Combining IoT and Intelligent Robotics: challenges and opportunities

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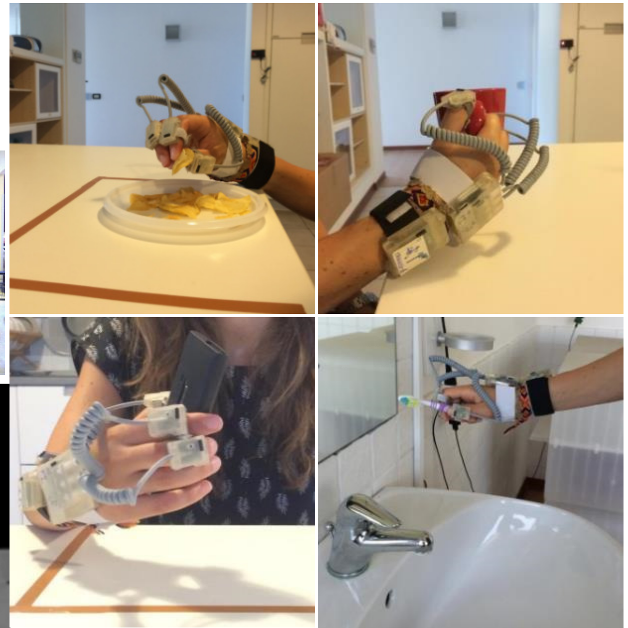
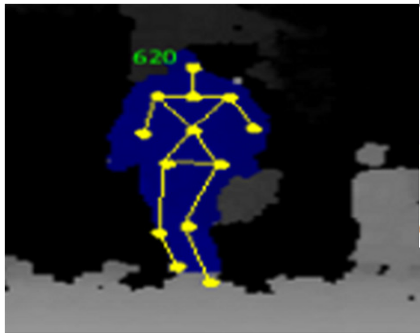
Question 1 - Added value: What is the (observed or potential) added value of integrating IoT and Robotics solutions in your experience? Give ONE specific example.

Improving robotic capabilities in human robot interaction and advanced tele-monitoring

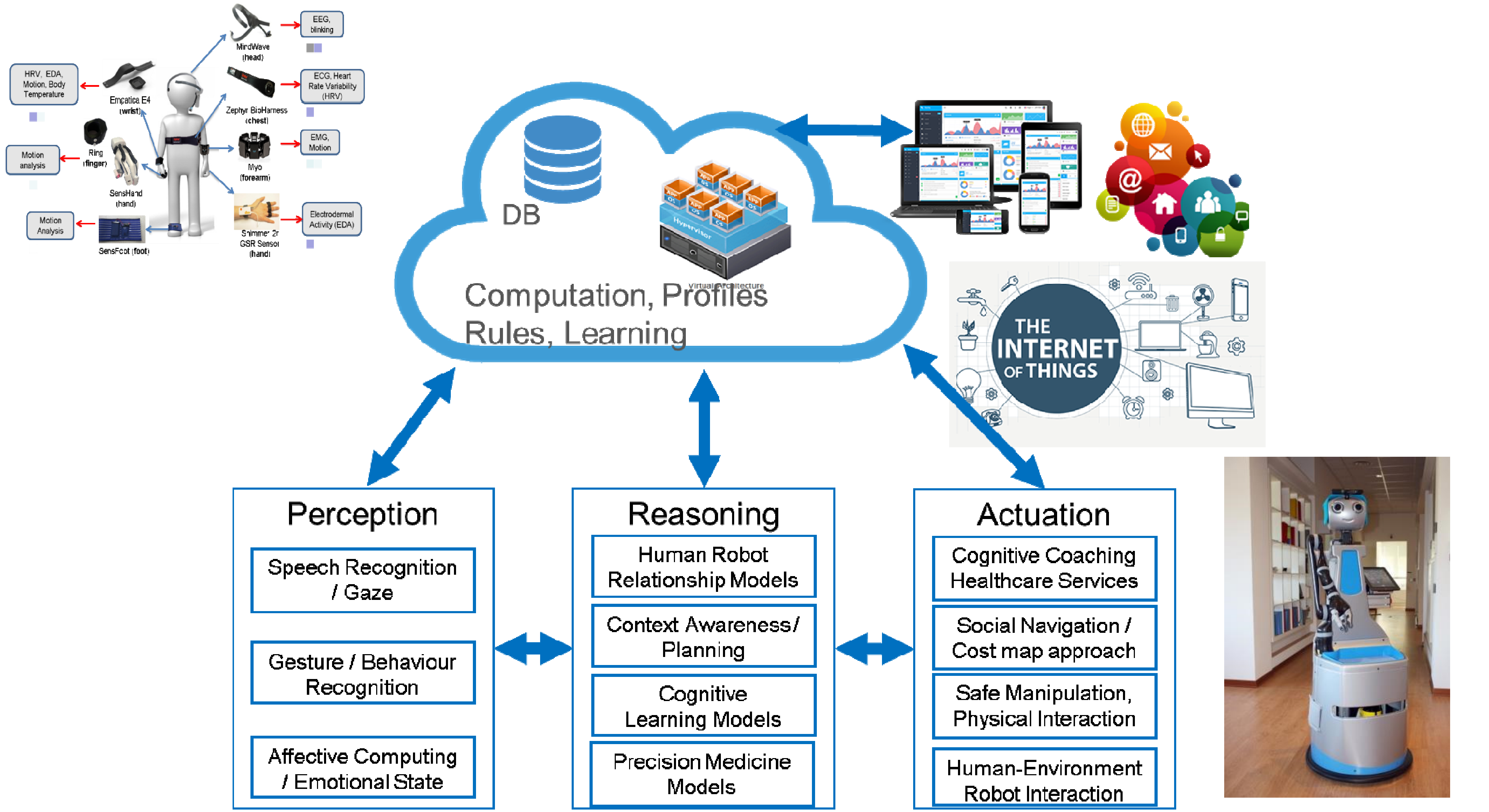
- Human identification
- Gesture / activity and behaviour recognition
- Emotion modelling
- Prevention of physical and cognitive degeneration
- Optimization and management of working life

Social Robotics
Social Artificial Intelligence





Enhancing social robotics capabilities in healthcare



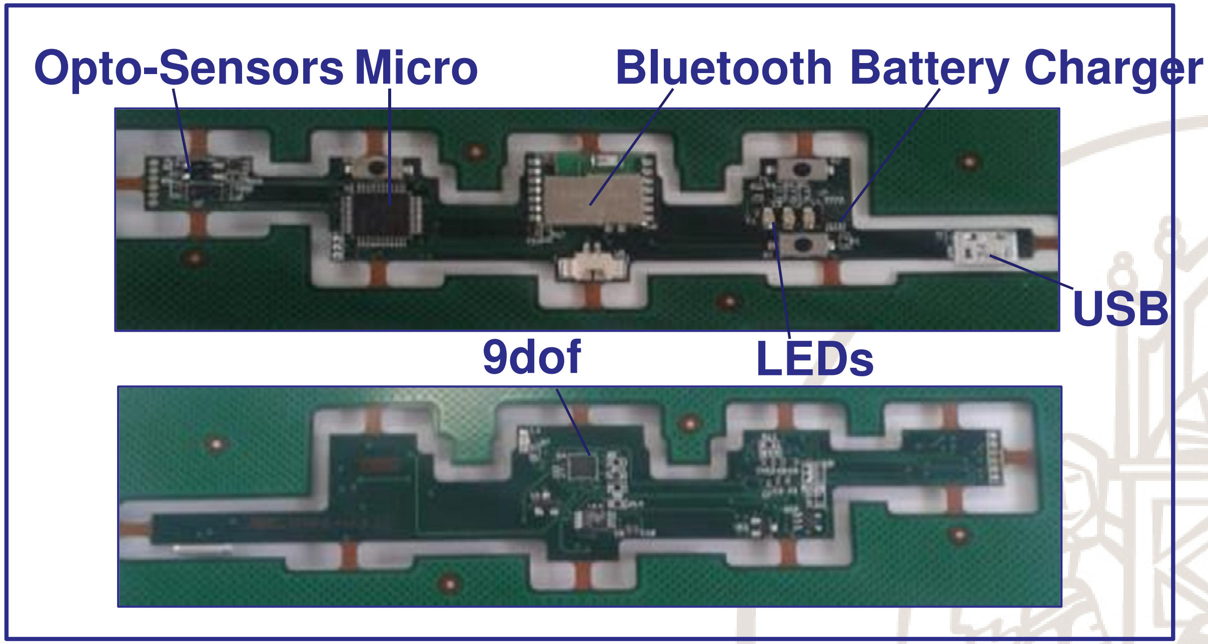
Robot-Era Video

iHAND

- 9-axis accelerometer, gyroscope and magnetometer
- STM32F1/4 Microcontroller
- Bluetooth 2.0 / 4.2
- USB recharge

