ELEctromagnetic DIAgnostics Research Center
ELEDIA@UniTN (University of Trento)
Via Sommarive 9, 38123 Trento, Italy
E-mail: andrea.massa@unitn.it
Web: www.eledia.org

EM Positioning for IoT

Fundamentals and Advances

Federico Viani, Alessandro Polo, Andrea Massa

IC1301 WIPE Cost Action – 2016 International Spring School
April 18-20, 2016 – Bologna, Italy

Copyright Notice

Outline

- **EM Positioning for IoT – Intro and Motivation**
- **Active Localization of Mobile Devices**
  - Localization through optimization
  - Semantic-based probabilistic approach
- **Passive Localization of Transceiver-free Targets**
  - Target tracking
  - Crowd detection
  - Indirect occupancy estimation
- **Conclusions and Actual Trends**

IoT Interpretation: Not only «Things»

"The IoT is a giant wireless network of connected *things*, <u>which also includes people</u>. The relationship will be between people-people, people-things, and things-things."

Forbes, 2015

IoT Evolution and Trends

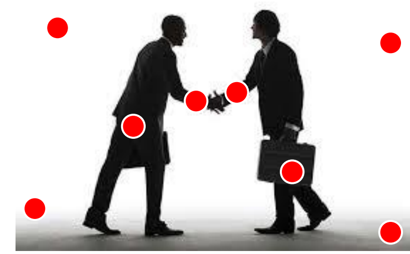
First smart object:
Internet Coke-machine

Transmits info about:
- Number of cokes
- Temperature

Smart Objects

Things understand the social behavior/needs of people

Objects adapt their actions according to:
- Human behavior
- Relational models
- Authority ranking
- …



Social Objects

(1982) *(2009)* *(when ?)*

Acting Objects

Example: Google Connected Car

Makes autonomous actions:
- Drives from A to B
- Stops at intersections
- Automatic parking

IoT Evolution and Trends

First smart object:
Internet Coke-machine

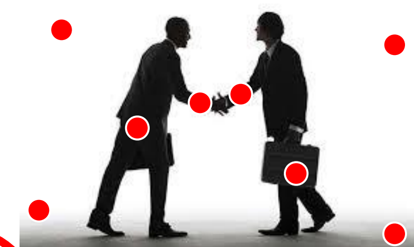
Transmits info about:
- Number of cokes
- Temperature

Smart Objects

(1982)

Things understand the social behavior/needs of people

Objects adapt their actions according to:
- Human behavior
- Relational models
- Authority ranking



Social Objects

(when ?)

The Objects-People Relations are more and more fundamental!

WHAT CHALLENGES?

mous actions:
m A to B
- Stops at intersections
- Automatic parking

Example: Google Connected Car

IoT Technological Challenges

Objects-People interactions introduce Nonstationarity and Spatio-temporal Variability in IoT architectures

Solutions under Investigation

CHALLENGES

- Ubiquitous Connectivity
- Autonomy and Resilience
- Low-cost
- Mobility

- Novel Antenna Design
- Passive Communication
- Near-field Focused Antenna

- Wireless Power Transfer
- Backscatter Communication
- Energy Harvesting

- RFID Technology
- Chipless Tags
- Textile Substrates

- Opportunistic EM Localization
- Ultrawideband Technology

IoT Technological Challenges

Objects-People interactions introduce Nonstationarity and Spatio-temporal Variability in IoT architectures

Solutions under Investigation

CHALLENGES

- Ubiquitous Connectivity
- Autonomy and Resilience
- Low-cost
- Mobility

Where are the moving targets/users respect to IoT architectures?

- Novel Antenna Design
- Passive Communication
- Near-field Focused Antenna

- Wireless Power Transfer
- Backscatter Communication
- Energy Harvesting

- RFID Technology
- Chipless Tags
- Textile Substrates

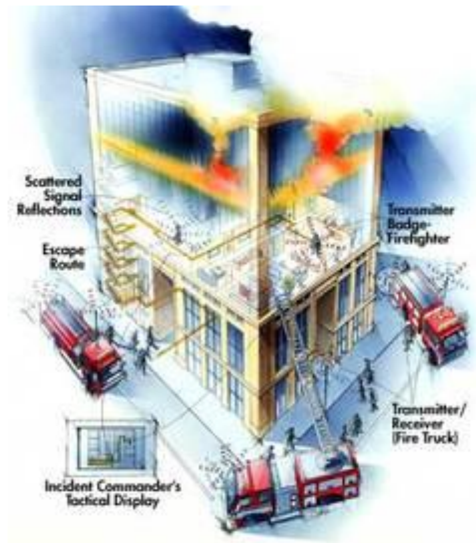
- **Opportunistic EM Localization**
- Ultrawideband Technology

