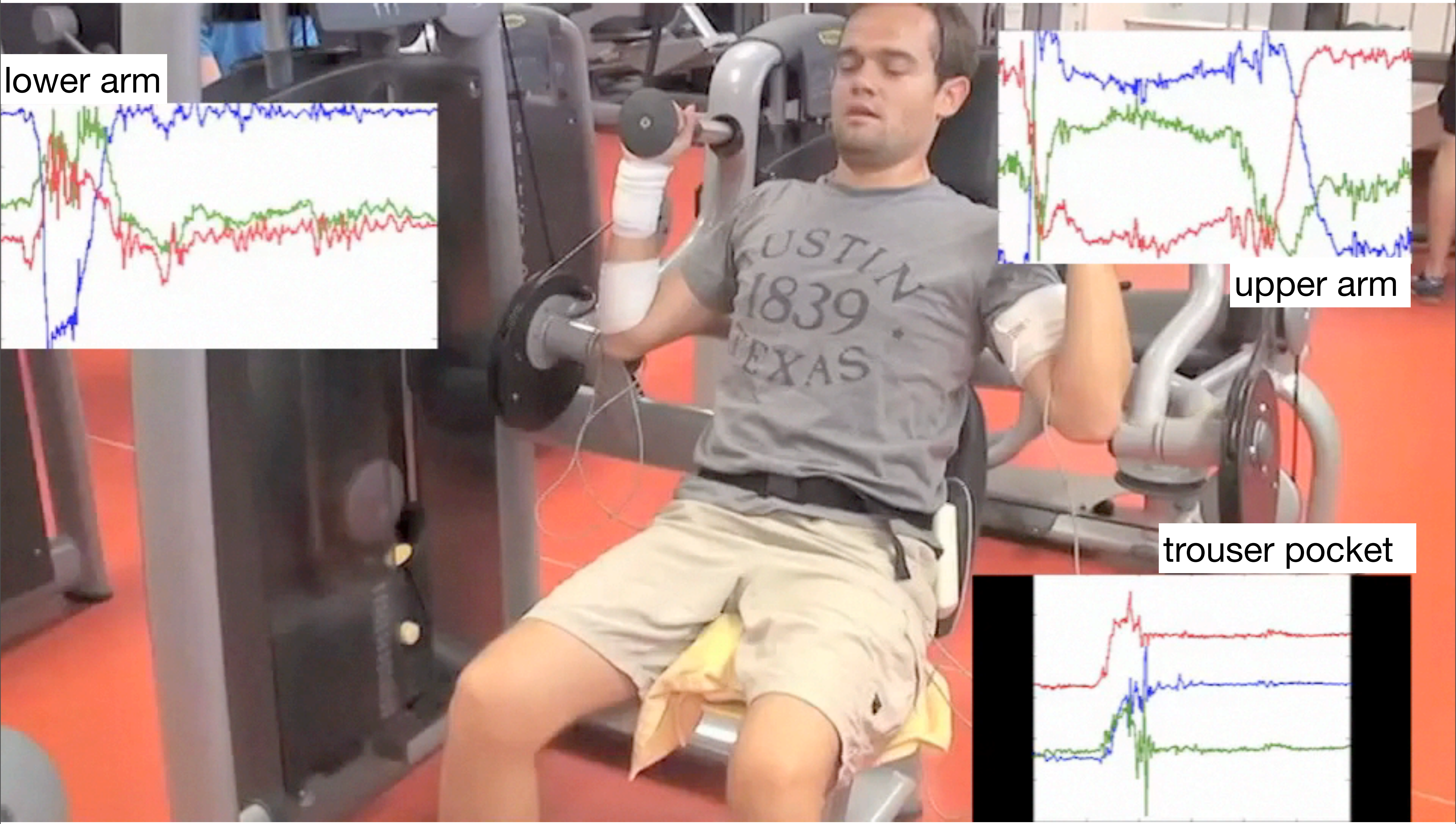
... using environment and onbody sensors

lower arm

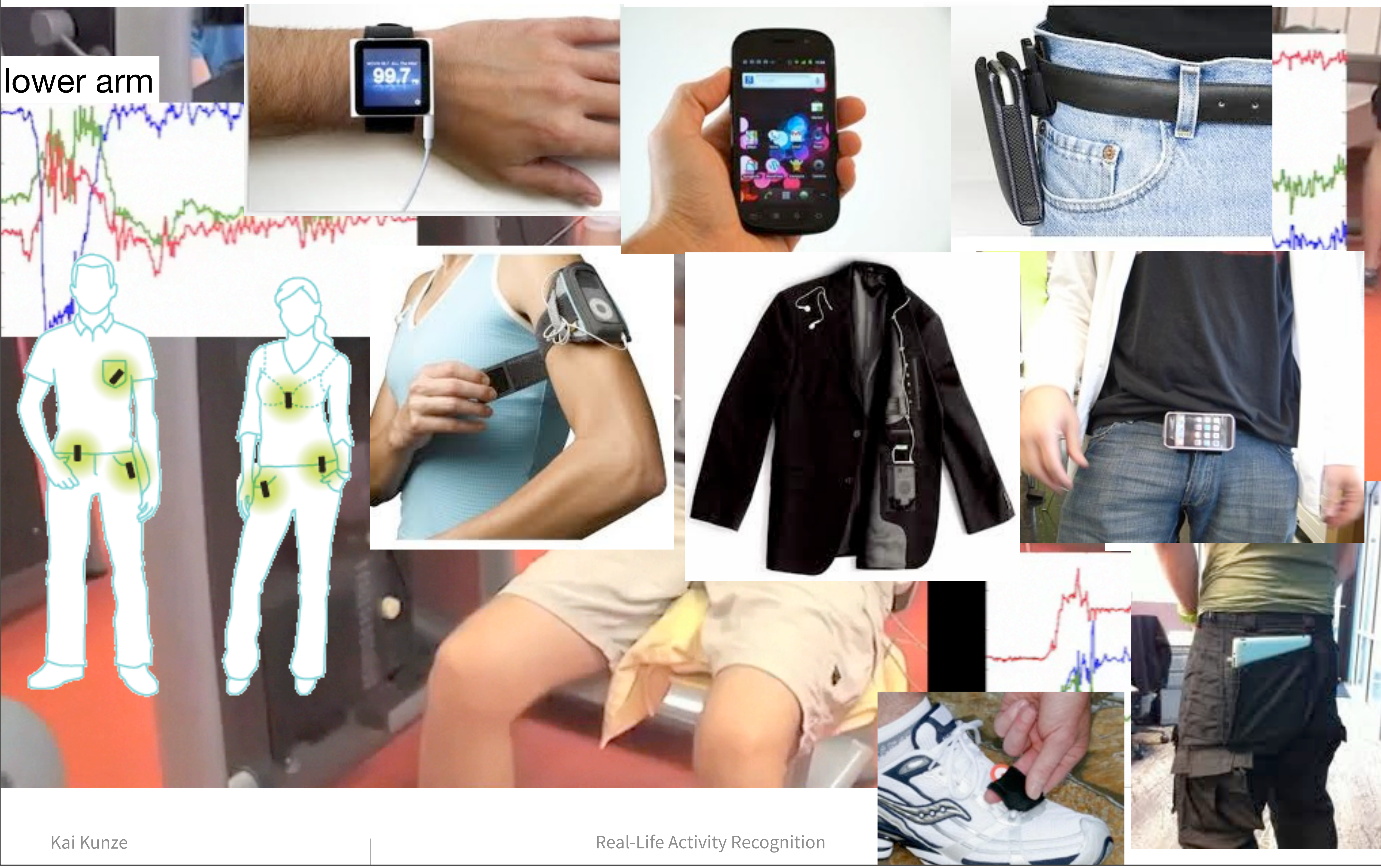
upper arm

trouser pocket

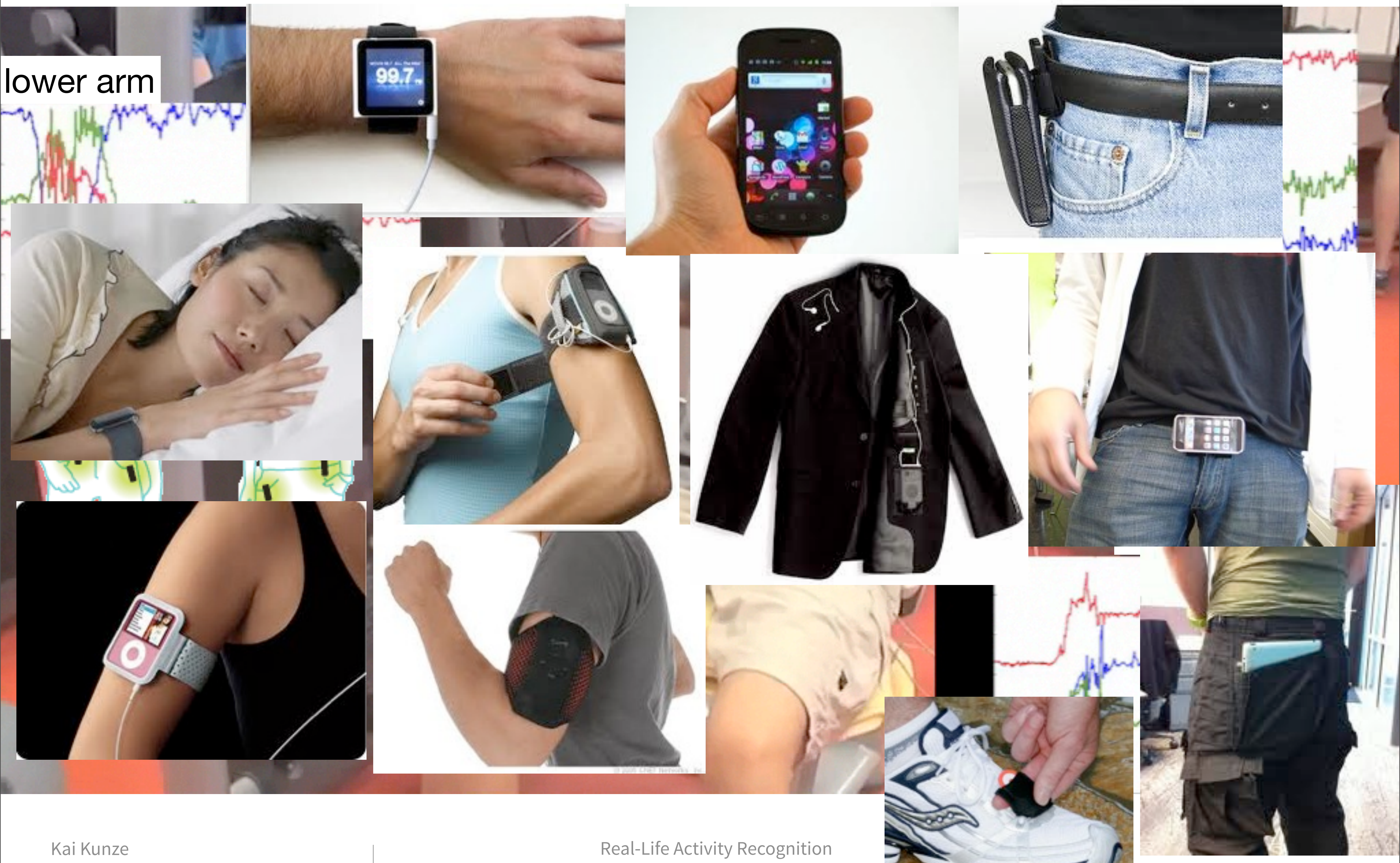
... using environment and onbody sensors



... using environment and onbody sensors



... using environment and onbody sensors



Compensating for On-Body Placement Effects in Activity Recognition

Kai Kunze

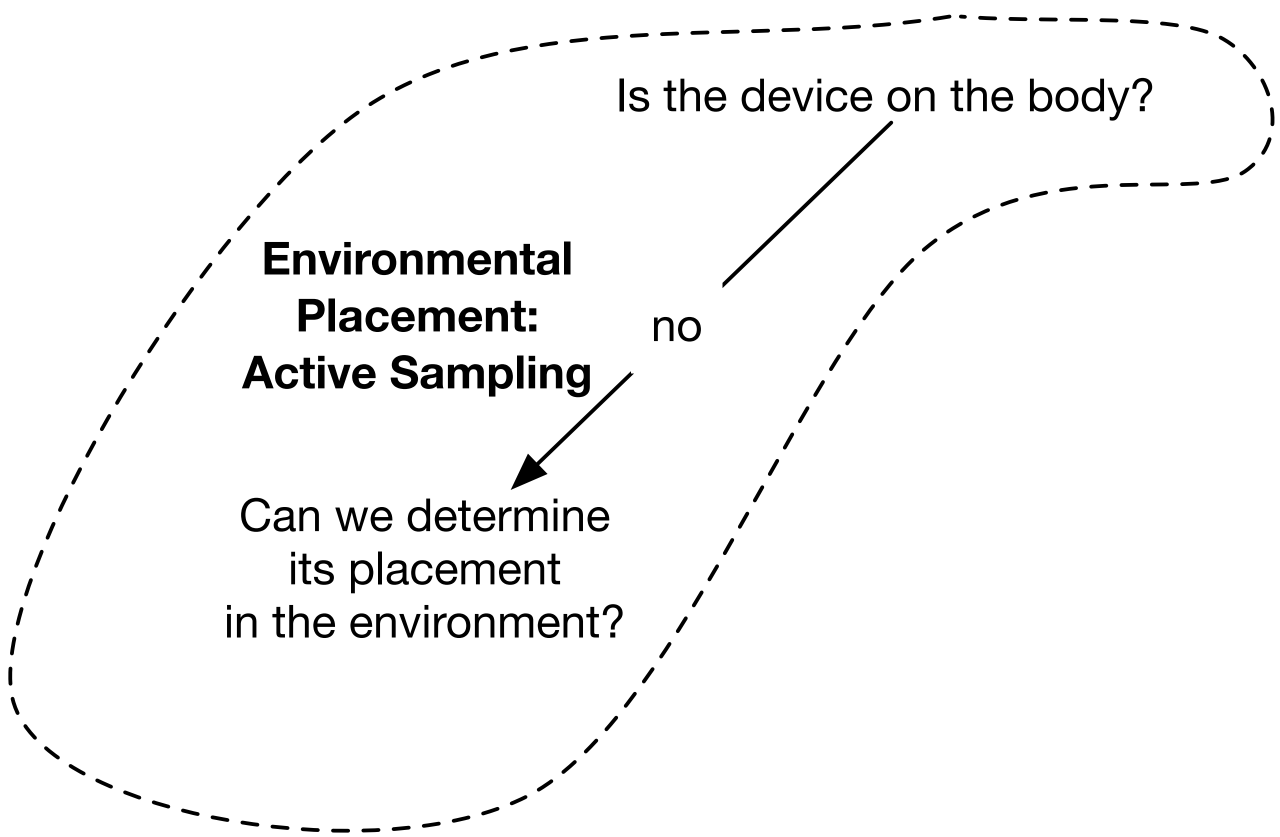
Overview and Contributions

Is the device on the body?

no

Can we determine
its placement
in the environment?

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

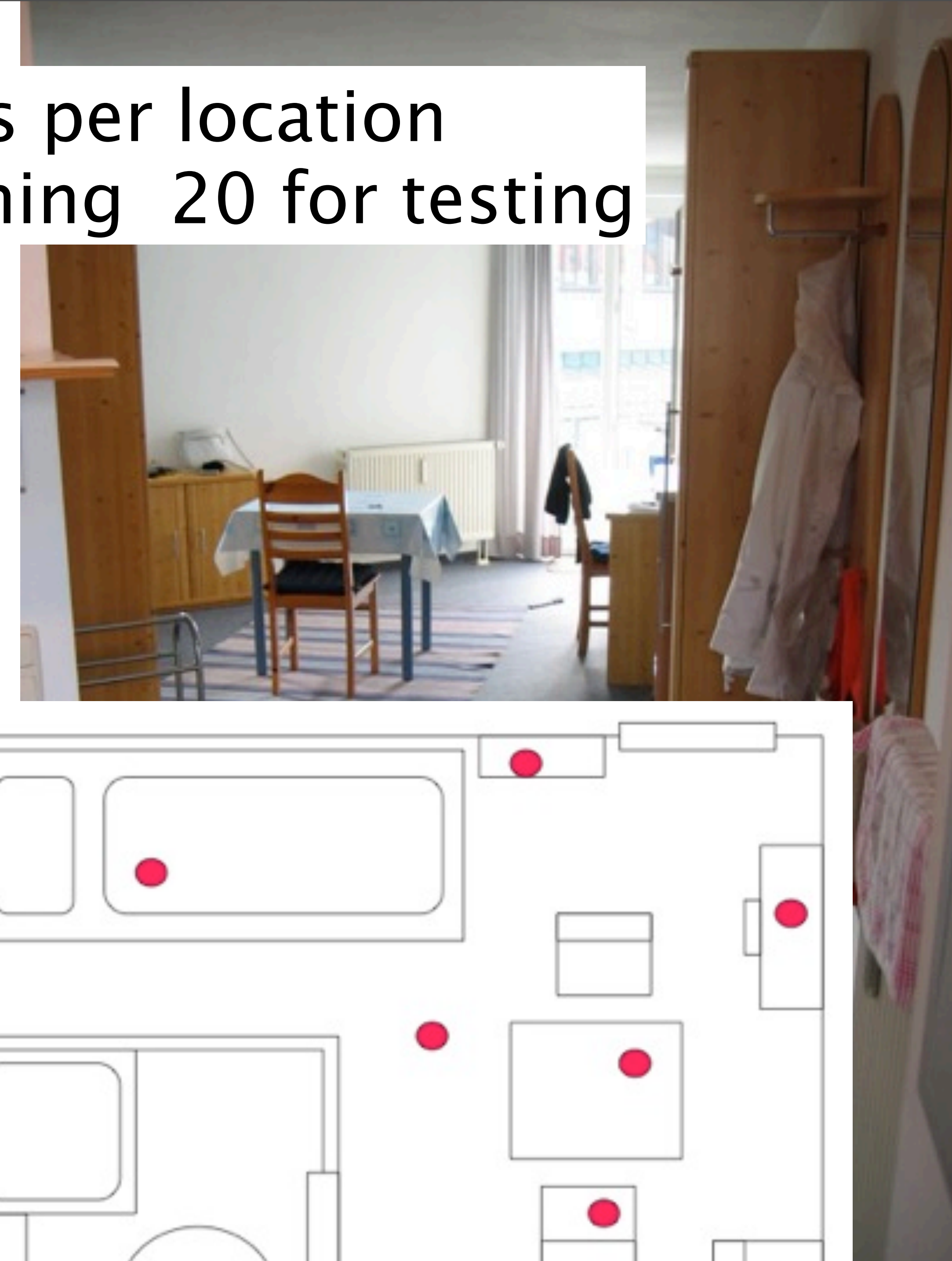
A mobile phone ringing or vibrating sounds differently depending on where it is.

