



ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Opportunity activity recognition challenge: Results and conclusions

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SMC conference, October 9, Anchorage, USA





“The image is probably **the most widely used test image** for all sorts of image processing algorithms (such as compression and denoising) and related scientific publications.”

Wikipedia, 5 Oct 2011

“...the image contains a nice mixture of detail, flat regions, shading, and texture that **do a good job of testing** various image processing algorithms.”

D.C. Munson, JR. “A note on Lena”, IEEE Trans Image Processing (5) 1, 1996

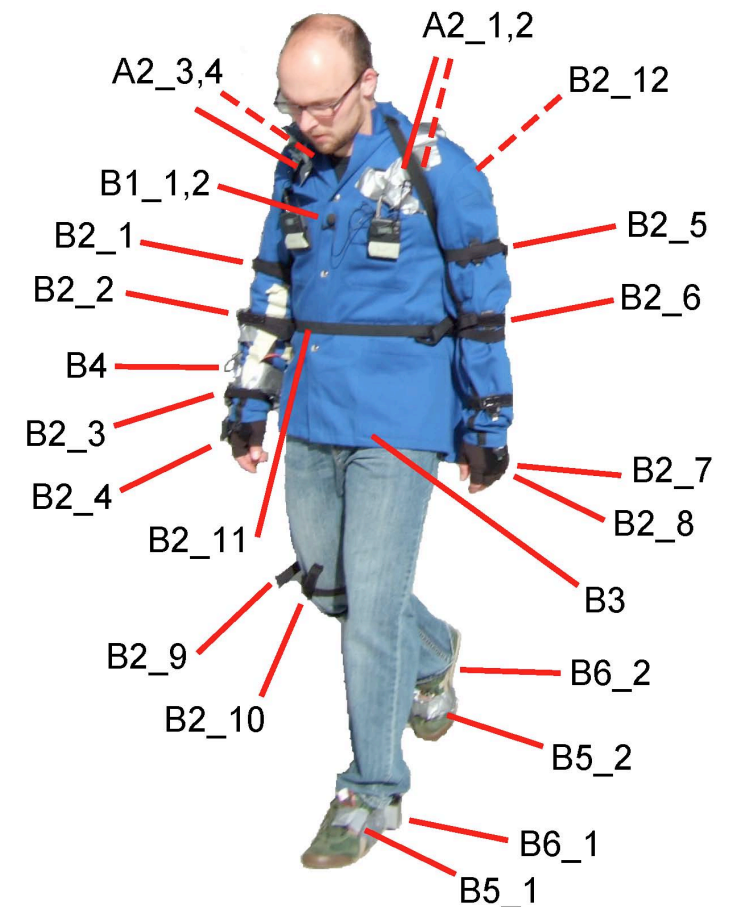
Looking for an AR Lena

- Currently each group test their methods on specifically designed, controlled experimental setups
 - Data is often not reused (despite large amount of resources devoted to collect it)
 - Provide means for replicable, fair comparison of different methods, by different groups
 - Encourage collaboration across groups
 - Further advance the field through healthy ‘competition’
- Provide a common platform to evaluate different methods for activity recognition

Looking for an AR Lena

- Provide a common platform to evaluate different methods for activity recognition
 - Common database for addressing different AR challenges
 - Realistic scenario
 - Variety of sensing modalities
 - Uneven number of samples per class
 - Unsegmented data
 - Annotated database
 - Easy to use

