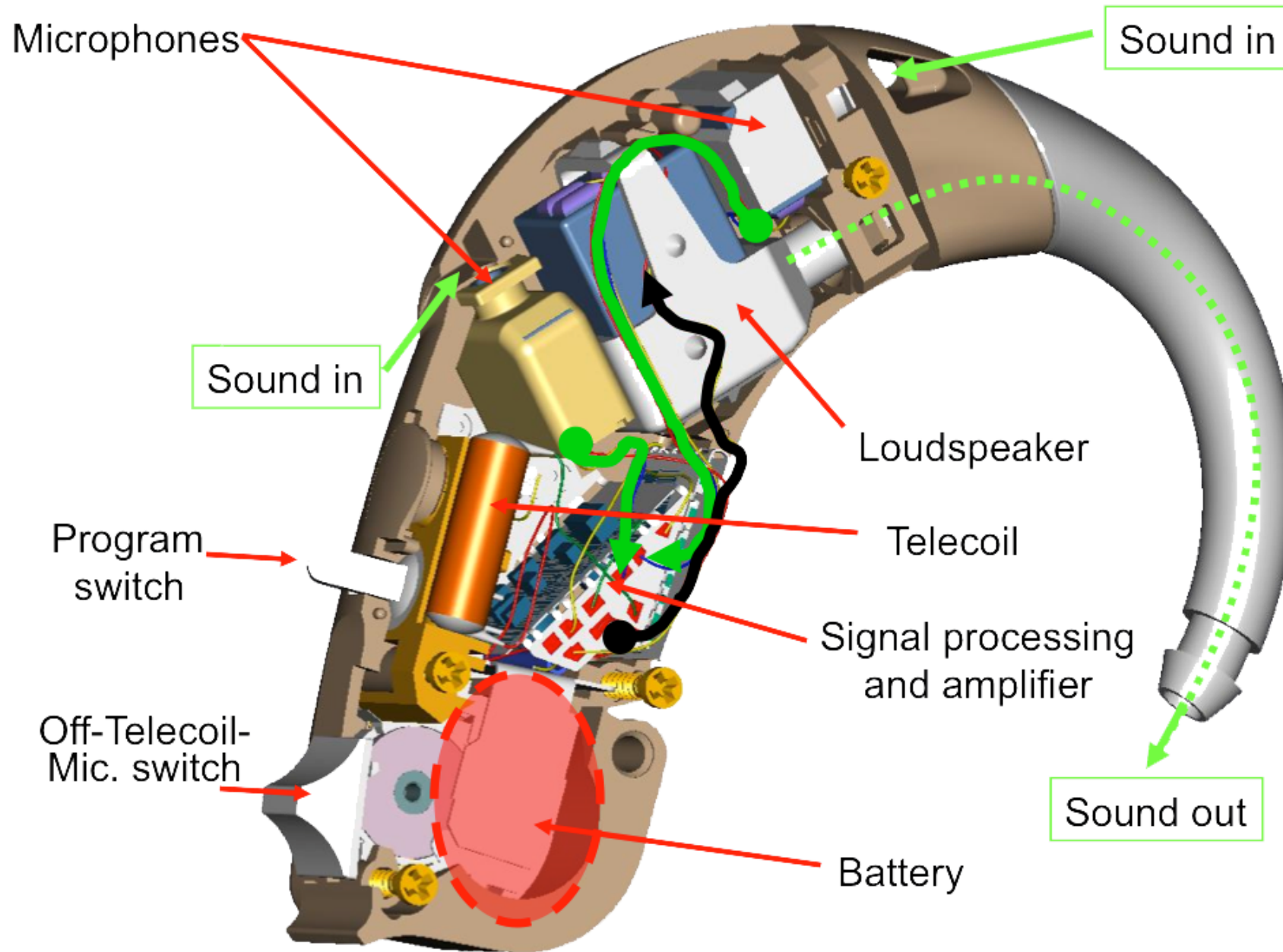


Activity/context-awareness in wearable computing

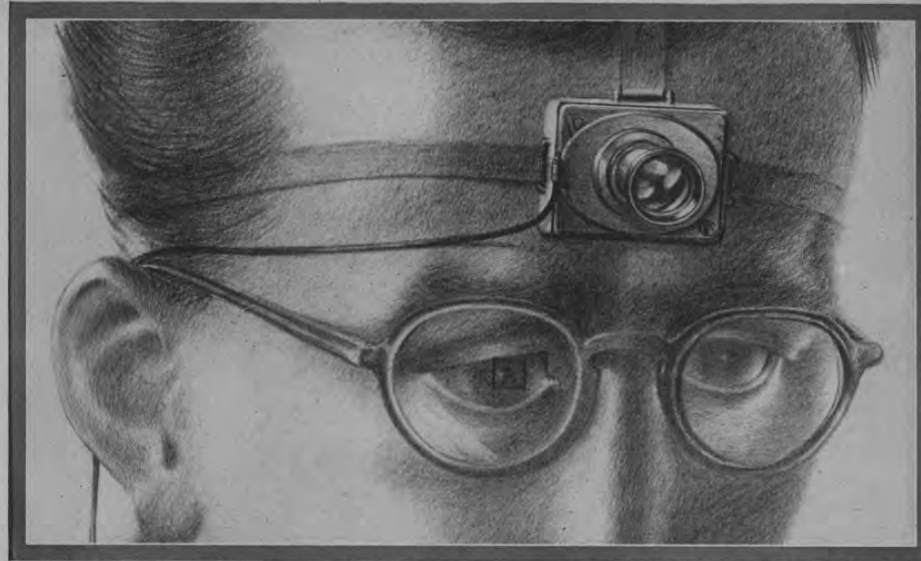


Sanxingdui

Dr. Daniel Roggen
September 2013



Naylor, G.: Modern hearing aids and future development trends,
http://www.lifesci.sussex.ac.uk/home/Chris_Darwin/BSMS/Hearing%20Aids/Naylor.ppt



A SCIENTIST OF THE FUTURE RECORDS EXPERIMENTS WITH A TINY CAMERA FITTED WITH UNIVERSAL-FOCUS LENS. THE SMALL SQUARE IN THE EYEGLASS AT THE LEFT SIGHTS THE OBJECT

AS WE MAY THINK

A TOP U. S. SCIENTIST FORESEES A POSSIBLE FUTURE WORLD
IN WHICH MAN-MADE MACHINES WILL START TO THINK

by VANNEVAR BUSH

DIRECTOR OF THE OFFICE OF SCIENTIFIC RESEARCH AND DEVELOPMENT
Condensed from the *Atlantic Monthly*, July 1945

This has not been a scientists' war; it has been a war in which all have had a part. The scientists, burying their old professional competition in the demand of a common cause, have shared greatly and learned much. It has been exhilarating to work in effective partnership. What are the scientists to do next?

For the biologists, and particularly for the medical scientists, there can be little indecision, for their war work has hardly required them to leave the old paths. Many indeed have been able to carry on their war research in their familiar peacetime laboratories. Their objectives remain much the same.

It is the physicists who have been thrown most violently off stride, who have left academic pursuits for the making of strange destructive gadgets, who have had to devise new methods for their unanticipated assignments. They have done their part on the devices that made it possible to turn back the enemy. They have worked in combined effort with the physicists of our allies. They have felt within themselves the stir of achievement. They have been part of a great team. Now one asks where they will find objectives worthy of their best.

* * *

There is a growing mountain of research. But there is increased evidence that we are being bogged down today as specialization extends. The investigator is staggered by the findings and conclusions of thousands of other workers—conclusions which he cannot find time to grasp, much less to remember, as they appear. Yet specialization becomes increasingly necessary for prog-

ress, and the effort to bridge between disciplines is correspondingly superficial.

Professionally our methods of transmitting and reviewing the results of research are generations old and by now are totally inadequate for their purpose. If the aggregate time spent in writing scholarly works and in reading them could be evaluated, the ratio between these amounts of time might well be startling. Those who conscientiously attempt to keep abreast of current thought, even in restricted fields, by close and continuous reading might well shy away from an examination calculated to show how much of the previous month's efforts could be produced on call.

Mendel's concept of the laws of genetics was lost to the world for a generation because his publication did not reach the few who were capable of grasping and extending it. This sort of catastrophe is undoubtedly being repeated all about us as truly significant attainments become lost in the mass of the inconsequential.

Publication has been extended far beyond our present ability to make real use of the record. The summation of human experience is being expanded at a prodigious rate, and the means we use for threading through the consequent maze to the momentarily important item is the same as was used in the days of square-rigged ships.

But there are signs of a change as new and powerful instrumentalities come into use. Photocells capable of seeing things in a physical sense, advanced photography which can record what is seen or even what is not, thermionic tubes capable of controlling potent forces under the guidance of



Mann, *Smart Clothing: The Shift to Wearable Computing*, Comm. of the ACM, 1996

Wearables as fashion statement



Why wearable?

- Augmenting senses, cognition, communication
- Discreet
- Eminently personal
- Continuously available
- Senses from my perspective
- Privacy (no cloud)

The science is about human activity understanding



- What did I do yesterday?.....
 - You went to the supermarket, and enjoyed a coffee with Lisa
- What am I doing in the kitchen?....
 - If you want to cook spaghettis, think of heating the water