For each finger and wrirst

iRingV1



Features:

- 9-axis IMU and microcontroller (STM32F103xB family)
- Proximity/gesture sensors
- 50Hz sampling frequency
- Digital and Kalman filtering
- Bluetooth standard of communication
- Battery supply
- Single ring or multipoint sensor network
- 3-4 hours of continuous working

Extreme miniaturization
Flexible Electronics

Daily gestures recognition with inertial rings and bracelets

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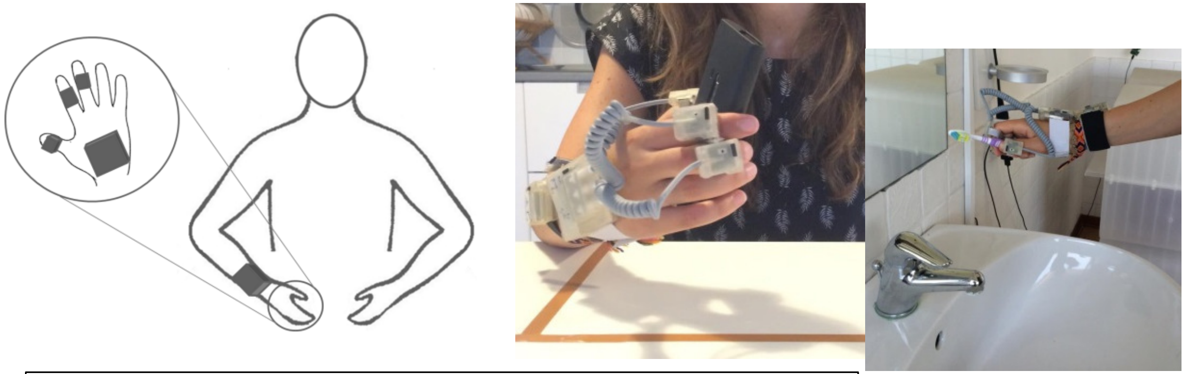
HUMAN FRIENDLY ROBOTICS

la Casa Domotica

Objective: Analysis of the best combination of sensors in terms of trade-off between accuracy and obtrusiveness through Supervised (DT and SVM) Personal and Impersonal Analysis



Participants: 20 healthy adults
(11 females and 9 males (29.3 years ± 3.4))

Gestures
HA: Eating with the hand
GL: Drinking with a glass
FK: Eating with a fork
SP: Eating with a spoon
CP: Drinking with a cup
PH: Answering the telephone
TB: Brushing the teeth with a toothbrush
HB: Brushing the hair with a hairbrush
HD: Using a hair dryer

Impersonal Analysis (Leave-one-subject-out cross validation) Results

Combination of Sensors
FS: Full system
W: Wrist
I: Index Finger
IW: Index Finger + Wrist
IT: Index Finger + Thumb
IWT: Index Finger+ Wrist+ Thumb

	F-measure		Accuracy	
	DT	SVM	DT	SVM
Configuration	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD
FS	0.880 ± 0.077	0.911 ± 0.081	0.890 ± 0.066	0.918 ±0.099
W	0.670 ± 0.120	0.622 ± 0.140	0.689 ± 0.108	0.650 ± 0.120
I	0.810 ± 0.091	0.812 ± 0.111	0.821 ± 0.081	0.820 ± 0.081
IW	0.855 ± 0.081	0.884 ± 0.075	0.863 ± 0.072	0.890 ± 0.091
IT	0.835 ± 0.075	0.883 ± 0.084	0.844 ± 0.068	0.889 ± 0.082
IWT	0.853 ± 0.080	0.908 ± 0.078	0.866 ± 0.067	0.913 ± 0.061

A. Moschetti, L. Fiorini, D. Esposito, P. Dario, and F. Cavallo, "Recognition of daily gestures with wearable inertial rings and bracelets," Sensors, vol. 16,no. 8, p. 1341, 2016

Toward an Unsupervised Approach for Daily Gesture Recognition in Assisted Living Applications

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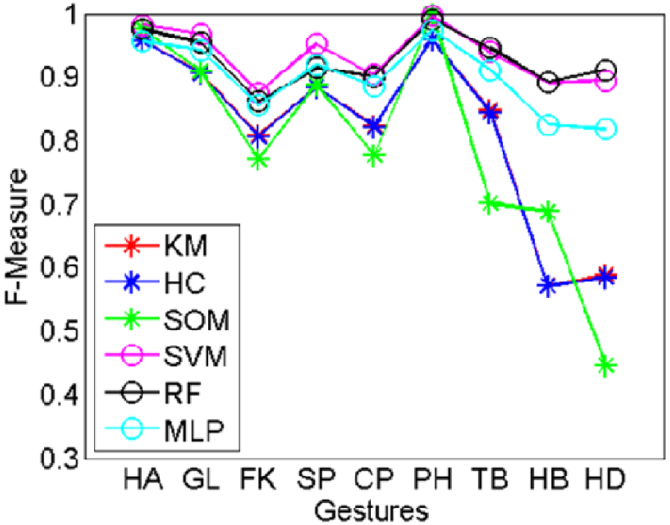
Objective: Comparison between unsupervised and supervised machine learning approaches to recognize nine daily gestures.

Sensors on wrist and index finger

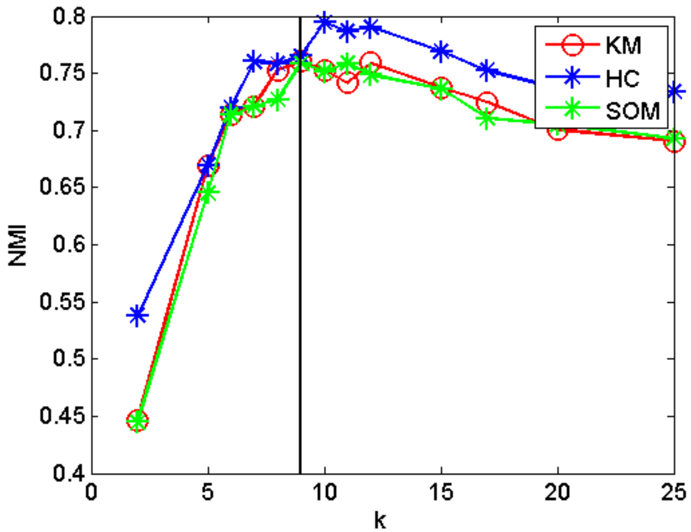
Supervised learning:
Random Forest (RF) Multilayer Perceptron (MLP) Support Vector Machine (SVM)
Unsupervised learning:
K-means (KM) Self-Organizing Maps (SOM) Hierarchical Clustering (HC)

	Accuracy	F-measure	Precision	Recall
Supervised				
RF	0.932	0.936	0.941	0.932
MLP	0.909	0.914	0.919	0.909
SVM	0.938	0.942	0.947	0.938
Unsupervised				
KM	0.818	0.818	0.818	0.818
SOM	0.817	0.816	0.816	0.817
HC	0.803	0.810	0.817	0.803

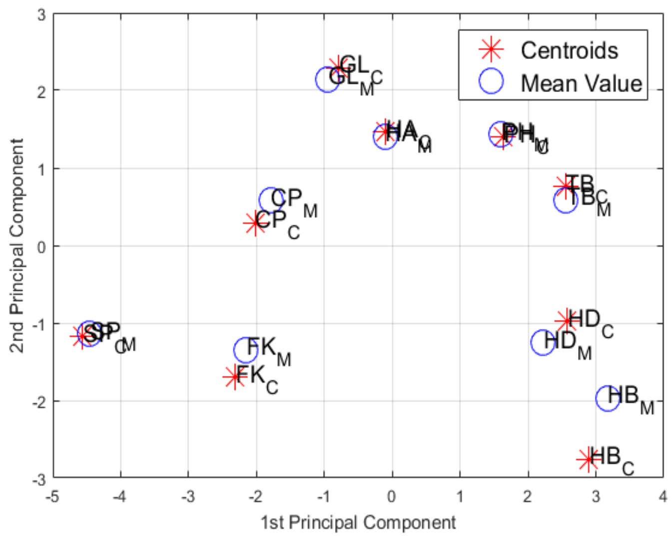
F-measure for each gesture



NMI index with # of clusters unknown



Feature Space Visualization



A. Moschetti, L. Fiorini, D. Esposito, P. Dario, and F. Cavallo, "Toward an Unsupervised Approach for Daily Gesture Recognition in Assisted Living Applications," *Submitted* to IEEE sensors journal.

