



Wearable Computing: Accelerometers' Data Classification of Body Postures and Movements

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UGULINO



DÉBORA



KATIA



EDUARDO



RUY



HUGO FUKS



UGULINO

**Research Area: on-body sensors
and hybrid sensors approaches**
(Wearable sensors from the Arduino Toolkit)



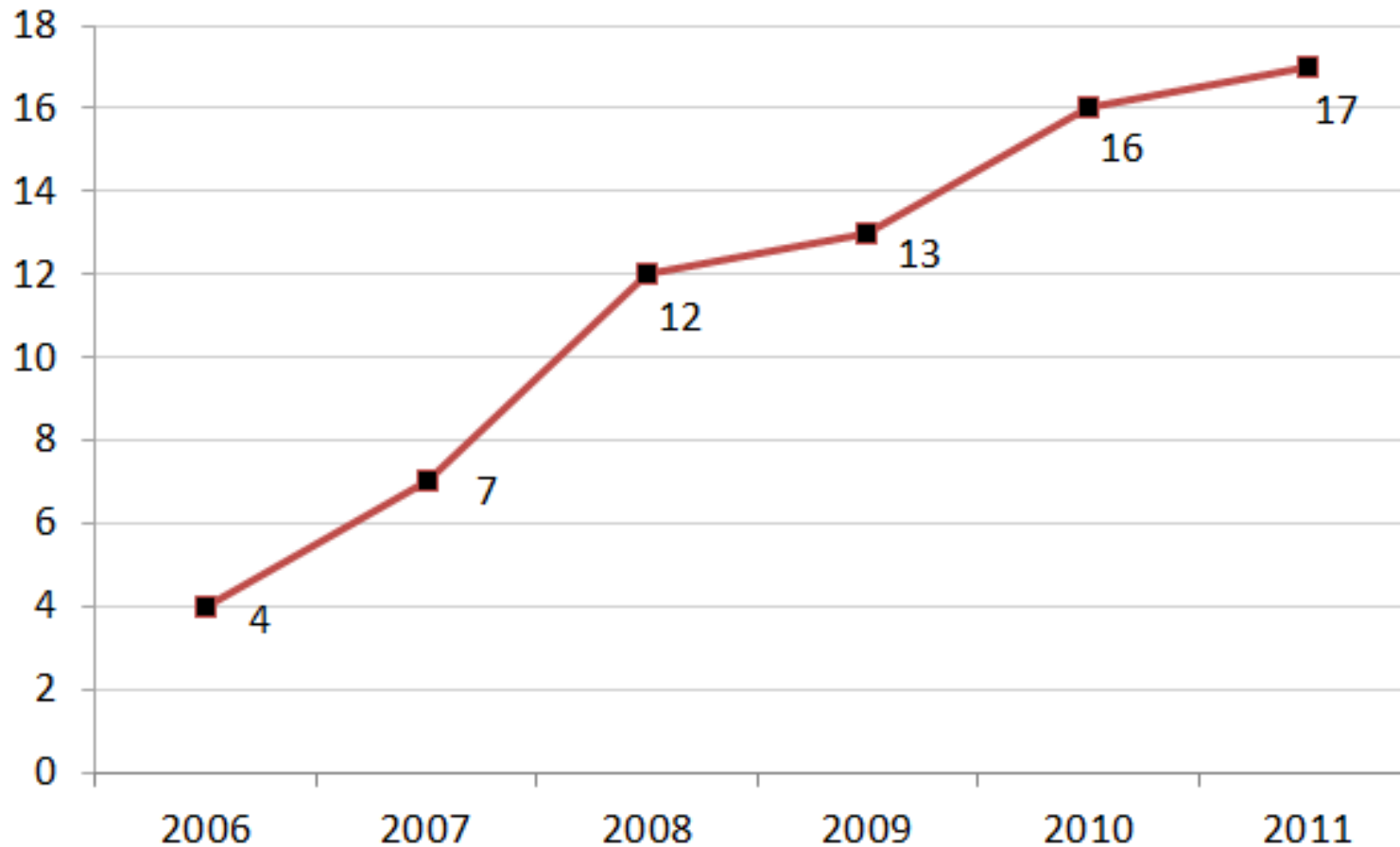
EDUARDO

Research Area: ambient sensors approaches
(mainly based on Microsoft Kinect, and
Interactive systems)