Looking for an AR Lena

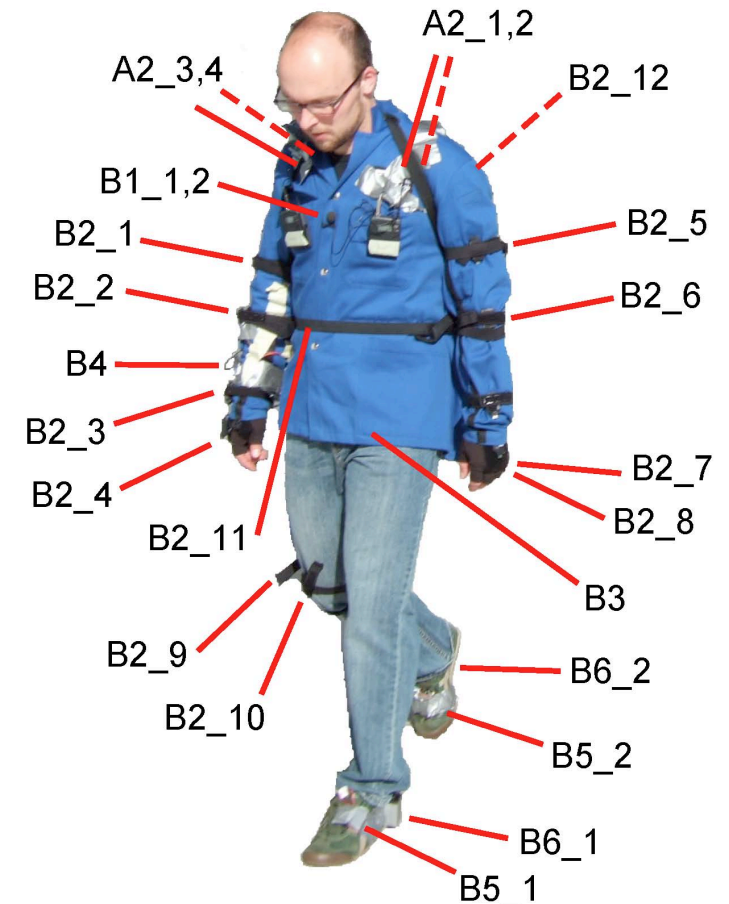


Looking for an AR Lena



“[...] a challenge on activity recognition aimed at:

- We call for methods for tackling questions [...] such as classification based on [multimodal recordings](#), [activity spotting](#) and [robustness to noise](#).”
- Provide a [common platform](#) that allows the comparison of different machine learning algorithms on the very same conditions.



Similar initiative

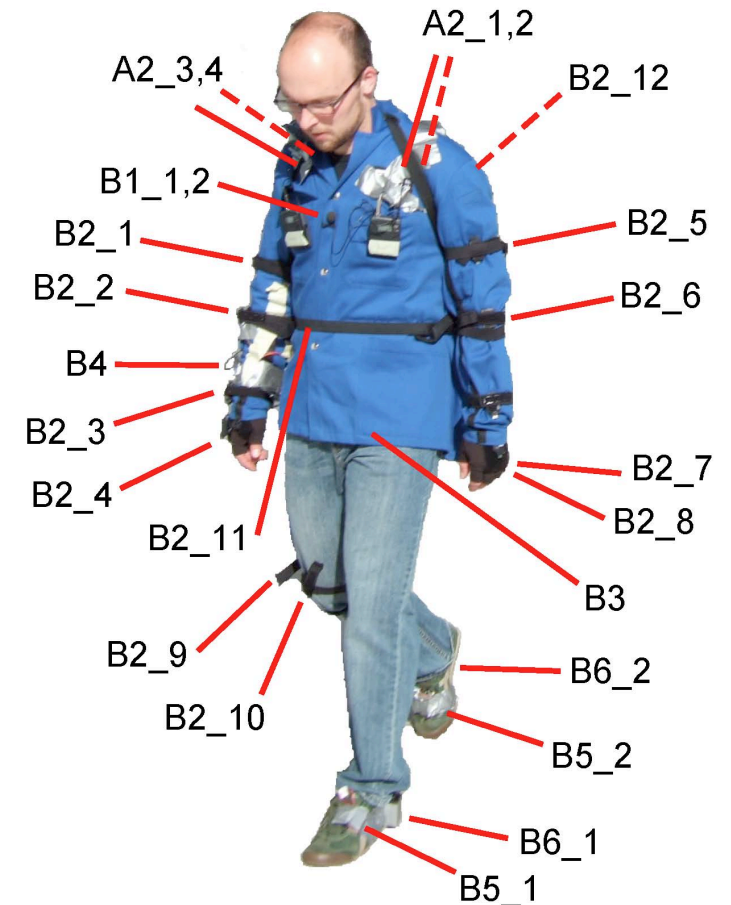
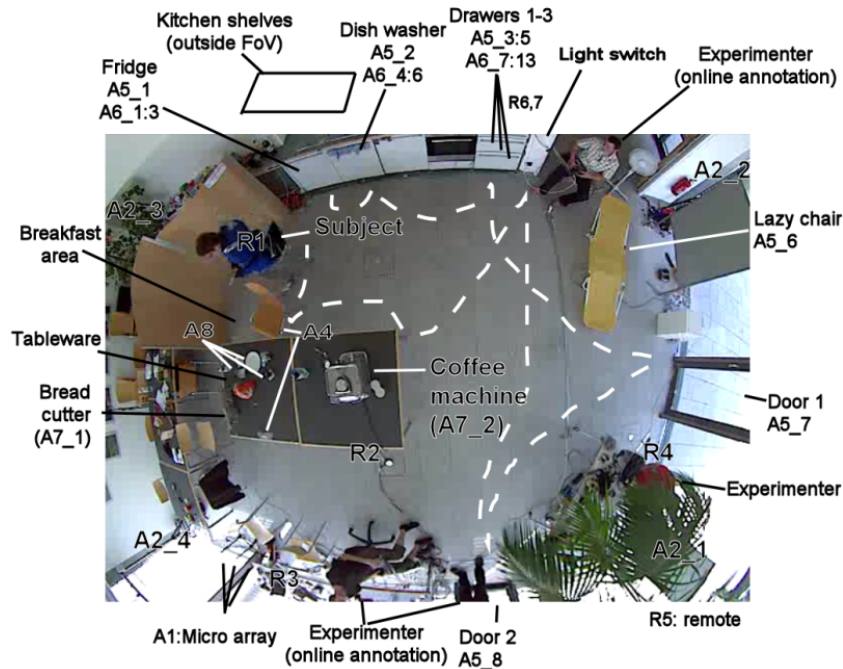
- Organizers
 - Roozbeh Jafari, UT Dallas
 - John Lach, U Virginia
- Dates: April 1 -> May 24 2011 (BSN 2011)
- Participants should submit results and code
- Three tasks, datasets from different groups
 - Action recognition (9 classes)
 - Stride time detection
 - Sit/Stand detection
- Evaluation: Accuracy without considering false negatives (insertions not counted as errors)
- Initially thought to run the tests on-place (2 hrs). Had to be changed to be performed remotely. Different format for test data. Organizers were required to release a sample test set
- 8 teams registered, 5 teams finally took part on it. No information available (yet) about submitted methods (AFAIK)