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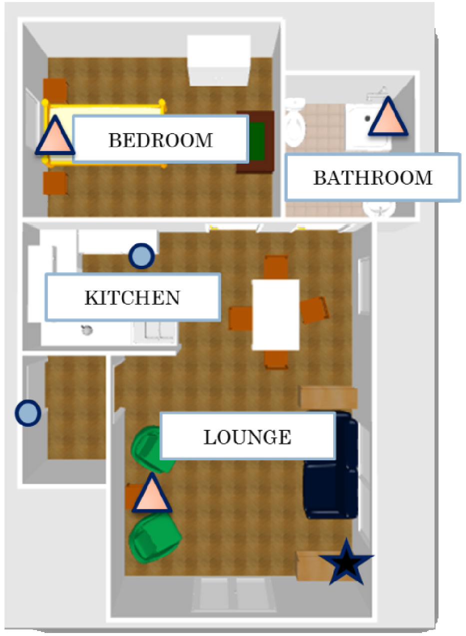
Unsupervised Machine Learning for Developing Personalised Behaviour Models Using Activity Data

la Casa Domotica

Objective

This work is based on unsupervised machine learning algorithms to discover potential **behaviour-related features** from low-level **sensors that can be easily installed in the home**.

Methods



Phase	Time
Night Time	23:00–5:59
Early Morning	6:00–9:59
Late Morning	10:00–11:59
Early Afternoon	12:00–13:59
Afternoon	14:00–16:59
Evening	17:00–19:59
Late Evening	20:00–22:59

Front Door/ Fridge Door

Temperature/Light/Humidity and Movement

Gatway

Features:

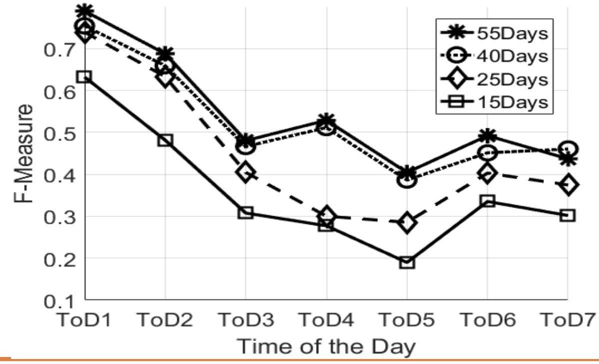
Busyness – Number of Events within a certain time of the day

Time between events -

$$\forall t \in TOD_k : TE = \frac{\sum_{i=1}^{m-2} \frac{(t_{i+2}-t_{i+1})+(t_{i+1}-t_i)}{2}}{m}$$

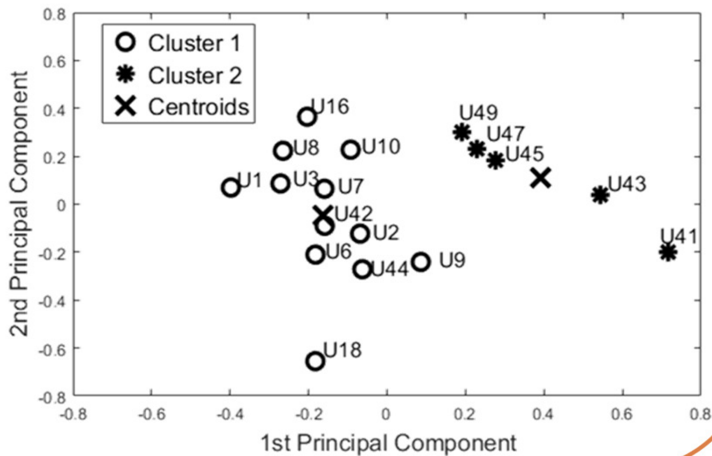
How many days?

The high value of F-Measure is for the "55-days" configuration for the training set corresponding to the night-time (ToD1–0.7896)



Cluster Analysis: Analysis of Night-time behaviour (55 days)

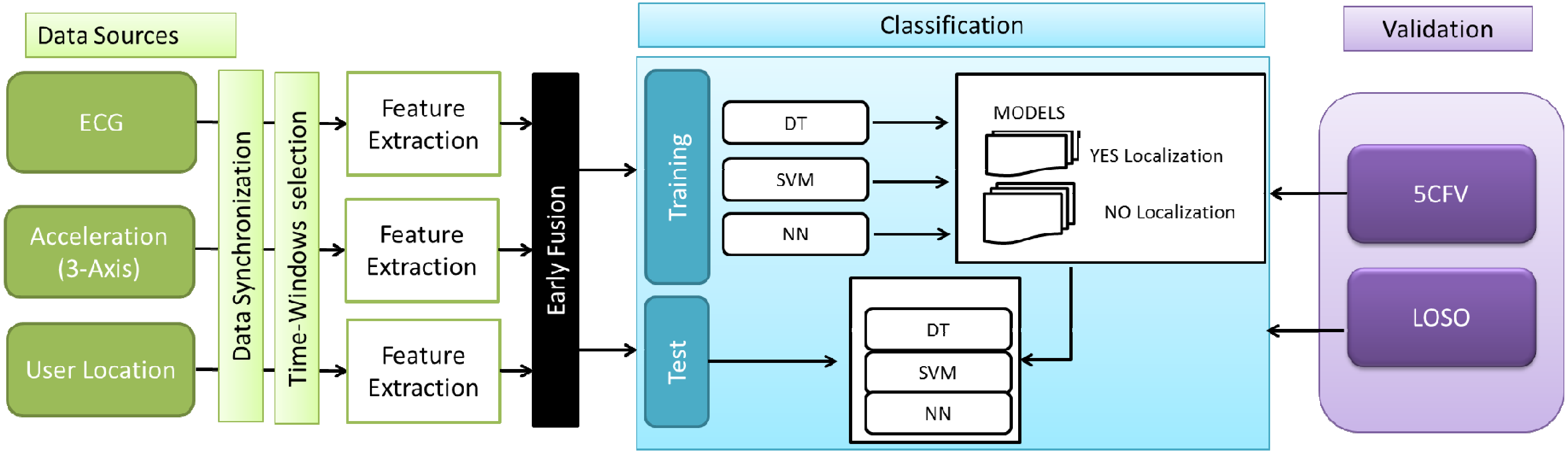
12 Uncorrelated Features. The test set comprised 23 unseen days, and both the algorithms clustered the participants in the same group as the learning set.