Activity understanding

- Implicit (micro-) interactions
- Proactive
- With the right modality



- Assisted living



- HCI / HRI



- Gaming



- Industry



- Sports



- Event management



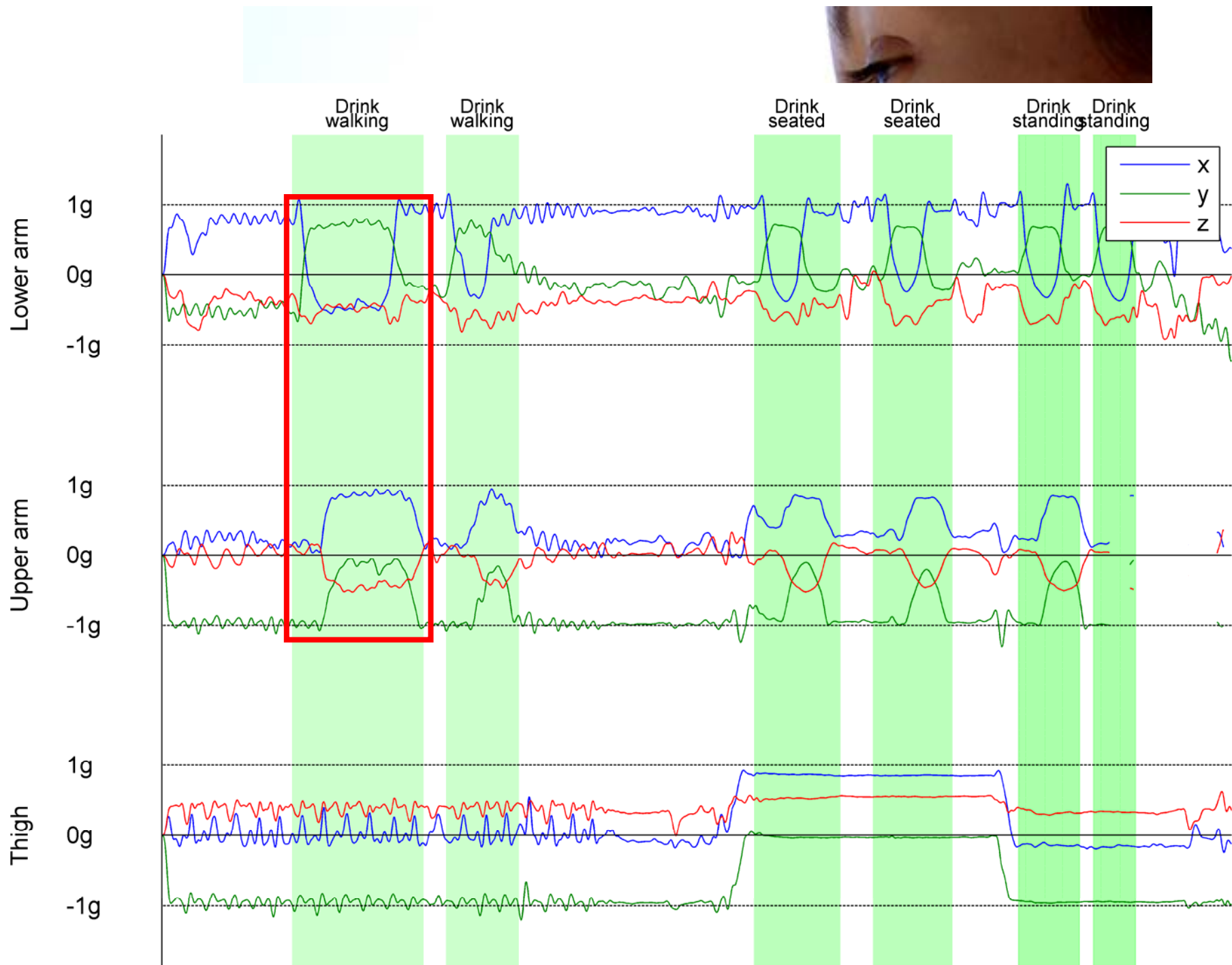
- Greener society

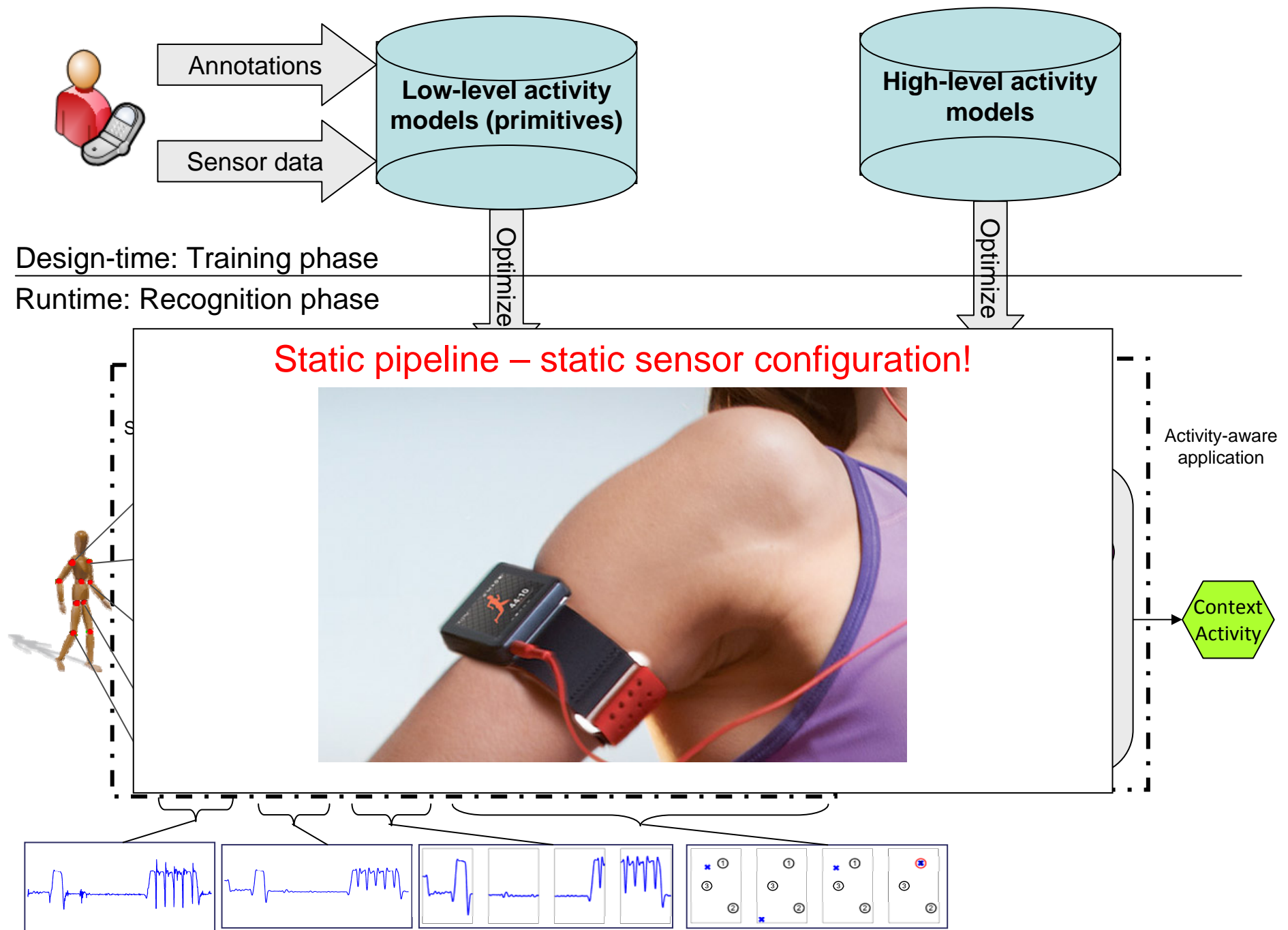


- Virtual reality

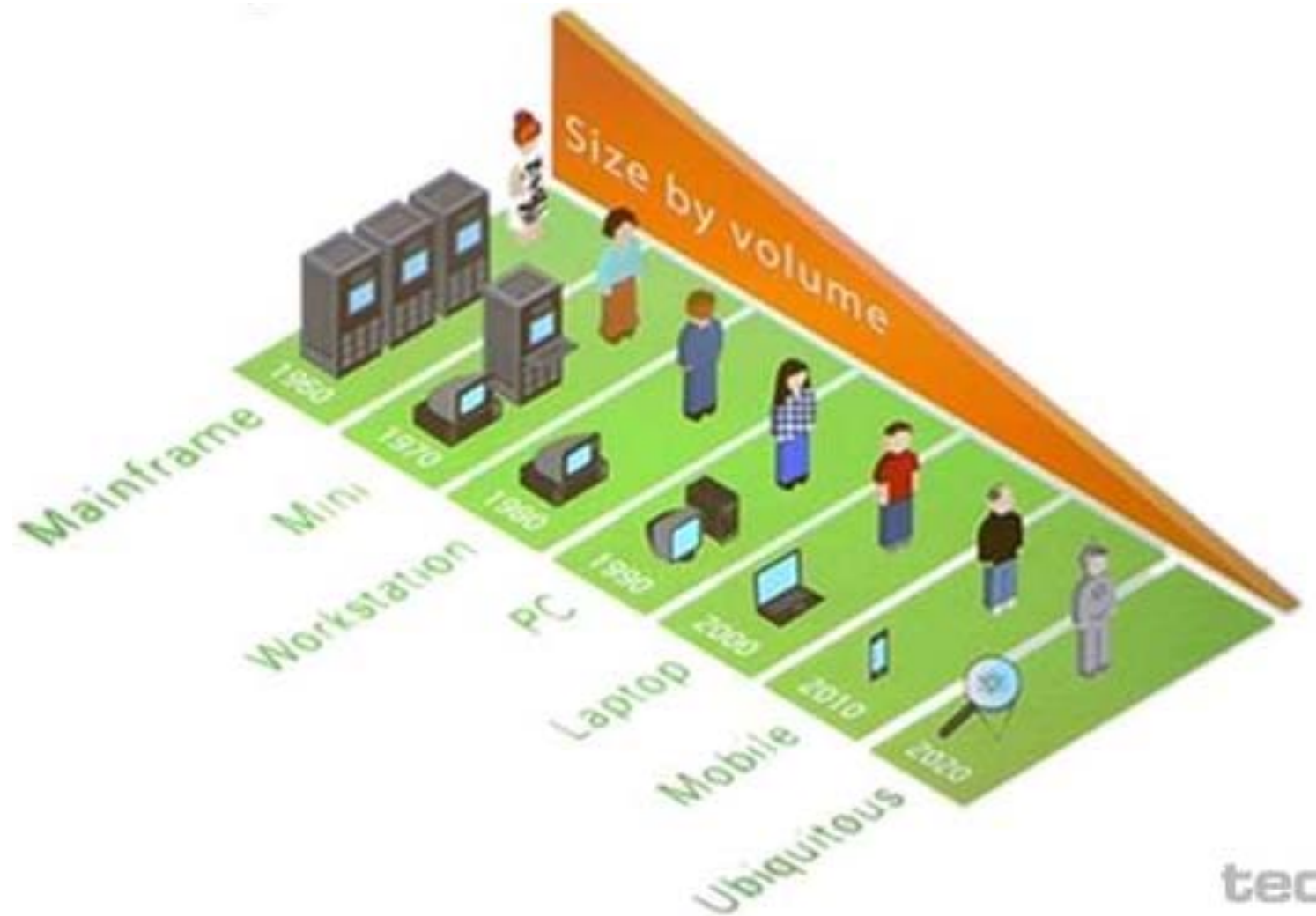


- Safety

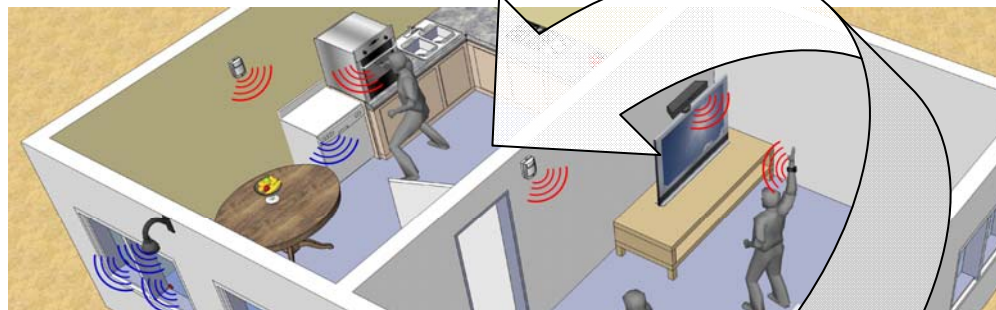




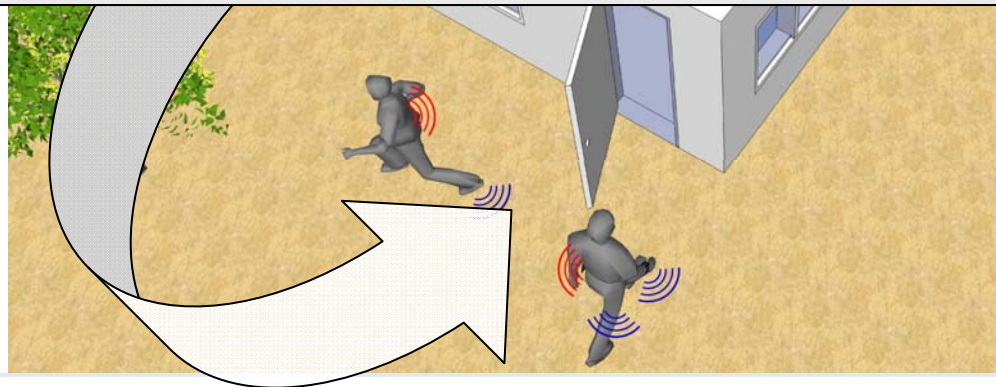
Size for « meaningful computing » is zero in 2020



Intel developer forum, 2012



pattern recognition in opportunistic configurations of sensors
(problem of distributed signal processing and machine learning)



Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich



Wearable Computing Lab.
ETH Zürich



JOHANNES KEPLER
UNIVERSITÄT LINZ | JKU

Institut für
Pervasive Computing
Technology for People



The OPPORTUNITY dataset for *reproducible* research (avail. on UCI ML repository)

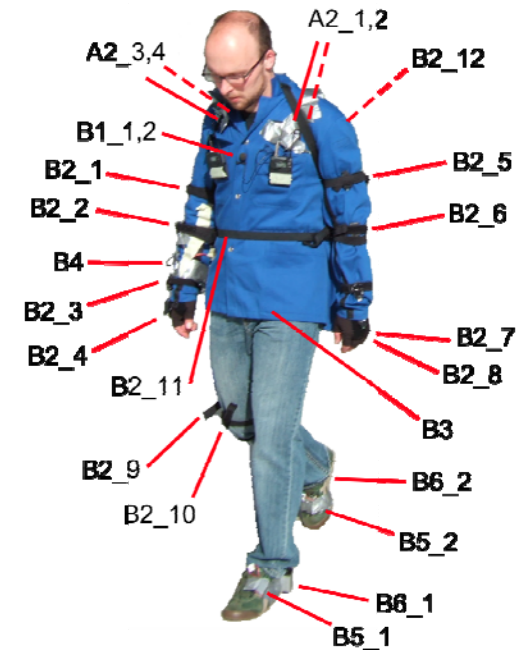


Activity of daily living

- 12 subjects
- > 30'000 interaction primitives (object, environment)

Sensor rich

- Body, objects, environment
- 72 sensors (28 sensors in 2.4GHz band)
- 10 modalities
- 15 wired and wireless systems

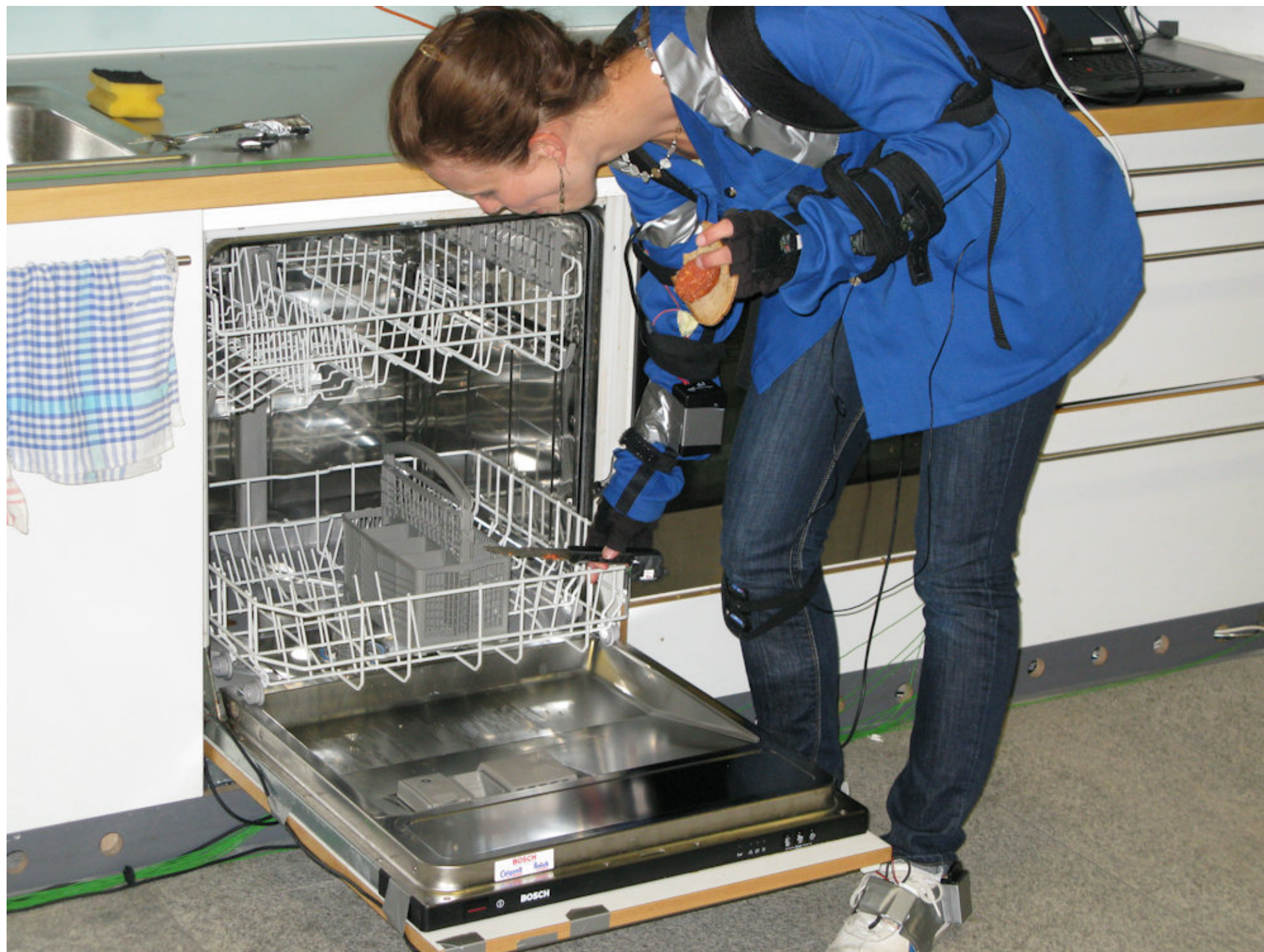


Roggen et al., *Collecting complex activity datasets in highly rich networked sensor environments*, INSS 2010
<http://opportunity-project.eu/challengeDataset>
<http://vimeo.com/8704668>