Relevance of Position Information

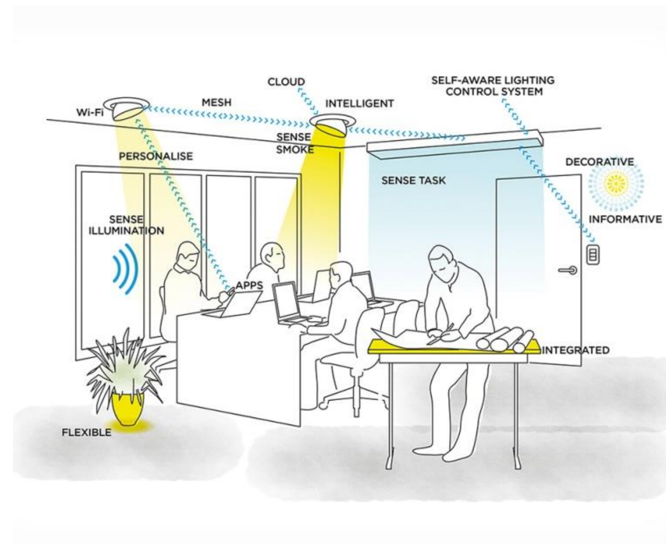
Examples of location-based services

Indoor Navigation
(you are here)

Emergency Team Localization



Smart Building management
(e.g., smart lighting)



Service:
Provide best routes to fit user needs

Service:
Support search&rescue operation / finding way of escape

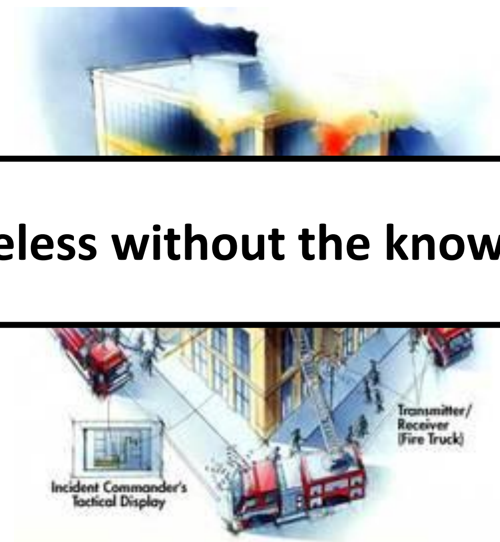
Service:
Building plants usage only where needed for energy saving

Relevance of Position Information

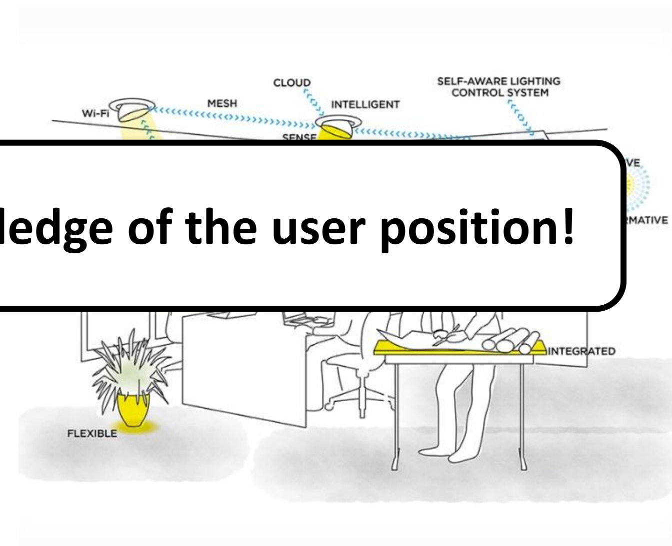
Examples of location-based services

Indoor Navigation
(you are here)

Emergency Team Localization



Smart Building management
(e.g., smart lighting)



Acquisition of IoT data is useless without the knowledge of the user position!