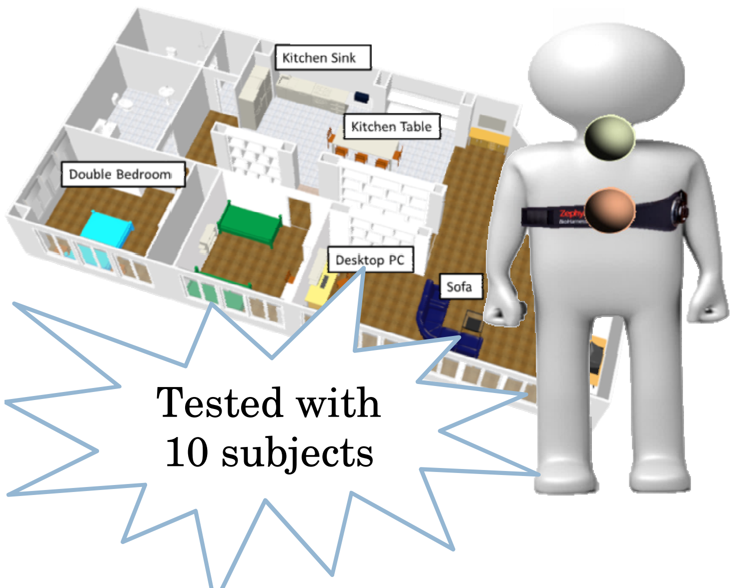


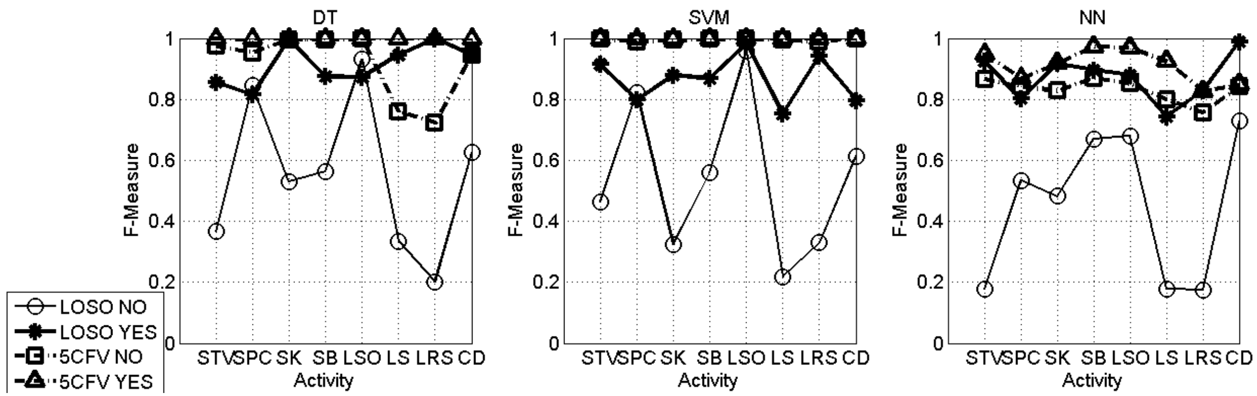
Fiorini, L., Cavallo, F., Dario, P., Eavis, A., & Caleb-Solly, P. (2017). Unsupervised machine learning for developing personalised behaviour models using activity data. Sensors, 17(5), 1034.

User Indoor Localization System enhances Activity Recognition

This work aims to go beyond the state of the art presenting a work where **information on body movement, vital signs and user indoor location** are aggregated to **improve the activity recognition task**







Fiorini, L., Bonaccorsi, M., Betti, S., Dario, P., & Cavallo, F. (2016, June). User Indoor Localisation System Enhances Activity Recognition: A Proof of Concept. In *Italian Forum of Ambient Assisted Living* (pp. 251-268). Springer, Cham.

FEASIBILITY STUDY ON THE ASSESSMENT OF AUDITORY SUSTAINED ATTENTION THROUGH WALKING MOTOR PARAMETERS

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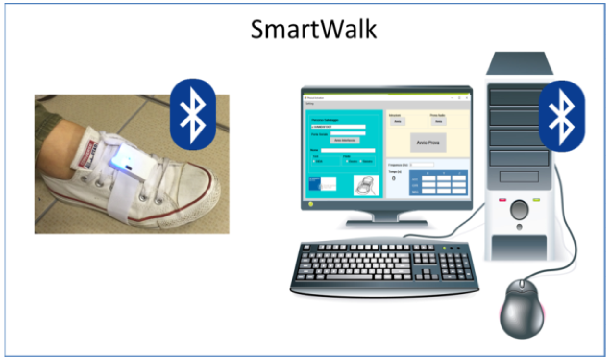
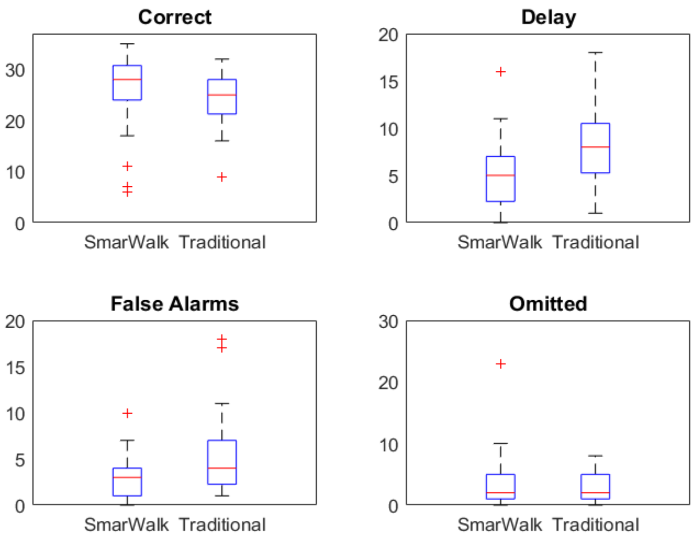
Scuola Superiore Sant'Anna
la Casa Domotica

the aim of this work is to **present an innovative sensorized approach** which combines **aerobic exercise** and **traditional cognitive tools** for sustained attention. Particularly, we aims at demonstrating that **the output** of the sensorized system **could be correlated** with the traditional test **in measuring the same cognitive domains**.



- the participant was asked to wear the SmartFoot on the dominant foot.
- the user was asked to walk at his/her own "natural velocity"
- Every time he/she observed a variation in the auditory sequence, he/she had to kick

Tested with 31 subjects



Pearson Coefficient

	Correct	Delay	False Alarms	Omitted	Mean	Median	SD
RHO	0.5109	0.1694	-0.08442	0.3960	0.3858	0.3235	0.3633
p	0.0033*	0.36	0.65	0.027*	0.032*	0.076	0.044*

It is worth to mention that "*Omitted*" and "*Correct*" scores are considered by neuropsychologists to be the most significant measures in the traditional subtest

L. Fiorini, M. Maselli, E. Castro, S. Tocchini, M.t. Sportiello, C. Laschi, F. Cecchi, F. Cavallo, Feasibility Study on the Assessment of Auditory Sustained Attention through Walking Motor Parameters in Mild Cognitive Impairments and Healthy Subjects, in proc. of EMBS 2017, Korea

PARKINSON CLASSIFICATION

- **Main Objective: Investigation of potential metrics to assess the Parkinson disease on clinical scale**
- **Introduced novel feature selection method to improve the machine learning classification performance based on Receiver operating characteristics curve**
- **Introduced novel classification method to classify the two group of Parkinson patients**