[About](#)
[Citation Policy](#)
[Donate a Data Set](#)
[Contact](#)

☒ Repository
 ☐ Web
 

[View ALL Data Sets](#)

UCI Machine Learning Repository
Center for Machine Learning and Intelligent Systems

OPPORTUNITY Activity Recognition Data Set








Download: [Data Folder](#), [Data Set Description](#)

Abstract: The OPPORTUNITY Dataset for Human Activity Recognition from Wearable, Object, and Ambient Sensors is a dataset devised to benchmark human activity recognition algorithms (classification, automatic data segmentation, sensor fusion, feature extraction, etc).



Data Set Characteristics:	Multivariate, Time-Series	Number of Instances:	2551	Area:	Computer
Attribute Characteristics:	Real	Number of Attributes:	242	Date Donated	2012-06-09
Associated Tasks:	Classification	Missing Values?	Yes	Number of Web Hits:	11471

- Plötz, Hammerla, Olivier. *Feature Learning for Activity Recognition in Ubiquitous Computing*, IJCAI, 2011
- Manzoor et al., *Identifying Important Action Primitives for High Level Activity Recognition*, Proc. European Conference on Smart Sensing and Context (EuroSSC), 2010
- Ploetz, Hammerla, Rozga, Reavis, Call, Abowd. *Automatic Assessment of Problem Behavior in Individuals with Developmental Disabilities*. Proc. 14th Int Conf on Ubiquitous Computing, 2012.
- Gordon, Czerny, Beigl. *Activity Recognition for Creatures of Habit: Energy-Efficient Embedded Classification using Prediction*. Personal and Ubiquitous Computing, 2013.
- Melibari et al, *Dynamic Sum-Product Networks*, Tech Rep University of Waterloo, 2013
- Helaoui et al., *Towards Activity Recognition Using Probabilistic Description Logics*, AAAI 2012
- Helaoui et al, *A Probabilistic Ontological Framework for the Recognition of Multilevel Human Activities*, Ubicomp, 2013

<u>Name</u>	<u>Scenario</u>	<u>Description</u>	<u>Availability</u>
Skoda mini checkpoint 	10 manipulative gestures performed in a car maintenance scenario.	<ul style="list-style-type: none"> • 10 manipulative gestures. • 10 3D acceleration sensor on left arm • 10 3D acceleration sensor on right hand • 1 subject 	Contact: Daniel Roggen Download here
Skoda mini checkpoint 			
BodyAttack fitness dataset 	6 fitness activity classes, done mostly with the legs.	<ul style="list-style-type: none"> • 6 fitness activity classes • 10 3D acceleration sensors on the leg • 1 subject 	Contact: Kilian Förster Download here
BodyAttack fitness dataset 			
HCI gestures dataset 	5 gestures done with the right hand in a vertical plane	<ul style="list-style-type: none"> • 5 gestures (Triangle upwards, square, circle, infinity, triangle downwards) • 8 3D acceleration sensors on the arm • 1 subject 	Contact: Kilian Förster Download here
HCI gestures dataset 			
Daphnet Freezing of Gait Dataset in users with Parkinson's disease 	Users with Parkinson disease walk in a corridor and various rooms, leading them to experience gait freeze.	<ul style="list-style-type: none"> • 2 classes: gait freeze, and not gait freeze (any of walking, standing, etc). • 3 3D acceleration sensors on the hip, thigh, ankle • 10 subjects 	Contact: Daniel Roggen Download here

Challenge 1: Data recording with heterogeneous sensor networks

Obtain synchronized data streams for further processing

Integration at system level

- + Central control & monitoring
- + Synchronized data acquisition
- Internals of sensor systems
- Fixed real-time merge

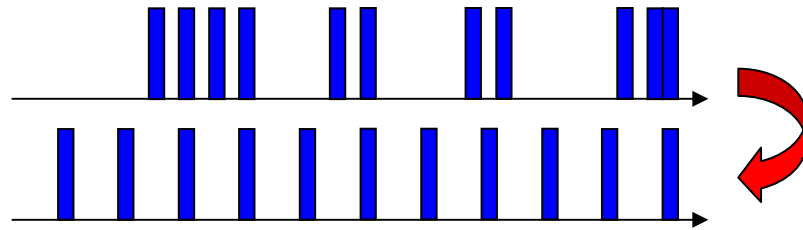
Integration at data level

- + Independent data recorders
- + Robustness, flexibility
- Complex control & monitoring
- Offline synchronization

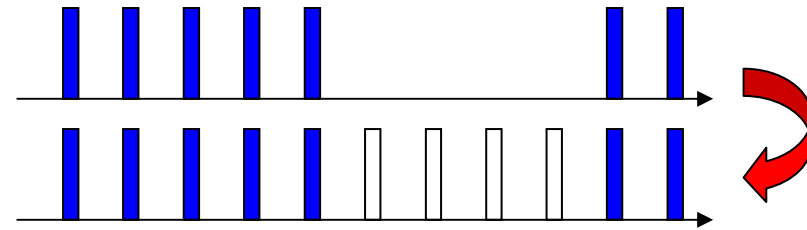
- 7 computers recording sensor data
 - Store data and data reception time
 - Coarse NTP synchronisation
 - Fine synchronisation with specific gestures (“jump and clap”)

ID	Records sensor systems	Nature and location	Data acquisition
R1	B2, B3, B4	Laptop, on body in a backpack	CRN Toolbox [10]
R2	A2, A4, A7	Desktop PC	CRN Toolbox
R3	B1, A1	Laptop (static)	Audio acq. software
R4	B5, B6	Laptop (carried by experimenter, following subject)	Commercial proprietary software
R5	A3	Laptop (static)	Axis proprietary
R6	A5	Laptop (static)	Dedicated software
R7	O1, A6	Laptop (static)	CRN Toolbox

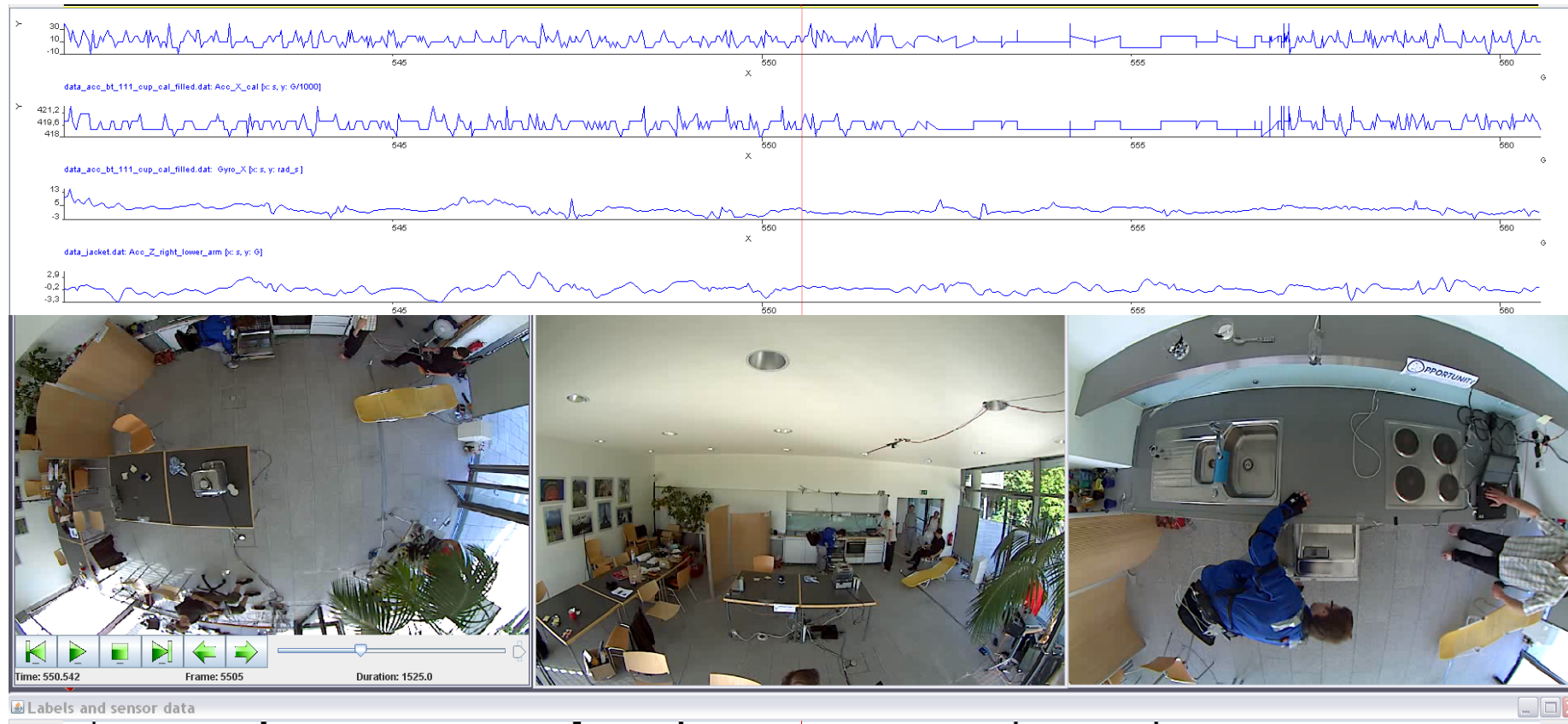
Challenge 2: data handling after recording



Burst equalization w/ streaming sensors

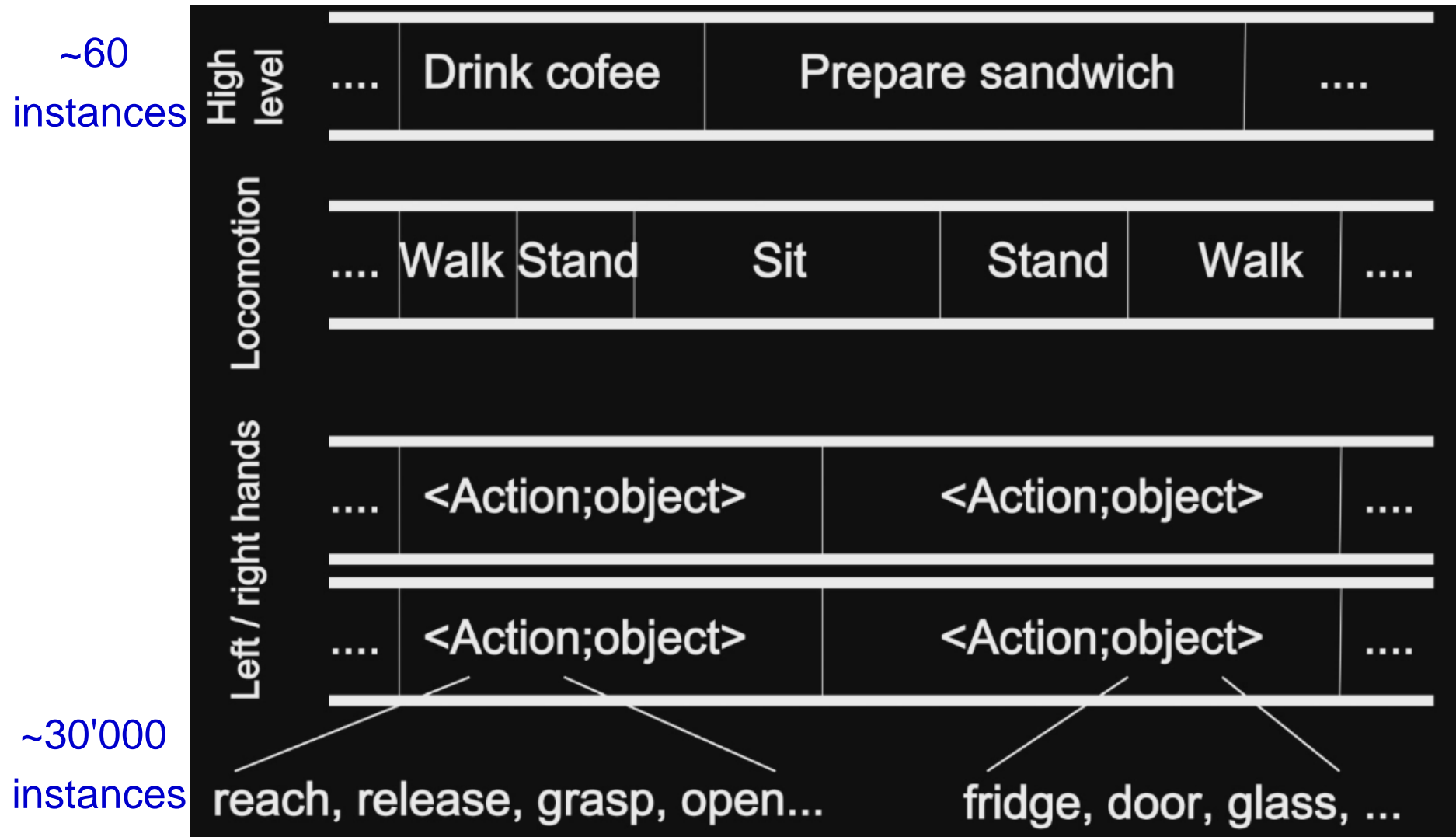


Missing data represented as NaNs



Stream alignment to video footage

Challenge 3: flexible activity annotations, at all levels



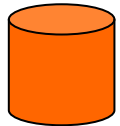
Solution: annotation on multiple tracks, hand-action-object representation