- Rise of Life Expectancy and ageing of population
 - UbiComp technologies have the potential to support elderly independent living.
 - Monitoring of Daily Living Activities.
 - Monitoring of Exercises (Weight Lifting, for example).
 - Qualitative Activity Recognition.
 - *Life log* to improve patient's chart.
- A new world, awash of sensors' data
 - How to interpret the raw data?

- On-body sensing
 - Outdoor activities (bicycle, jogging, walking)
 - A log for the whole day
 - Personal technology
 - Wearable devices are able to carry many information of a patient
- Ambient Sensing
 - More context information
 - Not so many informations from the patient (heart beating?)
 - Often restricted to indoor environments
 - Privacy issues

- Systematic approach (Reliability and construct validity)
- Research Question: What are the research projects conducted in recognition of human activities and body postures using accelerometers?
- Search string: (((("Body Posture") OR "Activity Recognition")) AND (accelerometer OR acceleration)). Refined by: publication year: 2006 – 2012;
- Results in IEEE database: 144 articles;
- Exclusion criteria
 - Smartphones, image processing, not human, composite activities, games, gesture input recognition, energy consumption
 - We used the most recent publication of same research
- Result: 69 articles



IEEE publications of HAR based on wearable accelerometers

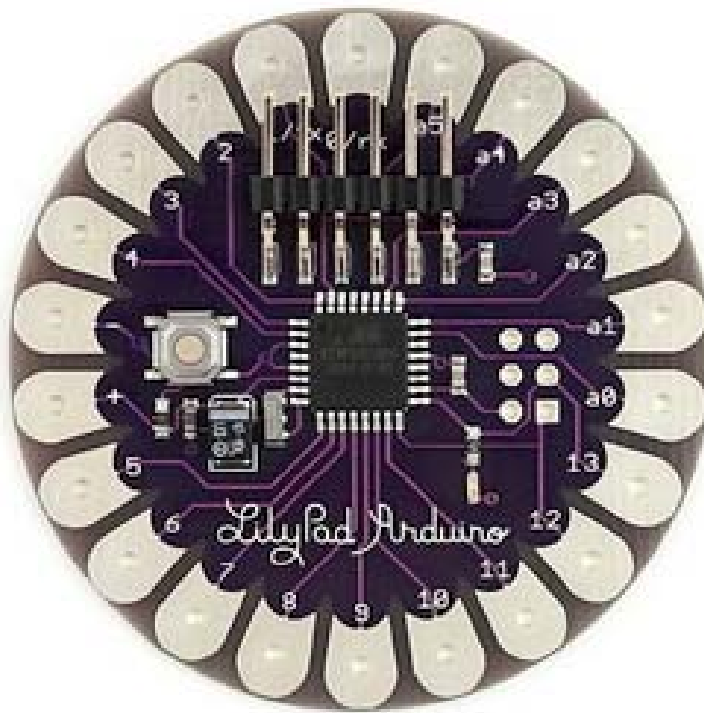
- Technique for activity recognition
 - Machine Learning (70%)
 - Supervised Learning (62%)
 - Unsupervised Learning (7%)
 - Semi-supervised Learning (1%)
 - Treshold-based algorithms (27%)
 - Others (3%)
 - Fuzzy finite state machines, ontology reasoning, etc.