Body Sensor Network Contest

<http://bsncontest.org/>

Opportunity activity dataset

- Activities of a daily living (breakfast scenario)
- On-body, object-based, ambient sensors
- 72 sensors of 10 modalities
- 12 subjects
 - 5 ADL, 1 Drill



Project-wide benchmark

Activity recognition and system adaptation

- Chavarriaga et al. **Ensemble creation and reconfiguration** for activity recognition: An information theoretic approach. IEEE SMC, 2011
- H. Sagha et al. **Detecting anomalies** to improve classification performance in an opportunistic sensor network, IEEE PerSens, 2011.
- A. Calatroni et al., **Automatic transfer** of activity recognition capabilities between body-worn motion sensors: Training newcomers to recognize locomotion, INSS, 2011
- M. Kurz et al. **Dynamic Quantification** of Activity Recognition Capabilities in Opportunistic Systems. Fourth Conference on Context Awareness for Proactive Systems, 2011
- A. Manzoor et al., Identifying Important **Action Primitives** for High Level Activity Recognition, EuroSSC 2010
- R. Chavarriaga et al. **Robust activity recognition** for assistive technologies: Benchmarking ML techniques, NIPS Workshop, 2010.

Data processing

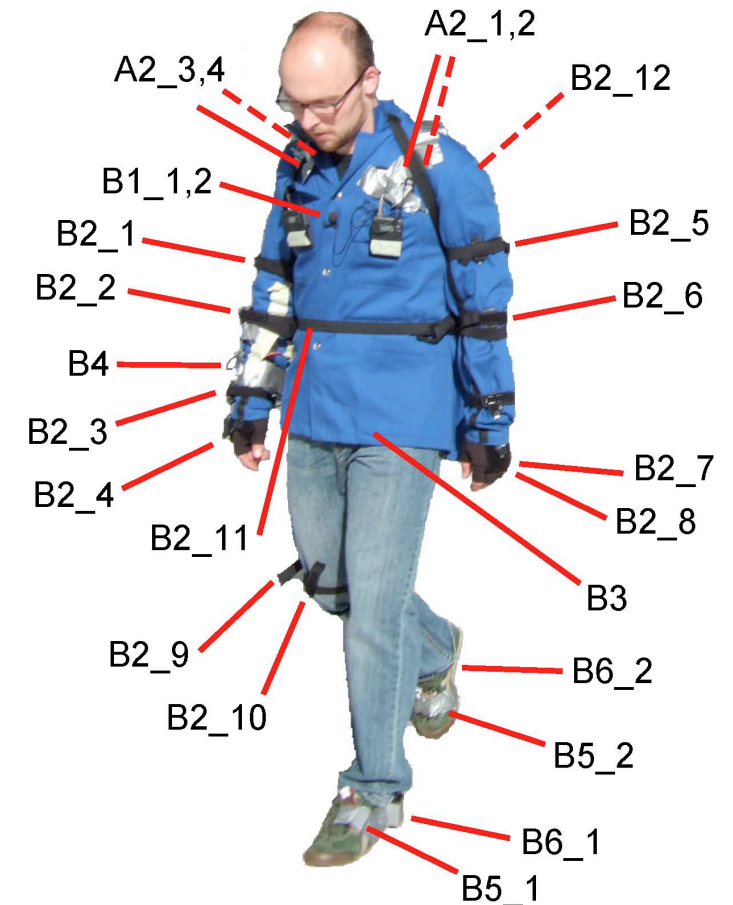
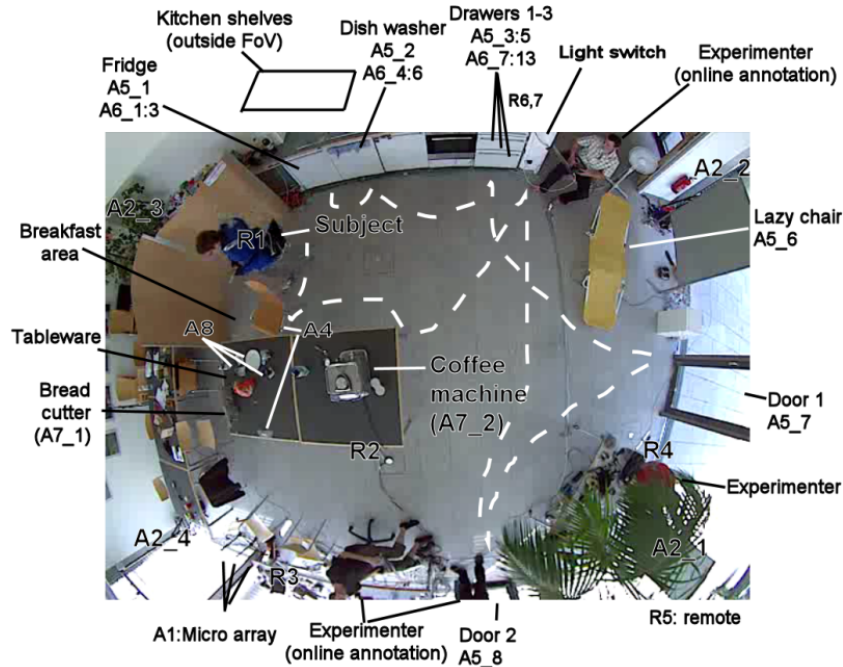
- The OPPORTUNITY Framework and **Data Processing Ecosystem** for Opportunistic Activity and Context Recognition, Int J Sensors, Wireless Communications and Control, 2011.
- A **Framework for Opportunistic** Context and Activity Recognition. Pervasive, 2011.

Data collection

- D. Roggen et al. Walk-through the **OPPORTUNITY dataset** for activity recognition in sensor rich environments, Pervasive Workshop, 2010
- P. Lukowicz et al. **Recording a complex, multi modal activity** data set for context , ARCS, 2010,