LEGO approach

Set of **methods** that can be **richly combined**

Inspiration from Artificial Intelligence



Domain knowledge

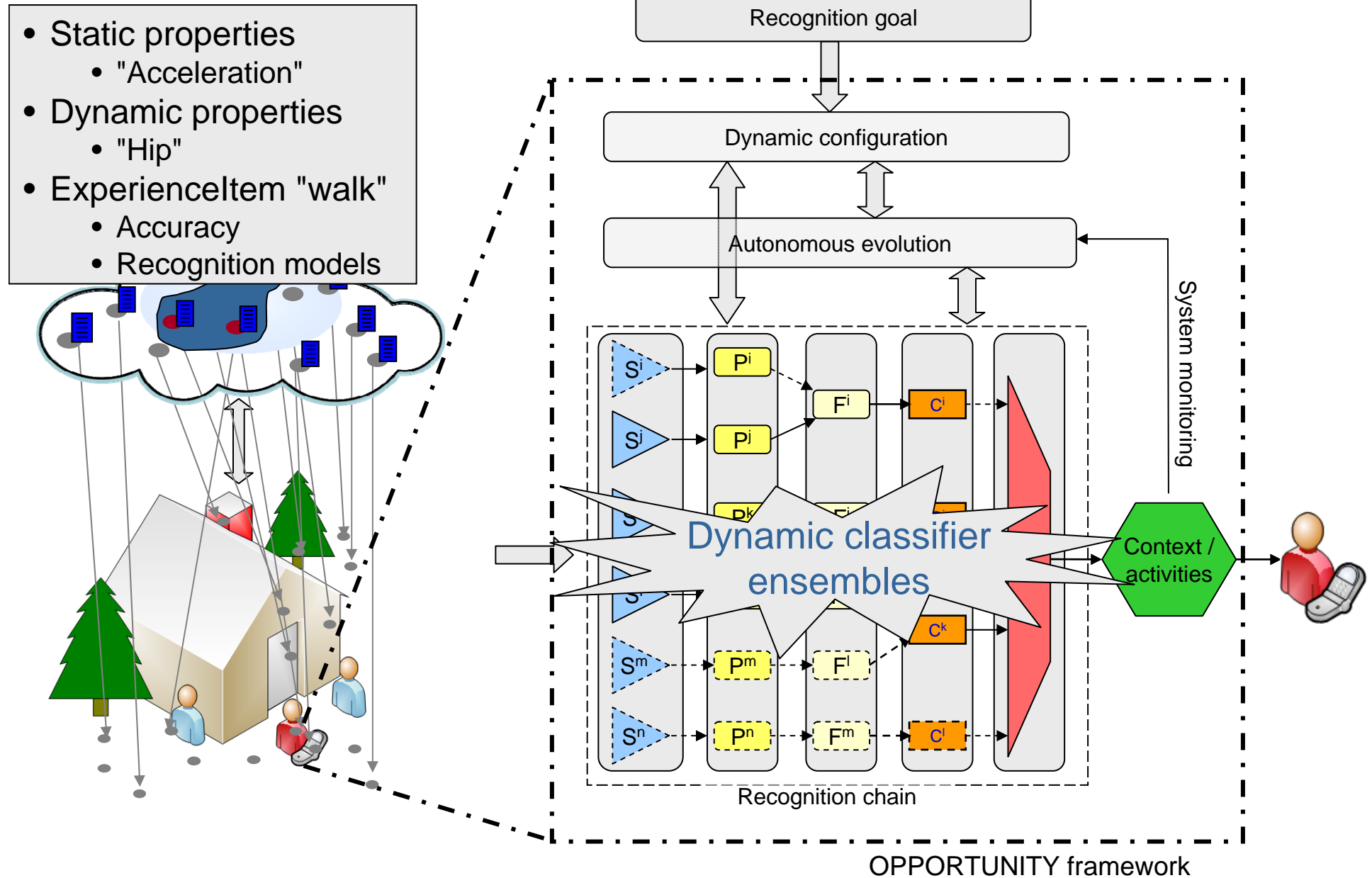
Solve the problem in an **initially restricted setup** out of the box,



Autonomous evolution

Discover new solutions at runtime

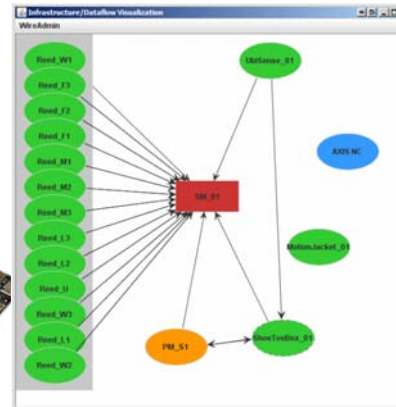
Opportunistic recognition pipeline



OPPORTUNITY Framework

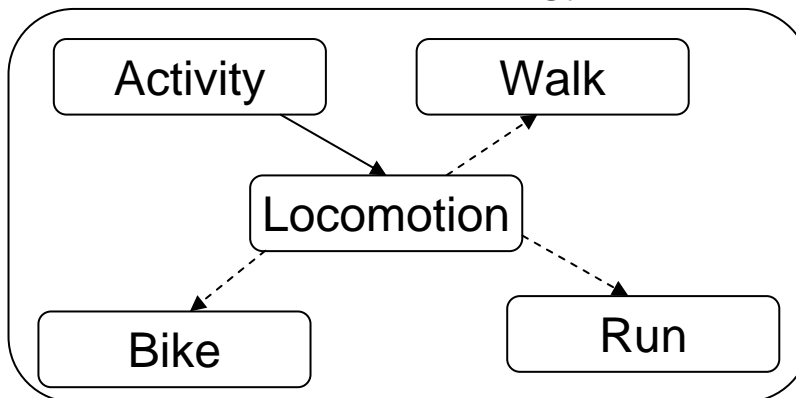
Planner-based recognition chain optimization

- Sensor management
- Standard recognition algorithms
- Java & OSGi bundles
- Runs on x86 or ARM

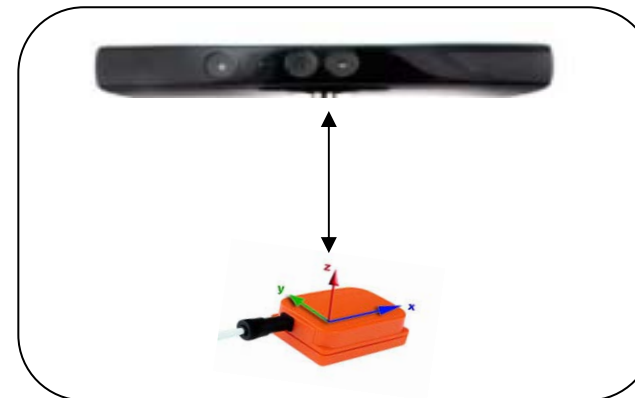


Domain-adaptable

Domain ontology

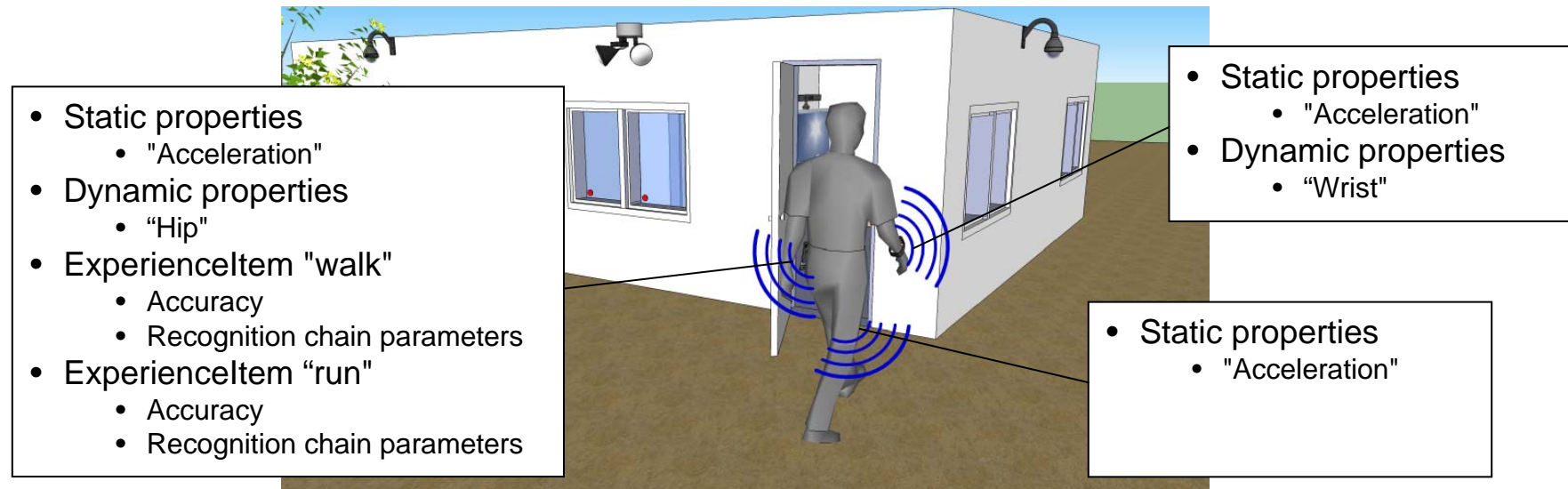


Sensor transformations



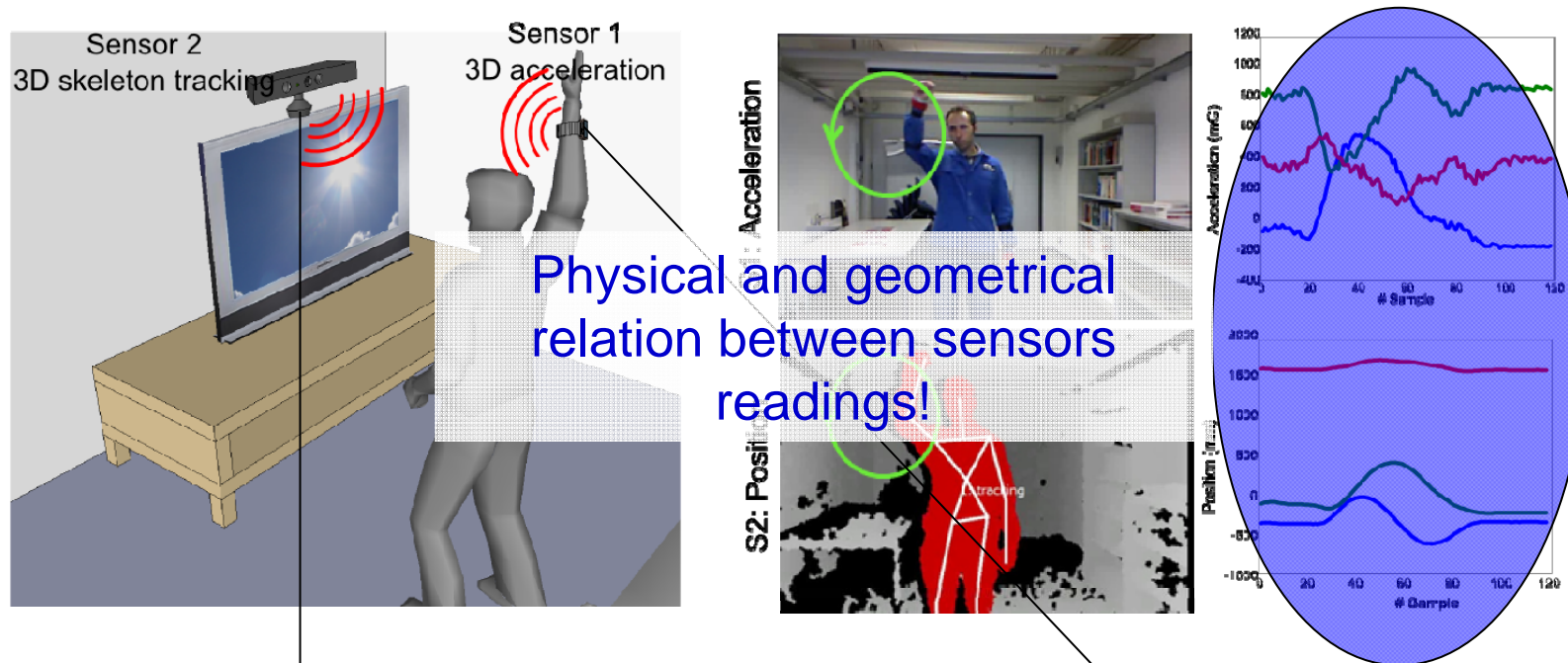
- Planner
 - Reconfiguration (Knapsack, LinearEfficiencyAnalysis, Inf Theoretical)
 - Self-monitoring: anomaly & change detection
 - Knowledge discovery