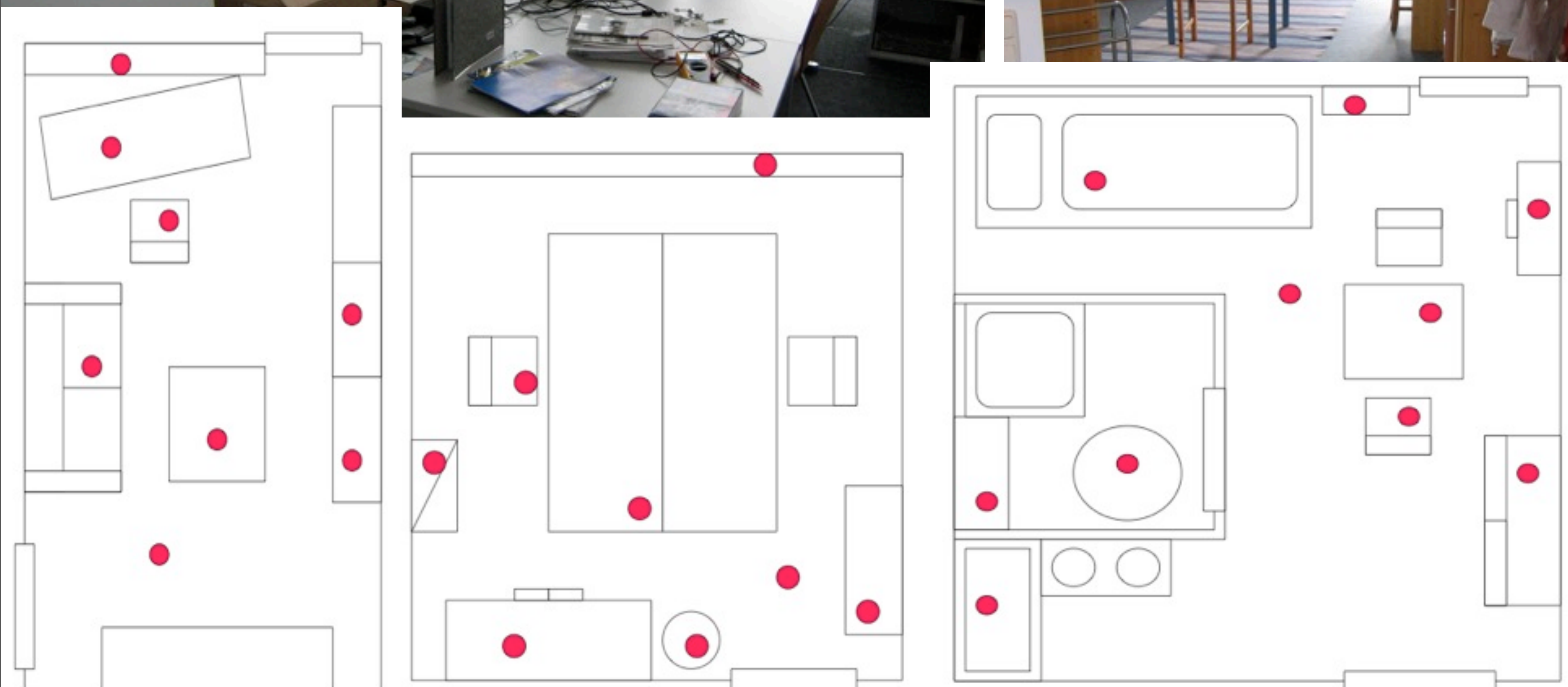
approach

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

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abstract classes

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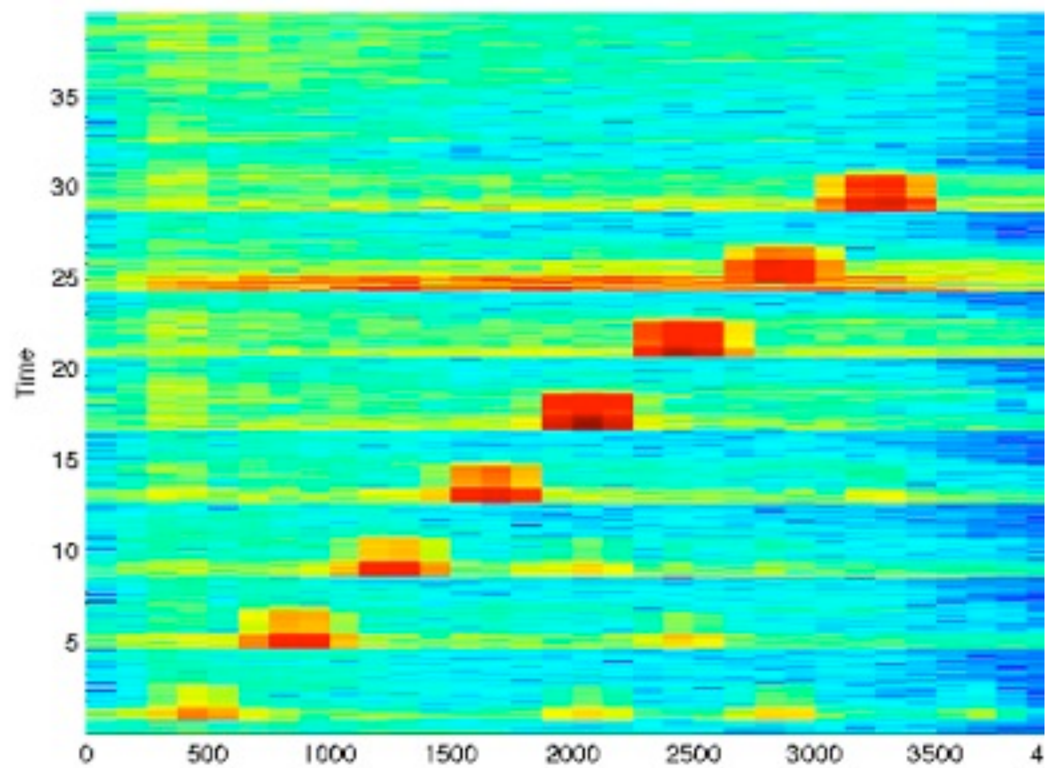
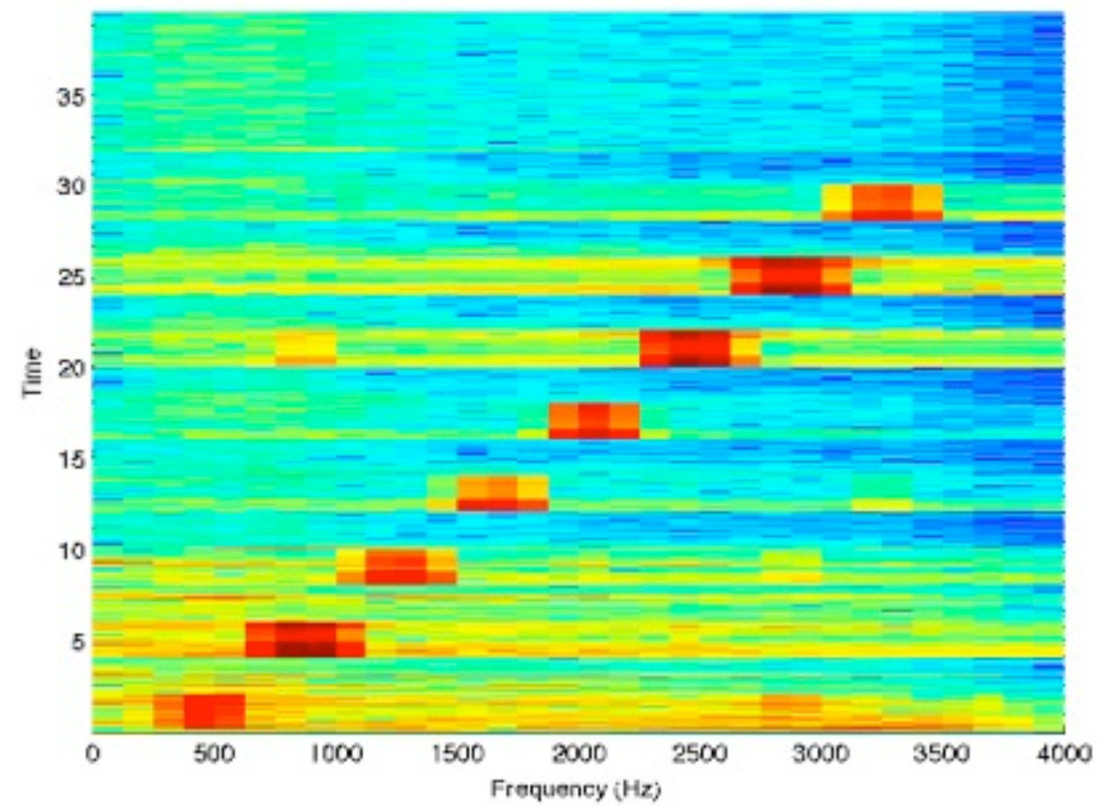
stone
wood
compartment:
Open/closed (except metal)

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

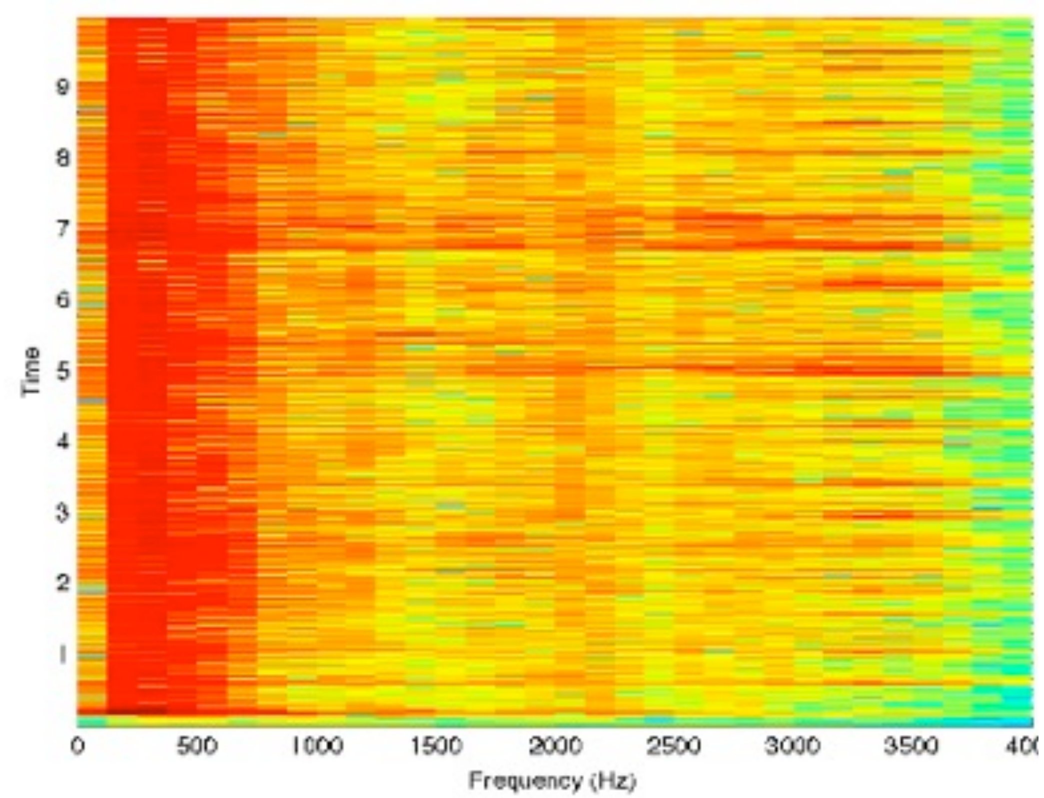
fingerprint and vibration sounds

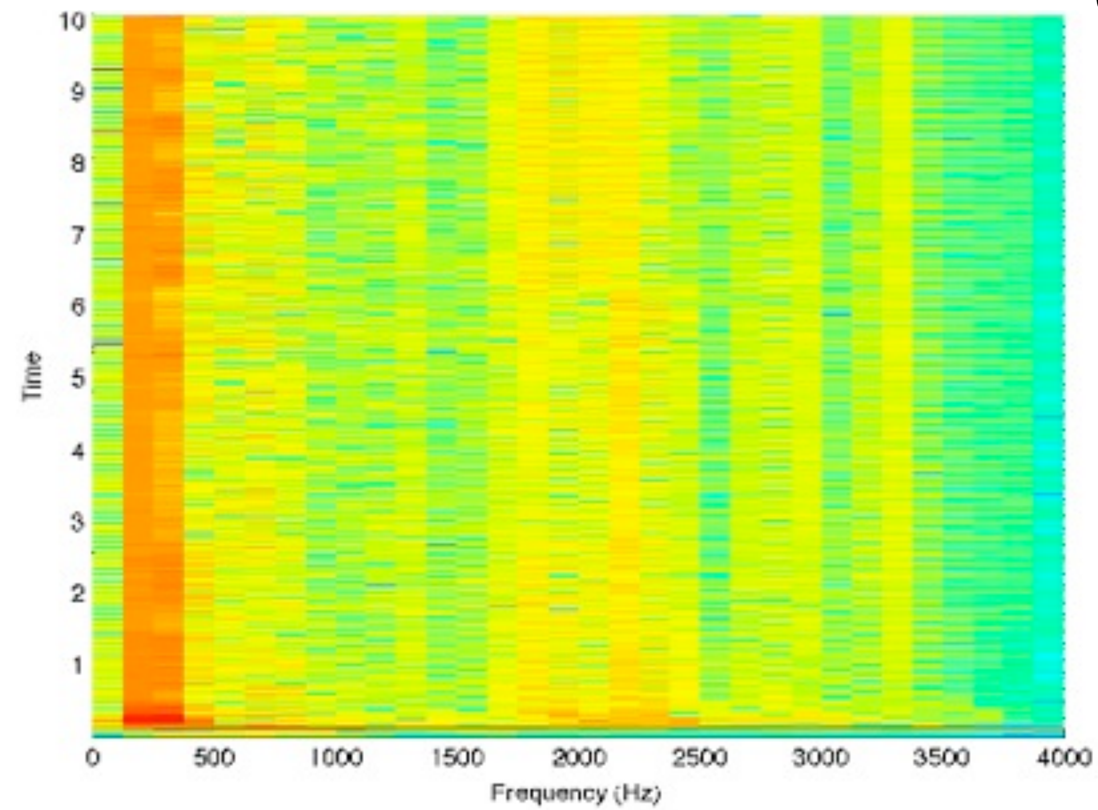




desk

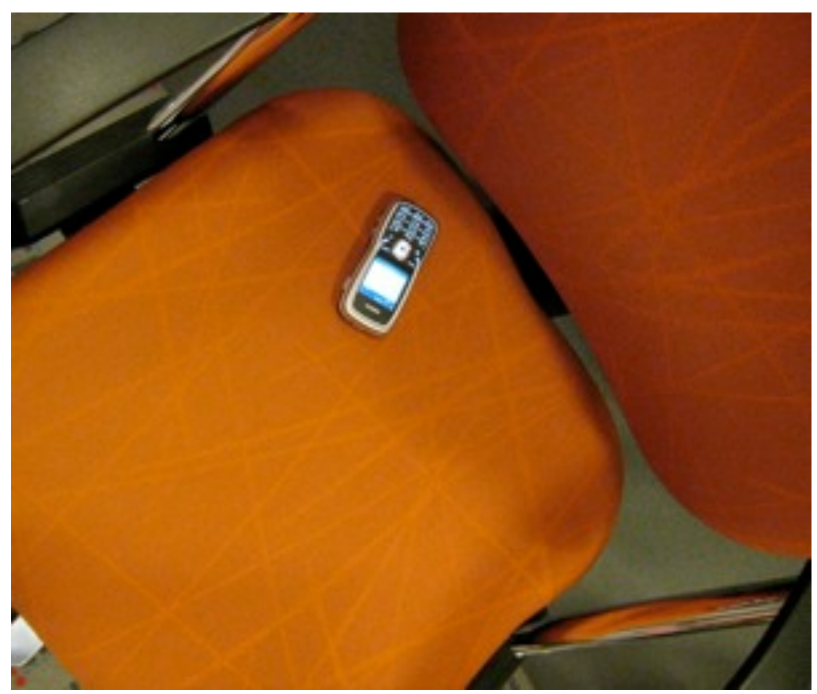
carpet

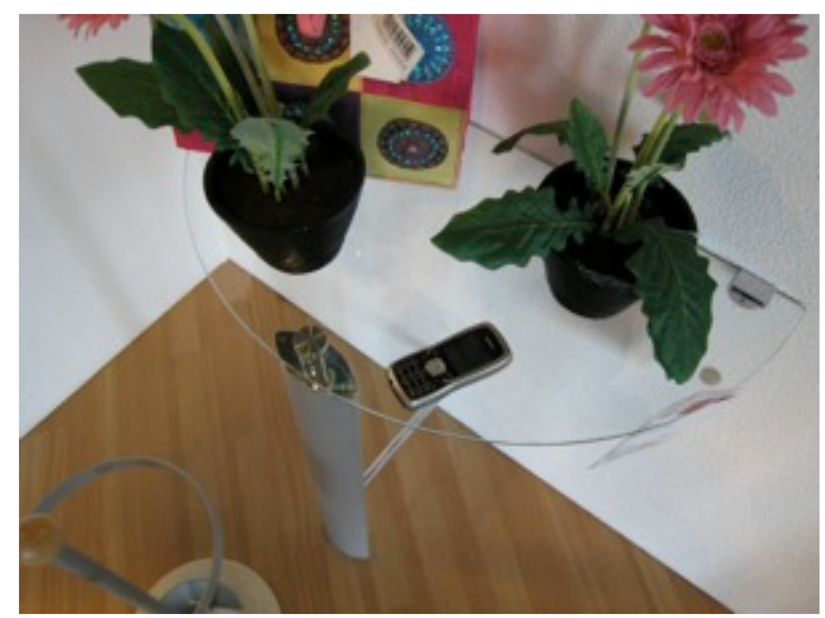




Kai K

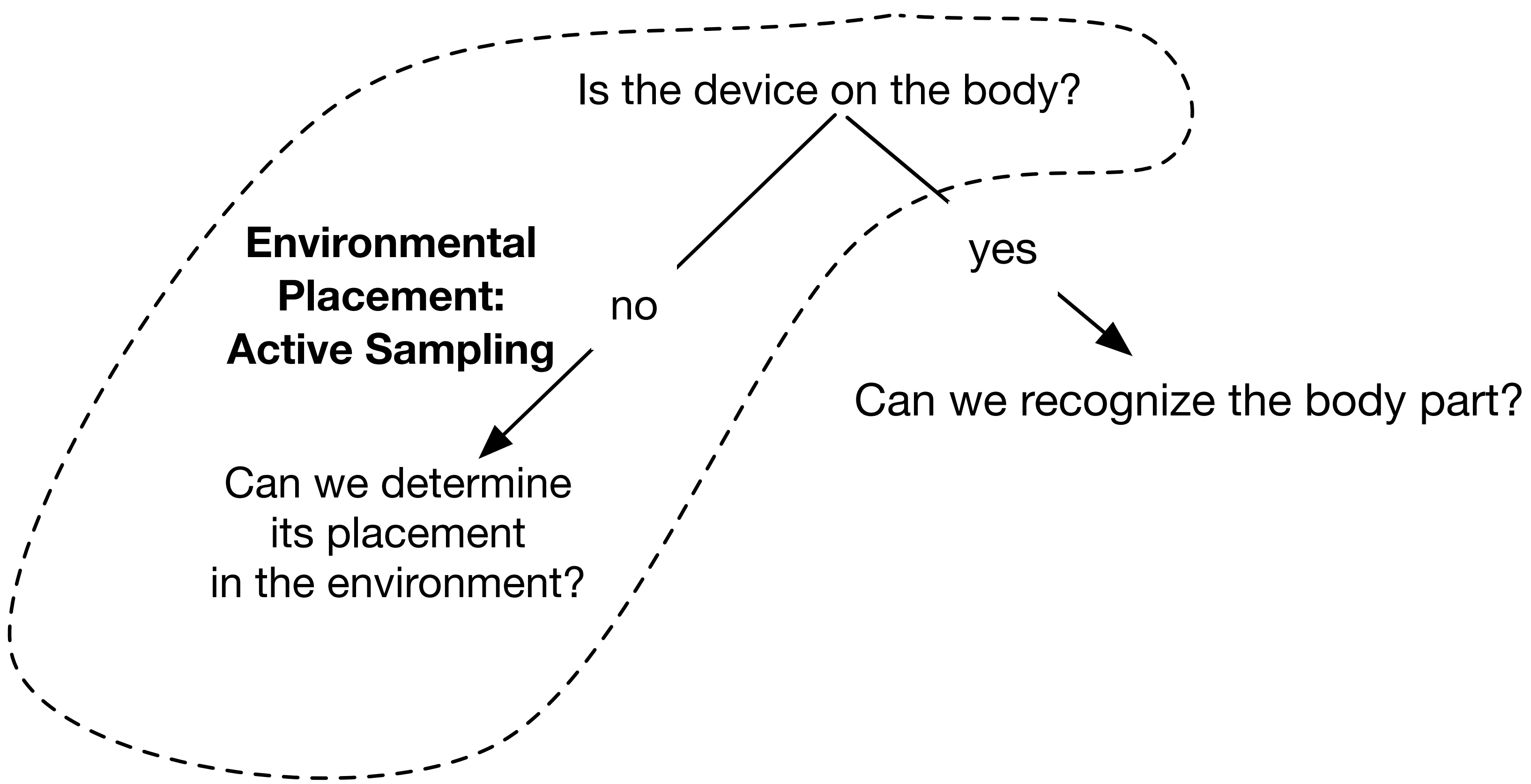
Environmental Placement Detection
-Active Sampling-