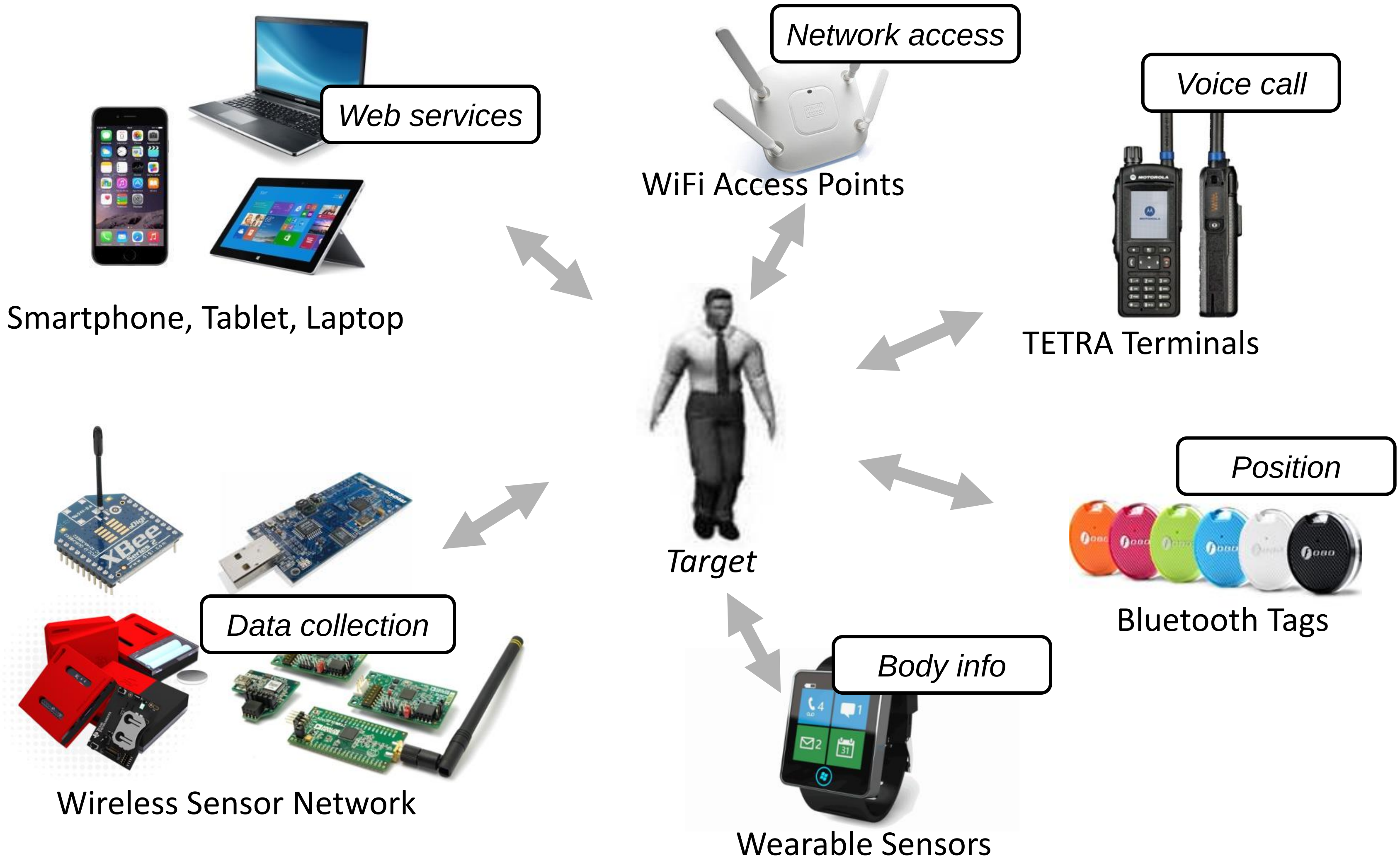
Service:
Provide best routes to fit user needs