Walkthrough: setting-up the recognition goal « Locomotion »



- Goal reasoning: locomotion = walk|run
- Instantiation of the RecognitionChain with Smartphone

Walkthrough: knowledge discovery - using unknown sensors

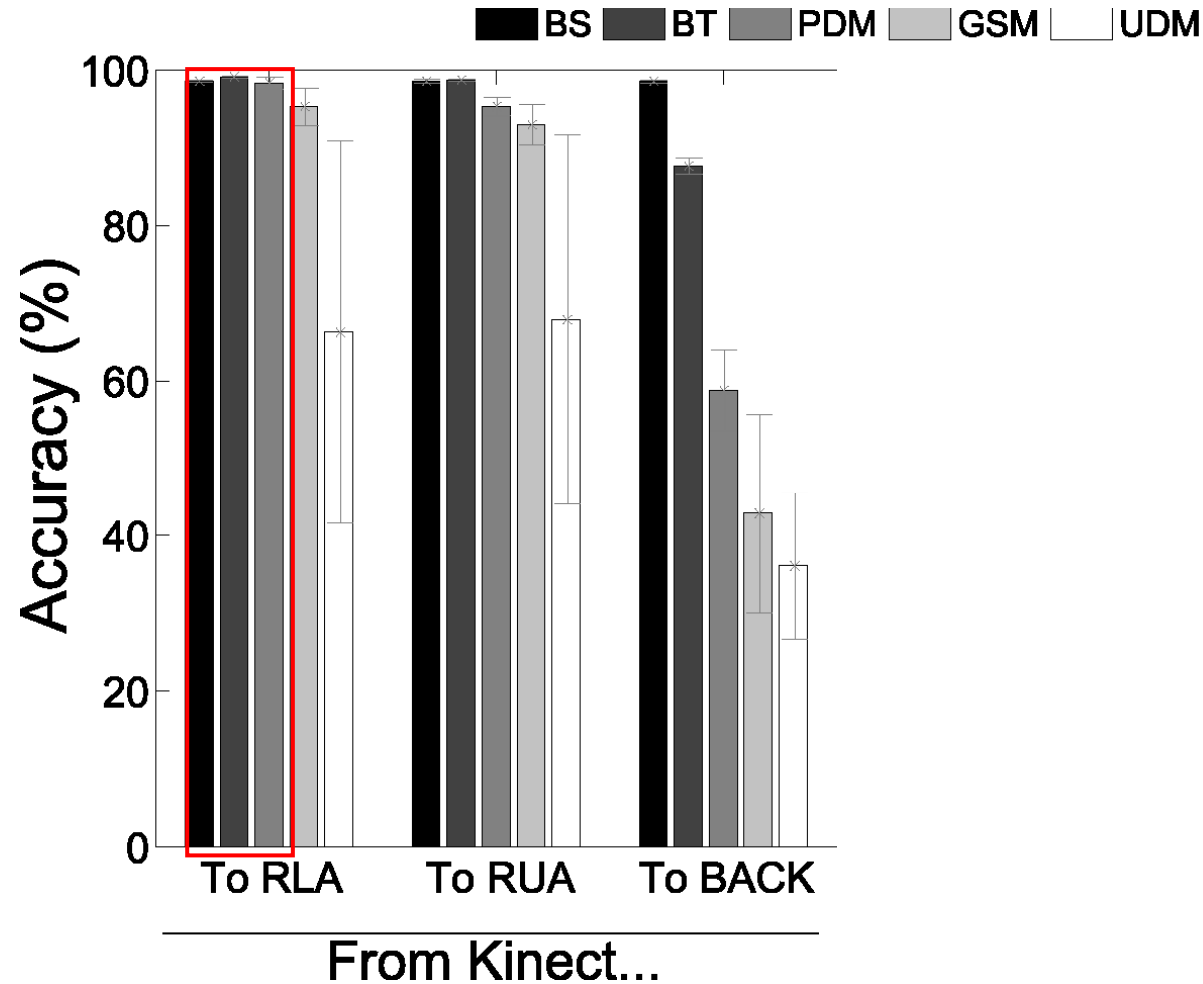


- Static properties
 - "3D skeleton"
- ExperienceItems "HCI-VolumeUp"
- ExperienceItems "HCI-VolumeDn"
- ExperienceItems "HCI-Next"
- ExperienceItems "HCI-Prev"

- Static properties
 - "Acceleration"
- Dynamic properties
 - "Wrist"

- Static properties
 - "Acceleration"
- Dynamic properties
 - "Wrist"
- ExperienceItems "HCI-VolumeUp"
- ExperienceItems "HCI-VolumeDn"
- ExperienceItems "HCI-Next"
- ExperienceItems "HCI-Prev"

Translation performance



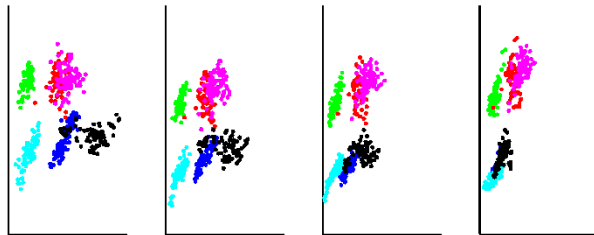
- Same limb translation: **accuracy <4% below baseline** (accuracy ~95%)
- System identification: 3 seconds
- **Self-spreading** of recognition capabilities!



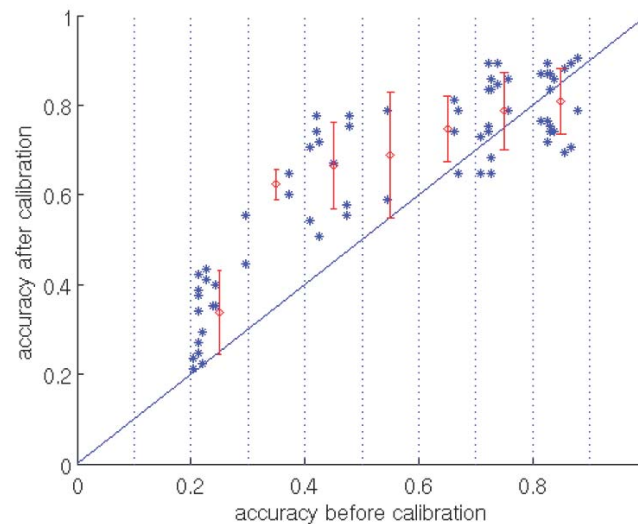
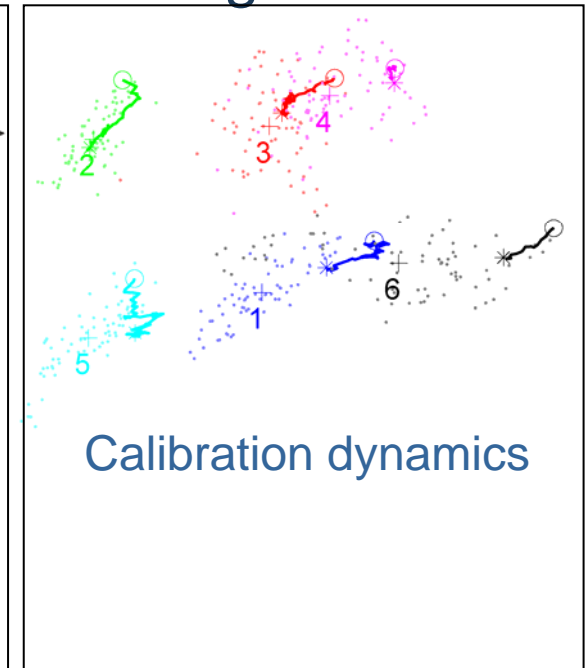
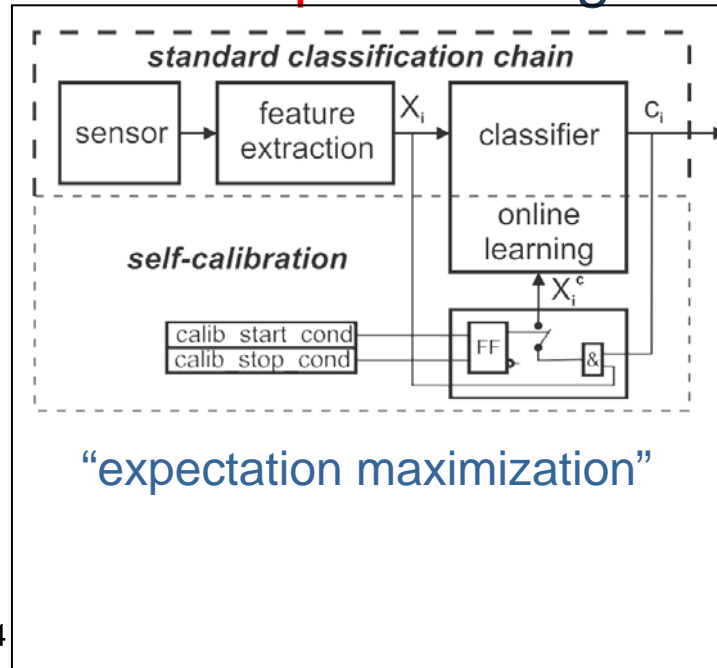
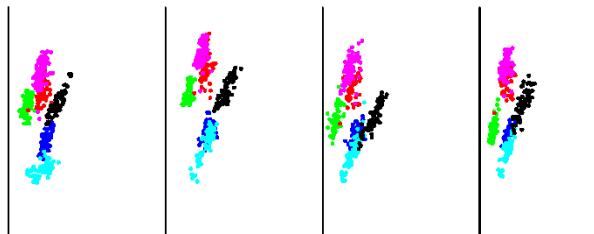
Walkthrough: self-adaptation to gradual changes



sensor 1 sensor 2 sensor 3 sensor 4



sensor 6 sensor 7 sensor 8 sensor 9



Self-calibration to displaced sensors increases accuracy:

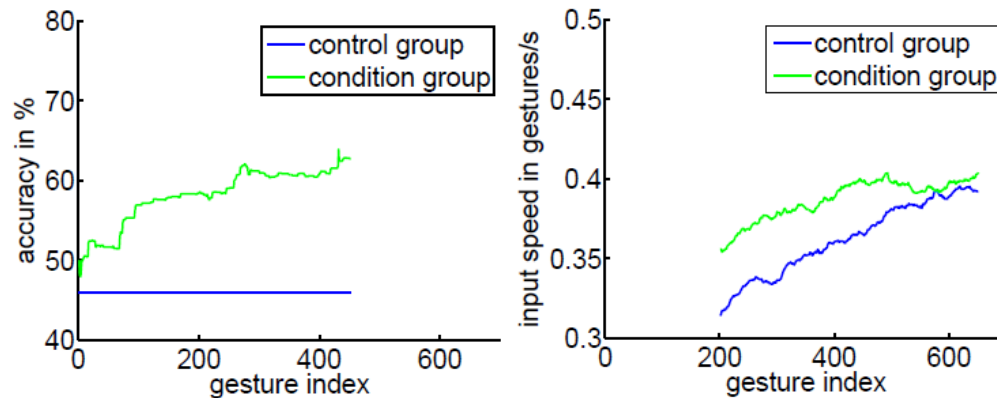
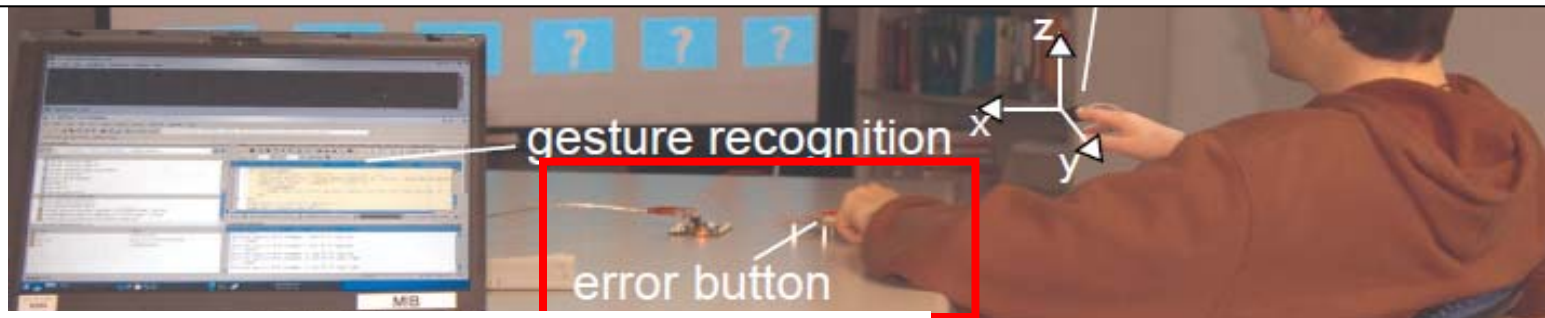
- by 33.3% in HCI dataset
- by 13.4% in fitness dataset