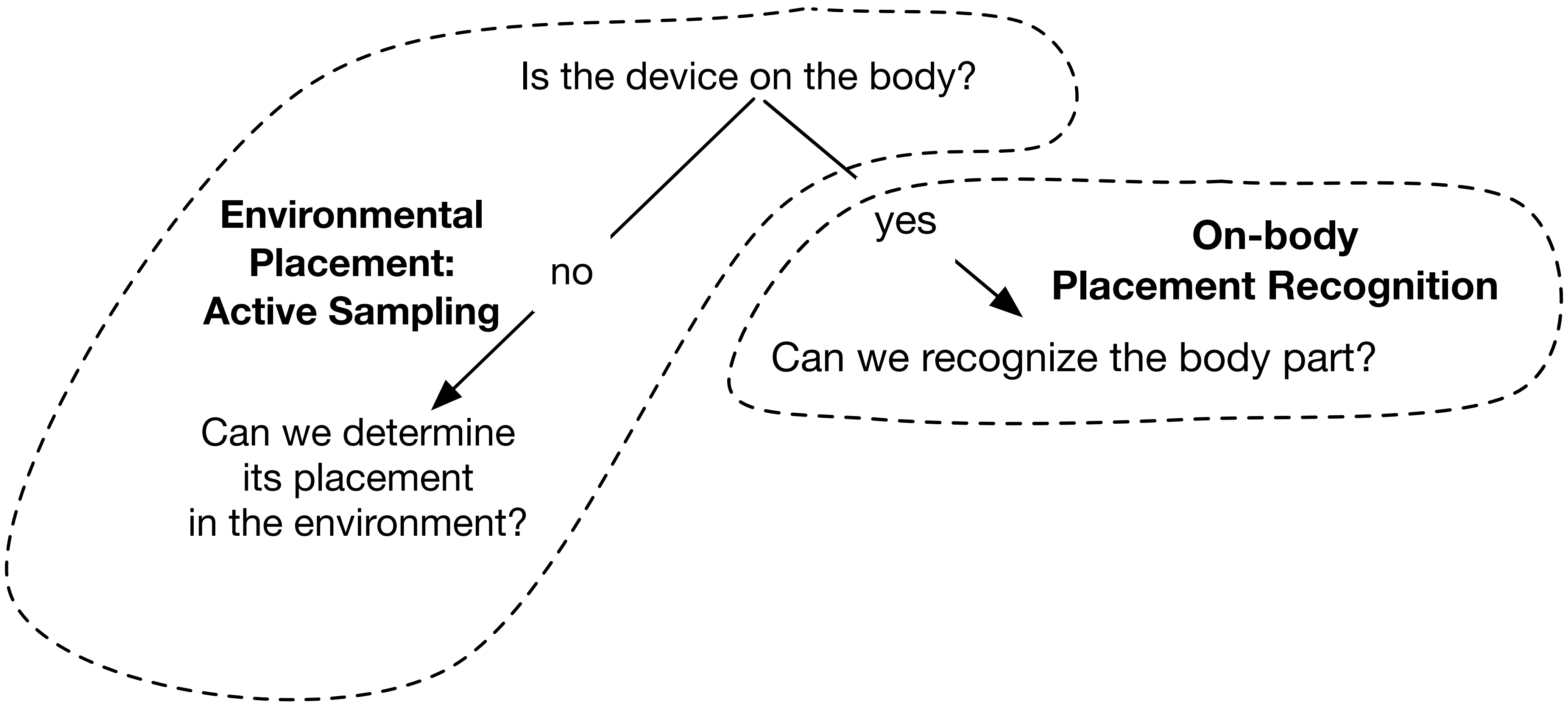


- up to 96 % per room
- up to 92 % for abstract classes

Overview and Contributions



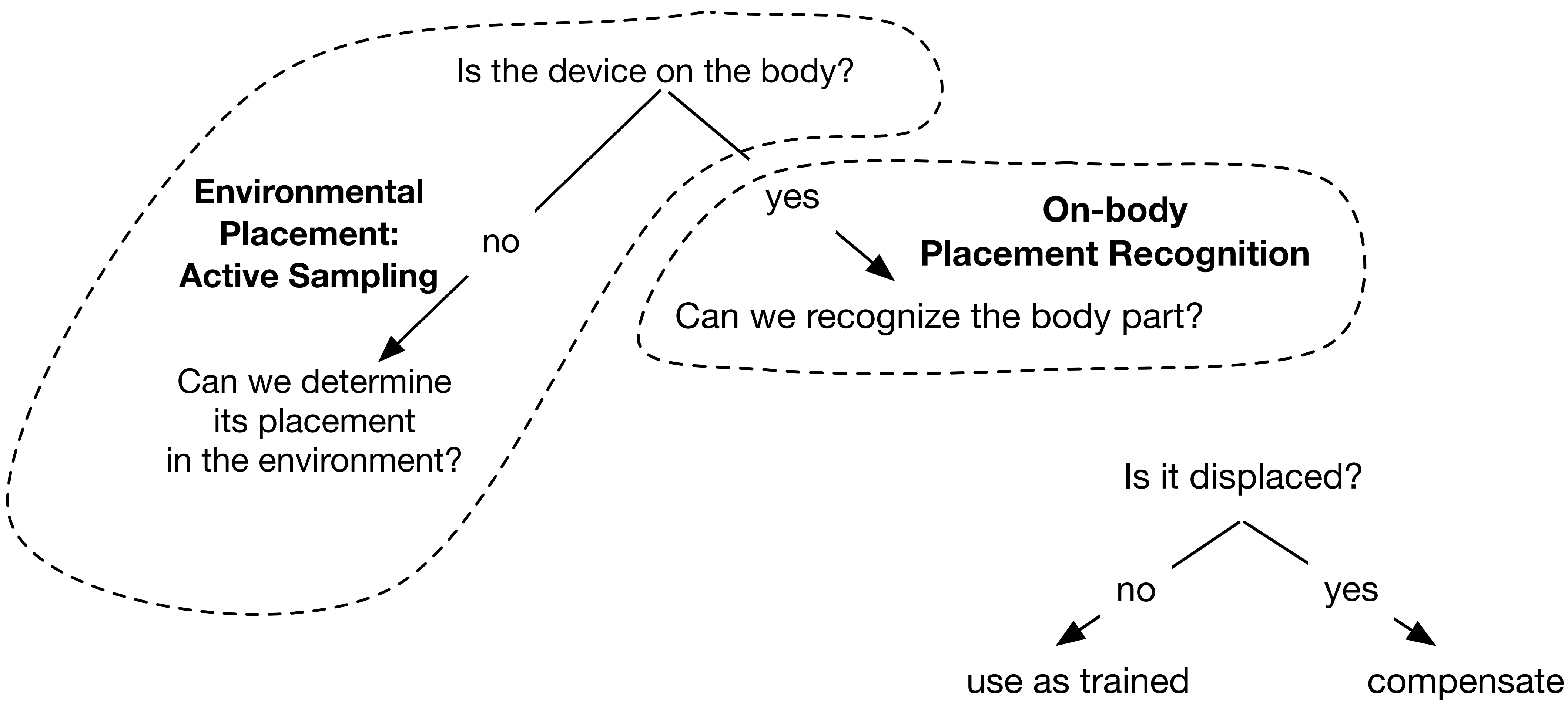
Overview and Contributions



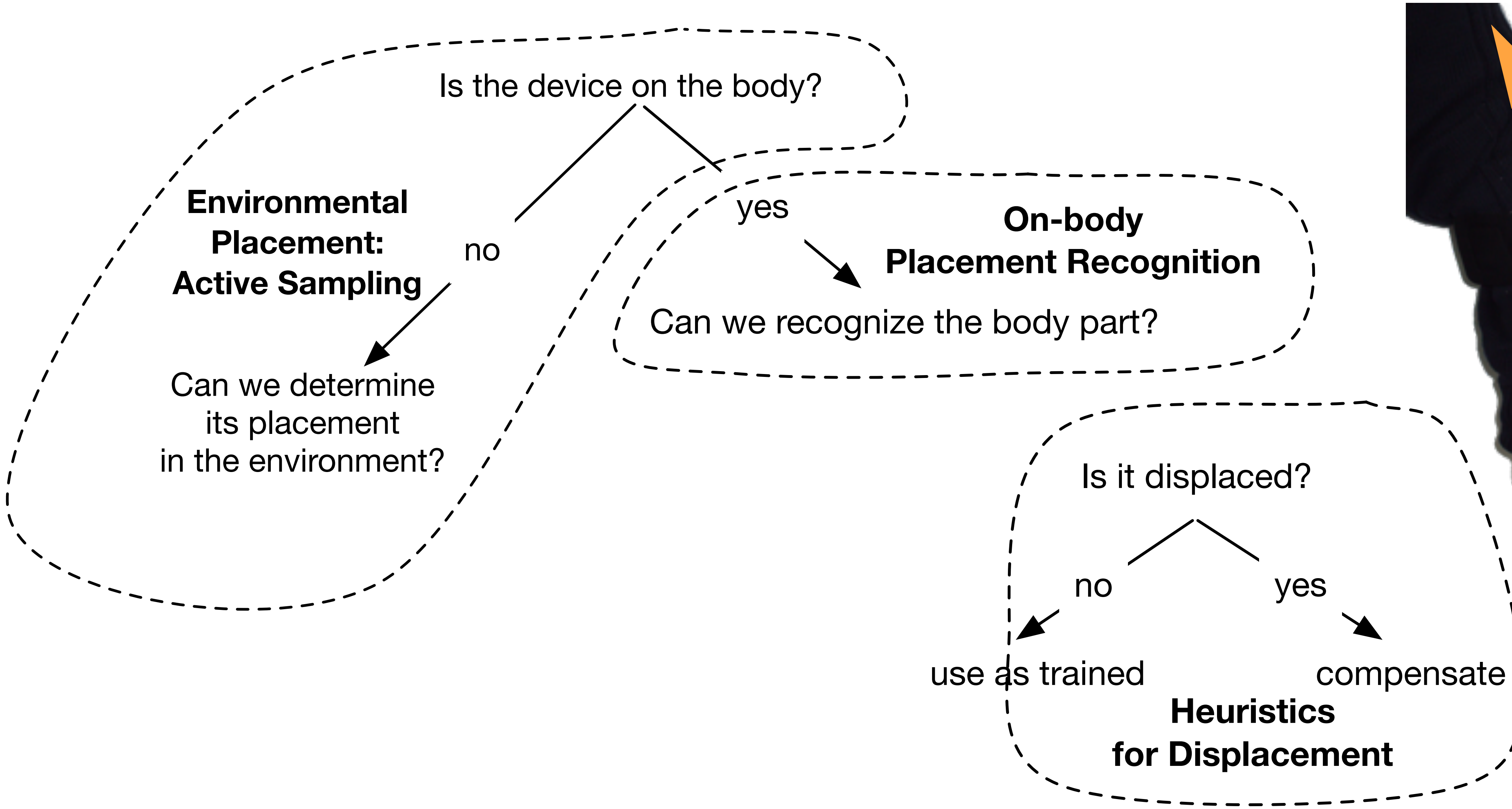
K. Kunze and P. Lukowicz. *Using acceleration signatures from everyday activities for on-body device location.* 11th IEEE International Symposium on Wearable Computers, Sep 2007.

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

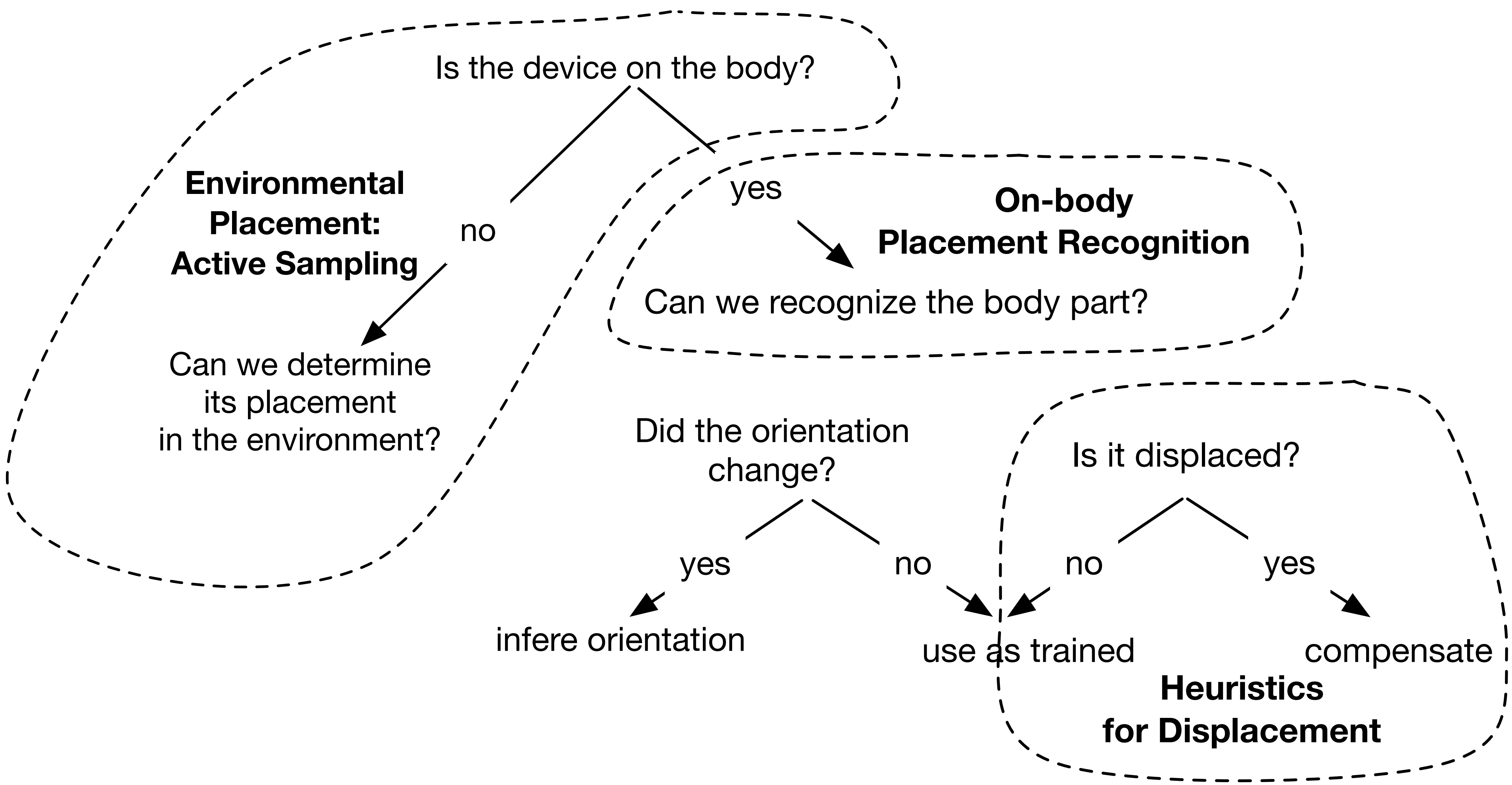


Overview and Contributions



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



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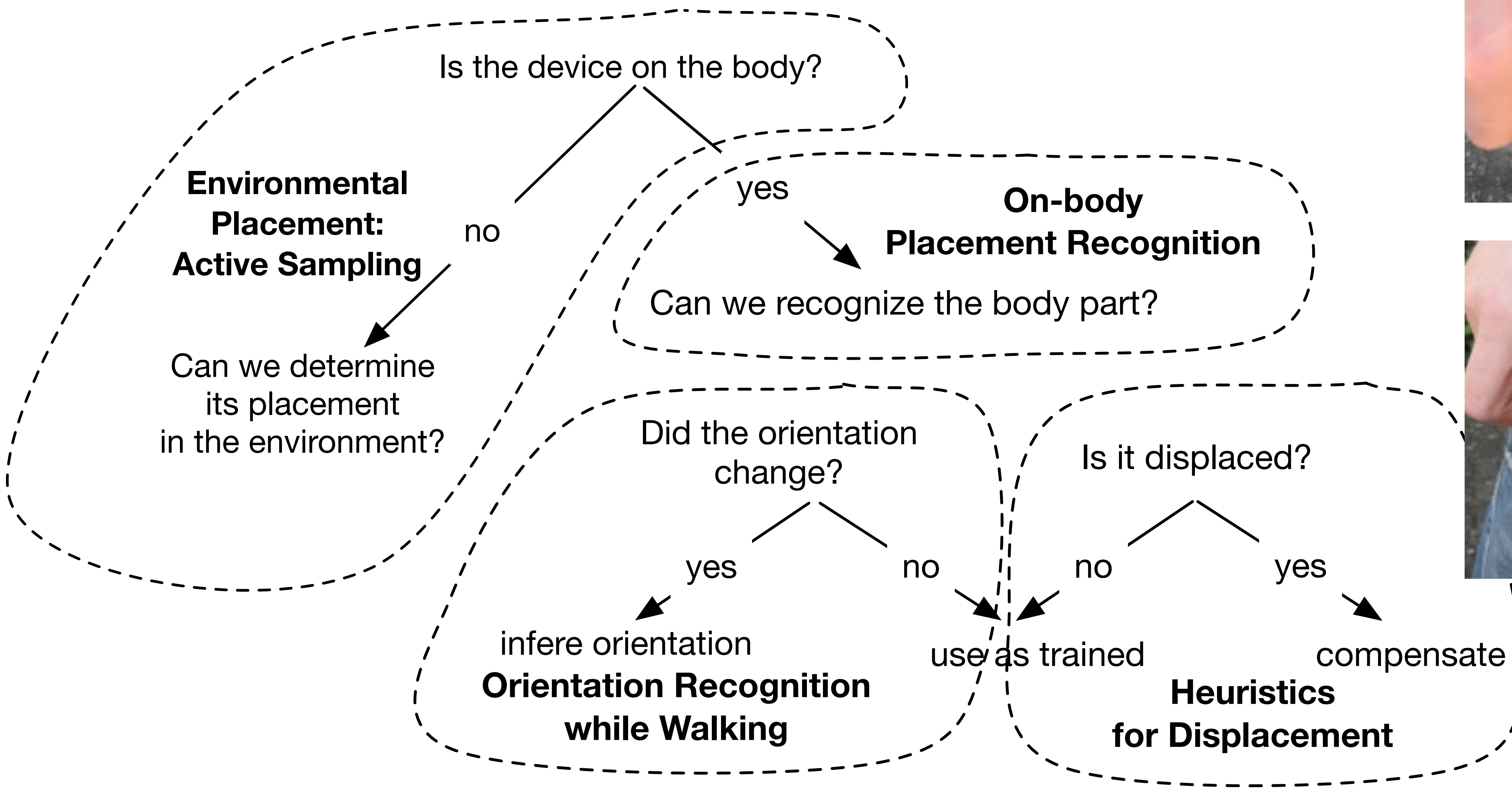
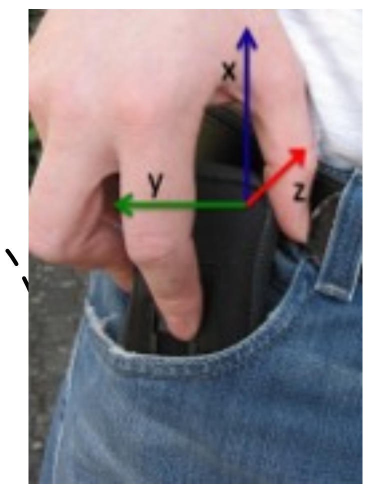
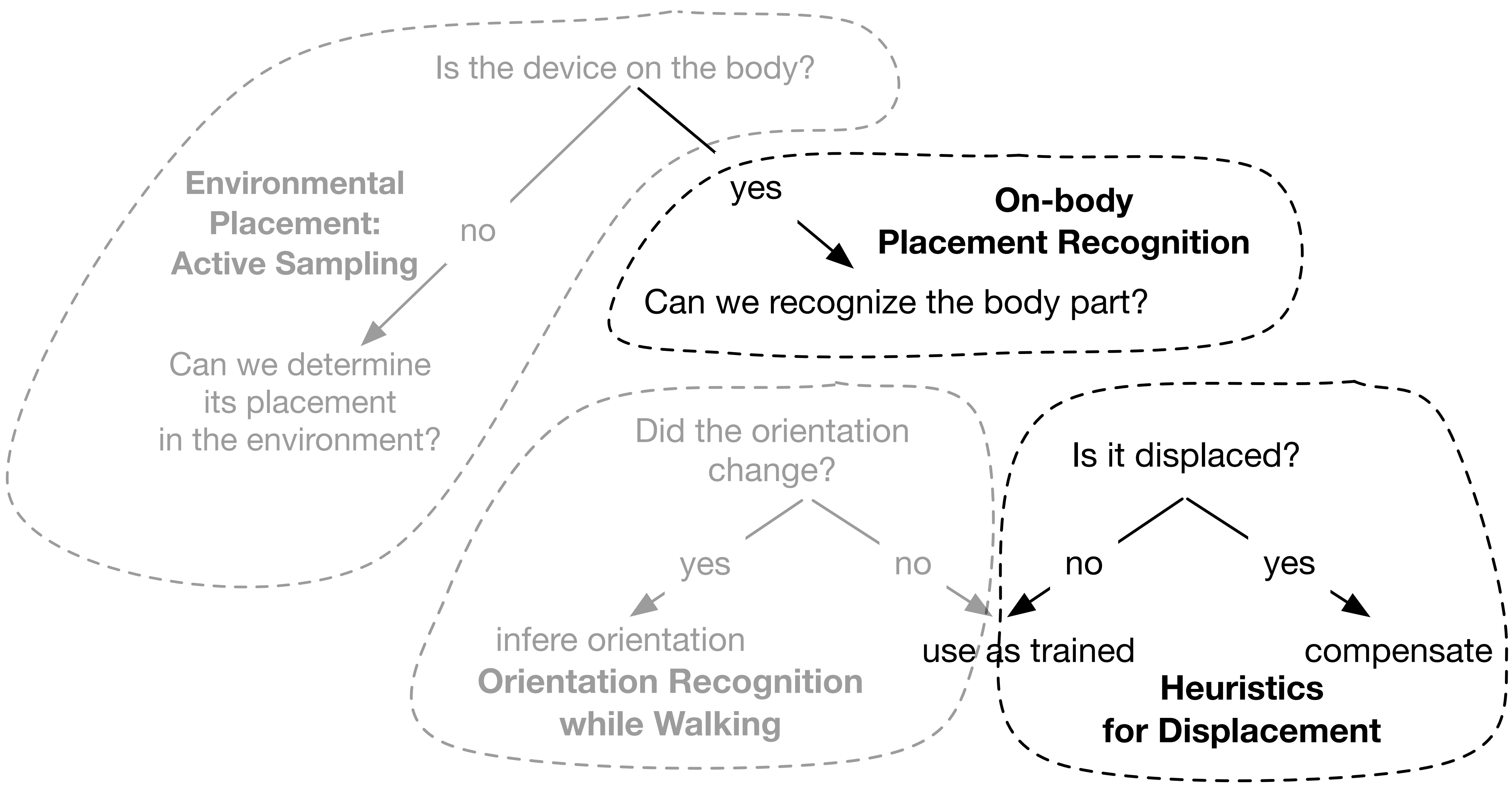


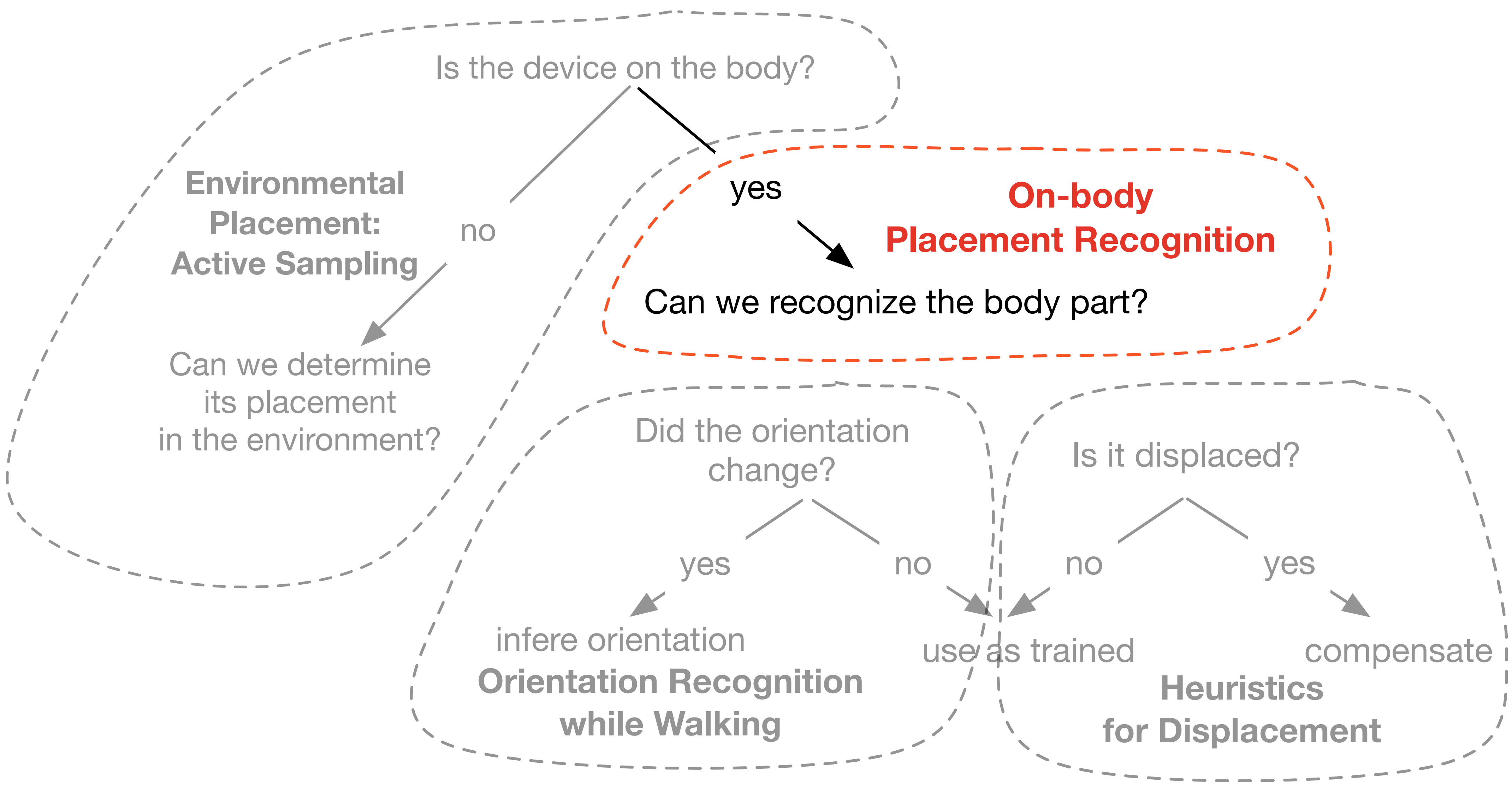


Kai Kunze, Paul Lukowicz, Kurt Partridge, Bo Begole, *Which Way Am I Facing: Inferring Horizontal Device Orientation from an Accelerometer Signal*, 13th IEEE International Symposium on Wearable Computers. Linz, Austria, 2009.