- Subject Independent analysis
 - Only 3 out of 69 papers (4.3%)

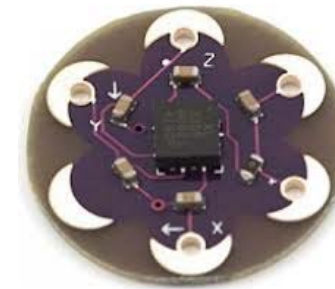
Research	# of sensors	Technique	# of users	Learning mode	Correct (%)
Liu et al., 2012	1	SVM	50	Supervised	88.1
Yuting et al., 2011	3	Threshold-based	10	--	98.6
Sazonov et al., 2011	1	SVM	9	Supervised	98.1
Reiss & Stricker, 2011	3	Boosted Decision Tree	8	Supervised	90.7
Min et al., (2011)	9	Threshold-based	3	--	96.6
Maekawa & Watanabe, 2011	4	HMM	40	Unsupervised	98.4
Martin et al., 2011	2	Threshold-based	5	--	89.4
Lei et al., 2011	4	Naive Bayes	8	Supervised	97.7
Alvarez et al., 2011	1	Genetic fuzzy finite state machine	1	Supervised	98.9
Jun-ki & Sung-Bae, 2011	5	Naive Bayes and SVM	3	Supervised	99.4
Ioana-Iuliana & Rodica-Elena, 2011	2	Neural Networks	4	Supervised	99.6
Gjoreski et al., 2011	4	Naïve Bayes, SVM, C4.5, Random Forest	11	Supervised	90
Feng, Meiling, and Nan, 2011	1	Threshold-based	20	--	94.1
Czabke, Marsch, and Lueth, 2011	1	Threshold-based	10	--	90
Chernbumroong, et al., 2011	1	C4.5 and Neural Networks	7	Supervised	94.1
Bayati et al., 2011	--	Expectation Maximization	--	Unsupervised	86.9
Atallah et al., 2011	7	Feature Selection algorithms*	11	Supervised	--
Andreu et al., 2011	1	fuzzy rule-based	--	Online learning	71.4

- A few datasets (publicly) available
 - Lianwen Jin (South China University)
 - No timestamp
 - Unsynchronized readings (you must choose one sensor to use)
 - 1278 samples
 - Available (you must send him a signed license agreement)