International Journal of
Distributed
Sensor Networks

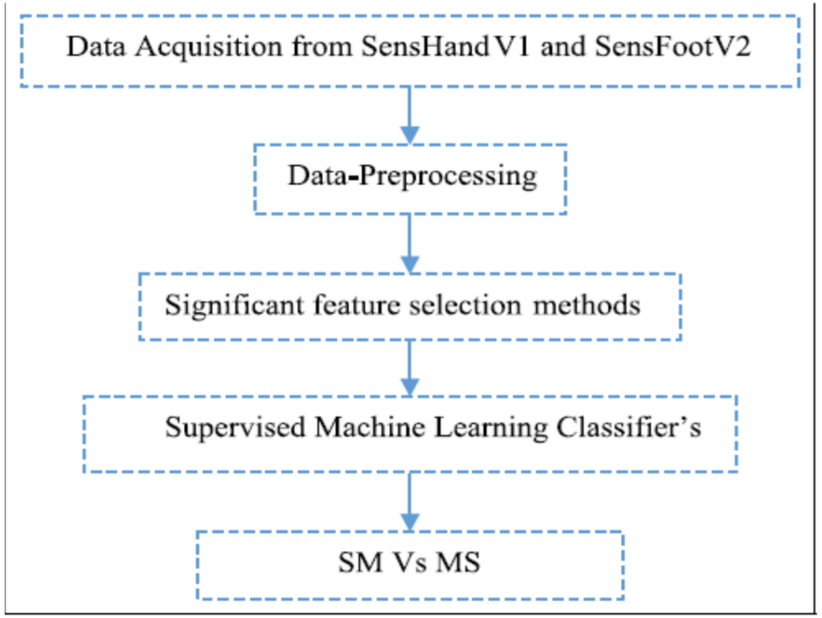


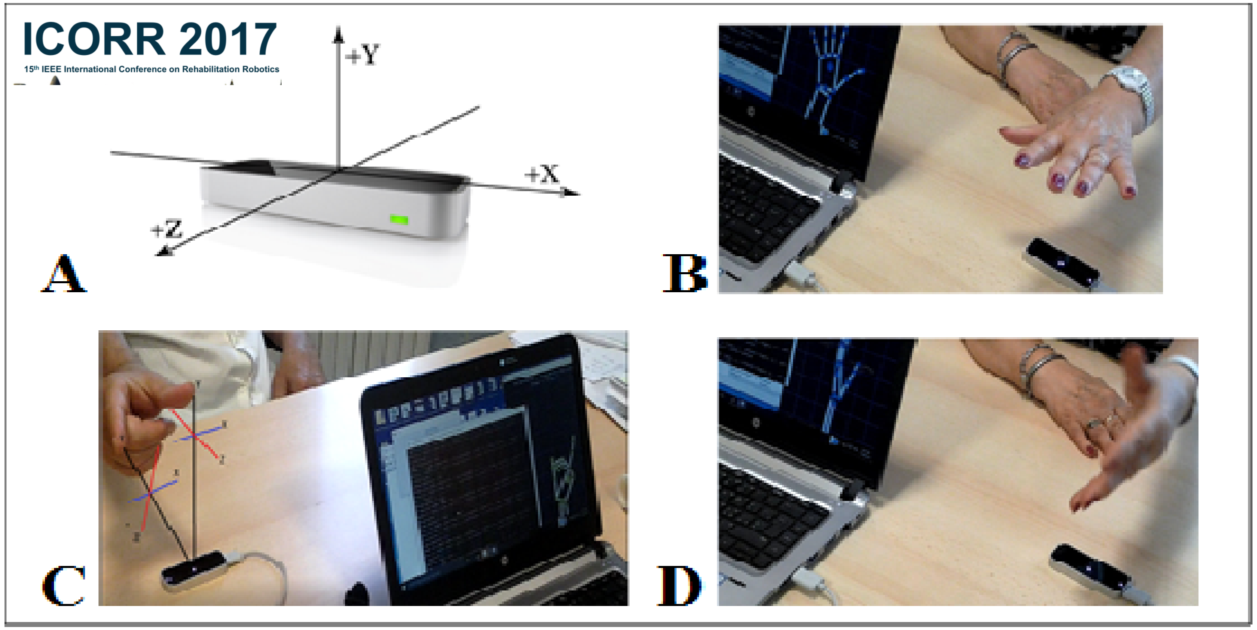
Table 7. Classification between MS and SM PwPD with NN, SVM, and LR with selected significant features through AUC.

NN classification			SVM classification			LR classification		
Total instances = 59			Total instances = 59			Total instances = 59		
Correctly classified = 49			Correctly classified = 47			Correctly classified = 45		
Incorrectly classified = 10			Incorrectly classified = 12			Incorrectly classified = 14		
AUC = 0.8890			AUC = 0.8709			AUC = 0.7832		
	Class 0	Class 1		Class 0	Class 1		Class 0	Class 1
Class 0	36	8	Class 0	35	3	Class 0	32	6
Class 1	2	13	Class 1	9	12	Class 1	8	13
TPR	94.73%	61.90%	TPR	92.10%	57.14%	TPR	84.21%	61.90%
Accuracy	83.10%		Accuracy	79.66%		Accuracy	76.27%	

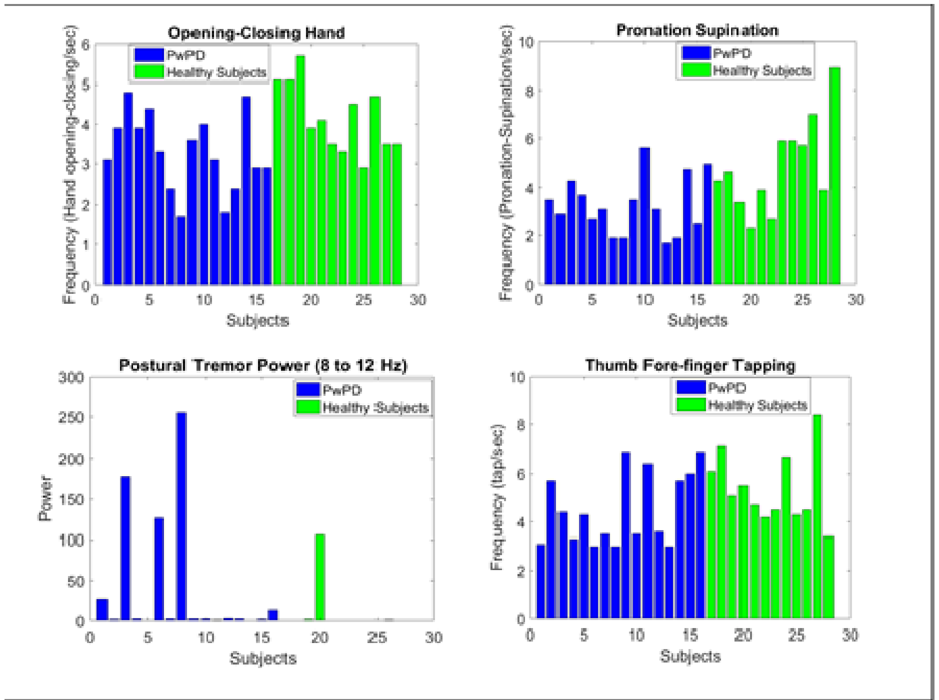
MS: moderate and severe; SM: slight and mild; PwPD: patients with Parkinson's disease; NN: neural network; SVM: support vector machine;

LEAP MOTION CONTROLLER

- **Main Objective: Investigate the potential of Leap motion controller to assess the motor dysfunction in Patients with Parkinson's disease**
- Investigation of potential metrics
- Clinical association of the extracted metrics
- Statistical significance of extracted metrics
- Selection of significant metrics
- Classification b/w healthy and Parkinson patients



Acquisition of Raw data → Segmentation → Feature extraction → Feature selection → Classification



IEEE Transactions on Biomedical Engineering in progress

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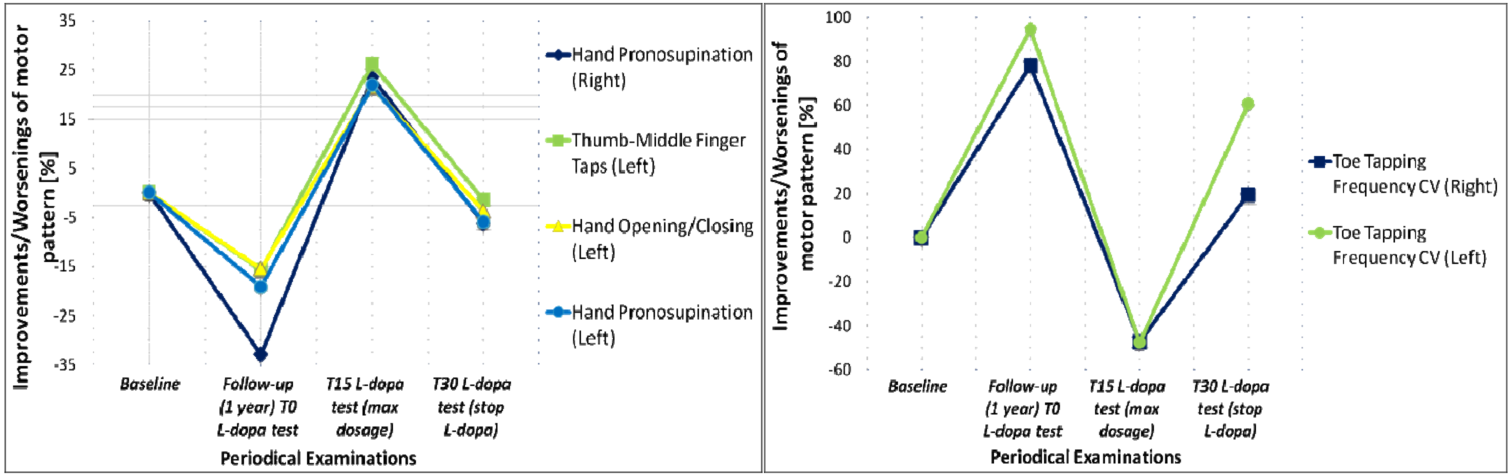
Early Diagnosis for Parkinson's Disease (PD)

HUMAN FRIENDLY ROBOTICS

la Casa Domotica

- **Objective**: to propose a step-by-step method to achieve preclinical PD diagnosis combining an olfactory test (IOIT) and motion analysis (with SensHand and SensFoot) in healthy subjects to identify those at risk to develop PD.