Service:
Support search&rescue operation / finding way of escape

Service:
Building plants usage only where needed for energy saving

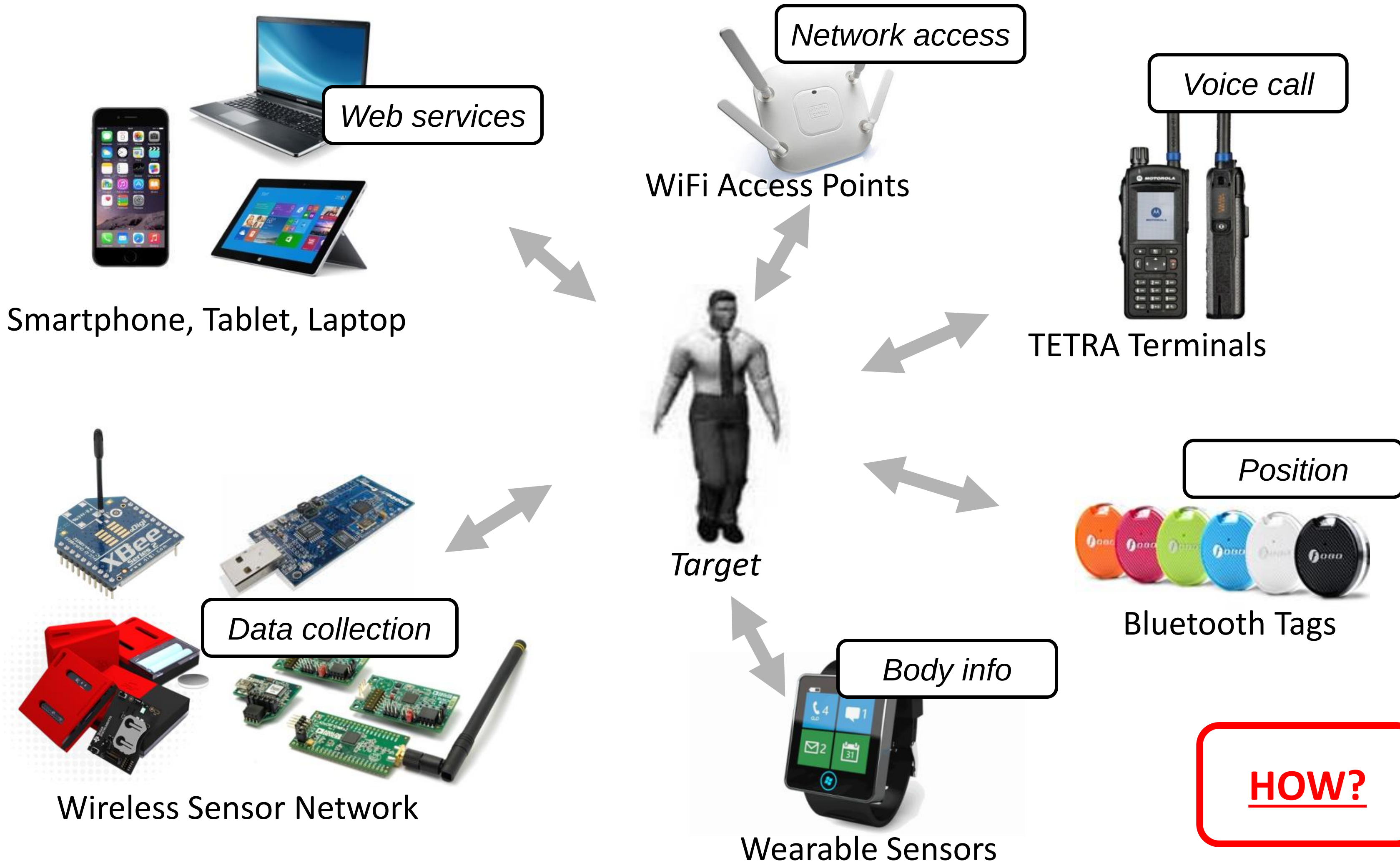
Exploit IoT for EM Positioning

OBJECTIVE Target Localization through **Opportunistic** Exploitation of Existing Wireless IoT Devices