Arduino LilyPad board

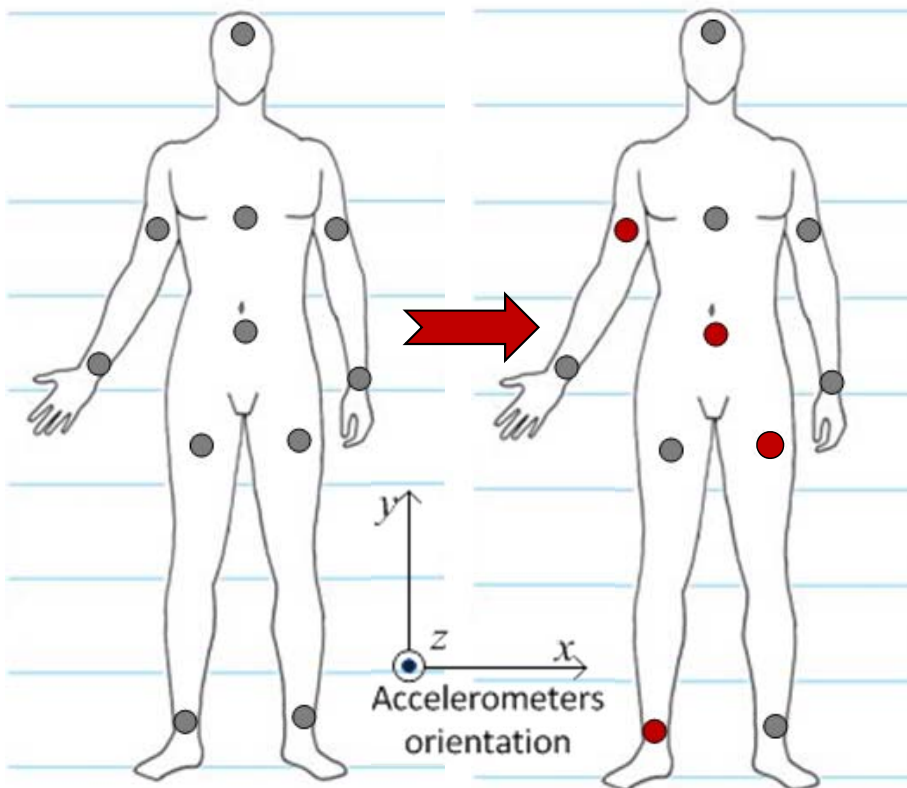


LilyPad Accelerometer (tri-axial, $\pm 3.6g$)

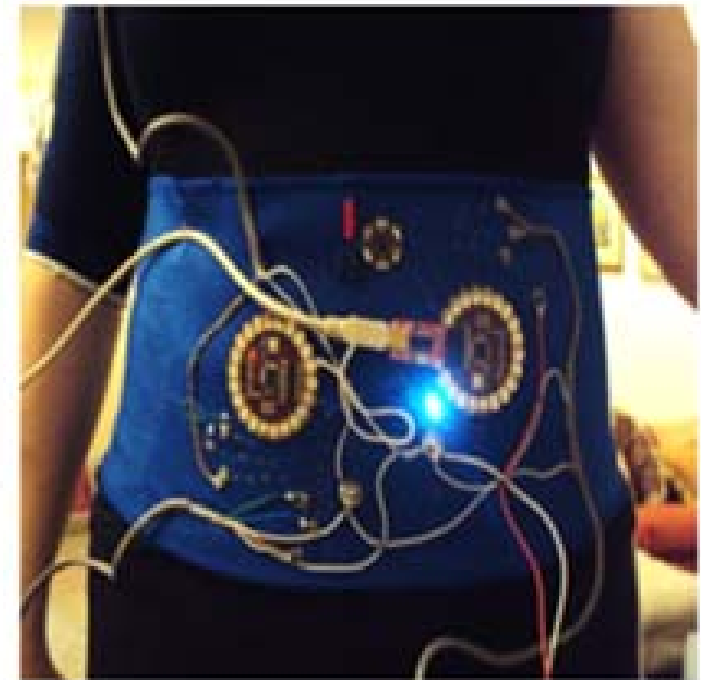


ADXL335 Frequency: 10hz

Positioning



User wearing the device



- Task

- Classifying task (multiclass)
- Output: sitting, standing, standing up, sitting down, walking
- Input:

@Accel \mathbf{x} _readings: $\langle x, y, z, m, r, p \rangle$

x, y, z : raw acceleration data from accelerometers

(m) Module of the acceleration vector

(r) Rotation over the x axis

(p) Rotation over the y axis

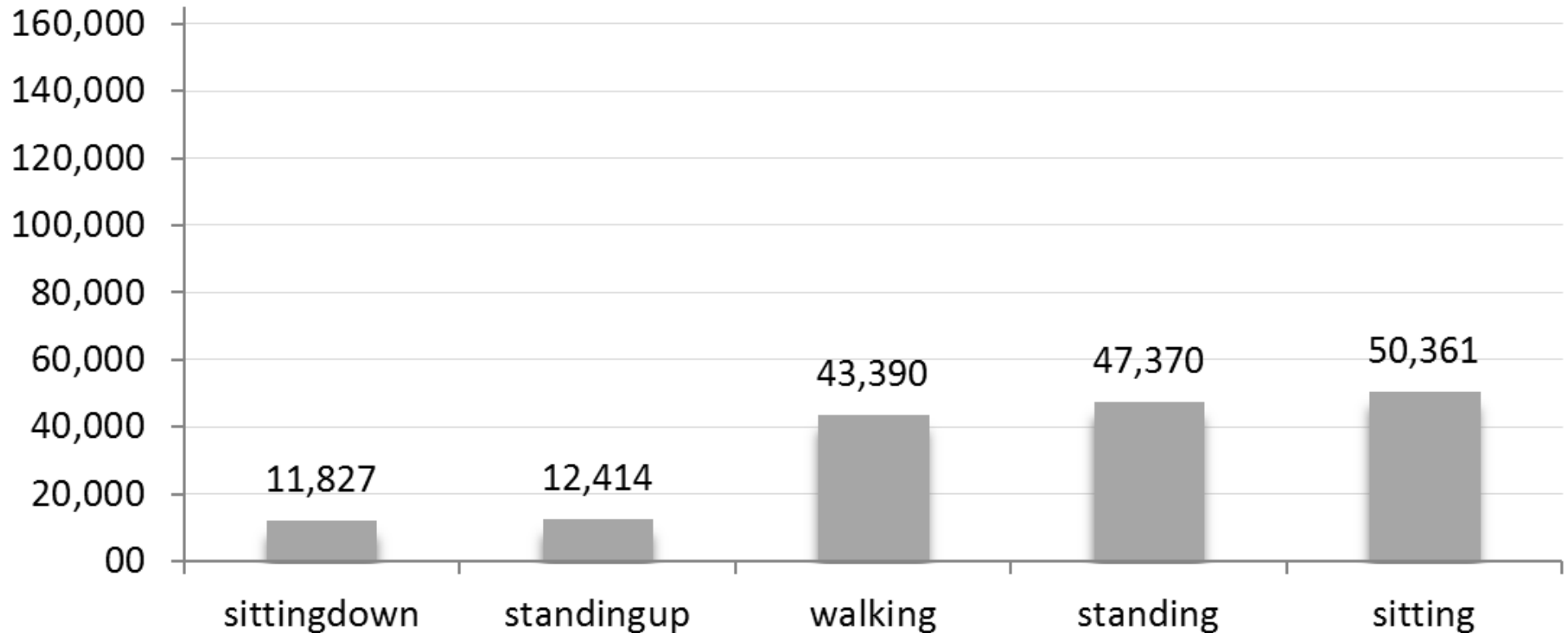
@class: nominal

(sitting, standing, standing up, sitting down, walking)

- 8h of activities
- 4 subjects (nearly 2 hours per participant)
- Participants' profiles

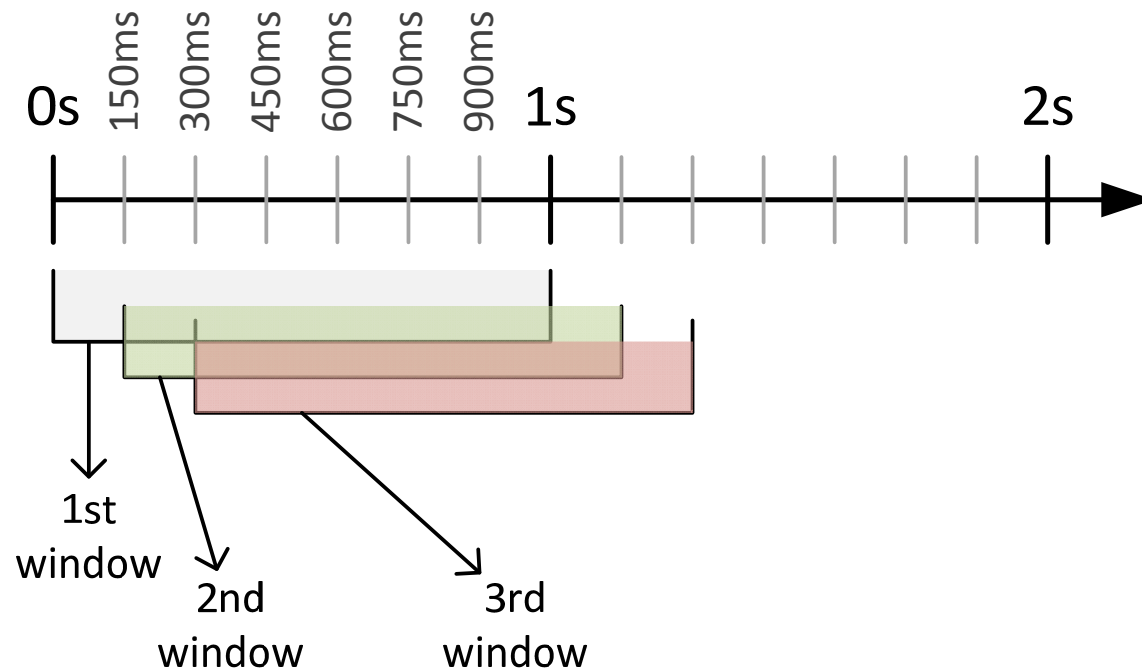
Participant	Sex	Age	Height	Weight	Instances
A	Female	46 y.o.	1.62m	67kg	51,577
B	Female	28 y.o.	1.58m	53kg	49,797
C	Male	31 y.o.	1.71m	83kg	51,098
D	Male	75 y.o.*	1.67m	67kg	13,161*