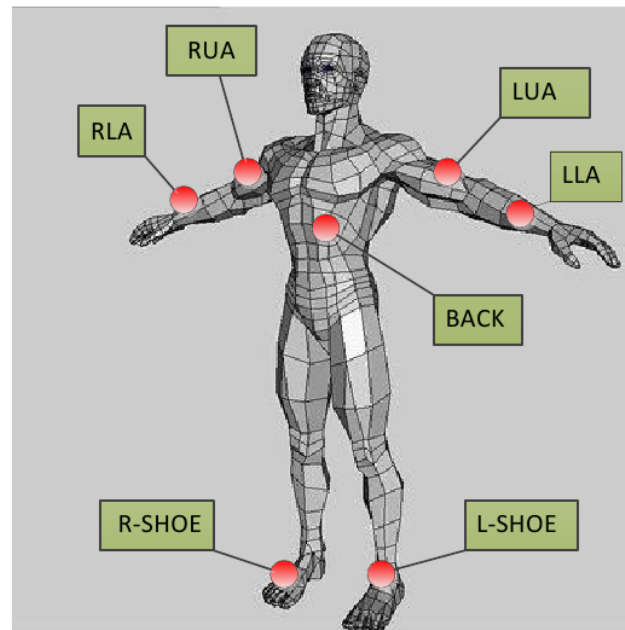
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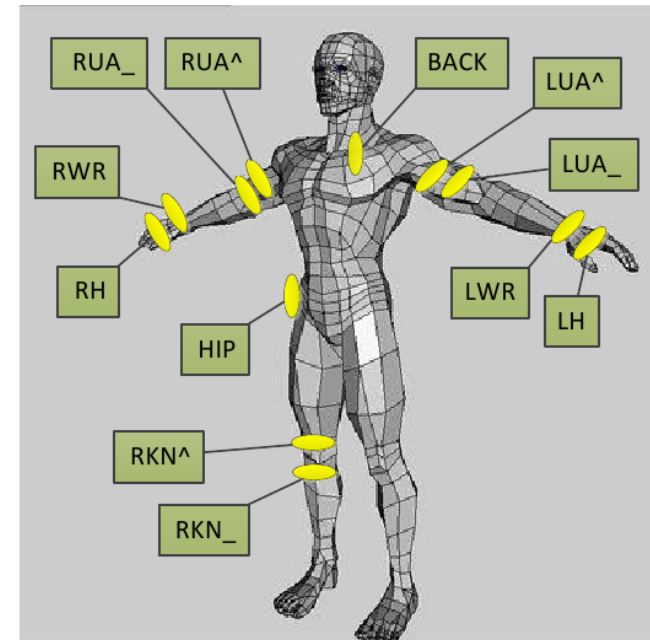


The Challenge dataset

- 19 on-body sensors
 - Motion Jacket (5 IMUs)
 - 12 bluetooth 3-axial accelerometers
 - InertiaCube3 on each foot



● = Complete Inertial Measurement Unit



● = Triaxial Accelerometer

The Challenge dataset

- 19 on-body sensors
 - Motion Jacket (5 IMUs)
 - 12 bluetooth 3-axial accelerometers
 - InertiaCube3 on each foot
- 4 subjects
 - 1 subject: training data
 - 3 subjects: training & test

	S1	S2	S3	S4
Drill	•	•	•	•
ADL 1	•	•	•	•
ADL 2	•	•	•	•
ADL 3	•	•	•	•
ADL 4	•	■	■	■
ADL 5	•	■	■	■

- Labelled
- Unlabelled

Tasks

- **Task A:** Multimodal activity recognition: Modes of locomotion
- **Task B1:** Automatic segmentation
- **Task B2:** Multimodal activity recognition: Gestures
- **Task C:** Robustness to noise: Gestures