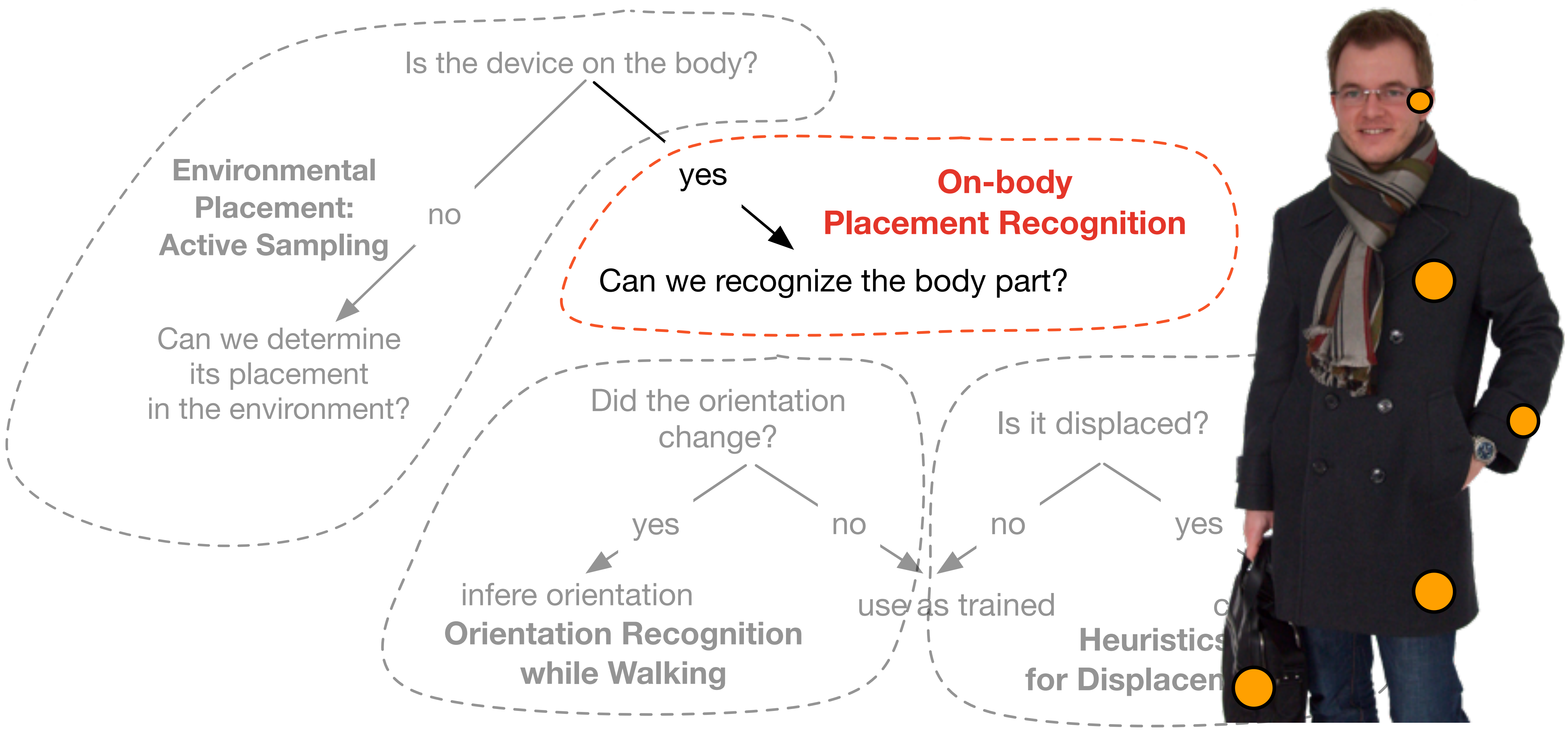
Overview and Contributions



Overview and Contributions



Overview and Contributions

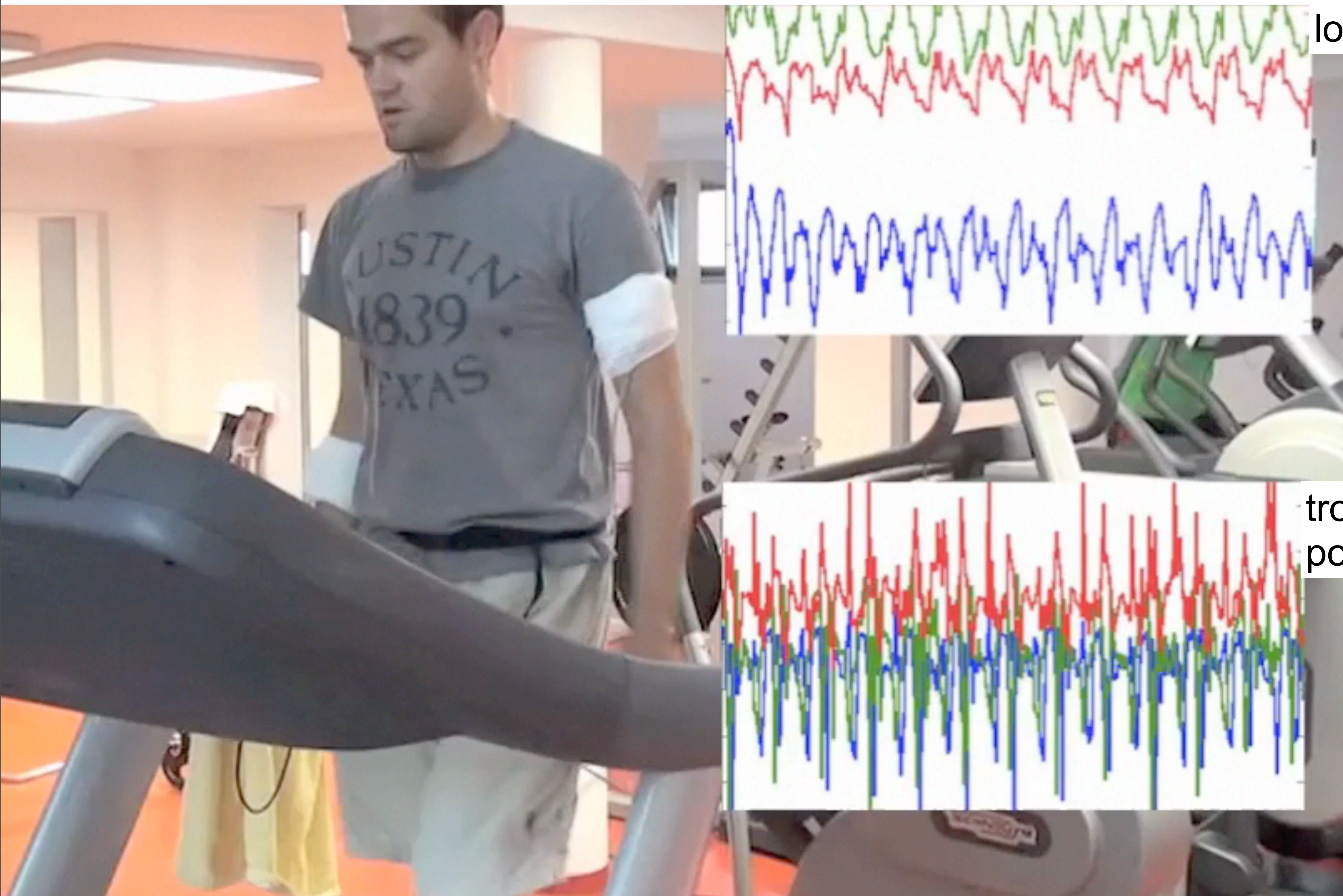


Walking

lower arm

trouser
pocket

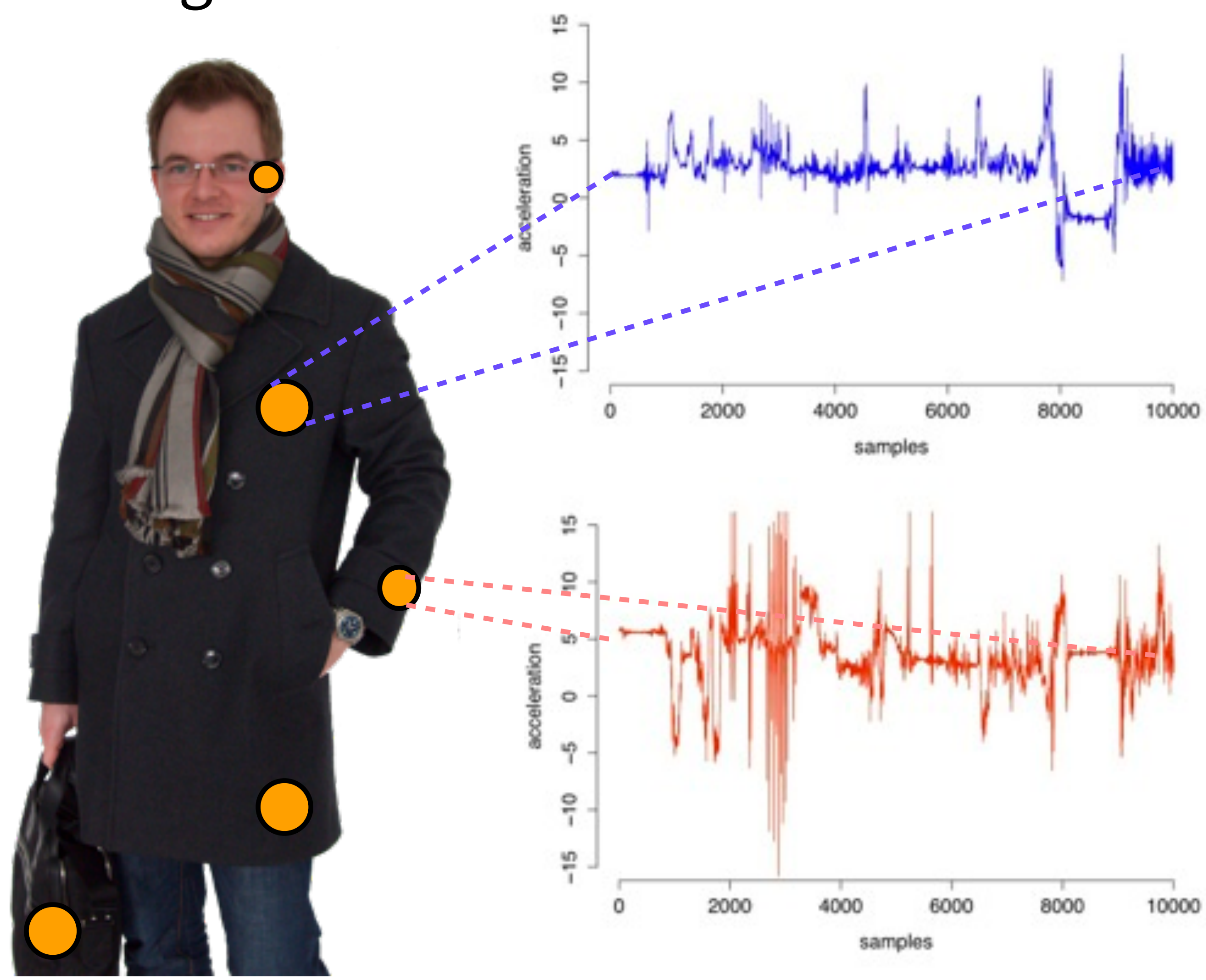
Walking



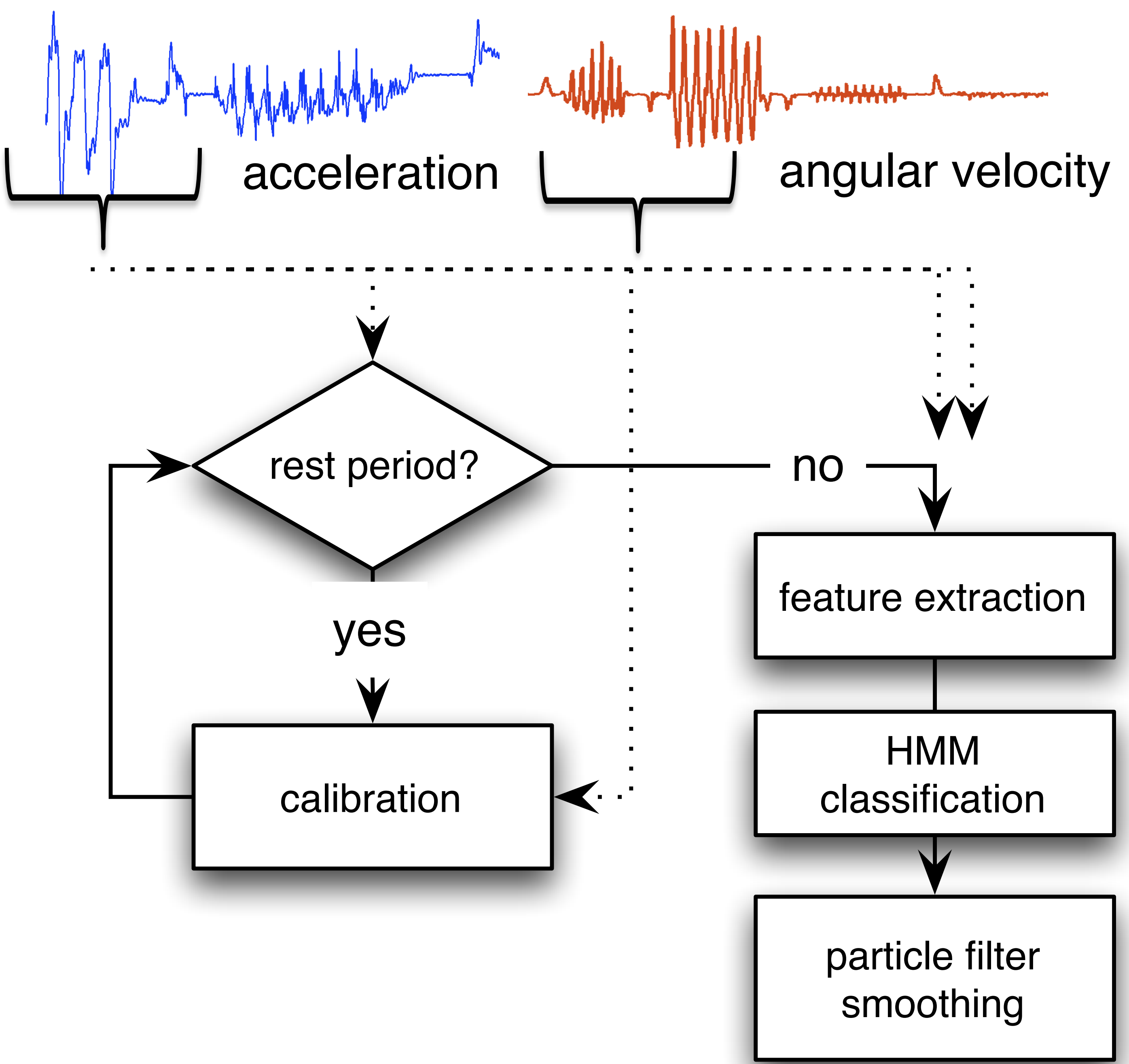
Unconstraint Onbody Placement Recognition

- 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

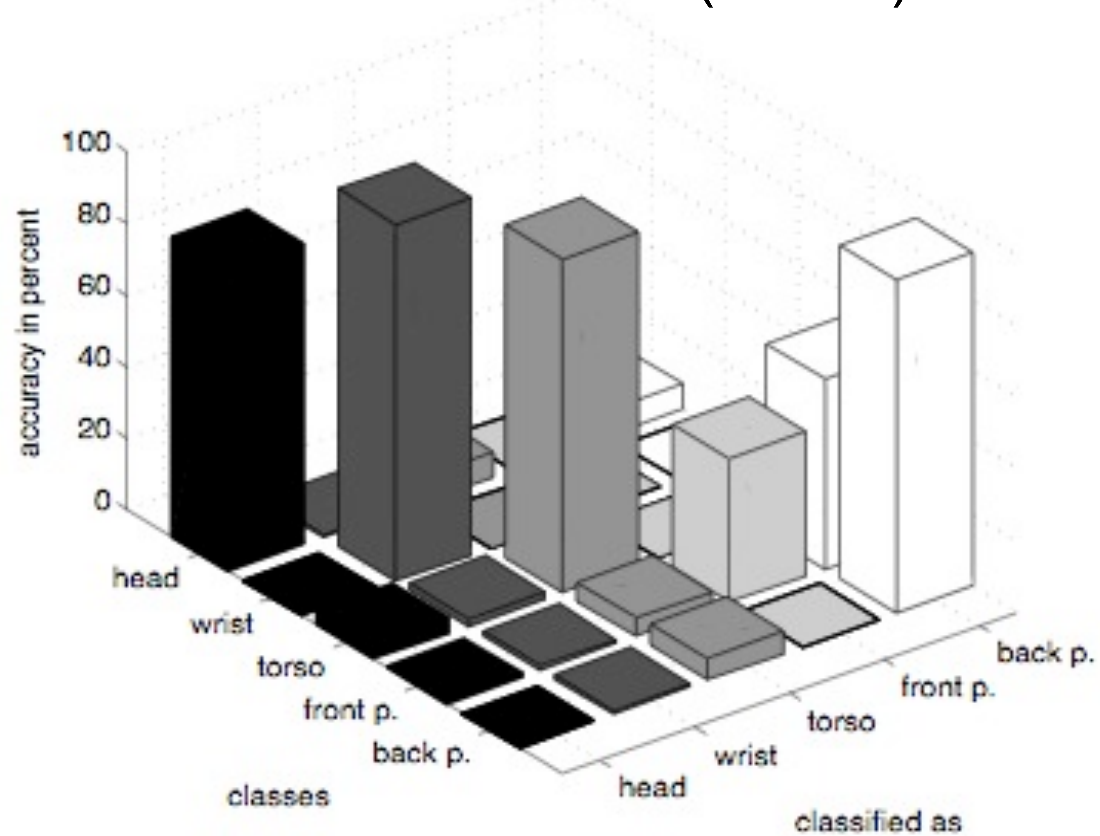
around 30 hours of sensor data

HMM Method without Particle Filtering

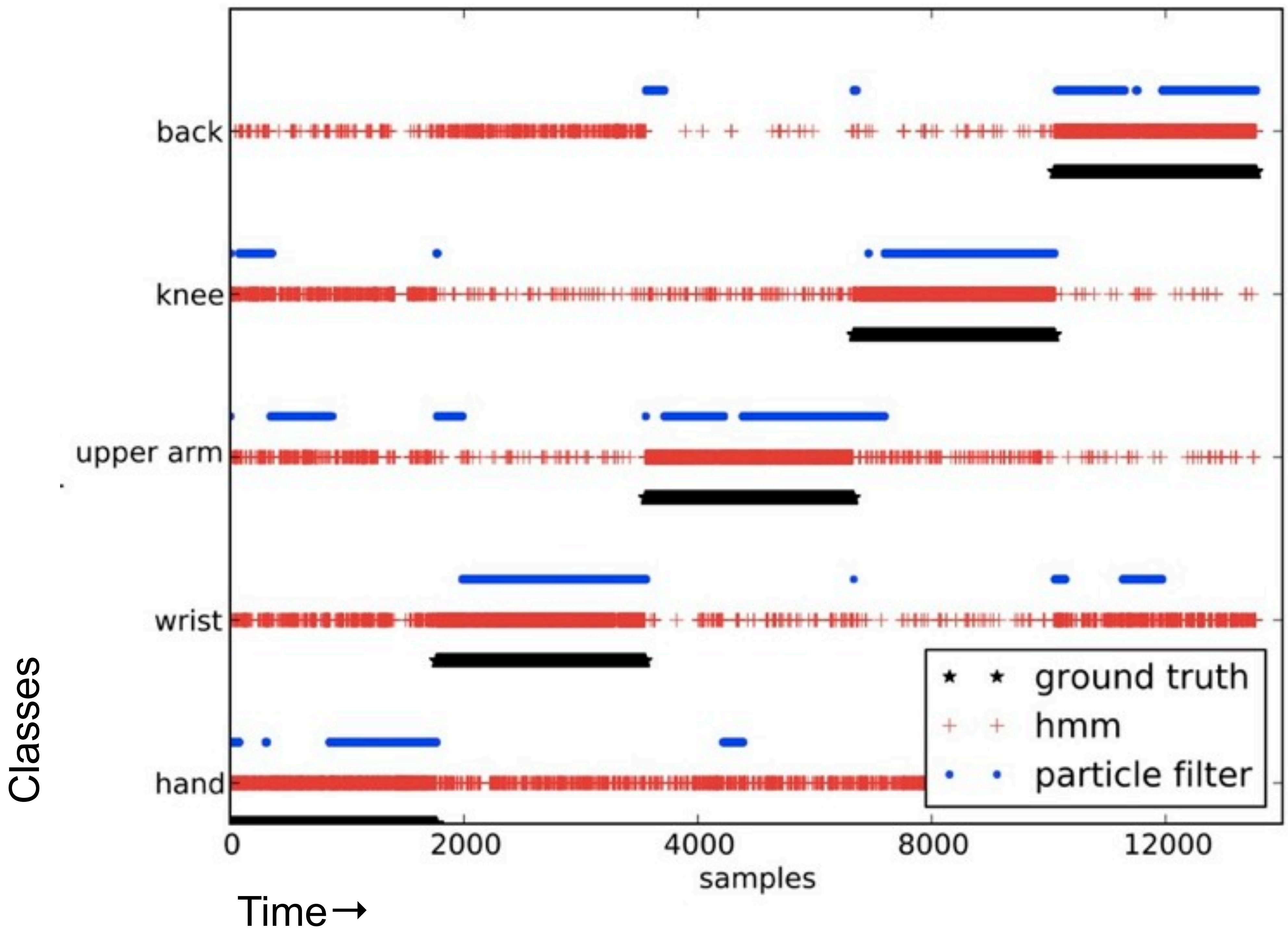
- Evaluation: 33% training, 66 %testing

Set / time	30 sec.	45 sec.	4 min.	5 min.
bicycle	43 %	67 %	83 %	84 %
house	32 %	65 %	82 %	79 %
opp. (accel)	20 %	59 %	80 %	82 %
drink and work	15 %	61 %	72 %	78 %

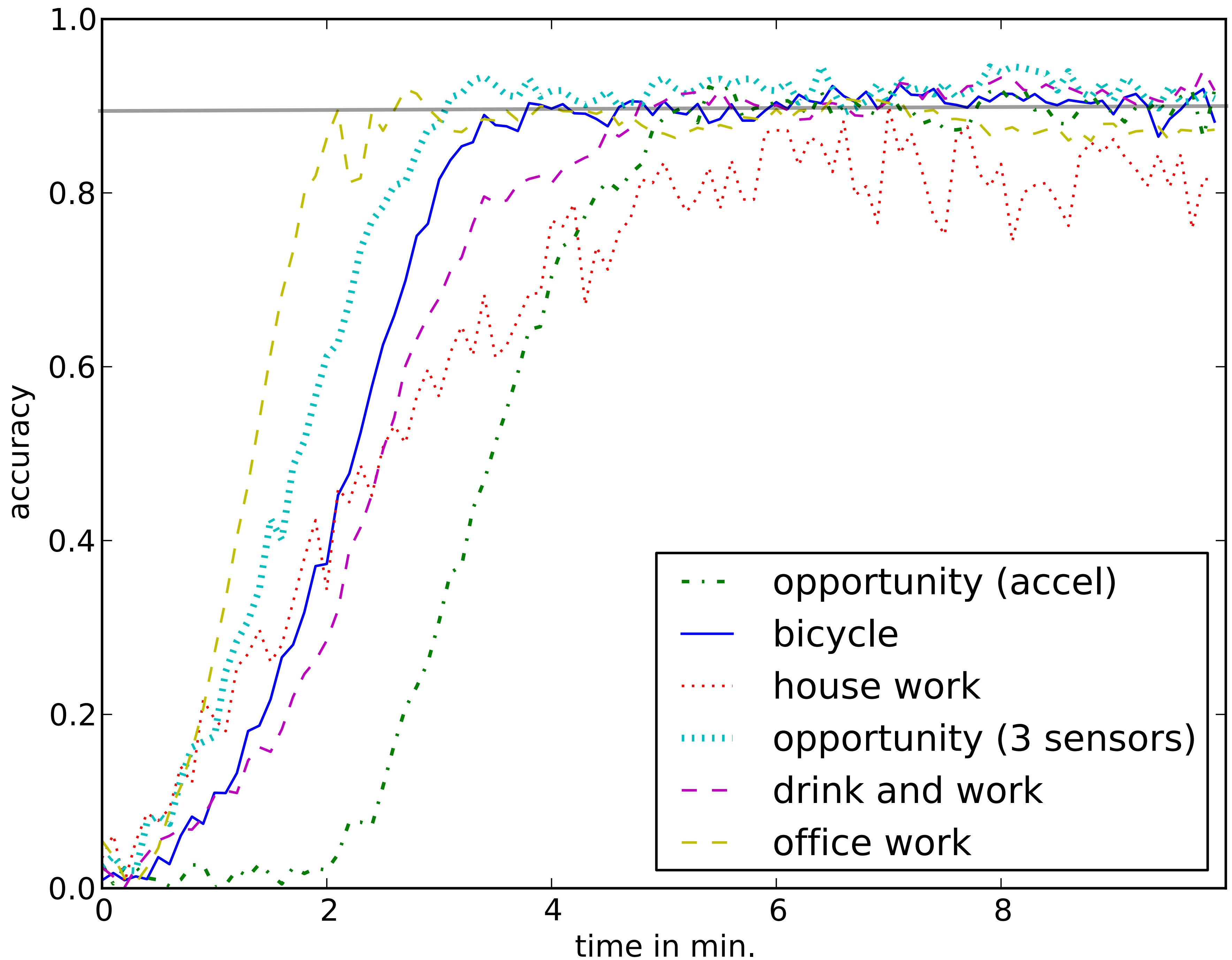
Confusion matrix
for house work (4 min.)