* A smaller number of observed instances because of the participant's age



Frequency of classes between collected data

- We defined a time window of 1 second, 120ms overlapping
 - After several experimental tests, we found 1 second more suitable to our list of activities



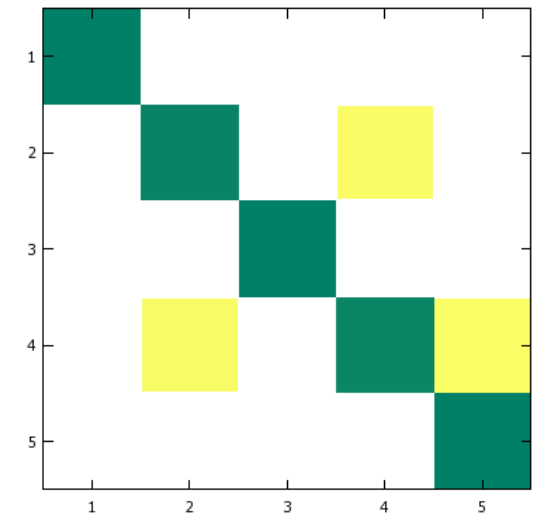
- Readings inside each window were statistically summarized according the instructions of Maziewski et al. [2009]

- Mark Hall's algorithm (BestFirst greedy strategy)
- 11 features were selected
 - Accelerometer #1 (waist)
 - Discretization of M1 (module of acceleration vector)
 - R1 (roll)
 - P1 (pitch)
 - Accelerometer # 2 (left thigh)
 - M2 (module of acceleration vector)
 - discretization of P2 (pitch)
 - Variance of P2 (pitch)
 - Accelerometer # 3 (right ankle)
 - Variance of P3 (pitch)
 - Variance of R3 (roll)
 - Accelerometer # 4 (right upper arm)
 - M4 (module of acceleration vector)
 - All sensors (combined)
 - Mean and standard deviation of (M1+M2+M3+M4)

- We tried: SVM, Voted Perceptron, MultiLayer Perceptron (Back Propagation), and C4.5
 - 67 tests!
- Better results: C4.5 and Neural Networks
- Top result
 - Adaboost + 10 C4.5 decision trees (0.15 confidence factor)
- Structured Perceptron + Induction Features method (Eraldo Fernandes, Cícero Santos & Ruy Milidiú)
 - Seems promising as it provides equivalent results of C4.5, but with better generalization (leave-one-person-out results)
 - We tried StrucPerc **AFTER** writing the paper

		Predicted class					Actual class
Sitting	Sitting down	Standing	Standing Up	Walking			
50,601	9	0	20	1	Sitting		
10	11,484	29	297	7	Sitting down		
0	4	47,342	11	13	Standing		
14	351	24	11,940	85	Standing up		
0	8	27	60	43,295	Walking		