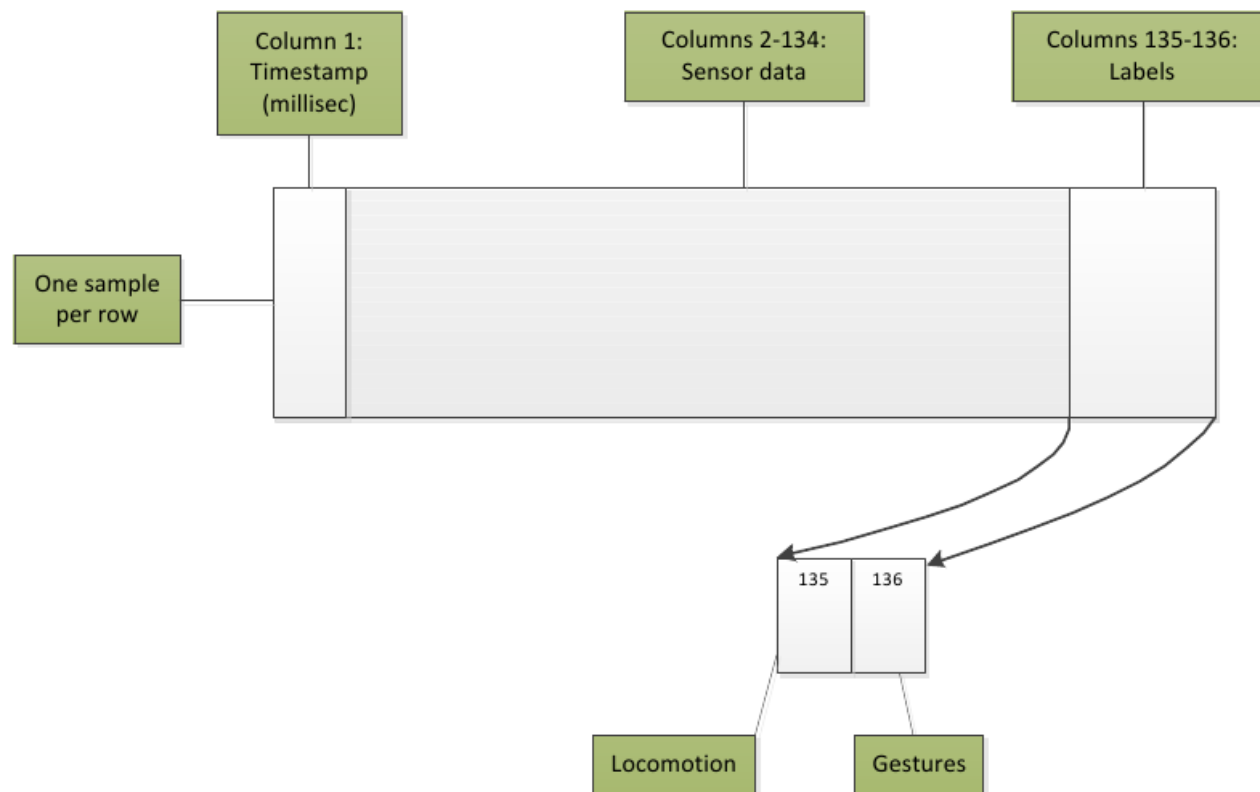
	S1	Tasks A, B1,B2		S4
		S2	S3	
Drill	•	•	•	•
ADL 1	•	•	•	•
ADL 2	•	•	•	•
ADL 3	•	•	•	•
ADL 4	•	■	■	■
ADL 5	•	■	■	■

Tasks

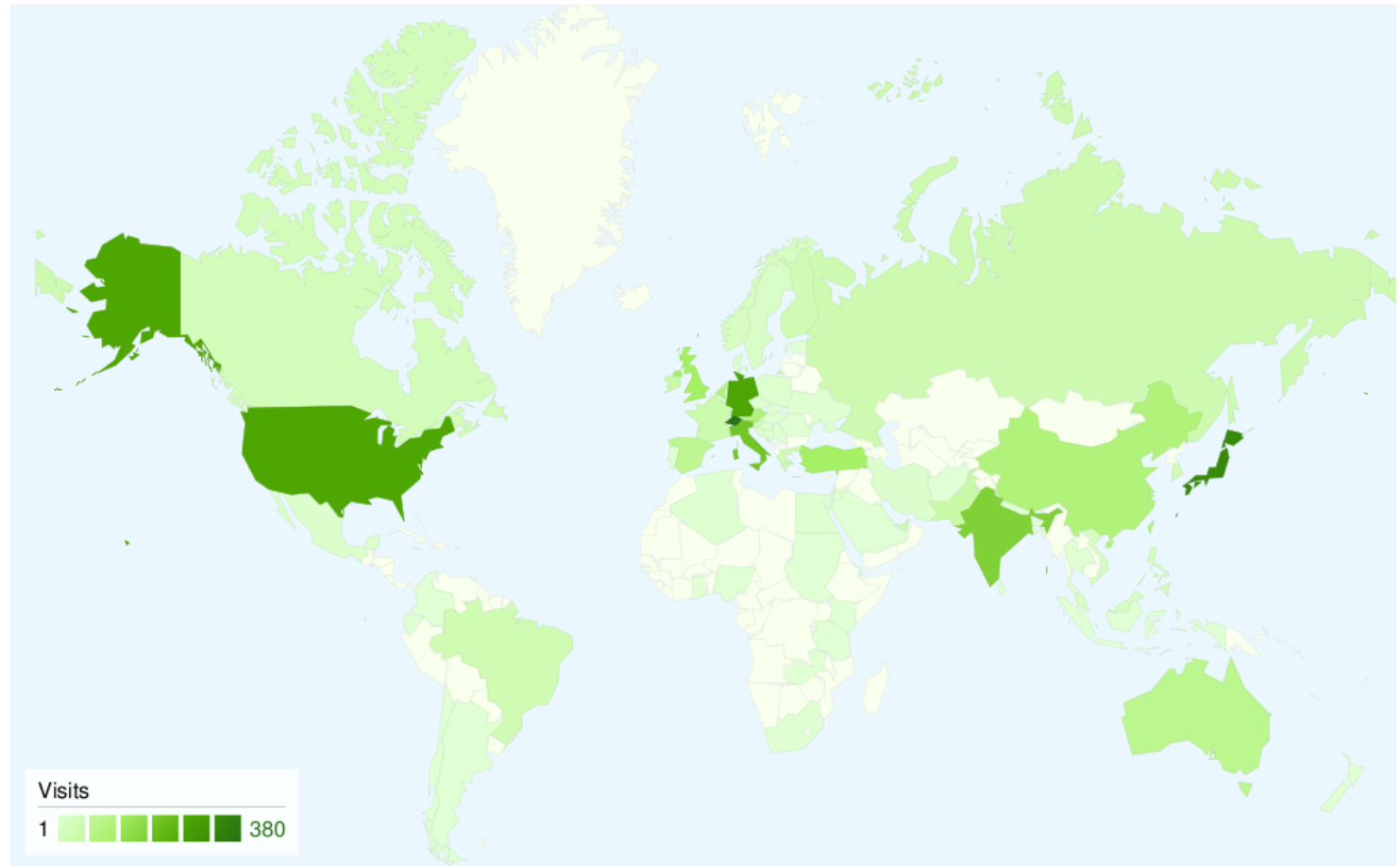
- Task A: Multimodal activity recognition: Modes of locomotion
- Task B1: Automatic segmentation
- Task B2: Multimodal activity recognition: Gestures
- Task C: Robustness to noise: Gestures