Exploit IoT for EM Positioning

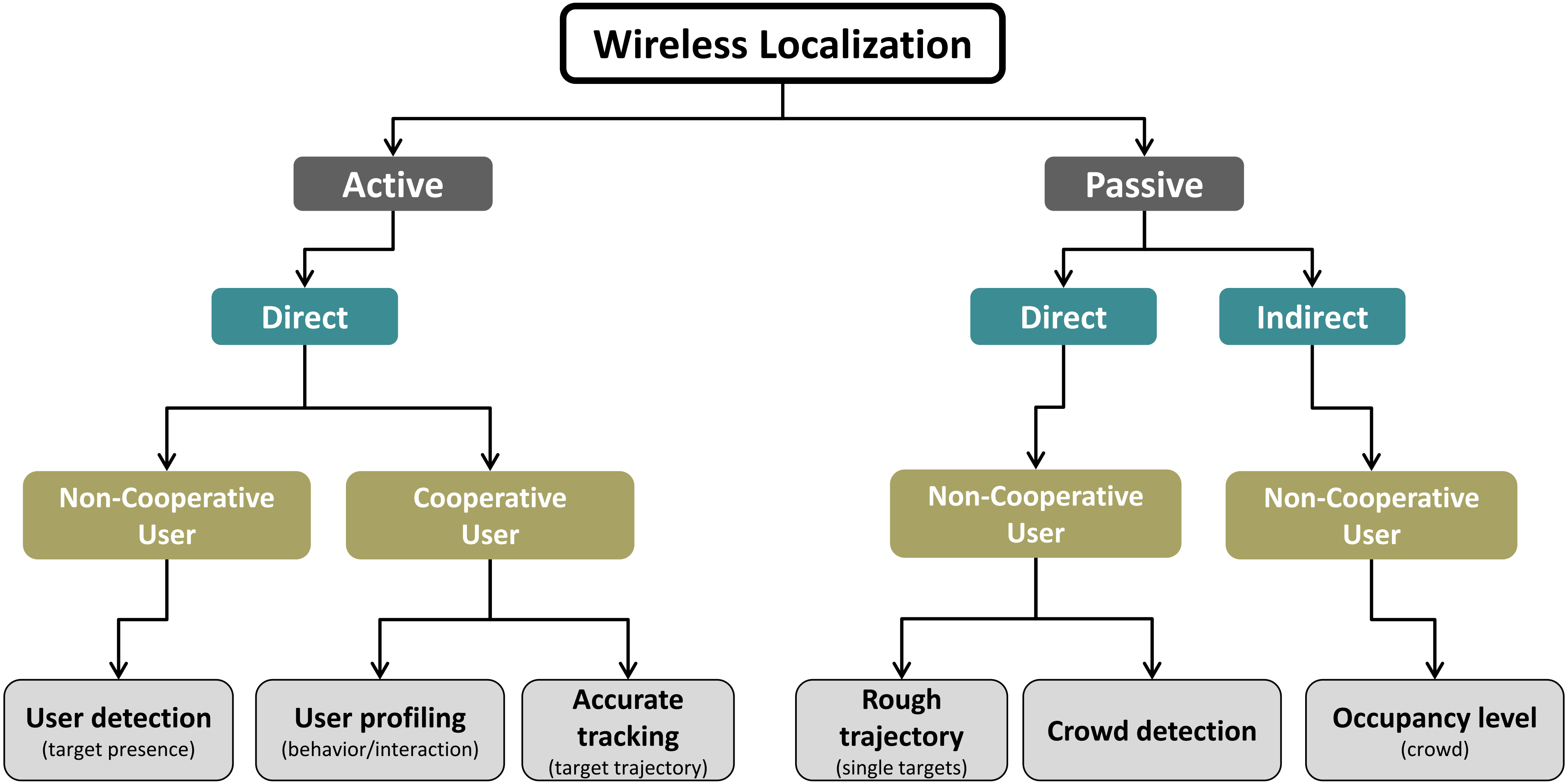
OBJECTIVE Target Localization through **Opportunistic** Exploitation of Existing Wireless IoT Devices



HOW?

Solutions for EM Positioning by IoT

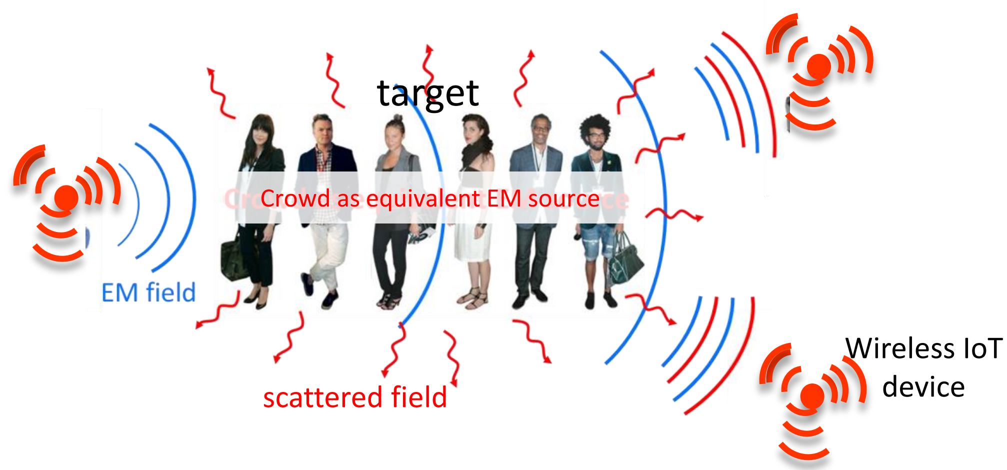
Definition Presence/Position/Movement estimation of targets moving throughout a domain monitored by IoT wireless technologies