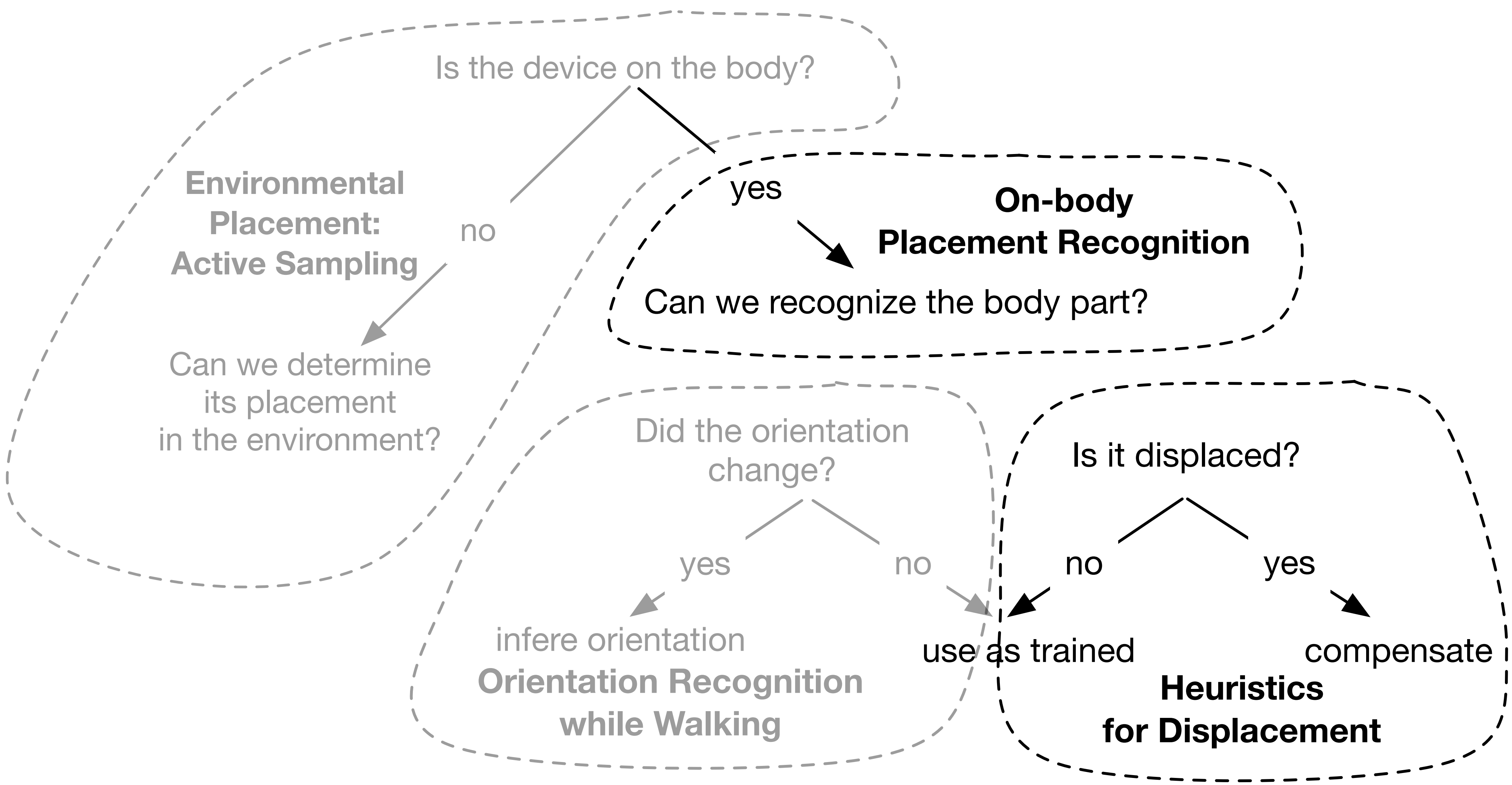
Smoothing: Particle Filtering



Results: Particle Filtering



Overview and Contributions



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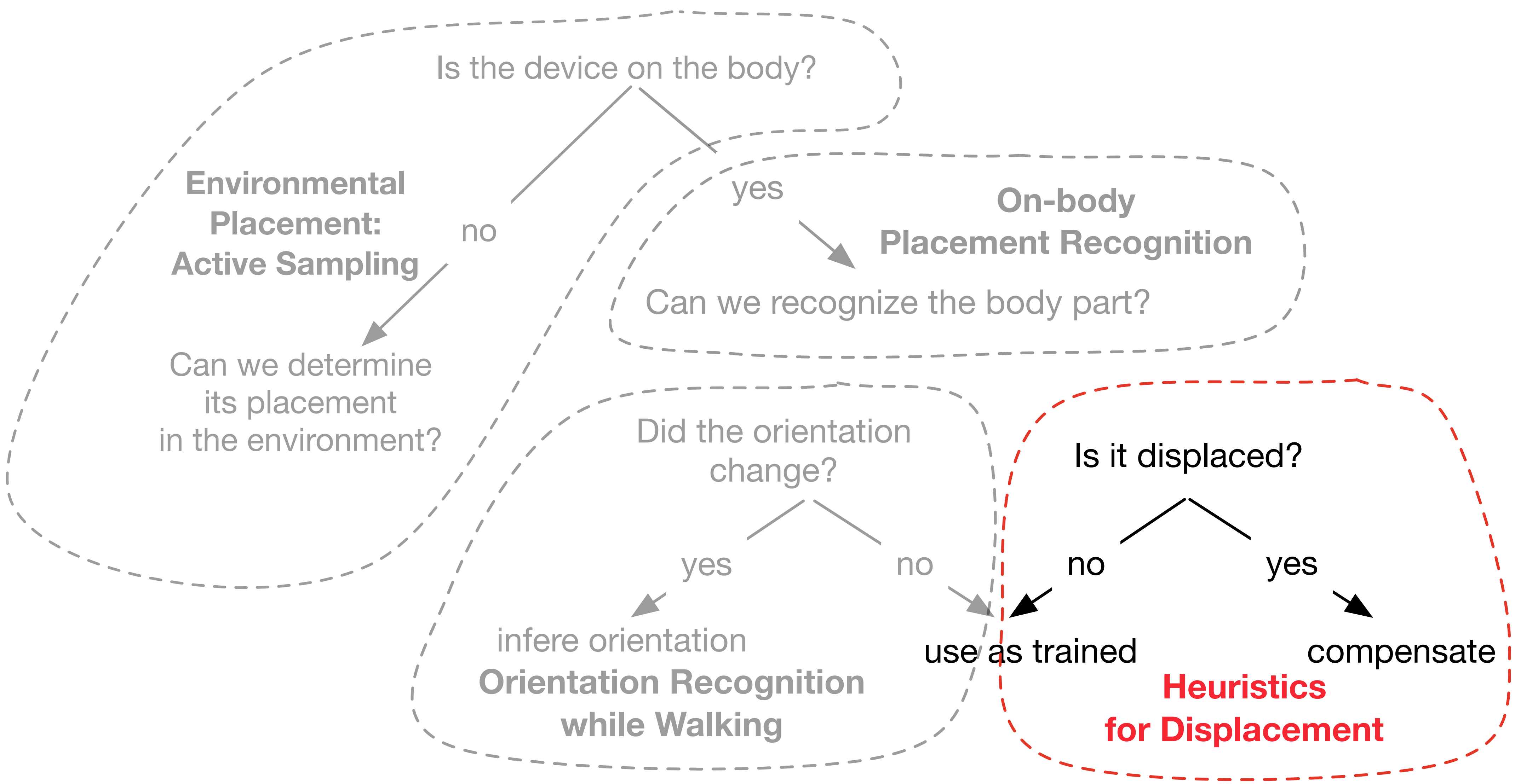

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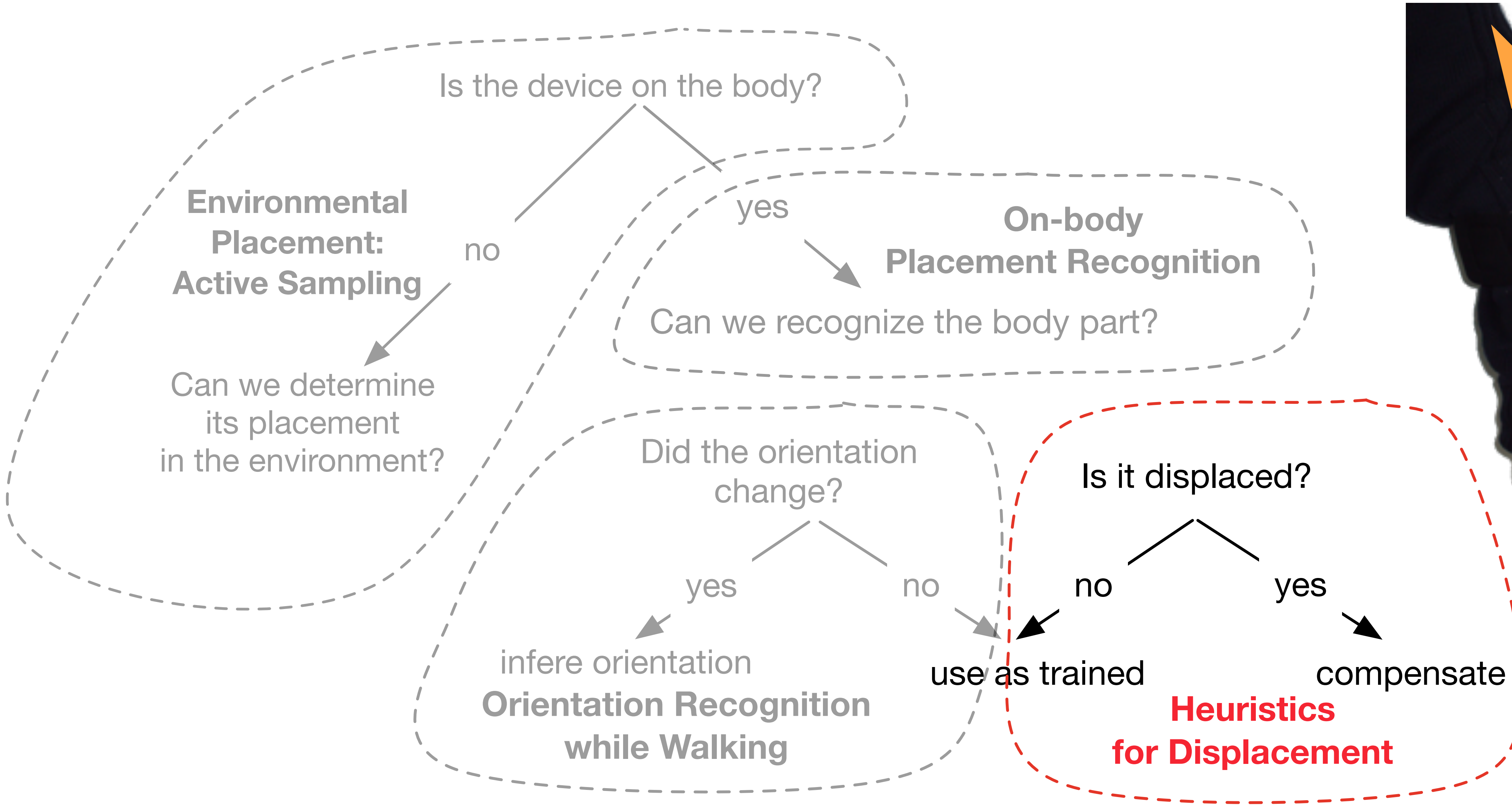

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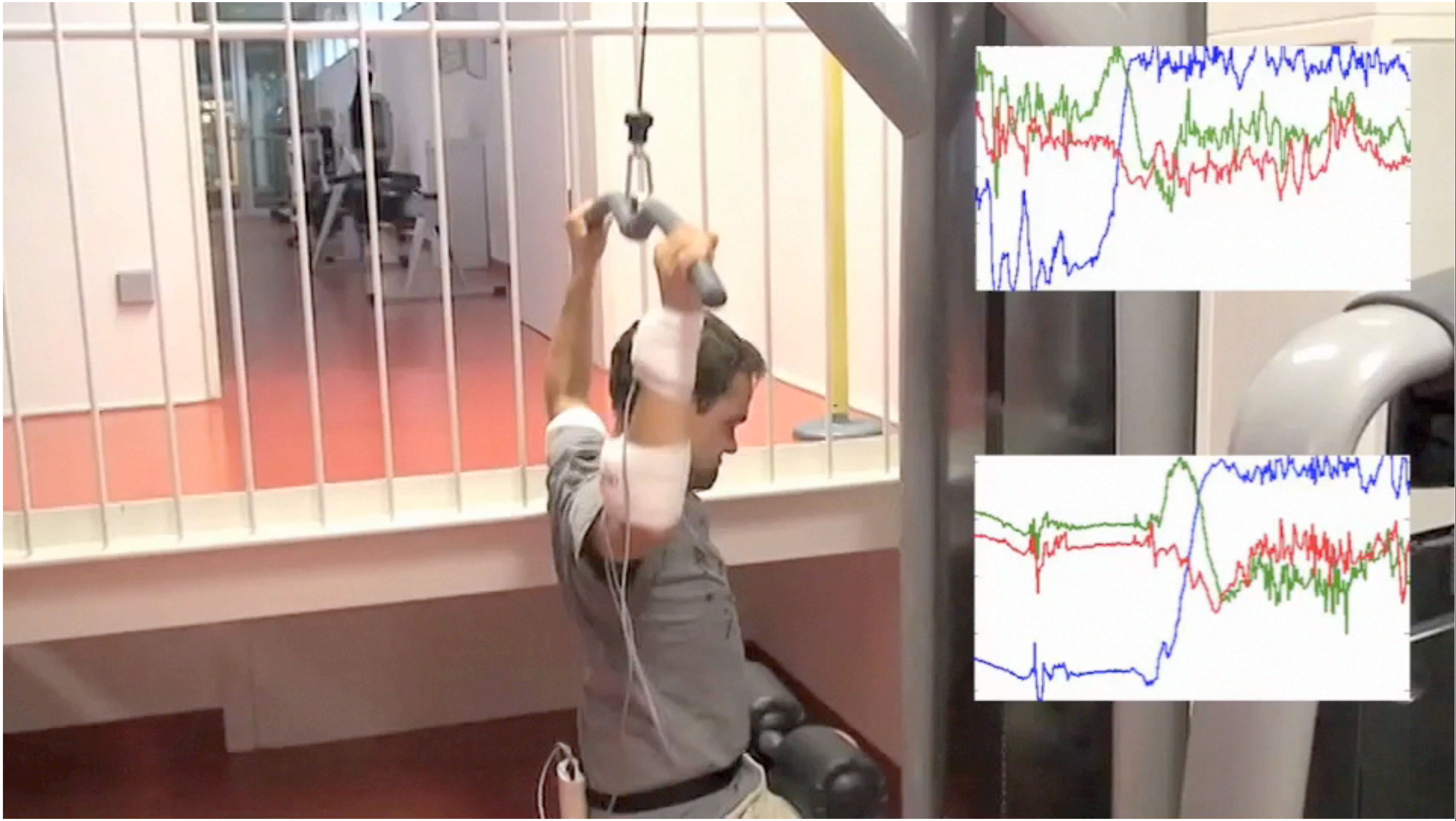
The issue