Förster, Roggen, Tröster, *Unsupervised classifier self-calibration through repeated context occurrences: is there robustness against sensor displacement to gain?*, Proc. Int. Symposium Wearable Computers, 2009

Walkthrough: minimally user-supervised self-adaptation



- Adaptation leads to:
 - Higher accuracy in the adaptive case v.s. control
 - Higher input rate
 - More "personalized" gestures

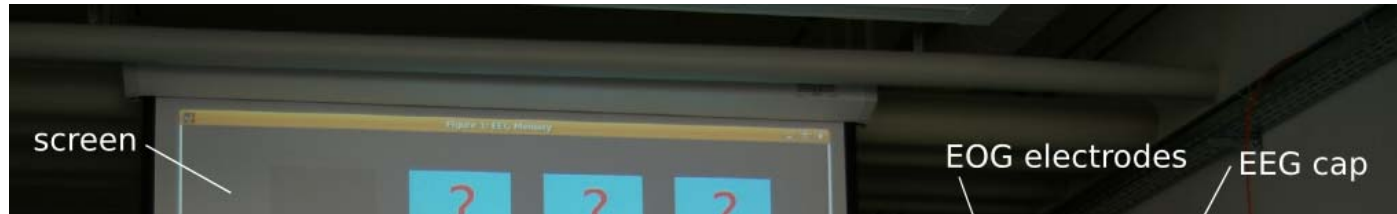


Group	Inter subject sim.	Intra subject sim.
condition	9.4	1.1
control	5.3	0.8

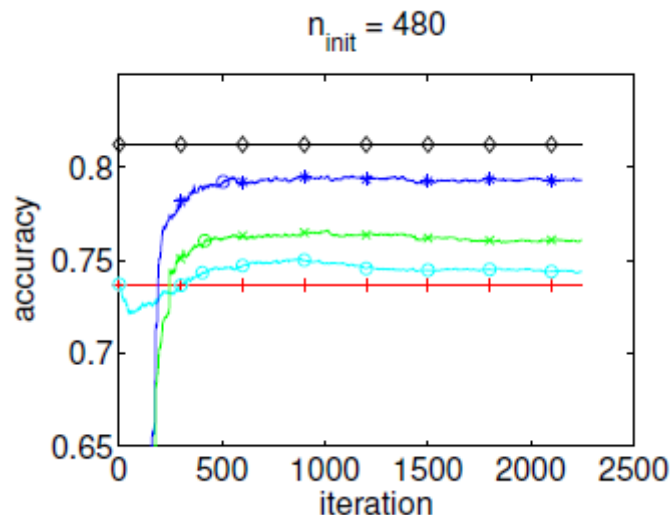
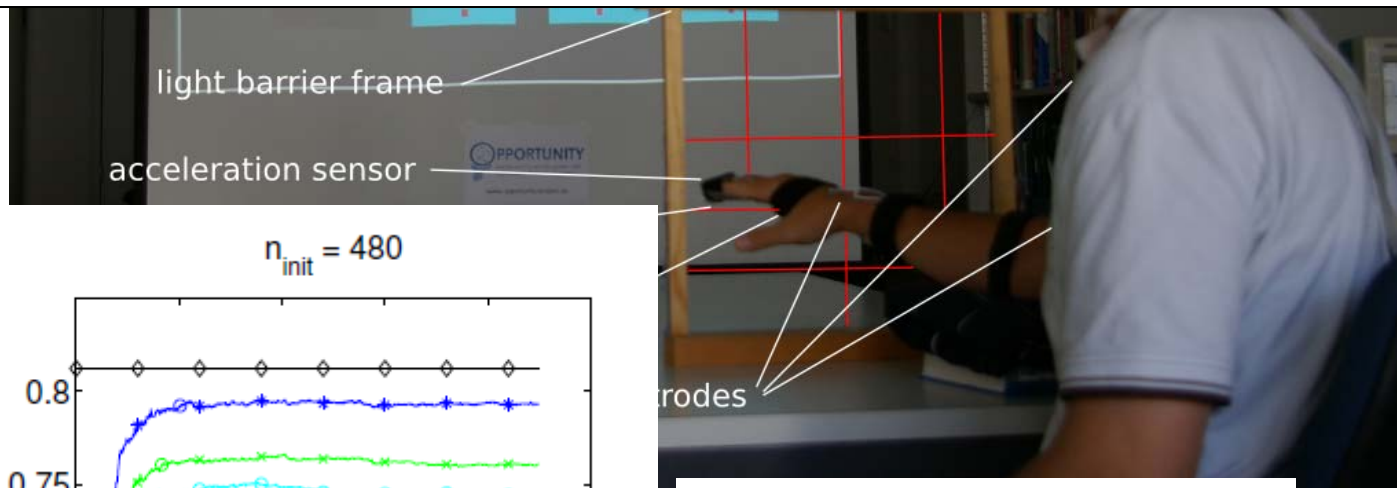
Förster et al., *Online user adaptation in gesture and activity recognition - what's the benefit?* Tech Rep.

Förster et al., *Incremental kNN classifier exploiting correct - error teacher for activity recognition*, ICMLA 2010

Walkthrough: brain-guided self-adaptation



- ~9% accuracy increase with perfect brain signal recognition
- ~3% accuracy increase with effective brain signal recognition accuracy
- Adaptation guided by the user's own perception of the system
- User in the loop



- + subject independent baseline
- ◇ subject dependent baseline
- adaptation strategy 1
- * adaptation strategy 2a
- x adaptation strategy 2b

What if activity recognition is possible “anytime and anywhere” ?



- Energy use: -17%
 - Implicit energy management
 - 15 households



- Health care costs: -400K£/day in UK
 - Ensuring regular training to avoid falls
 - Reduces fall rate by 50%

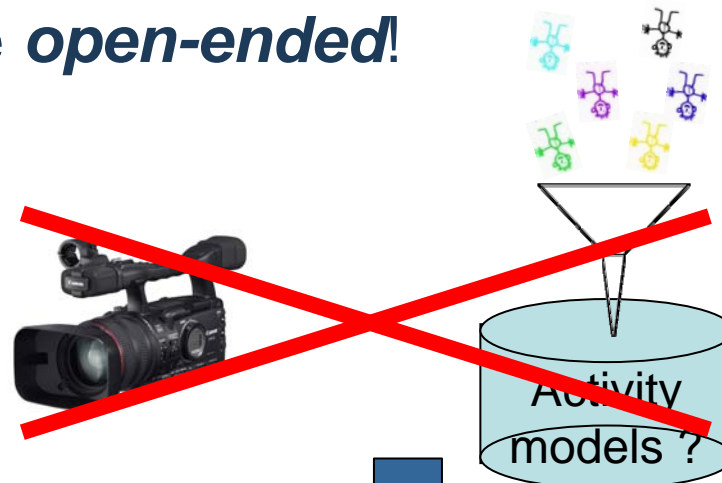
Daily Routine page 41



- 1 He wakes up.
- 2 He gets up/He gets out of bed.
- 3 He goes downstairs.
- 4 He goes jogging.

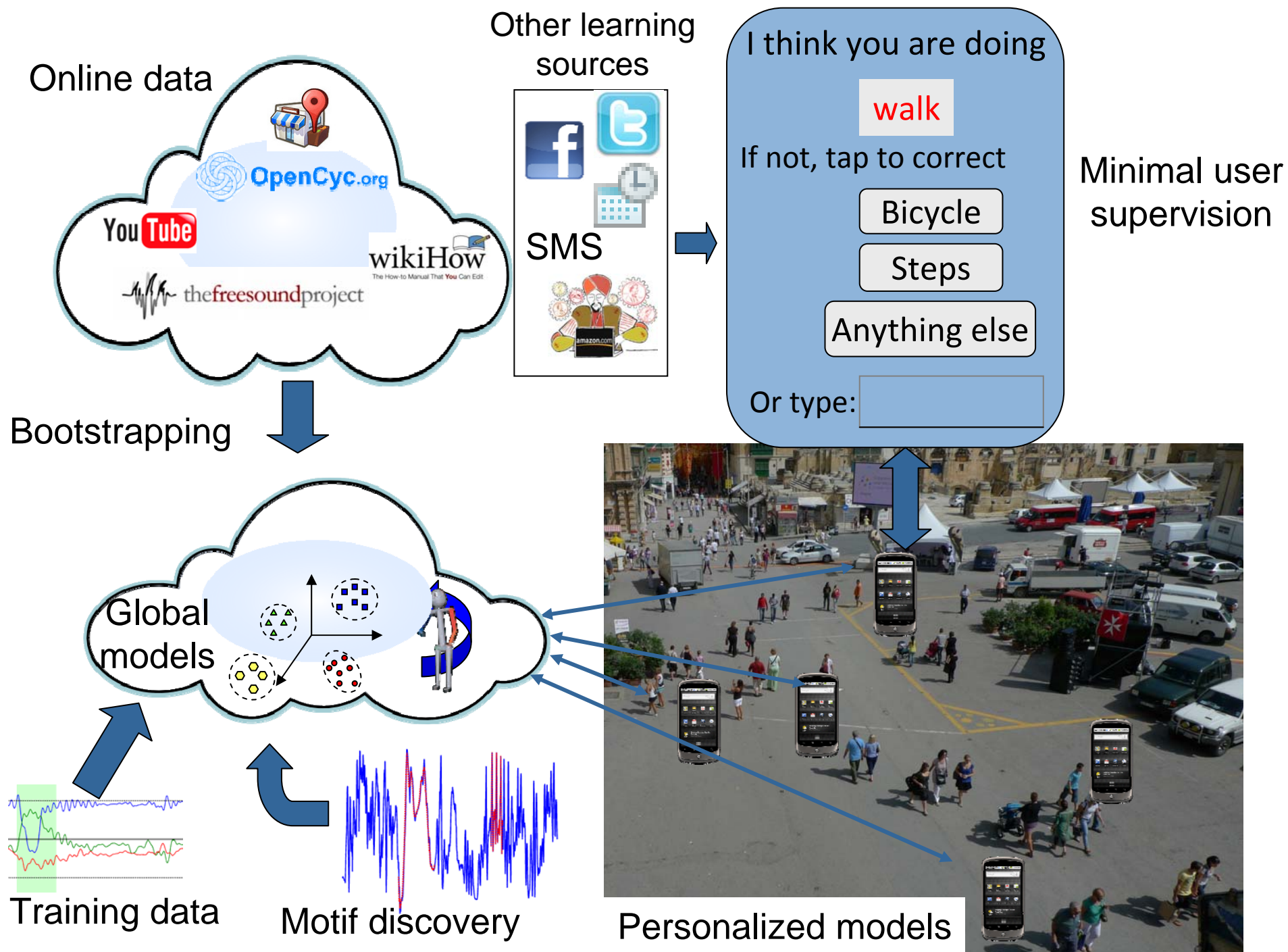


Daily routines are ***open-ended!***

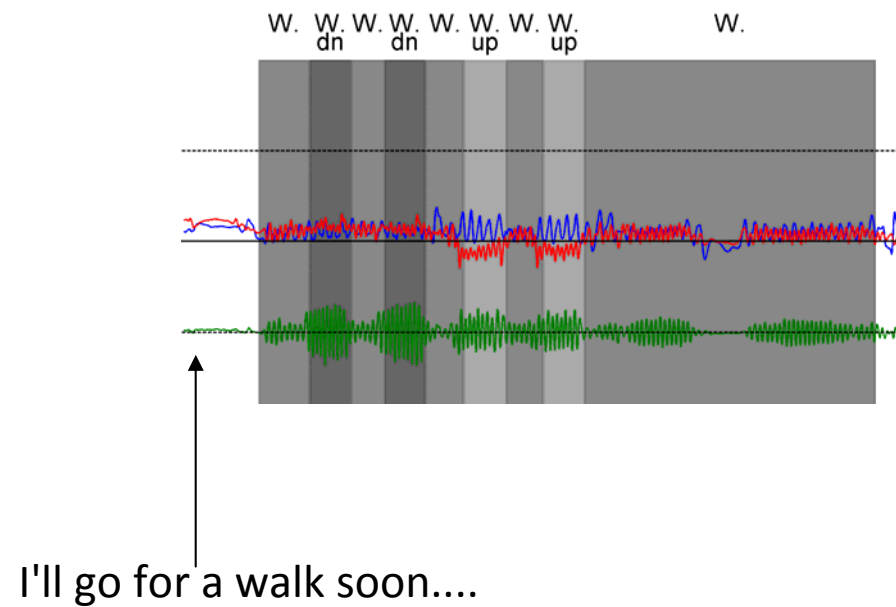
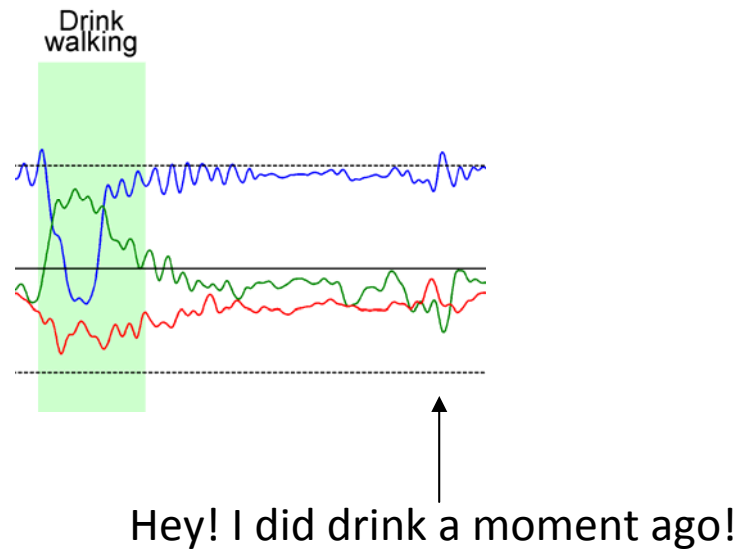