Active vs Passive

Active

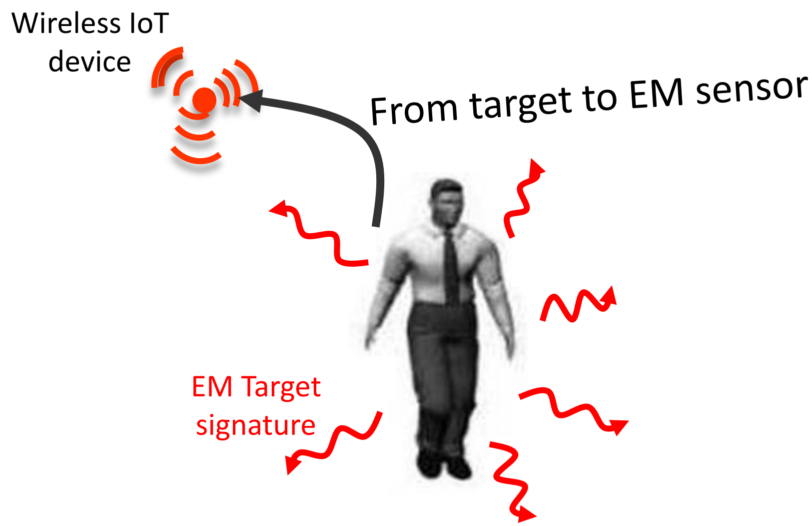
<u>Target is the transceiver</u>
Processing of received EM power of active wireless links



Passive

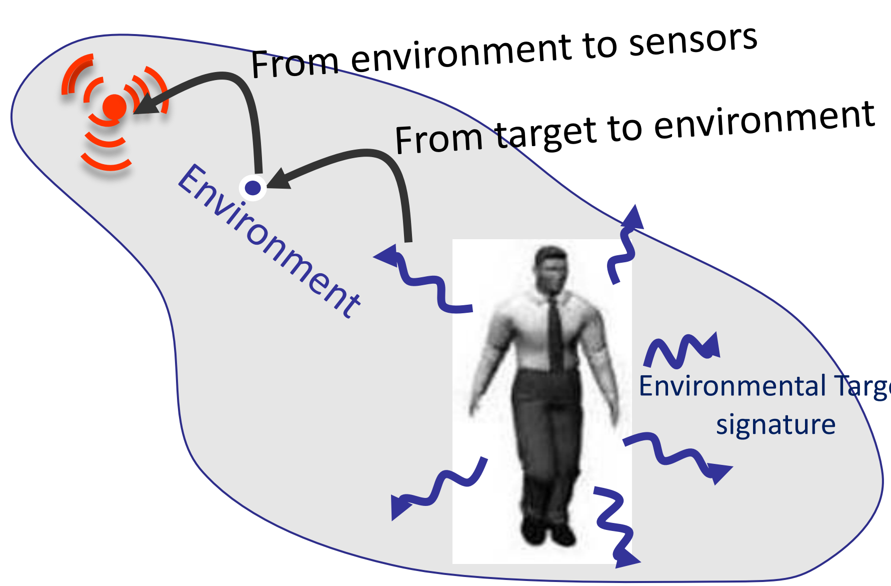
<u>Target is transceiver-free</u>
Analysis of EM perturbation caused by passive targets

Direct vs Indirect



Direct

The target presence is inferred from the EM perturbation



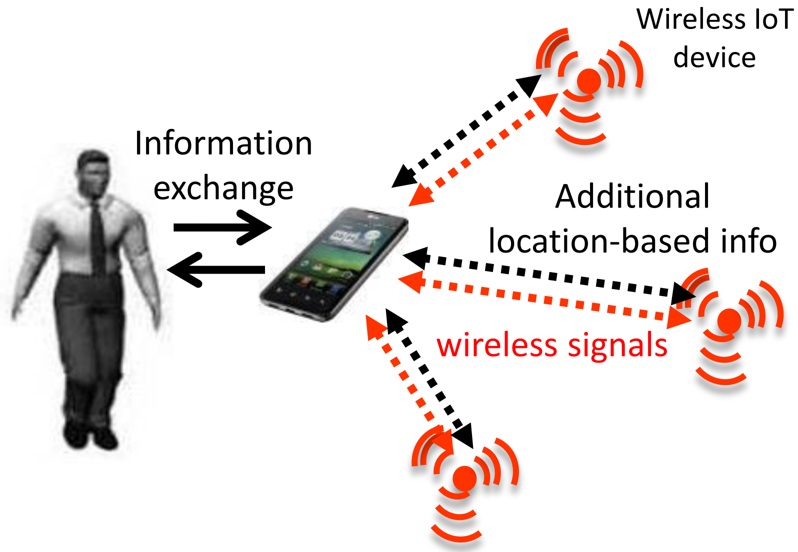
Indirect

The target presence is inferred from environmental changes measured by the sensors