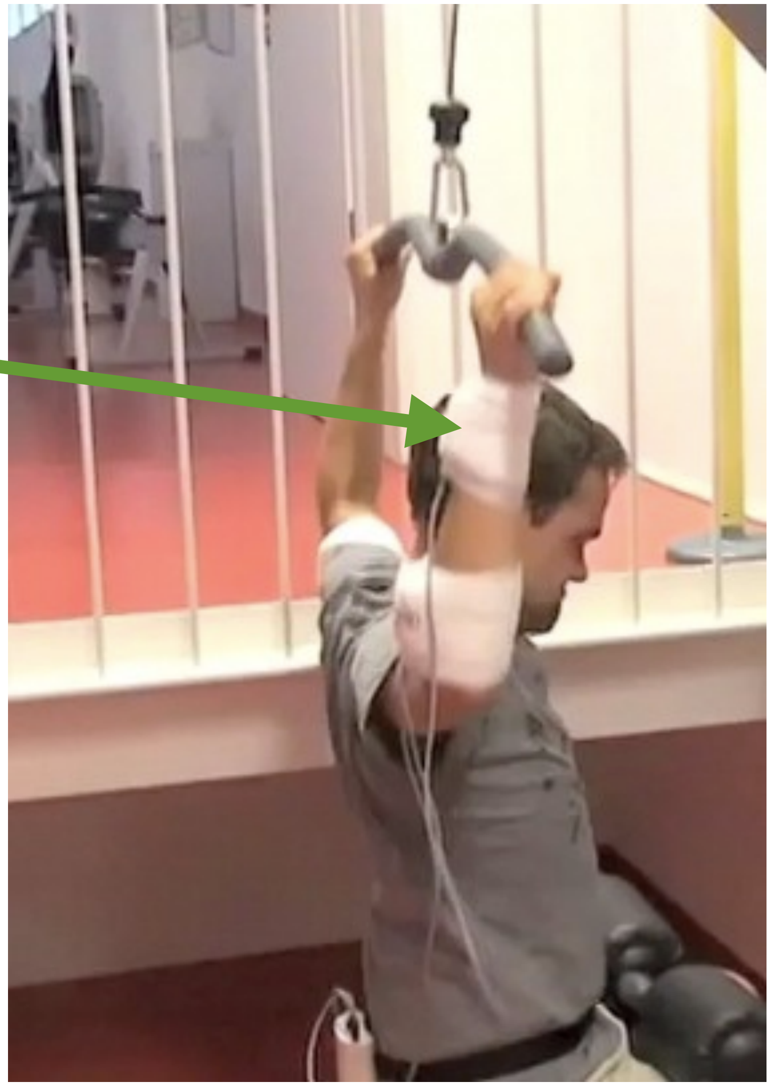
The issue



The Impact

Gym Exercises

Recognition algorithm trained on sensor 1



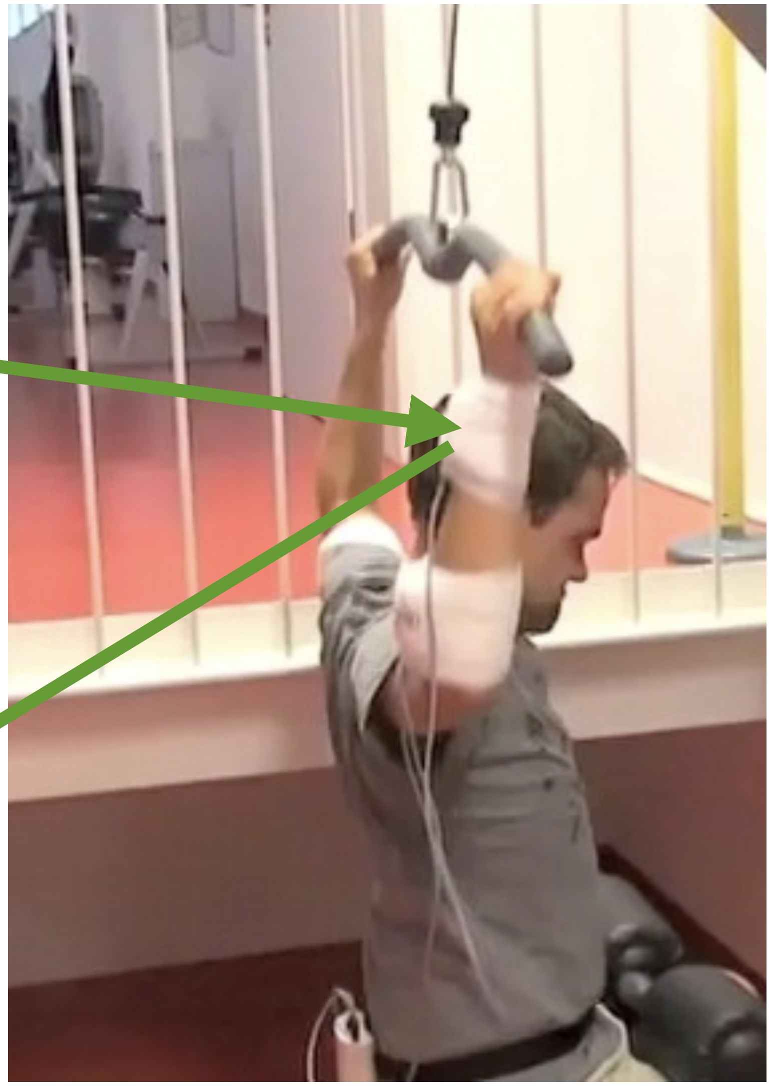
Modality
Acceleration
Gyroscope

The Impact

Gym Exercises

Recognition algorithm trained on sensor 1

evaluated on sensor 1



Modality	
Acceleration	100%
Gyroscope	80%

The Impact

Gym Exercises

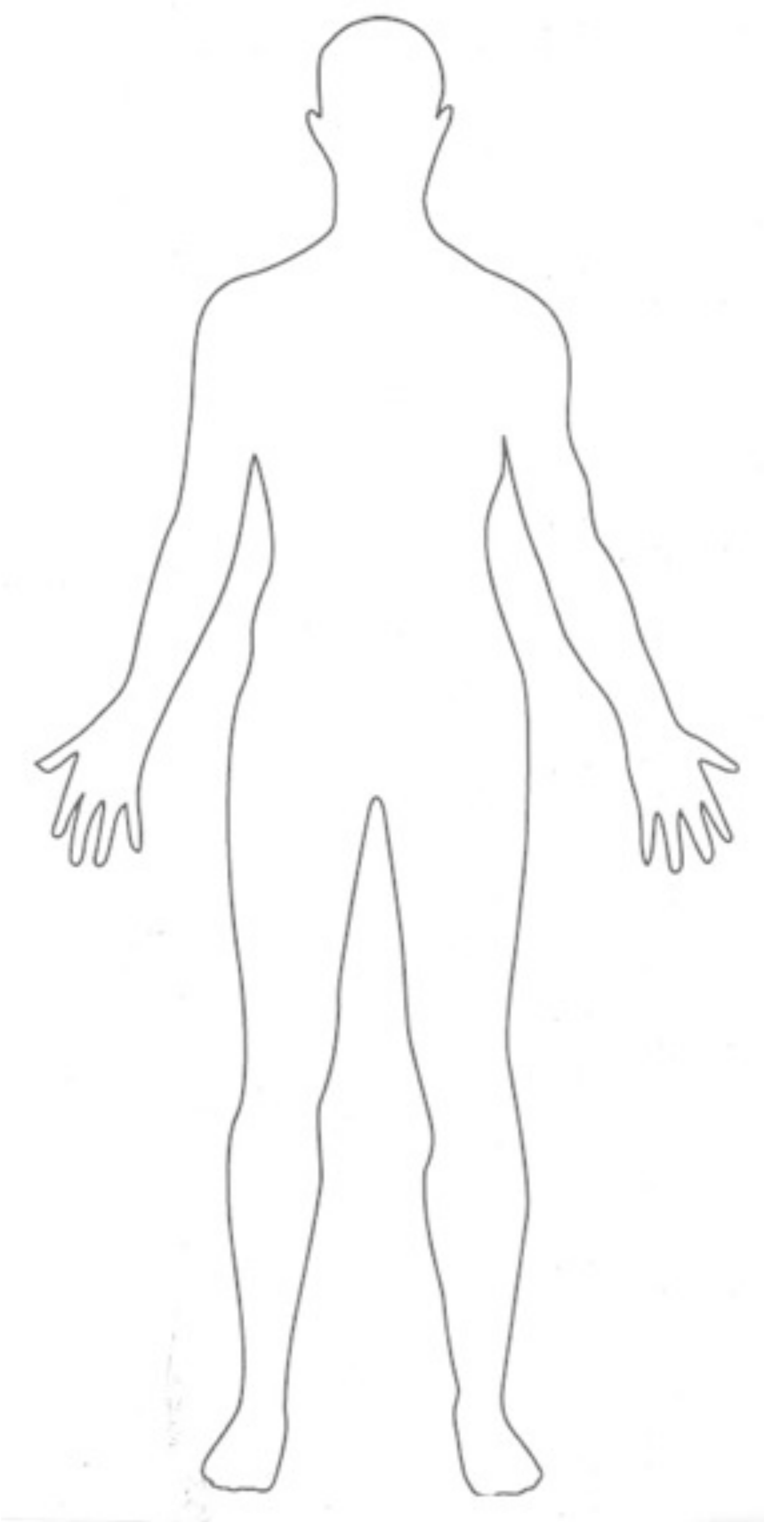
Recognition algorithm trained on sensor 1

evaluated on sensor 1

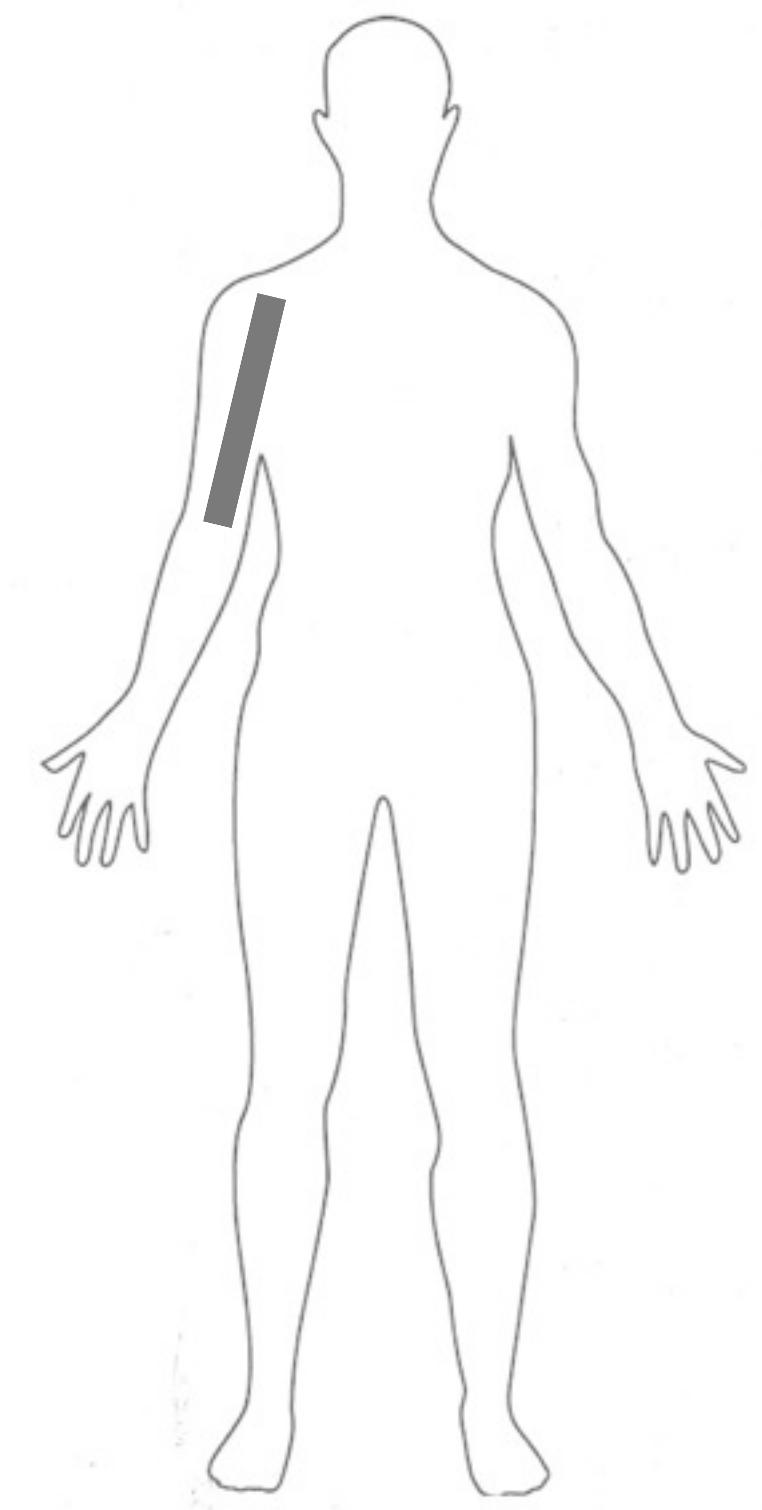
evaluated on displaced sensor

Modality		
Acceleration	100%	63%
Gyroscope	80%	72%

Rigid Body Approximation



Rigid Body Approximation



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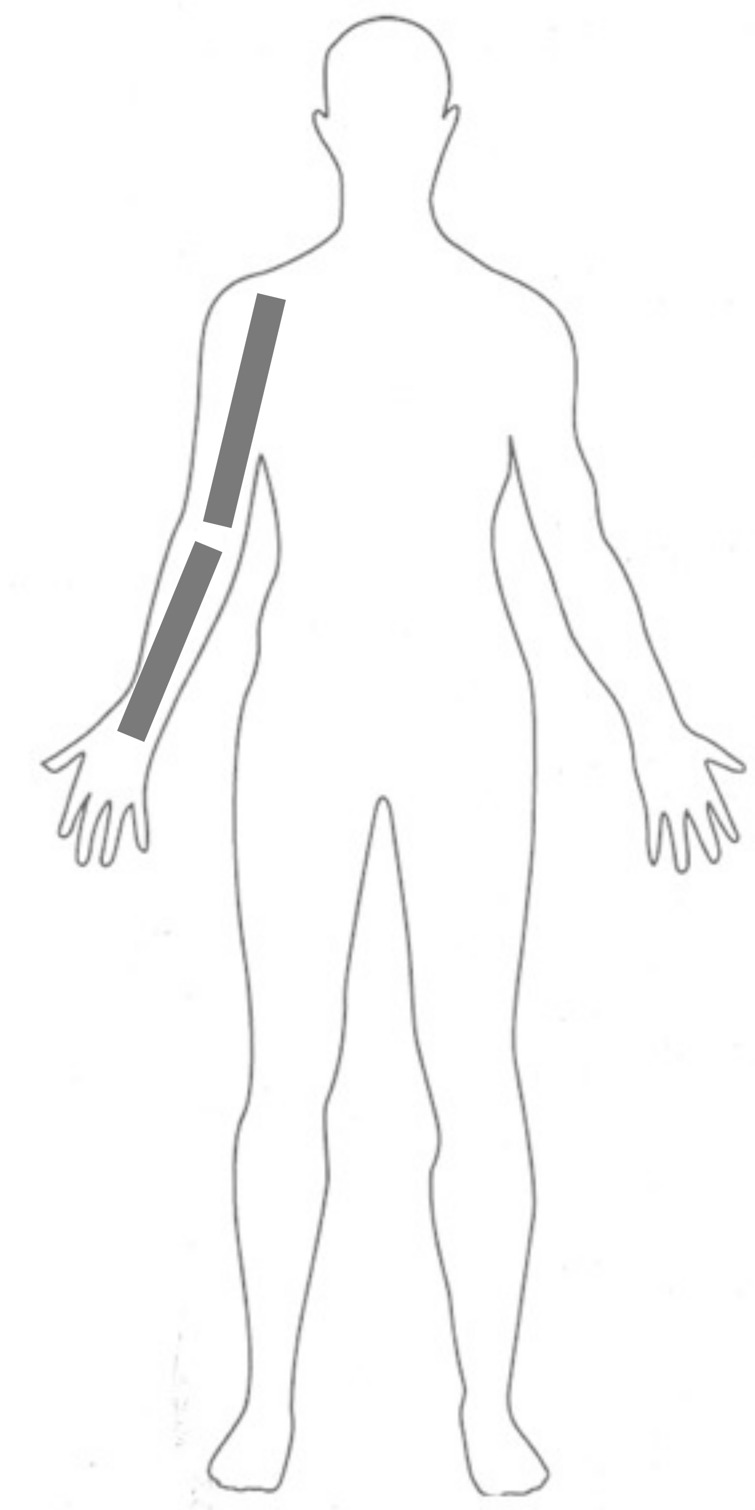

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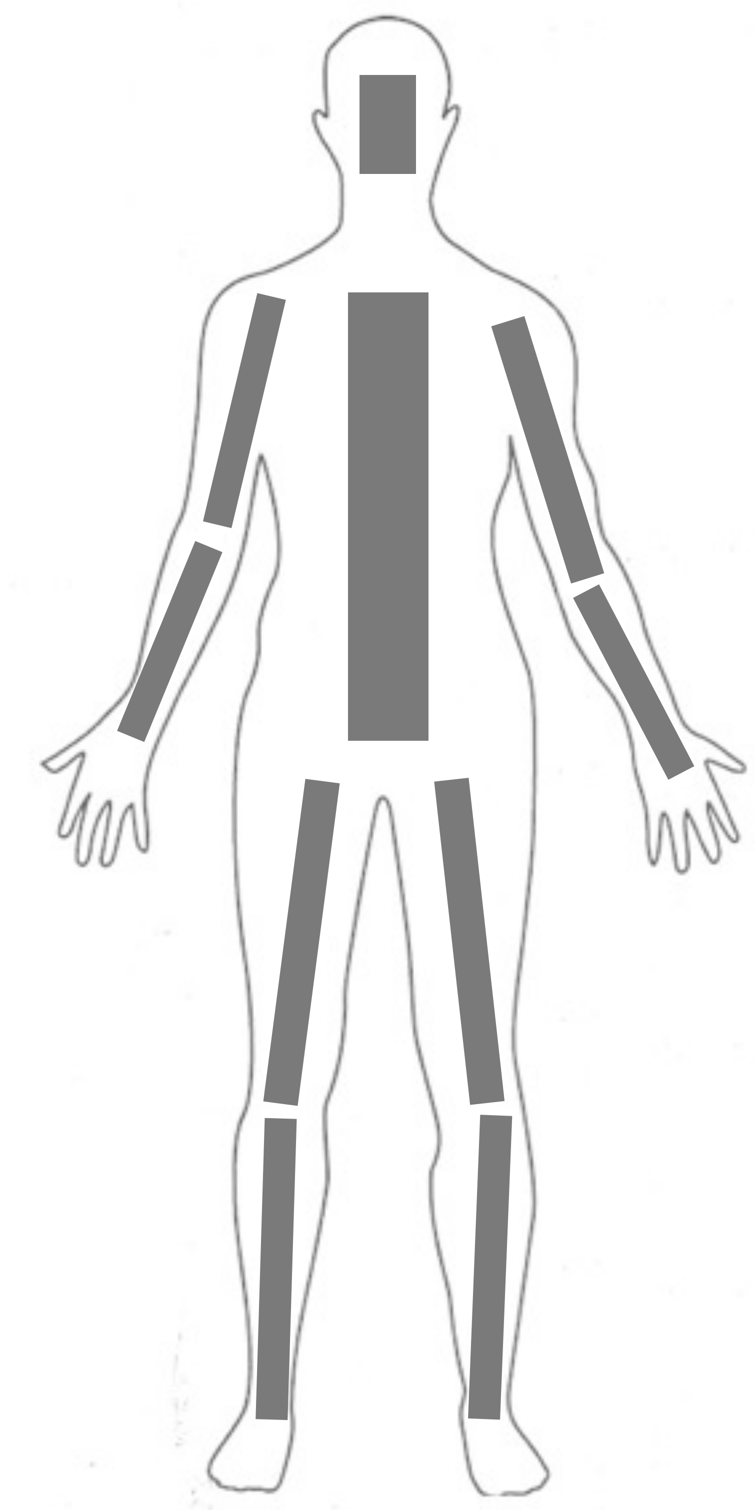
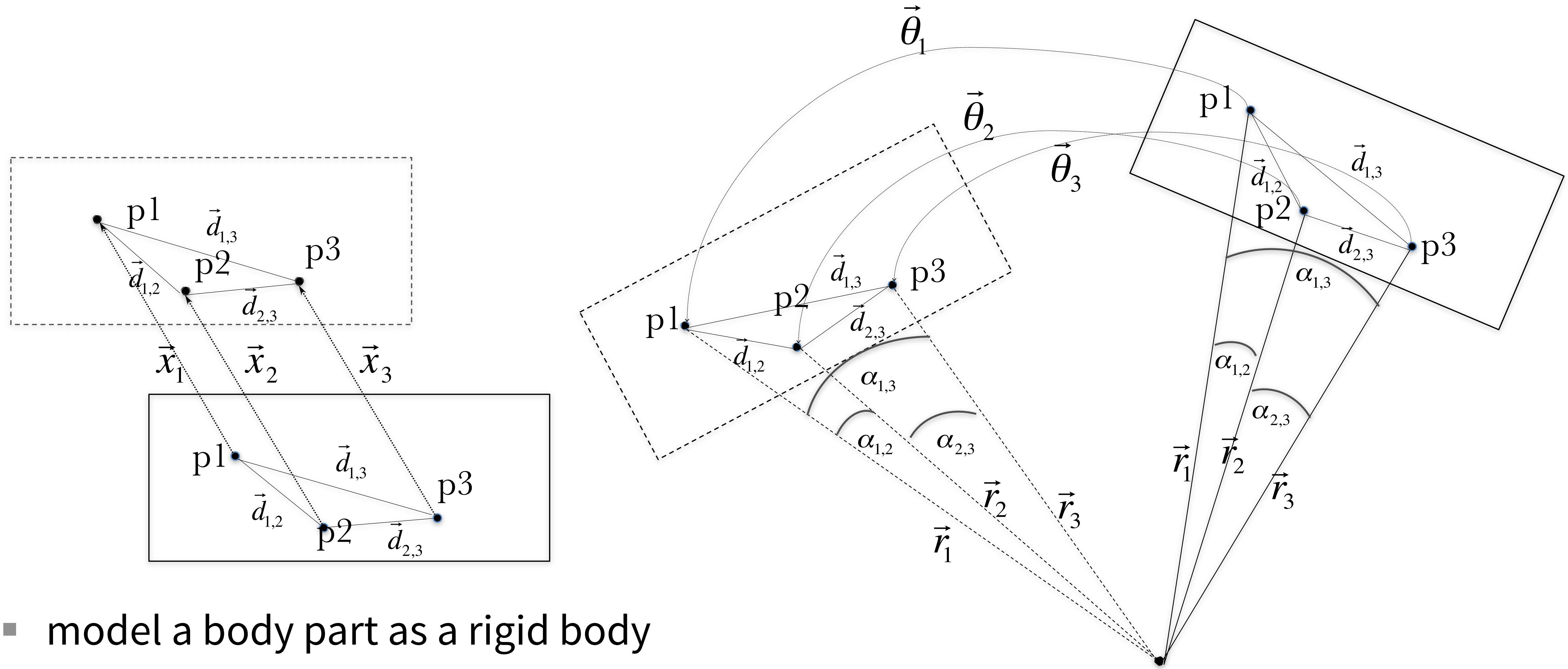


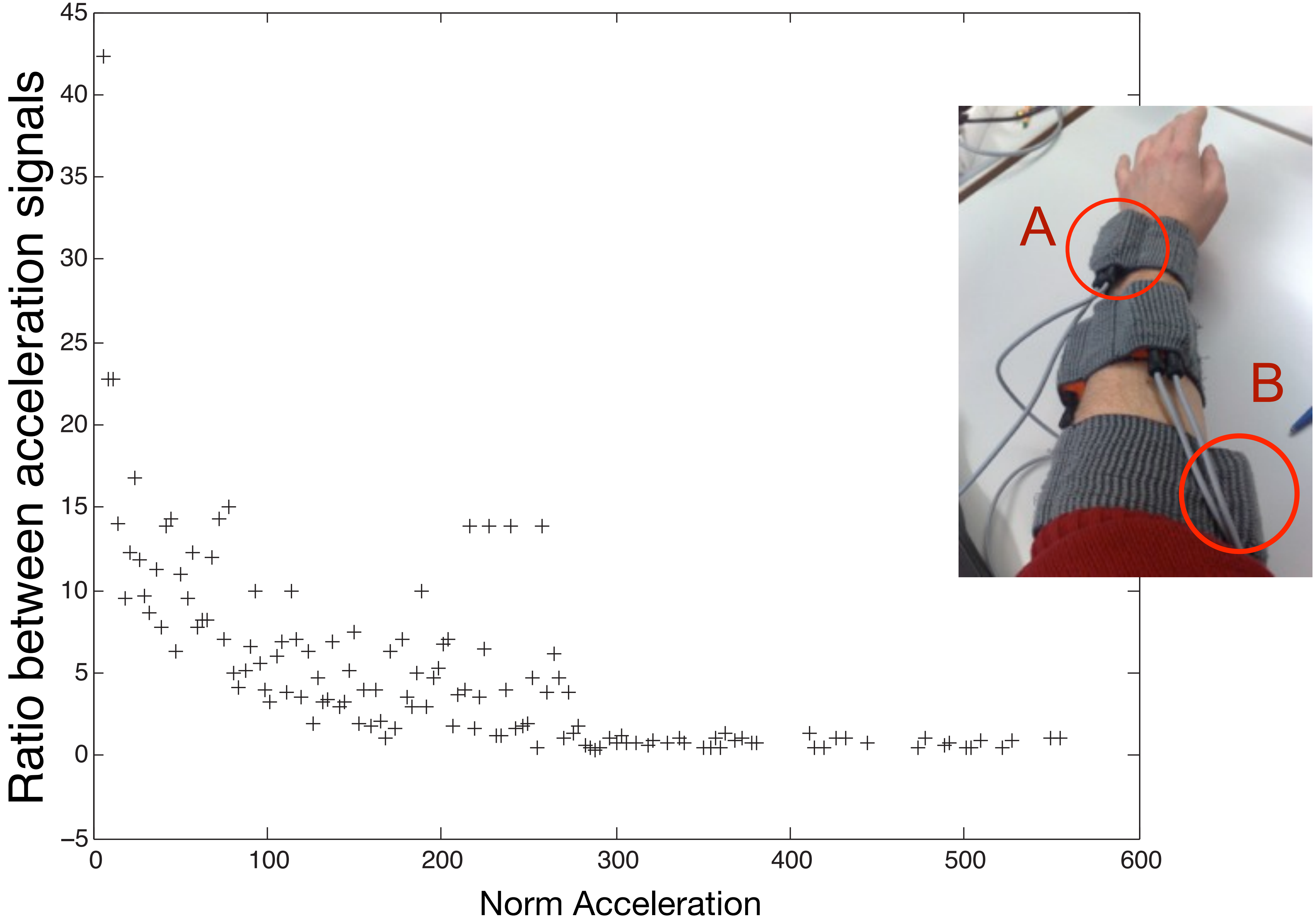
Rigid Body Approximation



- model a body part as a rigid body
- every movement can be described as a combination of rotations and translations
- for Translation + Rotation: Angular Velocity is displacement indifferent
- for Translation only: Acceleration is displacement indifferent
- How do we decide when to choose what?