12 He listens to music.

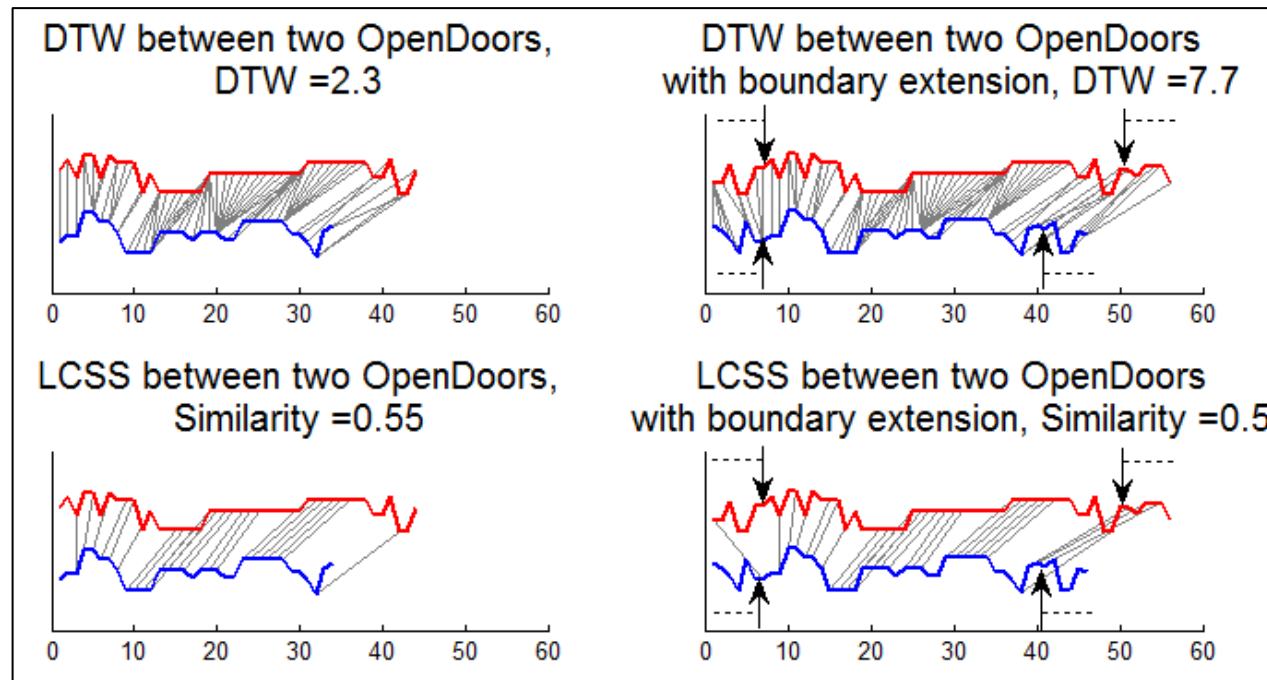
Lifelong learning + Crowd-sourcing



Exemplary challenge: label jitter



Labels with noisy boundaries: Longest Common Substring



Opportunity Dataset, avg \pm stdev of 4 users			
Method	Accuracy	F1_Null	F1_NoNull
Segmented DTW	0.37 \pm 0.02	0.37 \pm 0.03	0.33 \pm 0.03
Nonsegmented DTW	0.38 \pm 0.04	0.34 \pm 0.06	0.27 \pm 0.09
LCSS	0.48 \pm 0.03	0.48 \pm 0.04	0.44 \pm 0.08

+10% in high variability dataset

HCI Dataset			
Method	Accuracy	F1_Null	F1_NoNull
Segmented DTW	0.76	0.75	0.66
Nonsegmented DTW	0.78	0.78	0.72
LCSS	0.78	0.77	0.68

= in low variability dataset

Crowd-sourced annotations on Amazon's mechanical Turk



Task: Find Activities in Videos

Below you see 5 synchronized videos, showing a subject performing different tasks in a kitchen environment. Your task is to find the start time and end time and to select the correct activity label from the given set of activity labels.

In case an activity occurs more than once, please use the first occurrence for your answer.

Please use the provided fields to submit your answer in the form of a start/end/label triple. You can see your previously submitted information on the right hand side.

In order to get your work approved, you have to fill in the correct times in the first section and provide at least 10 tags in the second section. You can include as many tags as you want in section 1.



▶ Play all ⏮ Restart all 41 / 109 seconds

Section 1

Please provide the start time of the following activities.

Subject opens Brownie Bag 13 seconds

Subject takes small measuring Cup 24 seconds

Subject takes oil 58 seconds

Section 2

Start Time seconds

End Time seconds

Tag

+ Add Tag to list

Your Tags

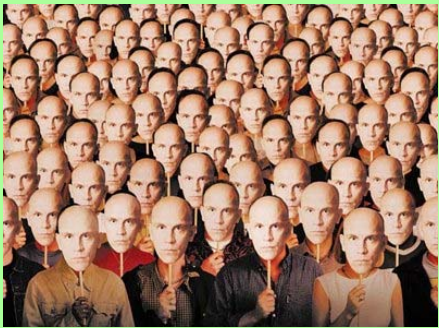
Start	End	Tag
1	9	open-brownie_bag
12	19	put-baking_pan-into-oven

→ Submit Answers



Experts tag Videos

- Accuracy: Accurate
- Time: 10hrs / 10mn Video
- Cost: $60 * 30\$ = 1800\$$ / hr Video



Crowdsourcing

- Accuracy: 80% / 10%
- Time: “overnight” if parallel
- Cost: ~100 \$ / hr Video



EC grant Nr FP6-018474-2

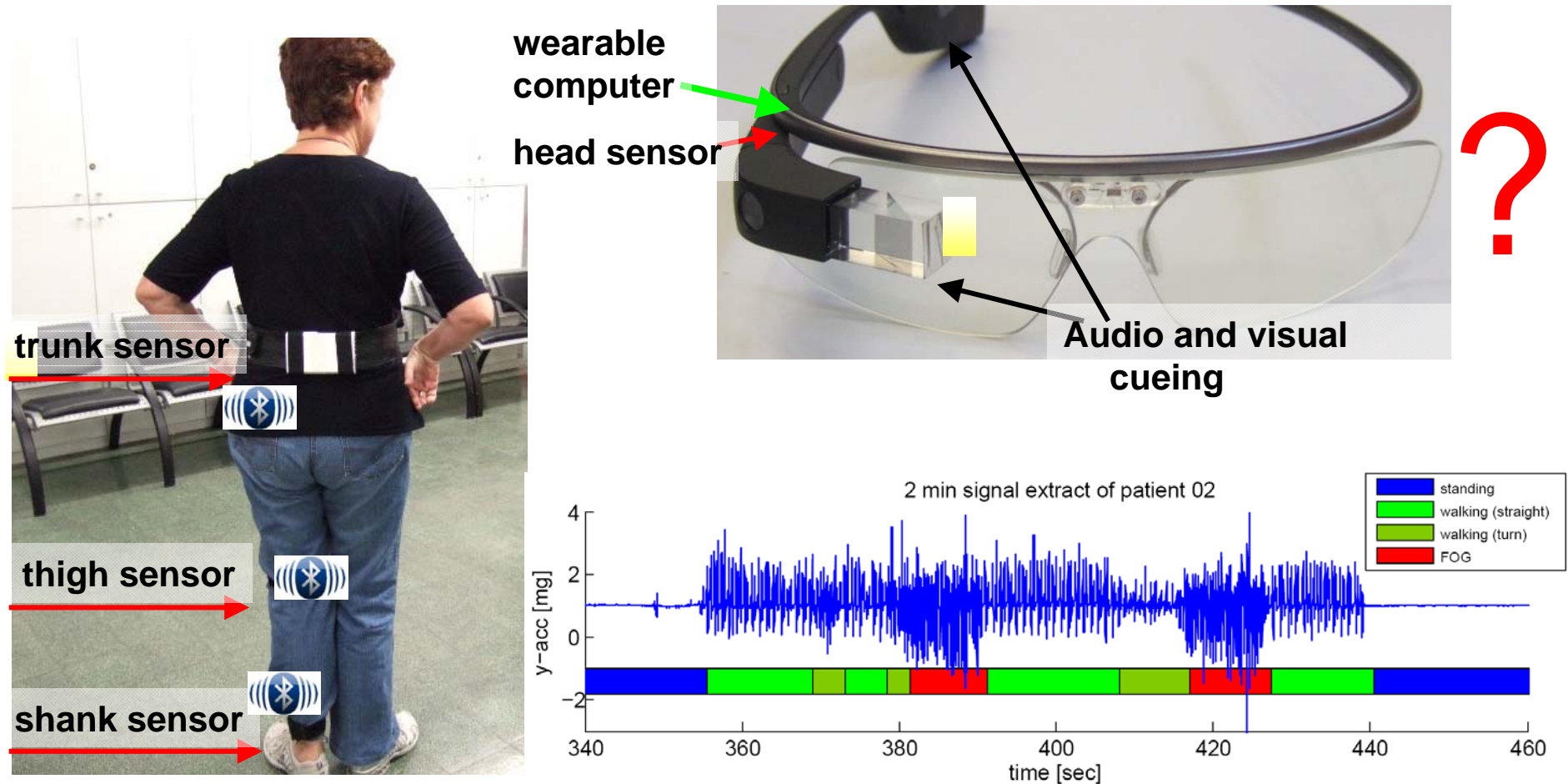


Closed-loop system for personalized
and at-home rehabilitation of people
with Parkinson's disease

EC grant FP7-288516

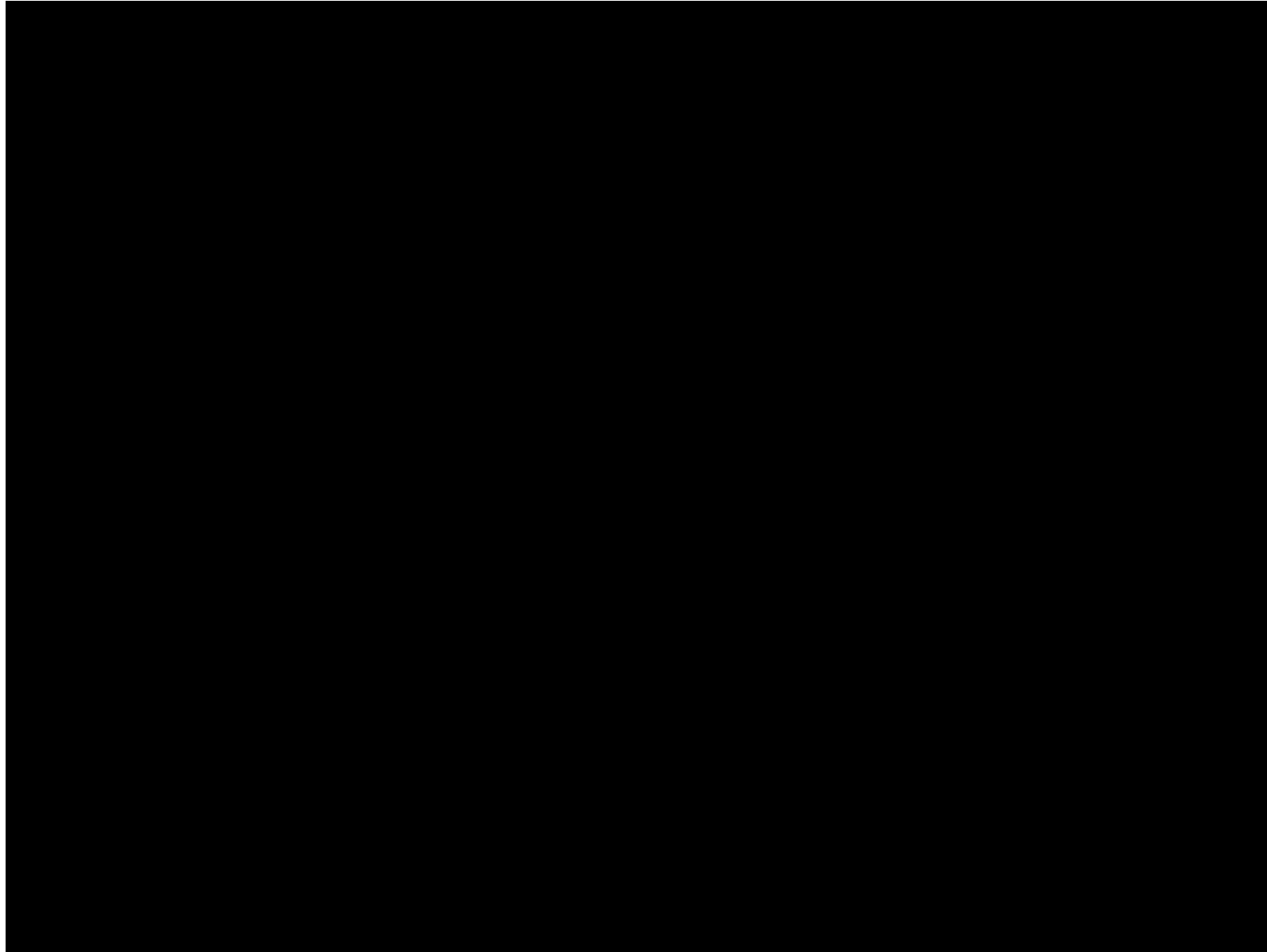


Freezing of gait (transient motor block)



M. Bächlin, M. Plotnik, D. Roggen, I. Maidan, J. M. Hausdorff, N. Giladi, and G. Tröster. Wearable Assistant for Parkinson's Disease Patients With the Freezing of Gait Symptom. IEEE Transactions on Information Technology in Biomedicine, 14(2):436 - 446, 2010.