Healthy Subjects → IOIT (Italian Olfactory Identification Test) → 20 Hyposmic Subjects → Motion Analysis: -Baseline -Follow Up (after 1 year) → 1 subject with significant motion worsening (>15%) → Levodopa Test + Motion Analysis: (T0-T15-T30) → Significant improvement in motor performance (>15%) → Imaging Test 123I-FP-CIT SPECT → 1 pre-clinical PD diagnosis



Motor performances of the subject with early PD (baseline, follow-up, L-dopa max and L-dopa stop) analysed with SensHand and SensFoot devices

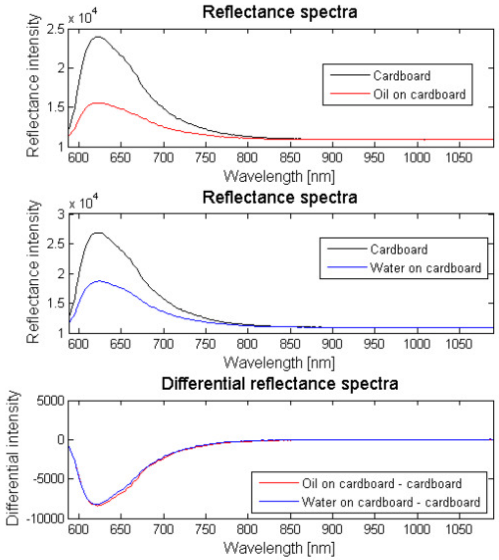
C. Maremmani, F. Cavallo, G. Rossi, E. Rovini, D. Esposito, A. Pieroni, C. Purcaro, S. Ramat, P. Vanni, B. Fattori, & G. Meco. (2017). "Motion analysis sensors in Parkinson's disease preclinical diagnosis: pilot study". In *Acta Neurologica Scandinava*

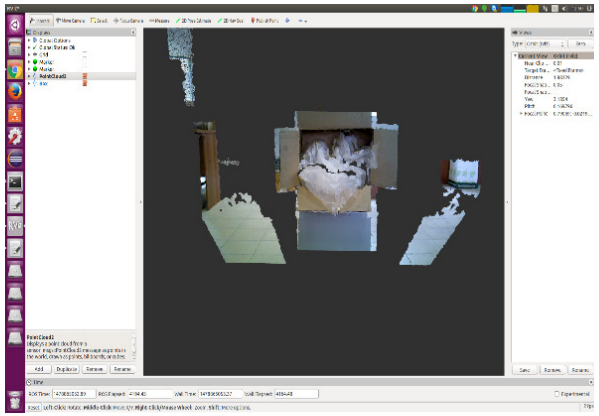
Question 1 - Added value: What is the (observed or potential) added value of integrating IoT and Robotics solutions in your experience? Give ONE specific example.

Improving robotic capabilities for Factory 4.0

- Sorting waste and logistic
- Process planning and optimization
- Human in the loop
- Material Perception and Distinction

Centauro Project
(April 2016 - March 2018)

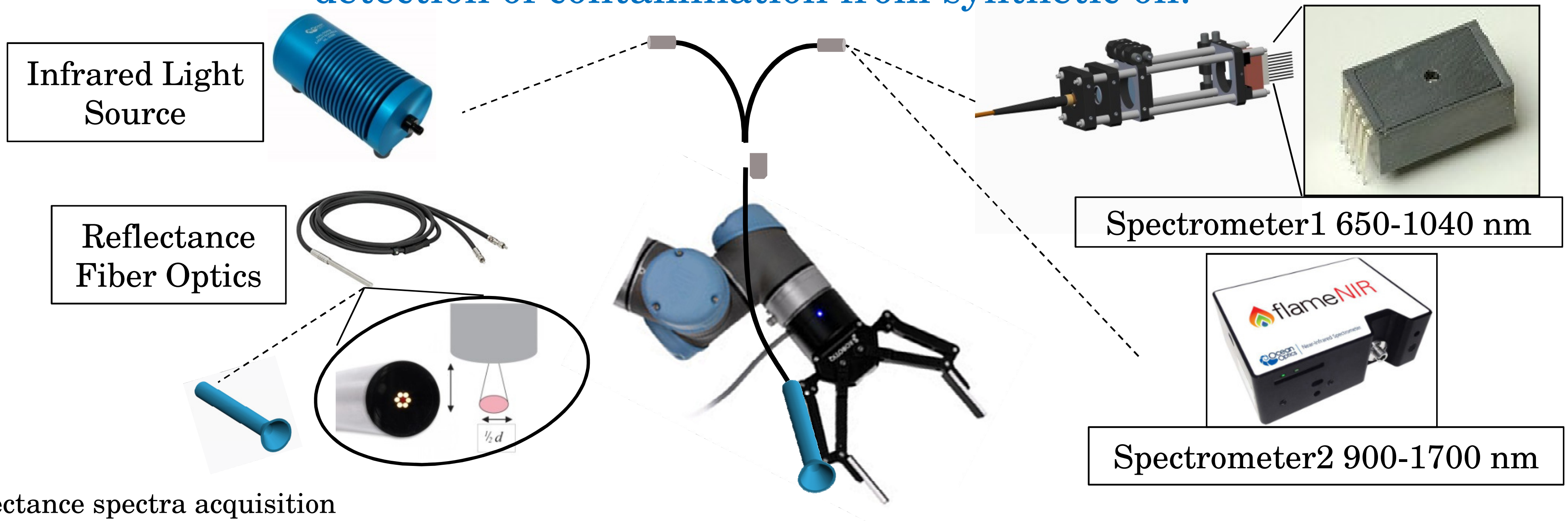




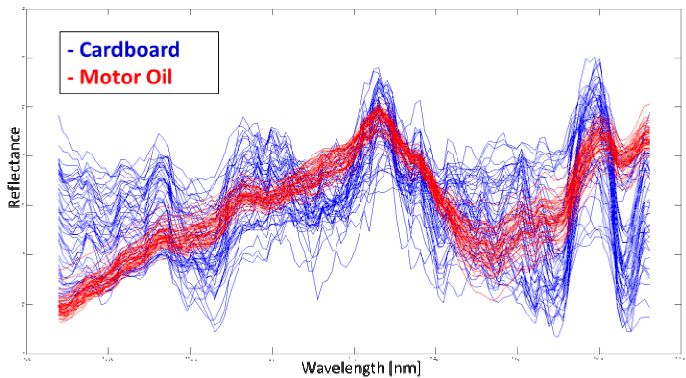
USE OF SPECTROSCOPY IN I4.0

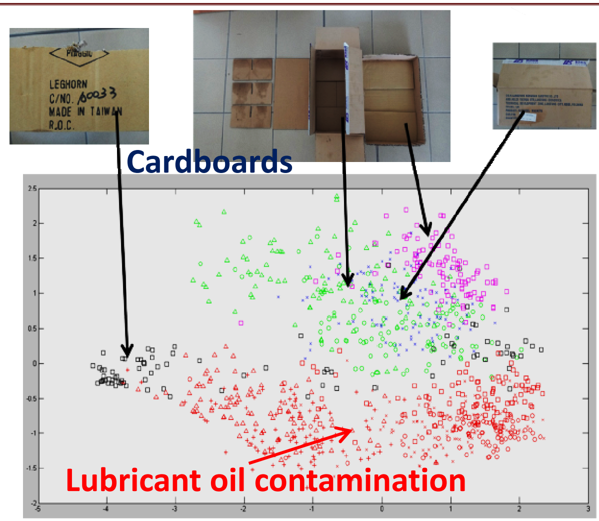
Spectrometry for sorting out contaminated waste

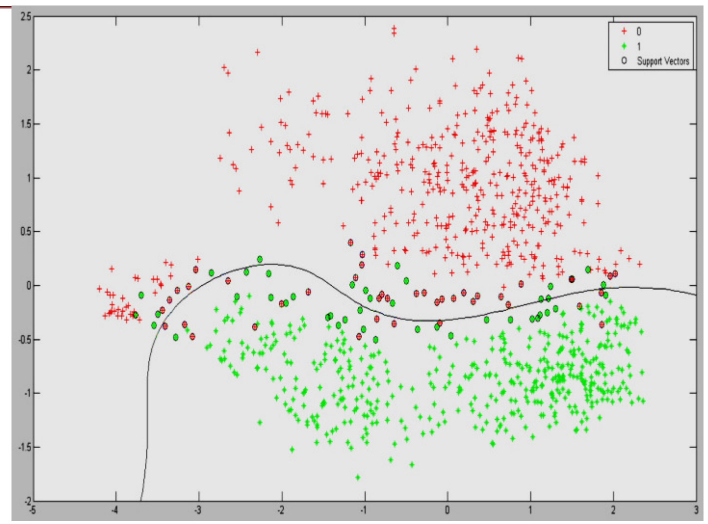
Objective: on-line discrimination of the main packaging materials and detection of contamination from synthetic oil.



1. Reflectance spectra acquisition
2. Pre-processing: outliers removal, standardization and normalization of spectra;
3. Multivariate analysis: PCA;
4. Classification: SVM.