Principle

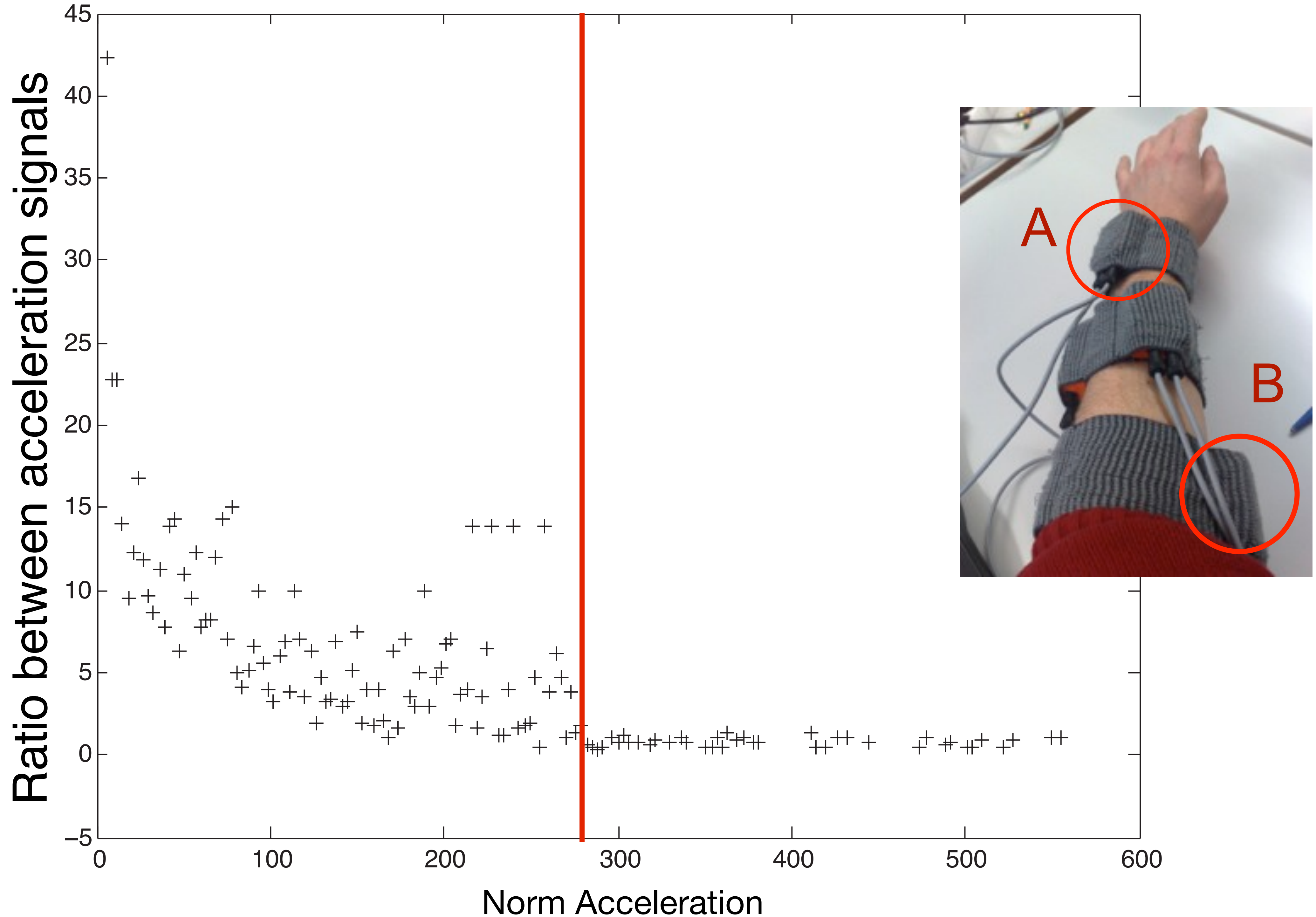
$$\frac{\lVert A \rVert}{\lVert B \rVert}$$



Norm Angle Velocity + Norm Angle Acceleration

Principle

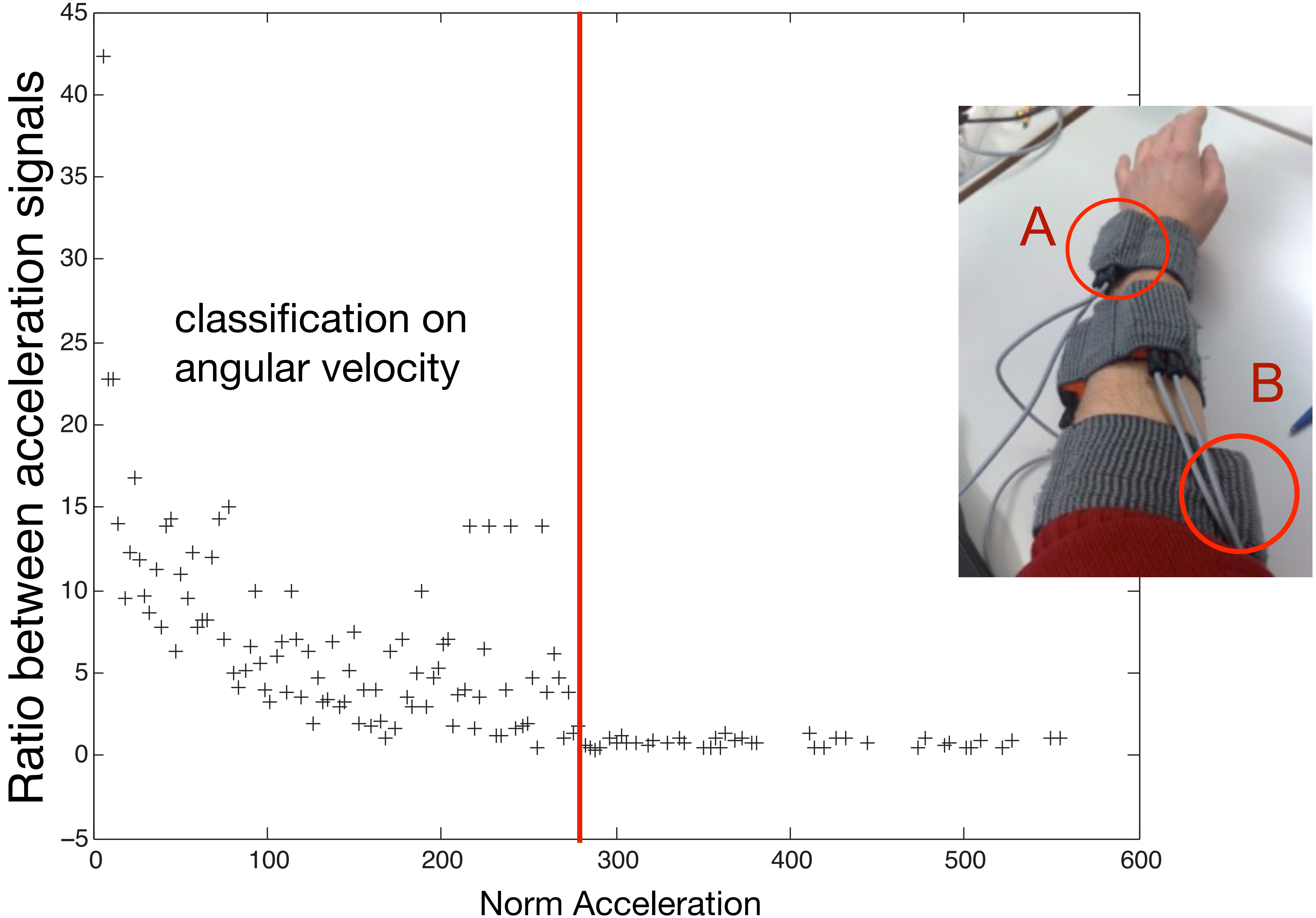
$$\frac{\| A \|}{\| B \|}$$



Norm Angle Velocity + Norm Angle Acceleration

Principle

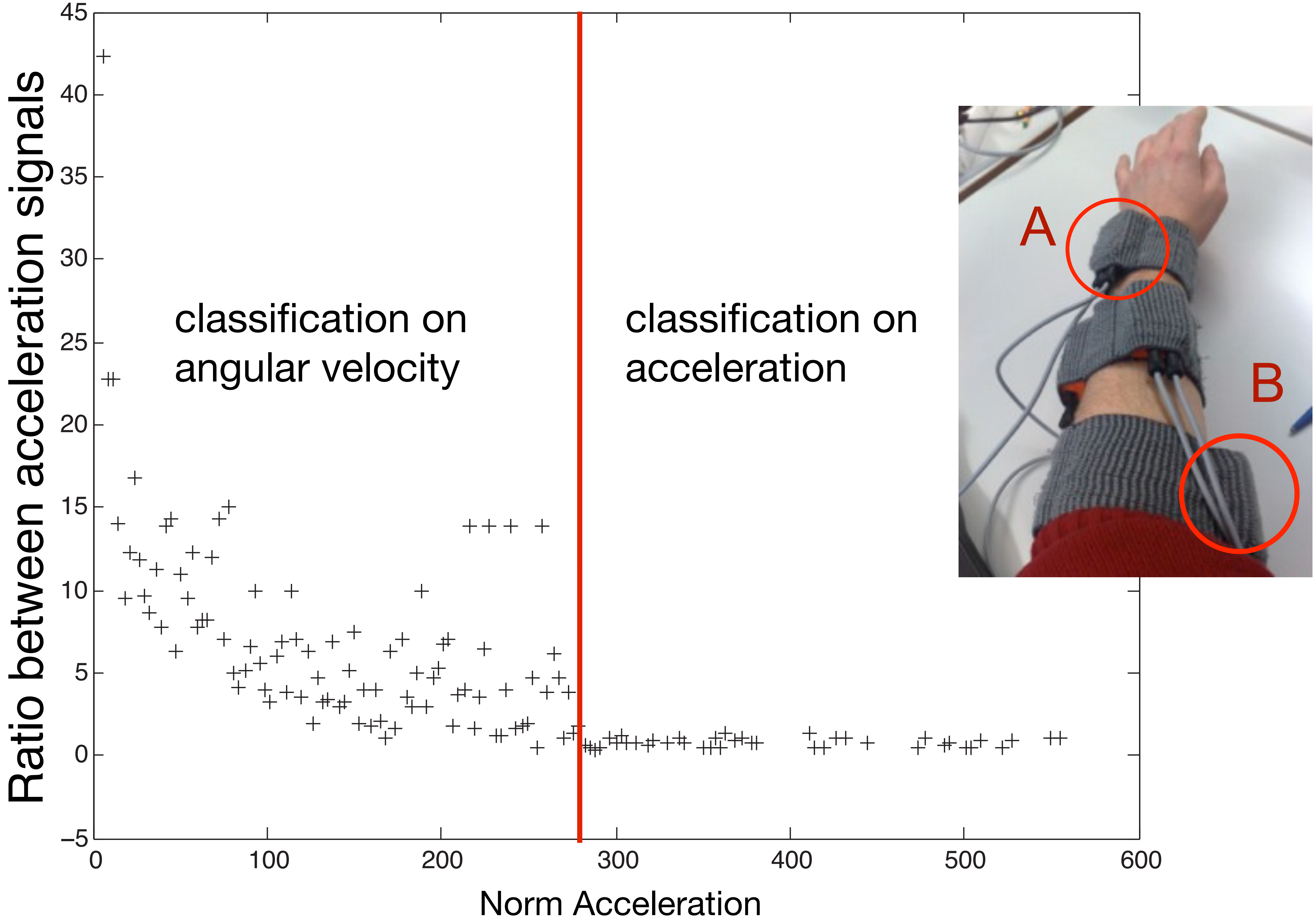
$$\frac{\|A\|}{\|B\|}$$



Norm Angle Velocity + Norm Angle Acceleration

Principle

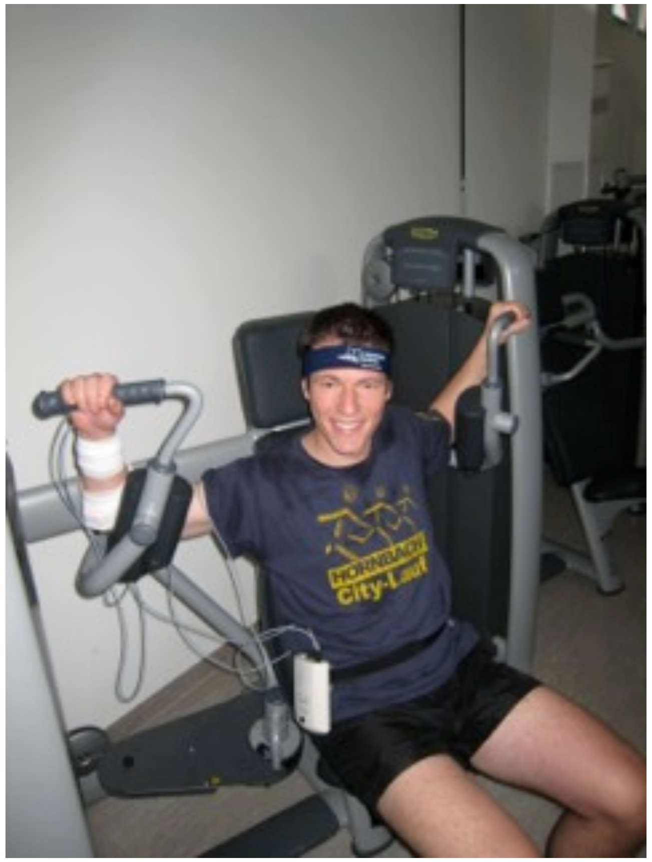
$$\frac{\| A \|}{\| B \|}$$



Norm Angle Velocity + Norm Angle Acceleration

Gym Exercises

- Same setup only on lower arm
- 3 users



8 Exercises: lat machine
pectorial
sholder press
upper back
arm extension
arm curl
pull down
chestpress

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Gym Exercise Results

continuous HMMs
15 sec. sliding window 3 gaussians
up to 4 hidden states

Modality	Same	Displaced
Acceleration	97%	24%

q	r	s	t	u	v	w	x	← classified as
75.6	0	0	0	0	0	0	24.4	q = lat
0	81.6	0	0	0	0	18.4	0	r = pectorial
0	0	88.6	0	11.4	0	0	0	s = shoulder press
0	0	0	100	0	0	0	0	t = upper back
0	0	13.3	0	76.7	0	10.0	0	u = arm extension
0	0	0	0	22.2	77.8	0	0	v = arm curl
12.0	0	0	0	8.0	0	80	0	w = pull down
0	0	0	20.8	0	0	0	79.2	x = chestpress

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Gym Exercise Results

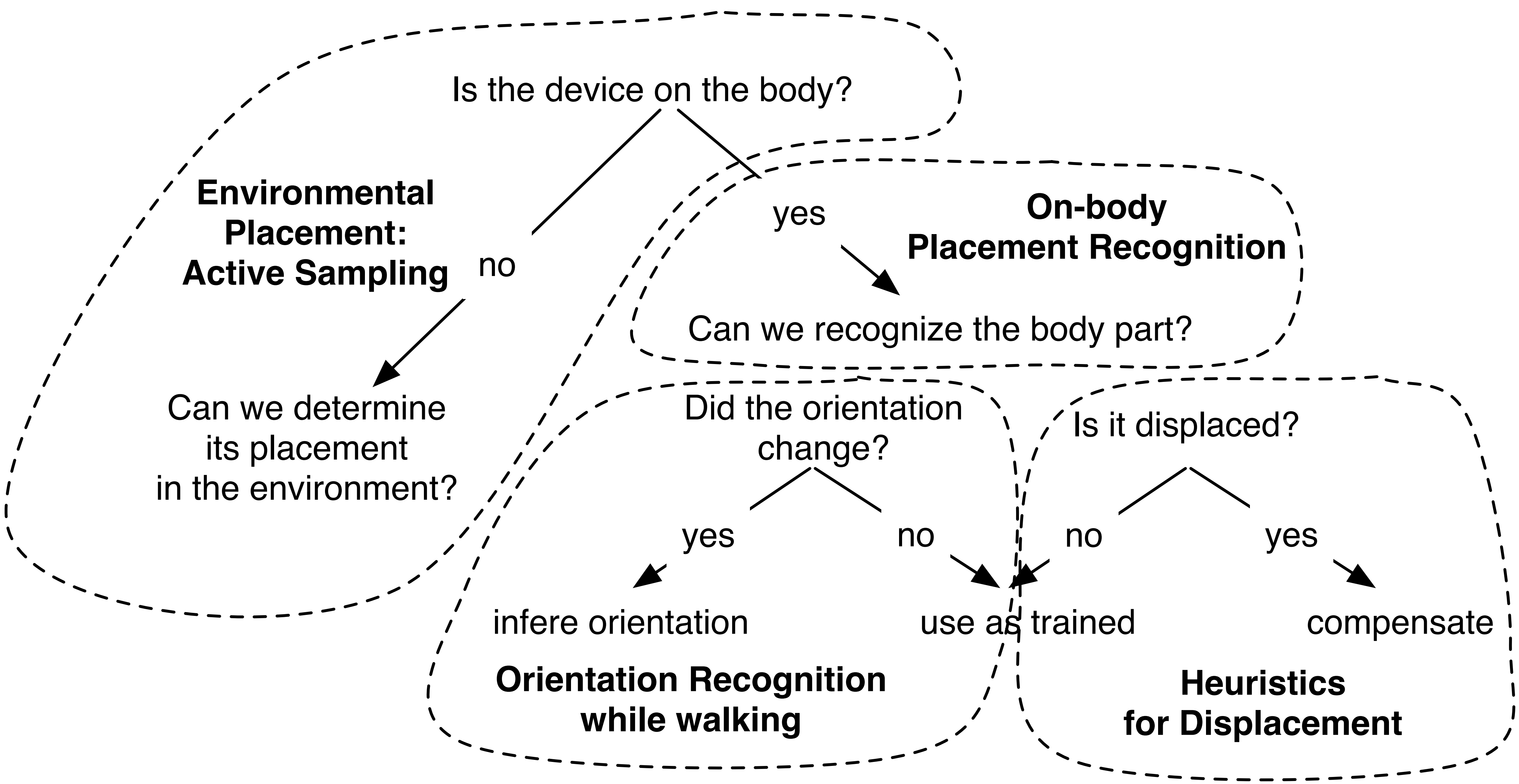
continuous HMMs
15 sec. sliding window 3 gaussians
up to 4 hidden states

Modality	Same	Displaced
Acceleration	97%	24%

Heuristic 74%

q	r	s	t	u	v	w	x	← classified as
75.6	0	0	0	0	0	0	24.4	q = lat
0	81.6	0	0	0	0	18.4	0	r = pectorial
0	0	88.6	0	11.4	0	0	0	s = shoulder press
0	0	0	100	0	0	0	0	t = upper back
0	0	13.3	0	76.7	0	10.0	0	u = arm extension
0	0	0	0	22.2	77.8	0	0	v = arm curl
12.0	0	0	0	8.0	0	80	0	w = pull down
0	0	0	20.8	0	0	0	79.2	x = chestpress

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.