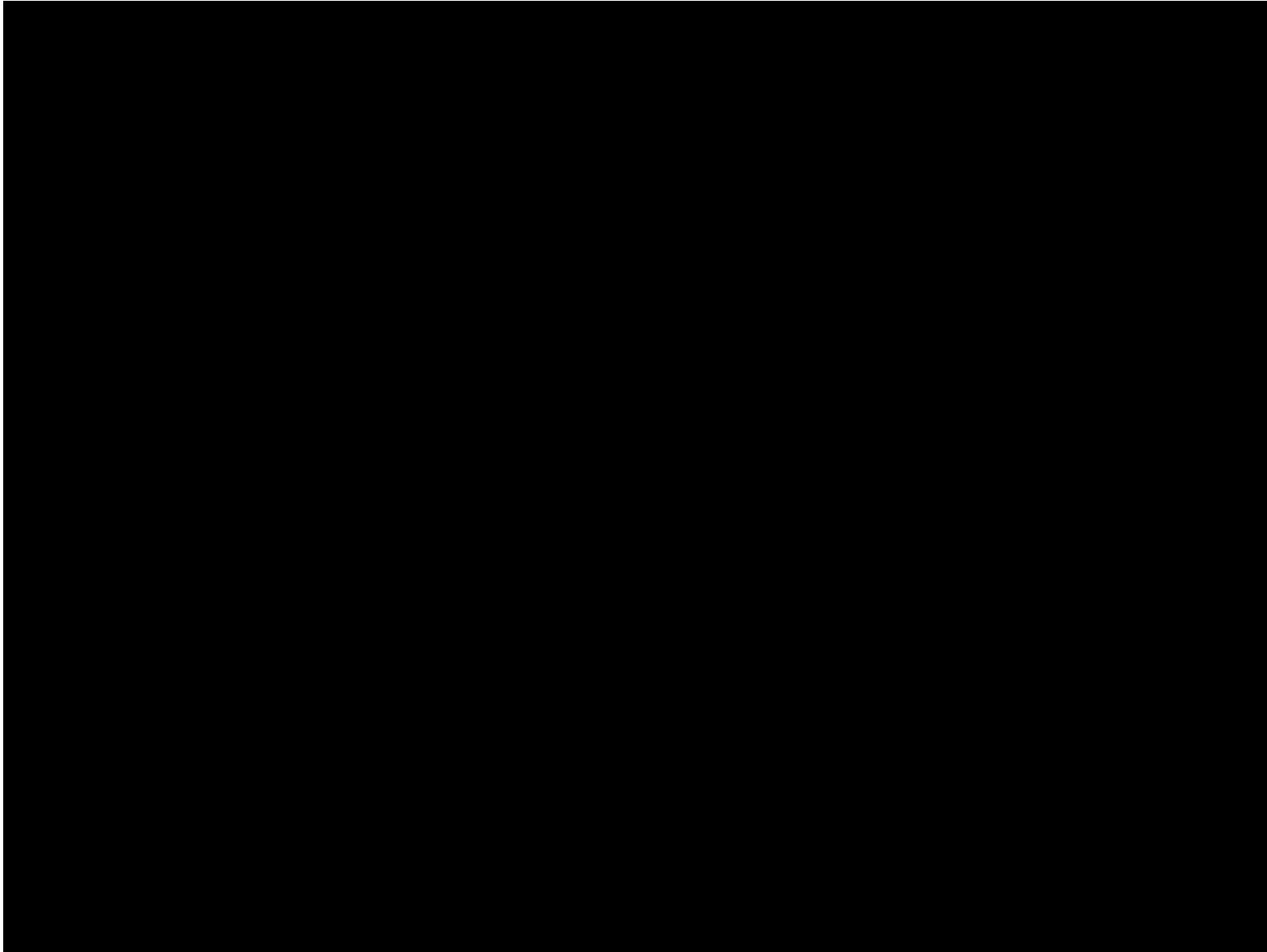
Indoor localization without (any ambient) infrastructure



Hardegger, Tröster, Roggen. Improved ActionSLAM for Long-term Indoor Tracking with Wearable Motion Sensors. ISWC 2013



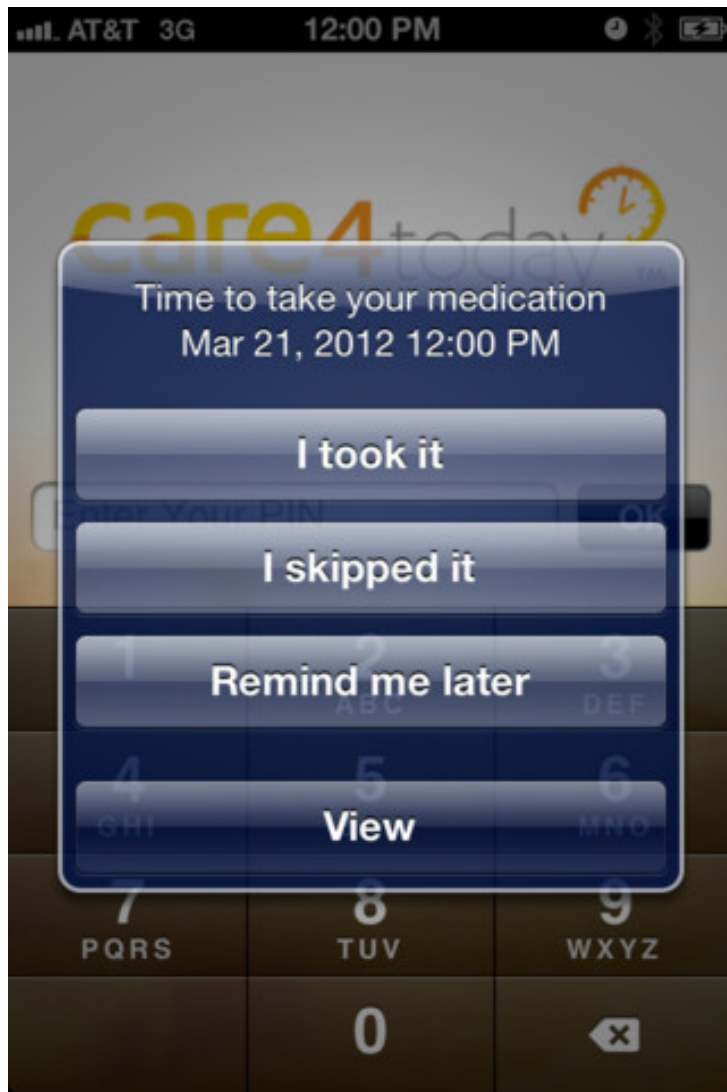
Indoor localization without (any ambient) infrastructure



Hardegger, Tröster, Roggen. Improved ActionSLAM for Long-term Indoor Tracking with Wearable Motion Sensors. ISWC 2013



Context-aware medication reminders



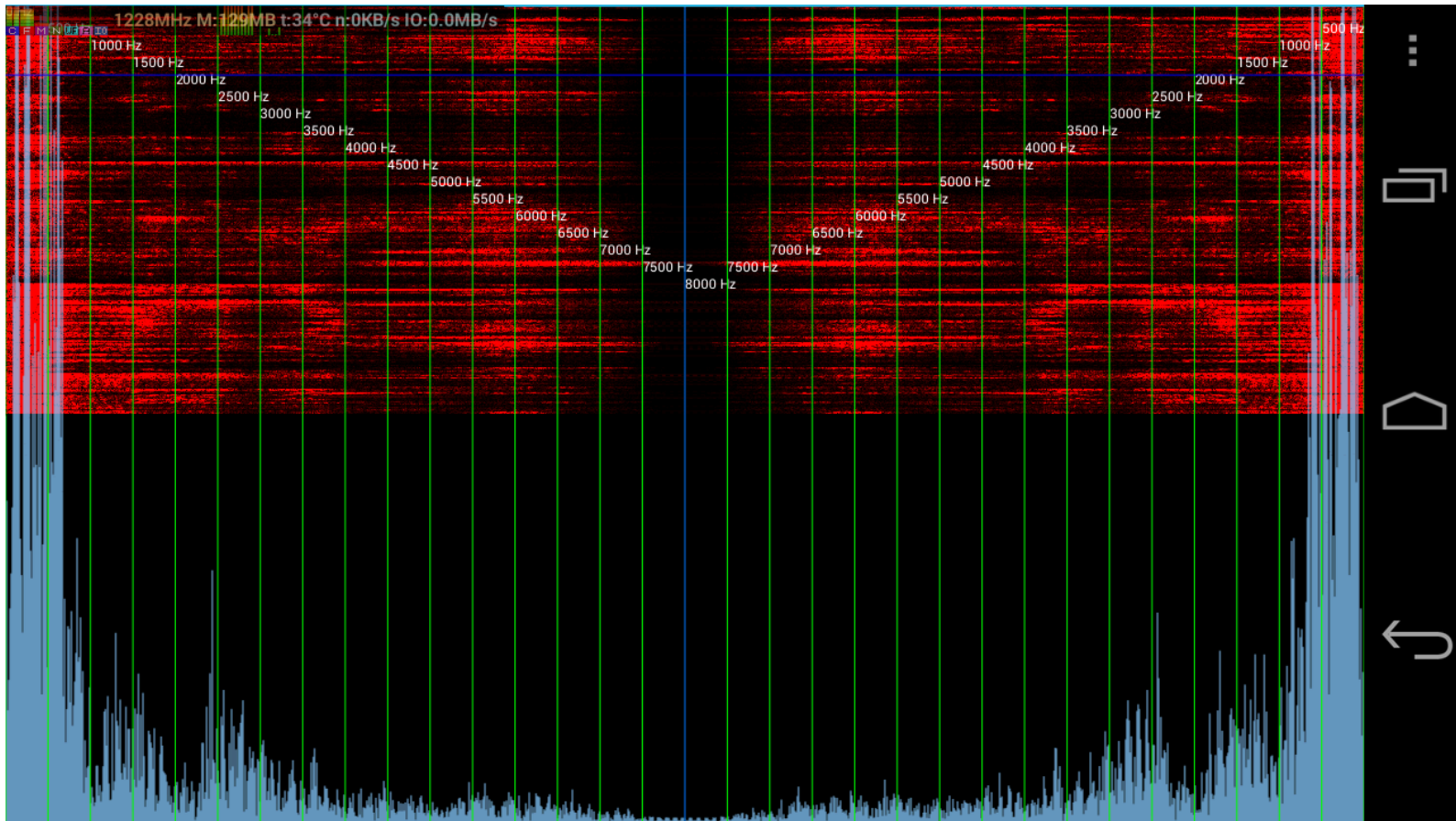
Janssen Care4Today phone application

- Main drug: Levodopa
 - Effect wears off quickly (2h-6h)
 - Abrupt “on”-”off” transitions
- Precise intake timing needed



- Context-aware reminders
- Anticipation of wear-off effect
- Automatic detection of intake

Speech loudness cueing



- Lee Silverman voice treatment
- Loudness & Intelligibility
- Training (at home) or live (in the wild)



Workshop @ Newcastle University (28.08.2013)



- 7 participants (3F, 4M)
- Discussion
 - Current artefacts used for self-management
 - Promotional videos of Glass & live Glass demo
- Glass tryouts
- Feedback

Briggs P, Blythe M, Vines J, Lindsay S, Dunphy P, Nicholson J, Green D, Kitson J, Monk A, Olivier P. Invisible design: exploring insights and ideas through ambiguous film scenarios. In: 9th ACM Conference on Designing Interactive Systems. 2012

Workshop @ Newcastle University (28.08.2013)

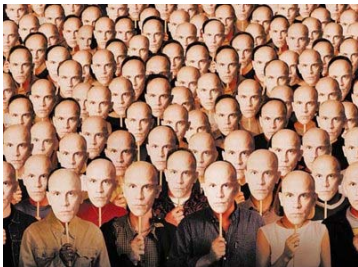


- Accept positive “Benefit – privacy” tradeoffs
- “Sharing under my control to whom I choose”
- “Same as a phone / computer”, “just another interaction”
- “Gives me confidence back, that is what I need”
- “I cannot use a phone with shopping bags and a stick, Glass would be always ready”
- “Everybody is different – interface should be customizable”

Summary



- Be opportunistic



- More digital traces == better!
 - Large datasets (many users, long-term recordings)
 - Mechanical Turk, online databases
 - More sensors (wearable & ambient)
 - Social platforms, emails



- Beyond "spotting" to "**understanding**"
 - (hidden context)



- Explore new sensor technologies

Intro to HAR & Wearable Computing:

<http://www.slideshare.net/danielroggen>

Part I: What is wearable computing?

Part II: Sensors

Part III: The activity recognition chain

Thanks!