WEARABLES FOR SAFETY

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OBJECTIVE: To test the ability of a selected set of wearable sensors to capture worker **stress** and to assess whether the detected changes in physiological signals correlate with changes in salivary cortisol level, which is a reliable, objective biomarker of stress.

METHODS

EEG

HRV

GSR

ACQUISITION DATA during Relax, Stress Mast test, Recovery

PREPROCESSING and FEATURES EXTRACTION

FEATURE SELECTION PROCEDURE Kruskal-Wallis and Spearman's analysis.

COLLECTION OF SALIVARY SAMPLES

SAMPLES ANALISYS and CORTISOL CONCENTRATION MEASURE

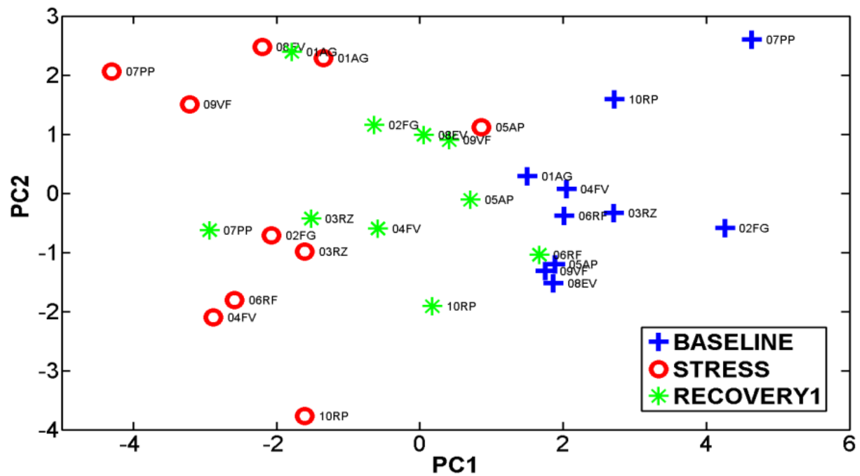
PHYSIOLOGICAL SIGNIFICANT FEATURES

CORRELATION ANALYSIS

CORTISOL CONCENTRATION VALUES

CLASSIFICATION ALGORITHM Traning Set, Test Set and SVM pattern recognition

RESULTS



SVM: Relax - Stress	Sens	Spec	Acc
	90 %	100 %	95 %

CORR	R^2	Mult R	P-value
	0.769	0.877	0.011

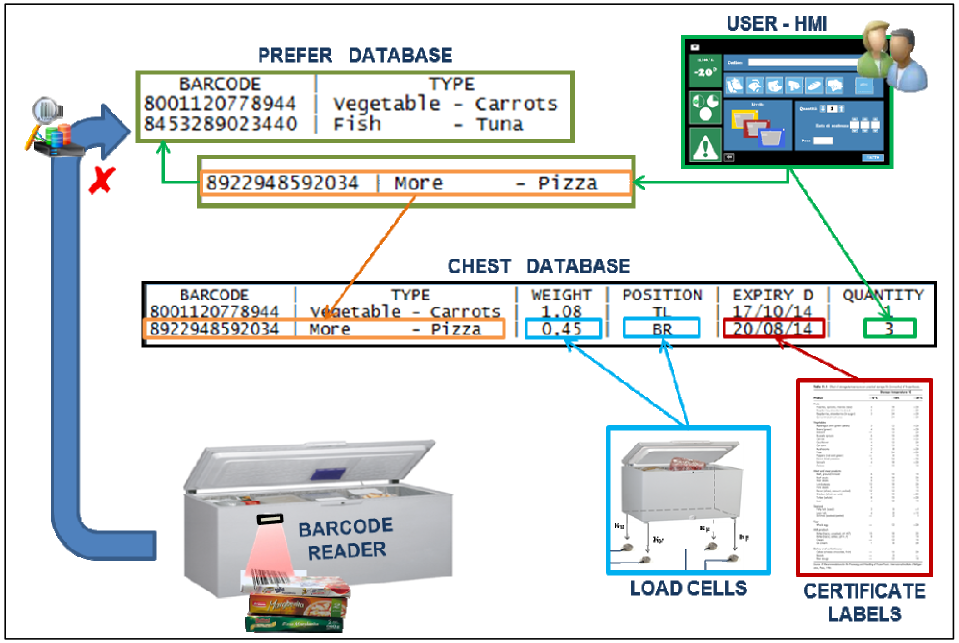
S. Betti, R. Molino Lova, E. Rovini, G. Acerbi, M. Cabiati, S. Del Ry, & F. Cavallo. (2017). "Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers" – TBME (Major revision)

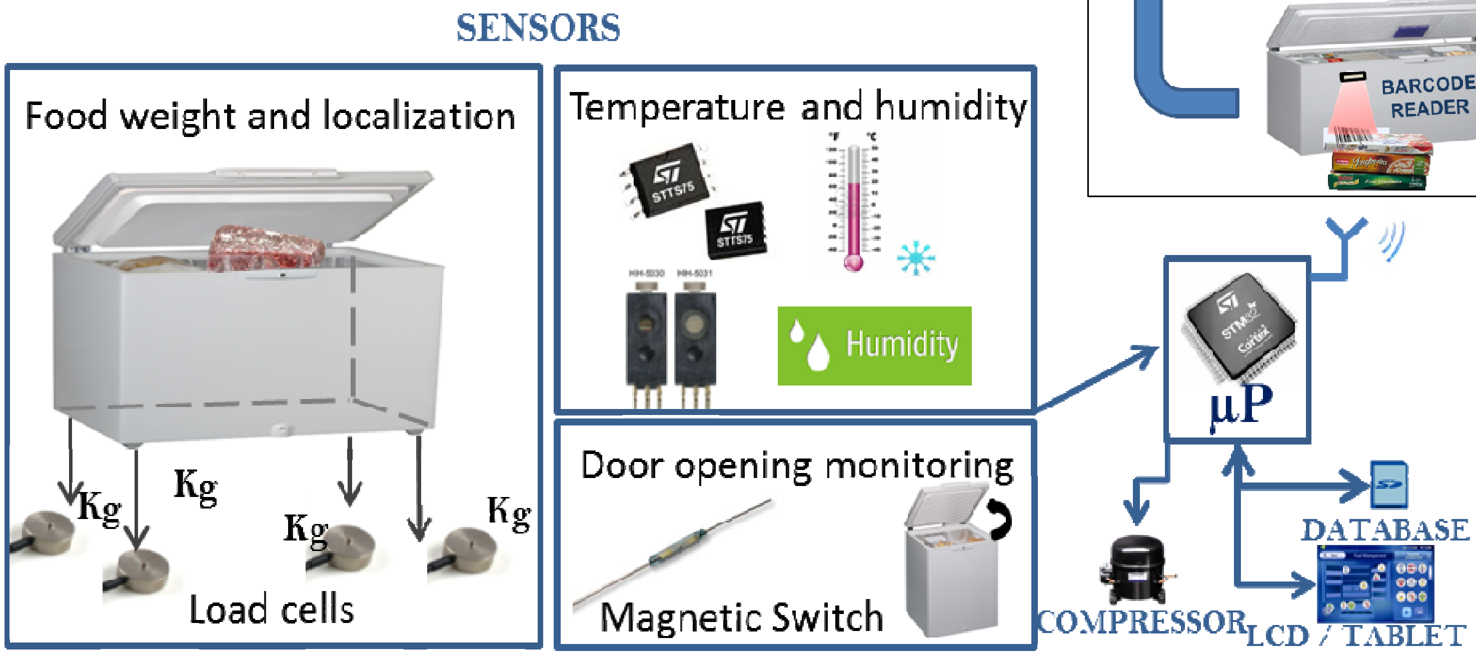
DIET COMPANION

Objective: energy-efficiency, better food management, reduce food wastage

Services:

- Automatic food inventary and localization;
- Smart storing depending on food type;
- Expiration reminding and recipe suggestion;
- Remote smart monitoring