Confusion Matrix



- The contributions are
 - From the literature review
 - The state-of-the-art of recent research on On-body sensing based HAR
 - From the experimental research
 - A dataset for benchmarking (available soon on our website)
 - A classifier (available soon on our website)





- New wearable (HARwear version 2)



- Data collection with 20 (or more) users
 - Profile: 18-21 years old
 - Body Mass Index ranging from 22-26
 - Male and female subjects
 - Activities comprising weight lifting exercises (for QAR)
- Qualitative Activity Recognition (QAR)
 - Recognize “how well” instead of “what” activity
 - We already collected data with 7 users (similar profile)
 - The task is harder, lower accuracy rate, but still promising


Feedback System

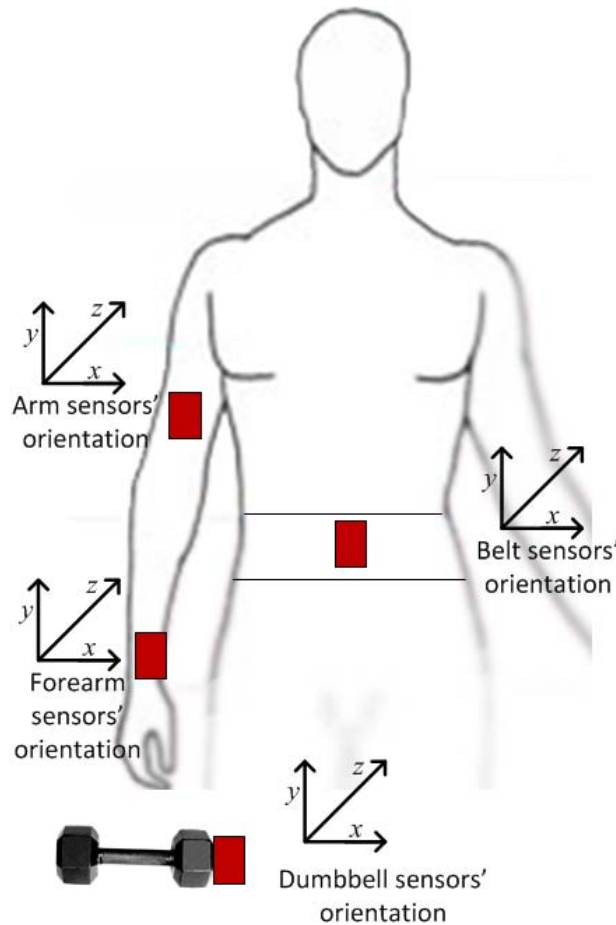
Lateral Dumbbell Raise

Back	Feet	Elbow	Range of motion	Speed
OK	OK	Bend your elbows a little more	Your range is too short	OK
				

Exercise Started

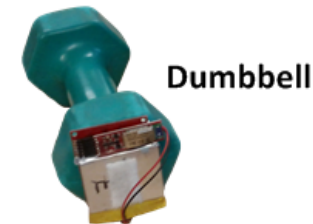
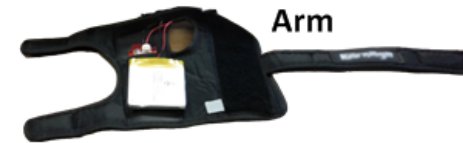
Reps *1*





The following symbol "■" designates one of the set of sensors described in the text

Wearable devices



- Pipeline of tasks?
 - From easier tasks to hard tasks
 - Inspired on the NLL community experience
- Organize tasks (and classes) in a graph?
 - Using ontology to describe and relate tasks
 - Ontology reasoning to select a branch of the graph to apply statistical reasoning on the selected branch
- Investigation of hybrid approaches
 - Ambient Sensing + On-body sensing \Rightarrow to recognize composite activities and social activities
- Structuring of raw data, adding semantics, sensor identifying, etc,



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