Cooperative vs Non-Cooperative

Cooperative Target

Target Interacts/participates to the localization process (e.g., through dedicated applications)



Non-Cooperative Target

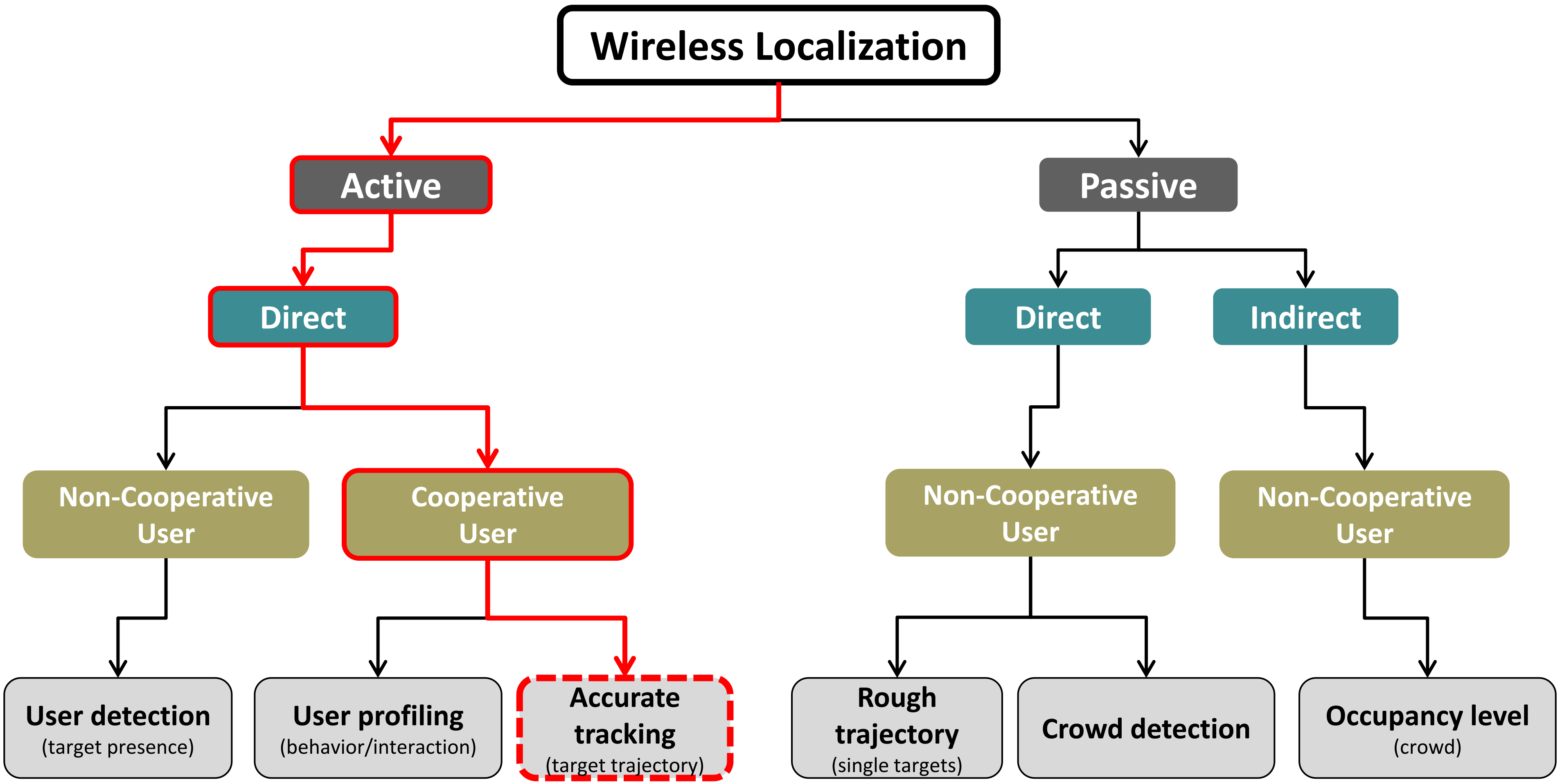
Target does NOT provide information to the localization system (eventually just wears a terminal, if active)

Outline

- EM Positioning for IoT – Intro & Motivation
- **Active Localization of Mobile Devices**
  - Localization through optimization
  - Semantic-based probabilistic approach
- Passive Localization of Transceiver-free Targets
  - Target tracking
  - Crowd detection
  - Indirect occupancy estimation
- Conclusions and Actual Trends

Active Localization

Objective Accurate tracking of wireless devices in indoor domains exploiting existing infrastructures



Applications & Goals

MAIN APPLICATIONS

location-based services through end-user devices

- Indoor Navigation
- Personalized Advertising

} benefits for the user

- Marketing Analysis
- Flows Management

} benefits for the provider

GOALS

✓ <u>Compatibility with commodity devices</u>

✓ <u>Exploitation of existing wireless IoT already connected</u>

localization technologies?..