Modes of locomotion				
Null	Stand	Sit	Walk	Lie
Gestures				
Null	clean Table	open Drawer1	close Drawer1	
open Dishwasher	close Dishwasher	open Drawer2	close Drawer2	
open Fridge	close Fridge	open Drawer3	close Drawer3	
open Door1	close Door1	open Door2	close Door2	
move Cup				

Data format



- Text file
- Not compact but easy to use (no learning curve required)
- Missing samples (due to bluetooth disconnections) coded as NaN



- Launched on week of 20th May
<http://www.opportunity-project.eu/challenge>



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 431 Unique Views

- Launched on week of 20th May

<http://www.opportunity-project.eu/challenge>

- 15 registrations before deadline
- 9 submissions
- 7 different teams



Challenge Results

	Task			
	A	B1	B2	C
Number of submissions	8	4	4	2

- No requests for early-feedback (available 12 weeks before deadline)
- 8 submissions for Modes of Locomotion (Task A)
 - (Rather) well defined classes
 - More balanced dataset
 - Fewer number of 'Null' samples
- 4 Submissions for Gesture-related tasks (Task B1,B2)
 - Arbitrary selection of gestures (app-dependent)
 - Higher uncertainty on task on/off set
 - Large number of 'Null' samples
- 2 of submissions for noisy data (Task C)
 - Presumably more challenging

Teams

Team	Institute	Person	Task			
			A	B1	B2	C
Tominaga	Univ. Tokyo,JP	Shoji Tominaga	•			
CSTAR	A*Star,SG	CAO	•	•	•	
NSTAR	A*Star,SG	Nguyen	•	•	•	
SSTAR	A*Star,SG	CAO	•	•	•	
Giuberti	Univ. Parma,IT	Matteo Giuberti	•	•	•	•
Aamena	Masdar Inst., UAE	Aamena Alshamsi	•			
Zabdallah	Monash, AU	Zahraa Abdallah	•			
Tenki	Nagoya, JP	Tianhui Yang	•			
NAGS	IIT, IN	Naveen				•

Methods

Team	Sensors	Missing data	Feature	Classifier
Tominaga		Skip+Repeat last decision	Mean+Var , Normalization, PCA	Adaboost of thresholding
CStar		Spline Interpolation	Scaled data	SVN+1-NN +Fusion +Smoothing
NStar		Spline Interpolation	Normalized data	1-NN
SStar		Linear Interpolation	Scaled data	SVM
Giuberti			Mean,Var,Max,Min,Time	Comparison
Aamena			PCA~66	1-NN
Zabdallah			-	Decision tree
Tenki	Acc		Mean+Var+Energy (256 samples, 56 overlap)	C4.5 decision tree
NAGS			-	HMM