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Compensating for On-Body Placement Effects in Activity Recognition

Recognizing Reading Activities

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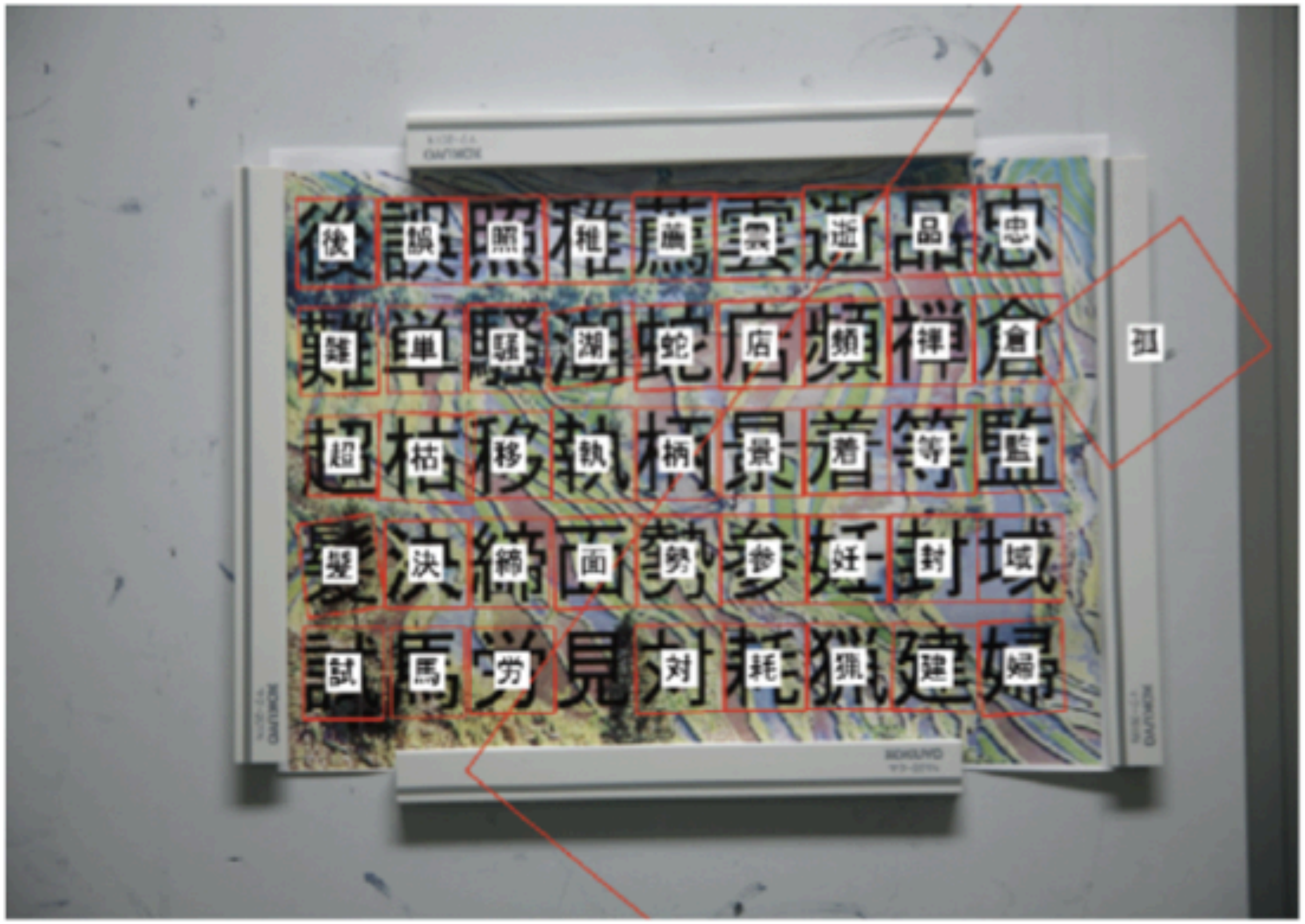
knowledge acquisition

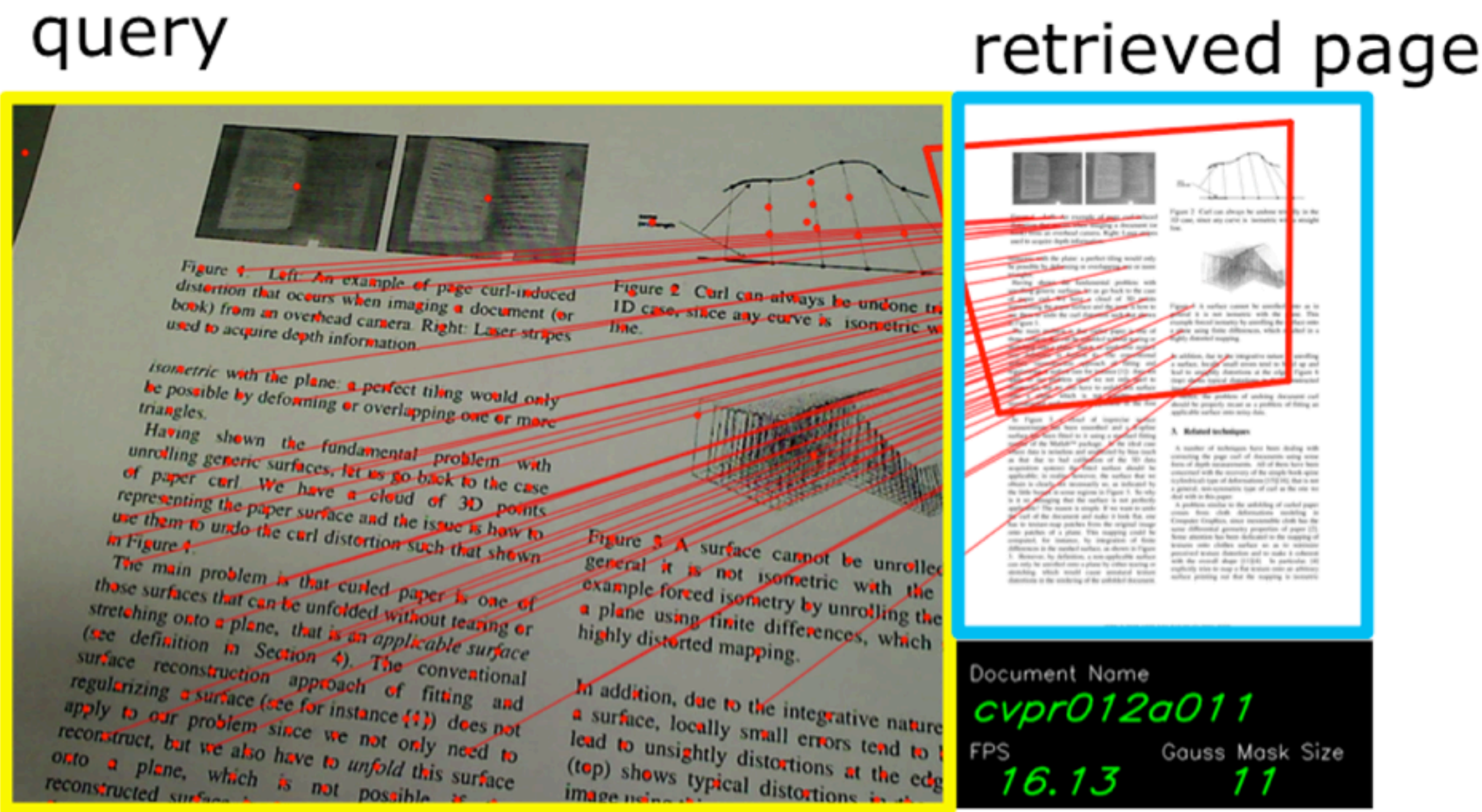
- very few in-situ studies concerning reading activities
- utilizing pervasive sensing and computer vision to recognize:
  - what you read
  - how you read it
- “Reading-life” Log

Character Recognition



Kanji under
background clutter

Document Image Retrieval



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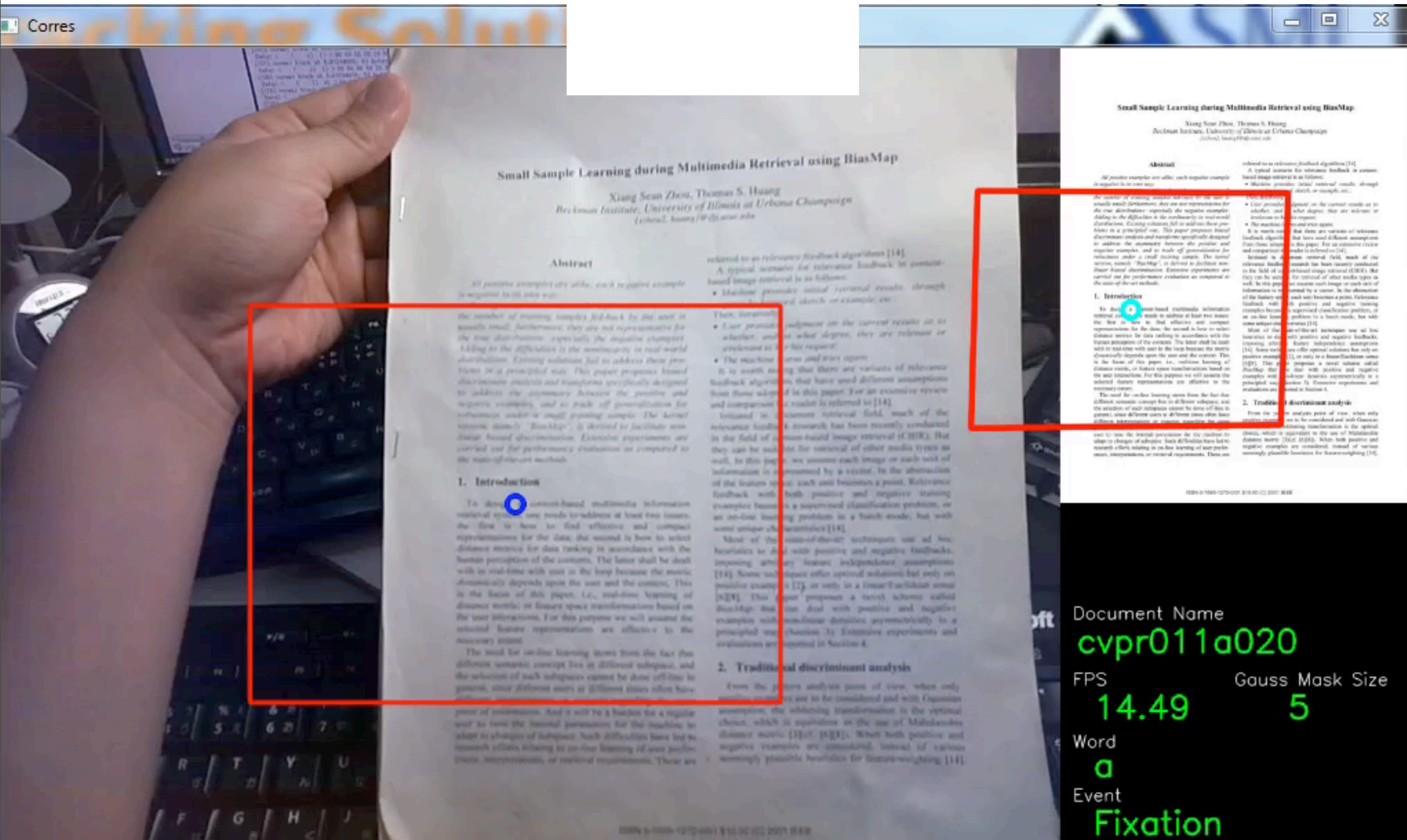
Eye-tracking with Document Image Retrieval



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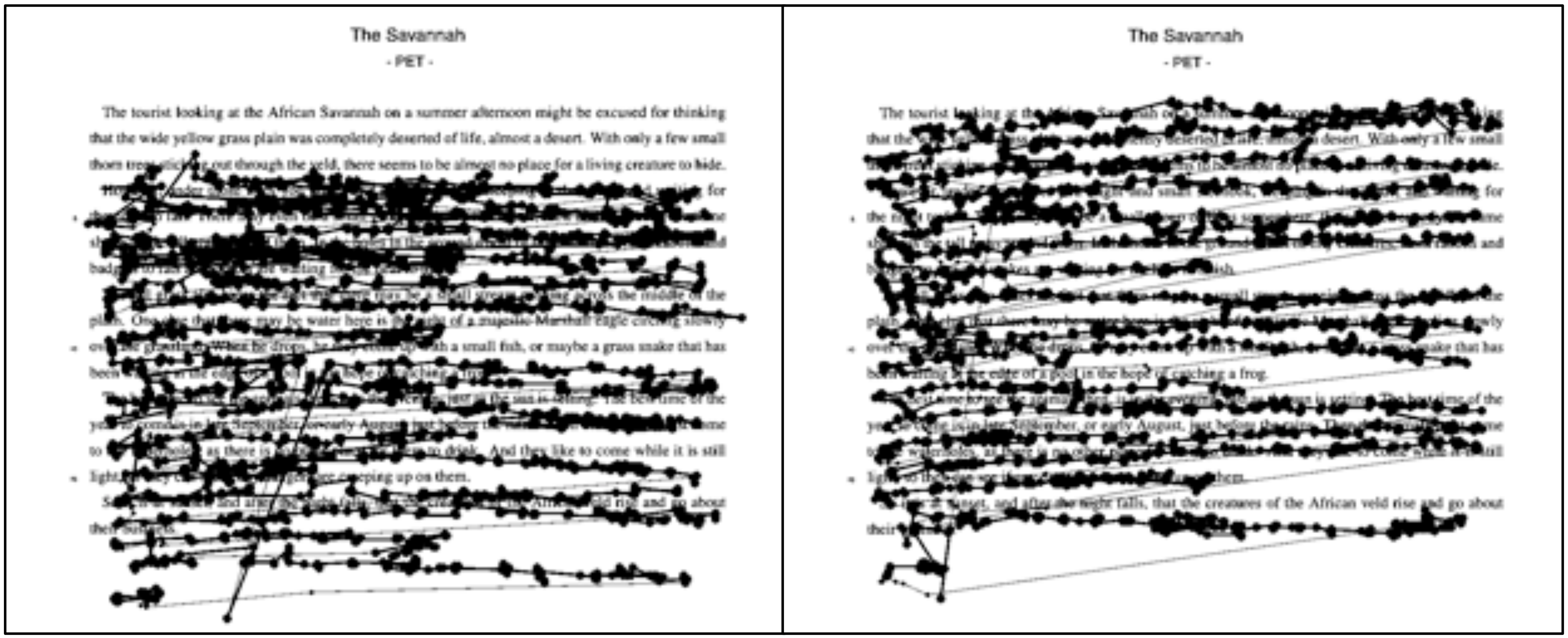
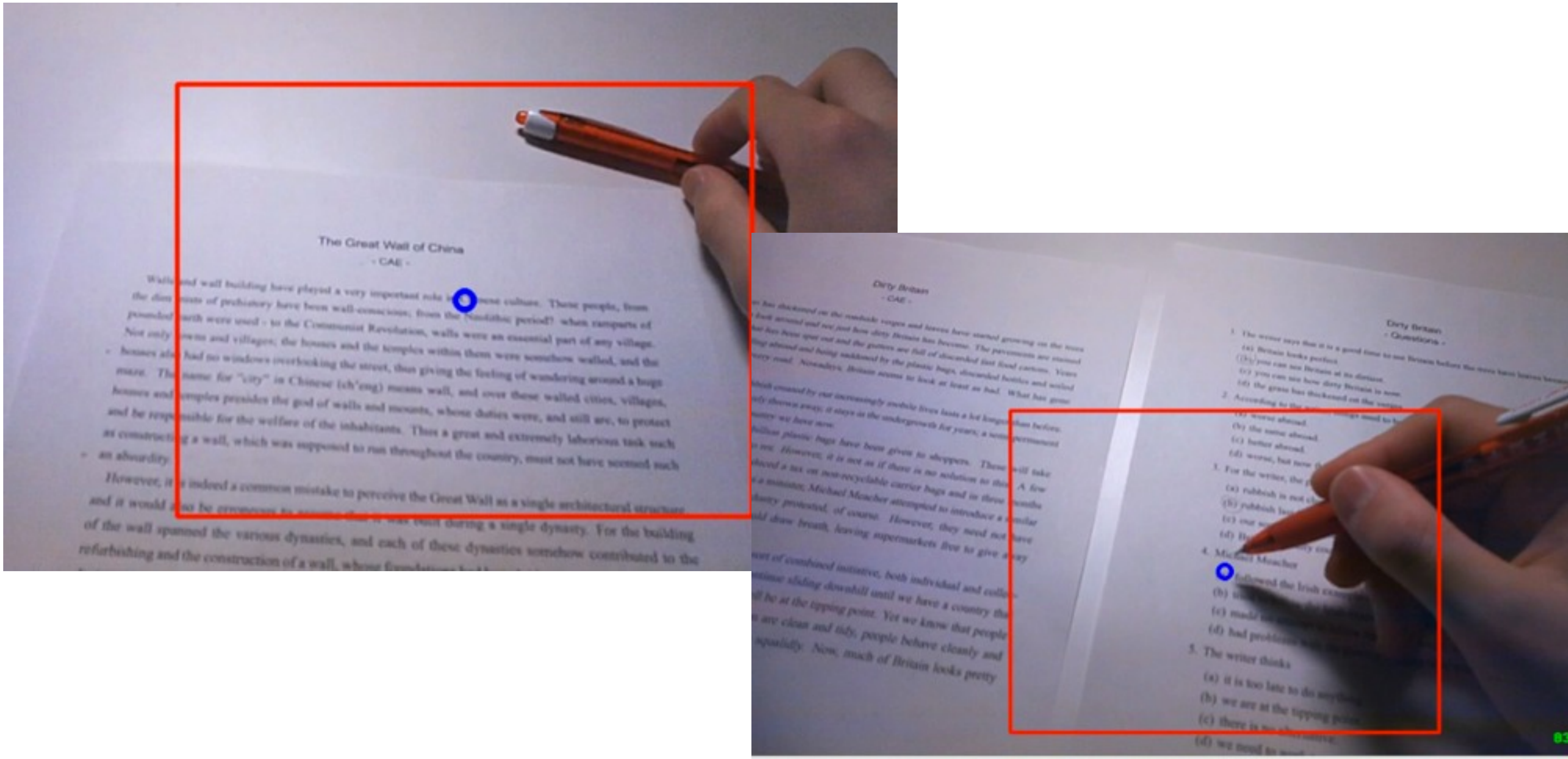
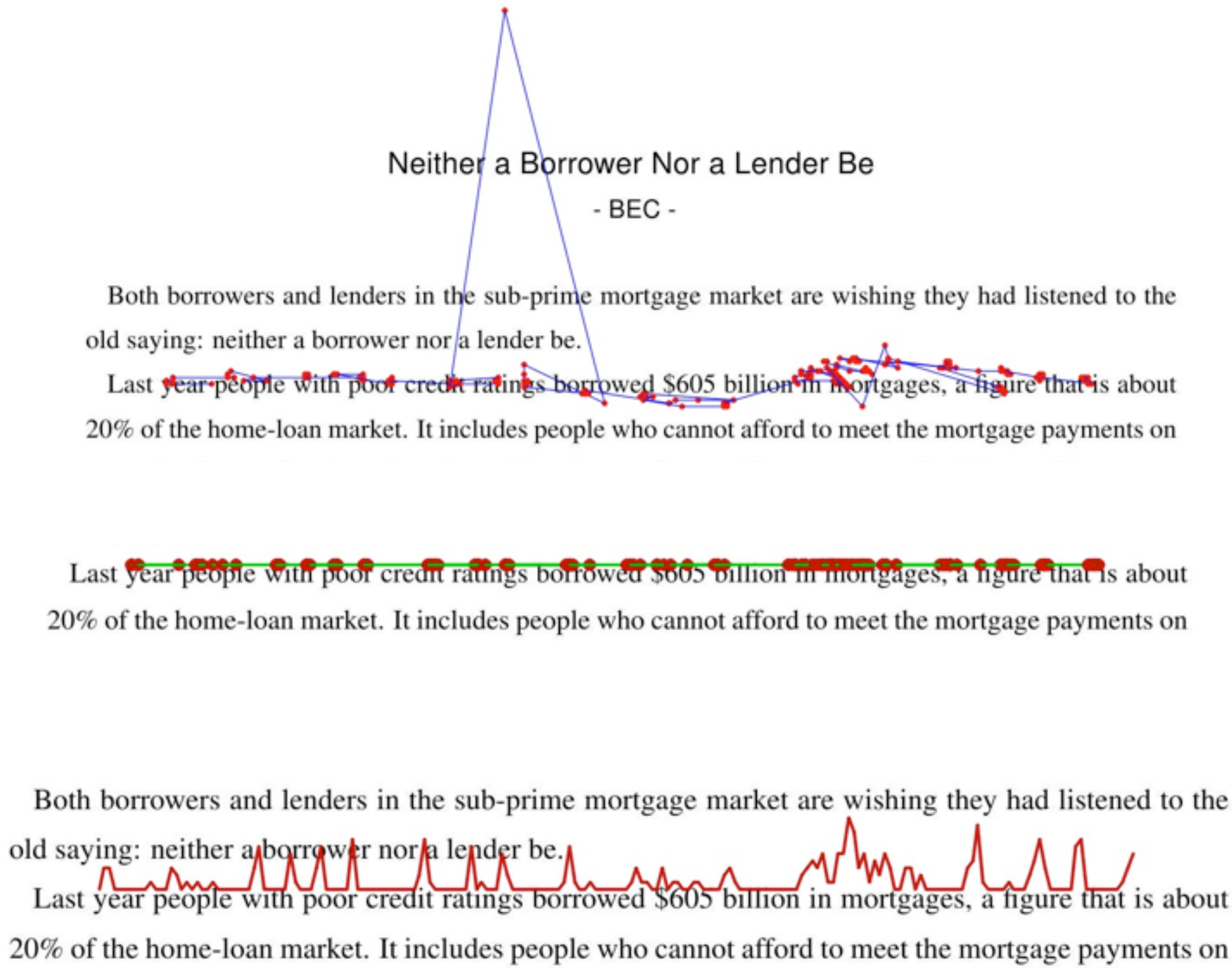
Mobile-Eyetracking with document image retrieval



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.


Neither a Borrower Nor a Lender Be
- BEC -
Both borrowers and lenders in the sub-prime mortgage market are wishing they had listened to the old saying: neither a borrower nor a lender be.
Last year people with poor credit ratings borrowed $605 billion in mortgages, a figure that is about 20% of the home-loan market. It includes people who cannot afford to meet the mortgage payments on
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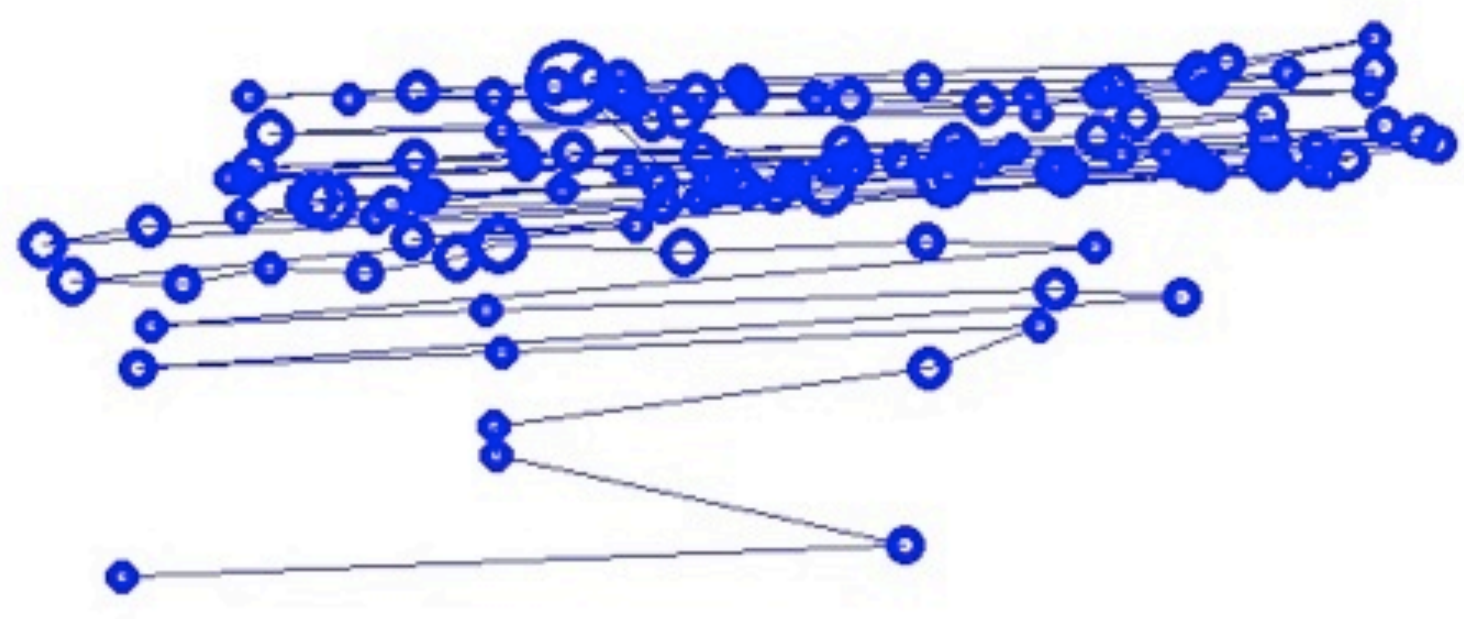
Questions, remarks, violent dissent?



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Augmented Human

- next year in Kobe
- http://www.augmented-human.com/

- The General Chair of AH'14:
  - Prof. Tsutomu Terada