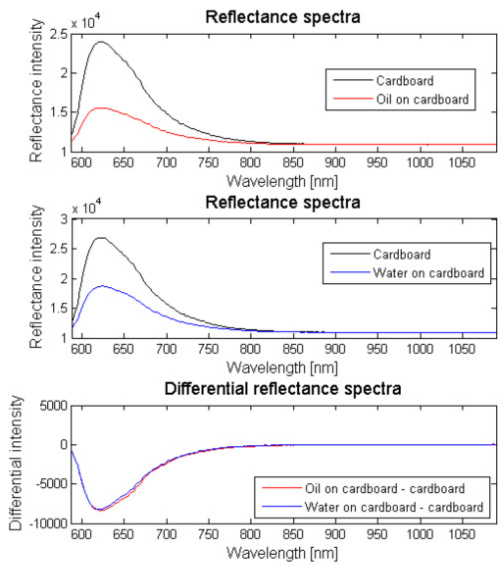


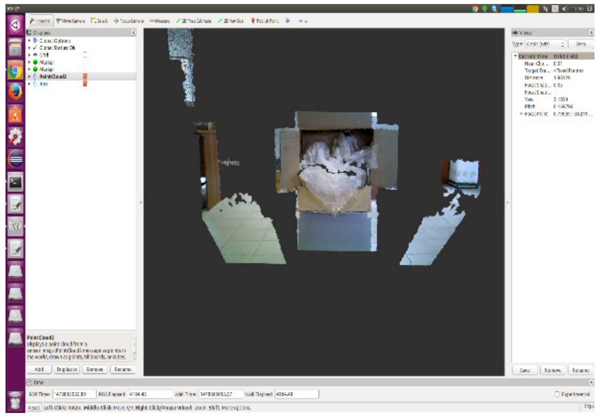
*Bonaccorsi M., Betti S., Rateni G., Esposito D., Brischetto A., Marseglia M., Cavallo F., 'HighChest': an augmented freezer designed for smart food management and eco-efficient behaviours promotion. *Sensors* Special Issue "Sensors for Home Automation and Security". Accepted.

Improving robotic capabilities for Factory 4.0

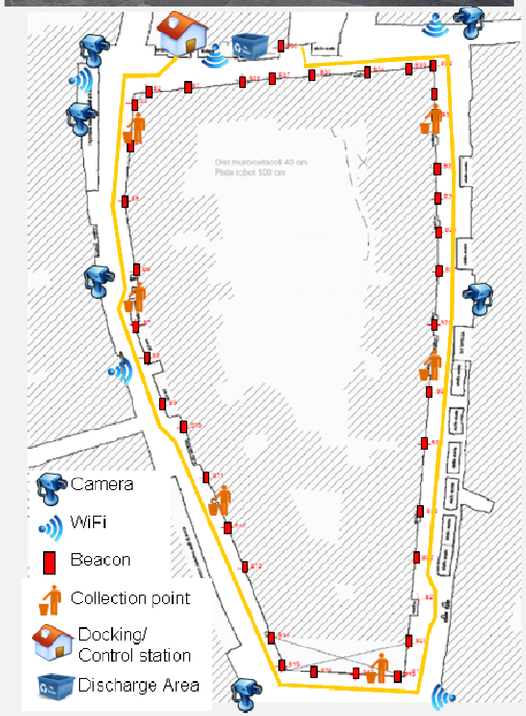
- Sorting waste and logistic
- Process planning and optimization
- Human in the loop
- Material Perception and Distinction
- Safety and security of workers

Centauro Project
(April 2016 - March 2018)





The DustBot system tested in Peccioli (Italy)



The EU DustBot Project

Serving citizens at home

The test campaign in Peccioli, Pisa:

- from June 15 to August 7, 2010-
- in the very heart of the town
- ➢ with real users: 24 families and 10 business activities
- ➢ 95% of users declaring satisfaction and ease of use

Logistic and good distribution for commercial activities and private homes

Coordination center for logistic

Personal mobility and transportation

Question 2 - Enablers: What AI and cognition enabler - if any - have you used in your experience?

Machine learning:

- Supervised learning (Random Forest, Multilayer Perceptron, Support Vector Machine)
- Unsupervised learning (K-means, Self-Organizing Maps, Hierarchical Clustering)
- Reinforcement learning
- Incremental learning

Cloud Technology (Azure, Fiware, …)

Question 3 - Platforms: What IoT and/or Robotics platforms you consider mature for your needs?

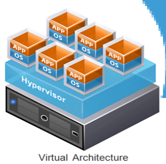
In progress

From ACCRA Project
H20202 – SC1-PM14-EU-JP
Dec 2016 – Jan 2020

ACCRA

FIWARE

DB



Computation, Profiles
Rules, Learning

UniversAAL Middleware

Context based ontologies

Interfaces ROS, Android, uAAL, Cloud

uAAL

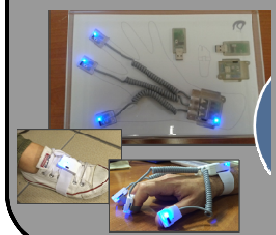
Robots

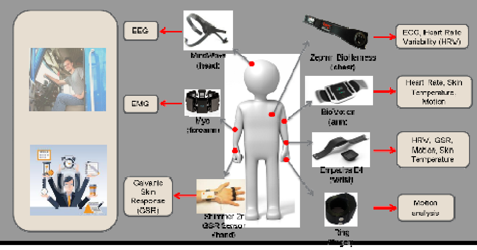
ROS

Astro

Buddy

IoT devices



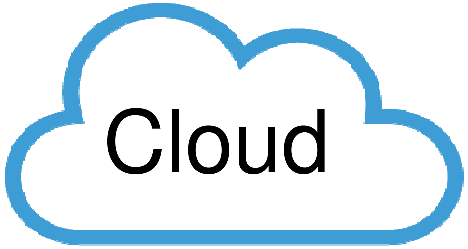


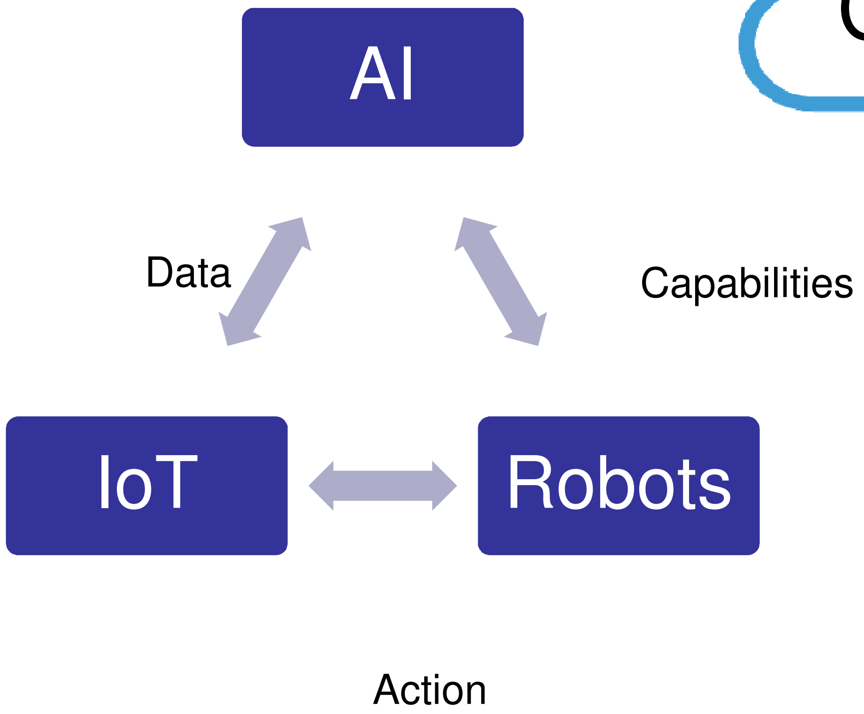
Question 4 - Obstacles: What are the obstacles to build integrated IoT-Robotics-AI systems today?

- Lack of a framework to easily integrate all technologies for large scale experimental tests;
- A lot of interoperability work should be done;
- AI approaches concretely working in real life (reliability, robustness);
- Learnability capabilities.

Question 5 - Lessons learned: can you share ONE single lesson learnt in your experience about integrating IoT, Robotics and AI?

A new paradigm is consolidating, that orchestrates Robots, Internet of Things and Artificial Intelligence.





- AI, Robot and IoT are strongly linked
- Robots connected to society
- Robots connected to cognitive agents
- IoT is enabler of Collaborative robots (Industry 4.0)
- Believable Business models, i.e. Circular Economy
- Cloud Robotics / Internet of Robotic Things (IoRT) or (IoIRT)

- Bonaccorsi, M., Fiorini, L., Cavallo, F., Saffiotti, A., & Dario, P. (2016). A cloud robotics solution to improve social assistive robots for active and healthy aging. *International Journal of Social Robotics*, *8*(3), 393-408.
- Fiorini, Laura, et al. "Enabling personalised medical support for chronic disease management through a hybrid robot-cloud approach." Autonomous Robots (2016): 1-14.