TASK A (Locomotion)

	Norm F1	Accuracy
Zabdallah	0.86912	0.86893
CStar	0.86833	0.8681
NStar	0.86326	0.86523
Aamena	0.86321	0.85267
SStar	0.86186	0.86101
Giuberti	0.8425	0.84082
Tenki	0.74939	0.73856
Tominaga	0.73296	0.73613

Team	Sensors	Missing data	Feature	Classifier
Zabdalla			-	Decision tree
CStar		Spline Interpolation	Scaled data	SVN+1-NN +Fusion +Smoothing
NStar		Spline Interpolation	Normalized data	1-NN

TASK B1 (Gesture Segmentation)

	F1	Accuracy
CStar	0.86134	0.90465
NStar	0.80397	0.86873
SStar	0.79237	0.89116
Giuberti	0.41375	0.65706

Team	Sensors	Missing data	Feature	Classifier
CStar		Spline Interpolation	Scaled data	SVN+1-NN +Fusion +Smoothing
NStar		Spline Interpolation	Normalized data	1-NN
SStar		Linear Interpolation	Scaled data	SVM

TASK B2 (Gestures)

Removing null AFTER F1 measure

	Norm F1	Accuracy
CStar	0.87688	0.87153
SStar	0.85623	0.85447
NStar	0.83978	0.83305
Giuberti	0.64452	0.62019

Removing null BEFORE F1 measure

	Norm F1	Accuracy
CStar	0.77142	0.70079
SStar	0.69559	0.60017
NStar	0.65275	0.56288
Giuberti	0.21705	0.14739

Team	Sensors	Missing data	Feature	Classifier
CStar		Spline Interpolation	Scaled data	SVN+1-NN +Fusion +Smoothing
NStar		Spline Interpolation	Normalized data	1-NN
SStar		Linear Interpolation	Scaled data	SVM

TASK C (Gesture + Noise)

	Norm F1	Accuracy
NAGS	0.71104	0.7541
Giuberti	0.6351	0.64128

Team	Sensors	Missing data	Feature	Classifier
NAGS			-	HMM
Giuberti			Mean,Var,Max,Min,Time	Comparison

Sum up

Task A	Task B1	Task B2	Task C
Zabdallah(DT)	CSTAR	CSTAR	NAGS(HMM)
CStar (SVN+1NN)	NStar	SStar	Giuberti
NStar(1-NN)	SStar	NStar	
Aamena (1-NN)	Giuberti	Giuberti	
SStar(SVN)			
Giuberti			
Tenki(C4.5)			
Tominaga (Adaboost)			

General remarks

- Excellent feedback from community
 - Request for using the database for other uses than challenge.
 - Feedback from participants allowed us to identify inconsistencies in the labelling and further improve it
- Nobody asked for early-feedback (available 12 weeks before deadline)
- Generalized use of standard methods and tools (e.g. Weka)
- Only one team send code (suggested by not enforced by the rules)

About the methods

- Classification methods
 - Well-known widely used methods.

Are they really good enough?

- Missing values
 - Only 2 teams specifically addressed this issue (including the best performers)
 - Other groups discarded these sensors
- Feature selection
 - Not dedicated method for feature selection (despite rather large feature space)
 - Hand-picked features
 - Some PCA

Deterrents to submission?

- Scenario not interesting enough
- (Perceived) difficulty of the task
- Uneasiness of working with someone else's data
- Lack of ground truth on the 'test' data
- Afraid of sharing new methods (Preclude future publications)
- Doesn't lead immediately to a publication
- Busy calendar (too many conferences)
- Fear of bad ranking
- ??

Last thoughts

- Time is ripe to have common test platforms
- Community is (probably) less motivated to allow others to test their methods

“...When can I have the test labels?”

- Need to gather feedback to better understand the needs and drives of the community
- Sharing the data is a challenge by itself
 - Formats, Documentation, Labelling

This can be crowdsourced !!!



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Workshop on Robust machine learning techniques for human activity recognition

R. Chavarriaga (EPFL), D. Roggen (ETHZ), A. Ferscha (JKU)
SMC conference, October 9, Anchorage, USA

A venue to discuss machine learning techniques for human
activity recognition, as well as the need for proper
benchmarking datasets and tools