Which Wireless Technology?

QR Codes

- ↓ Proximity only
- ↓ Require user interaction (take picture)

Wireless passive tags

- ↓ Proximity only
- ↓ Require infrastructure (deploy tags)
- ↑ High localization accuracy

Custom devices

- ↓ Require dedicated infrastructure
- ↓ Prone to technology progress

Wi-Fi networks

- ↓ Not designed for localization
- ↓ Infrastructure-dependent performance
- ↑ Highly diffused
- ↑ High coverage

opportunistic approach?..

Exploit Wireless Signal Characteristic

which information?

Time of Arrival (TOA)

↓ Requires accurate time synchronization

Angle of Arrival (AOA)

↓ Requires dedicated infrastructure and calibration

Received signal strength (RSS)

↓ Very noisy indicator
↓ Amplitude only information
↑ No impact on the infrastructure
↑ Available on all transceivers

opportunistic approach?..

Exploit Wireless Signal Characteristic

which information?

Time of Arrival (TOA)

- ↓ Requires accurate time synchronization

Angle of Arrival (AOA)

- ↓ Requires dedicated infrastructure and calibration

Received signal strength (RSS)

- ↓ Very noisy indicator
- ↓ Amplitude only information
- ↑ No impact on the infrastructure
- ↑ Available on all transceivers

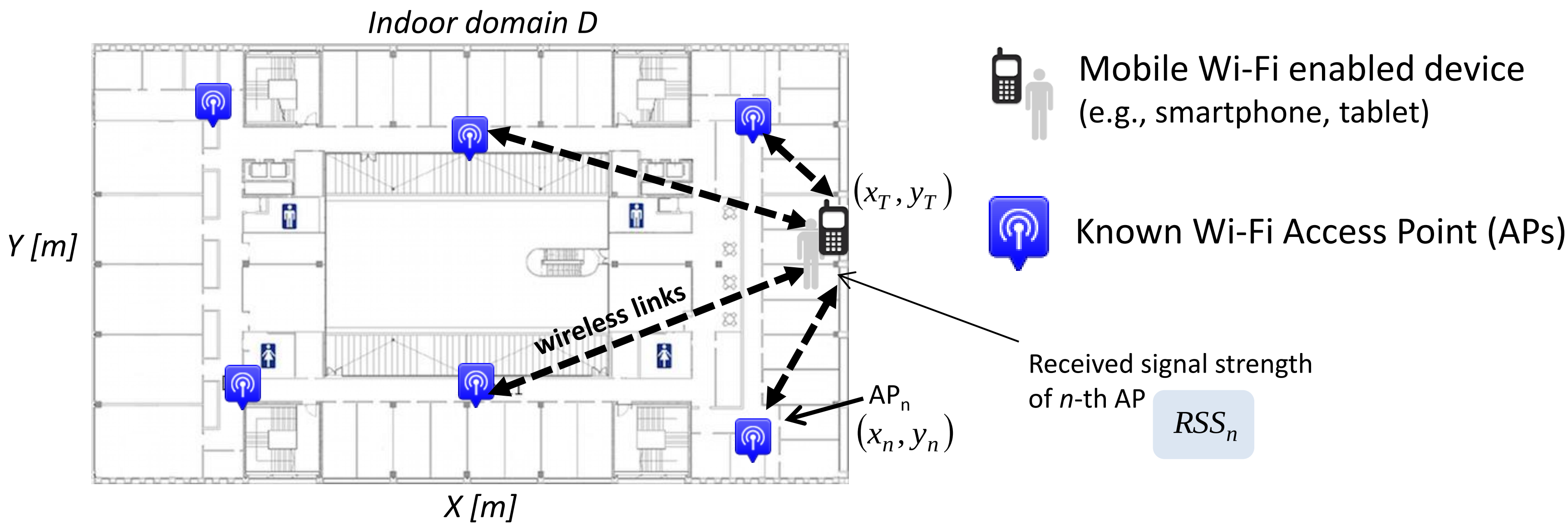
opportunistic approach

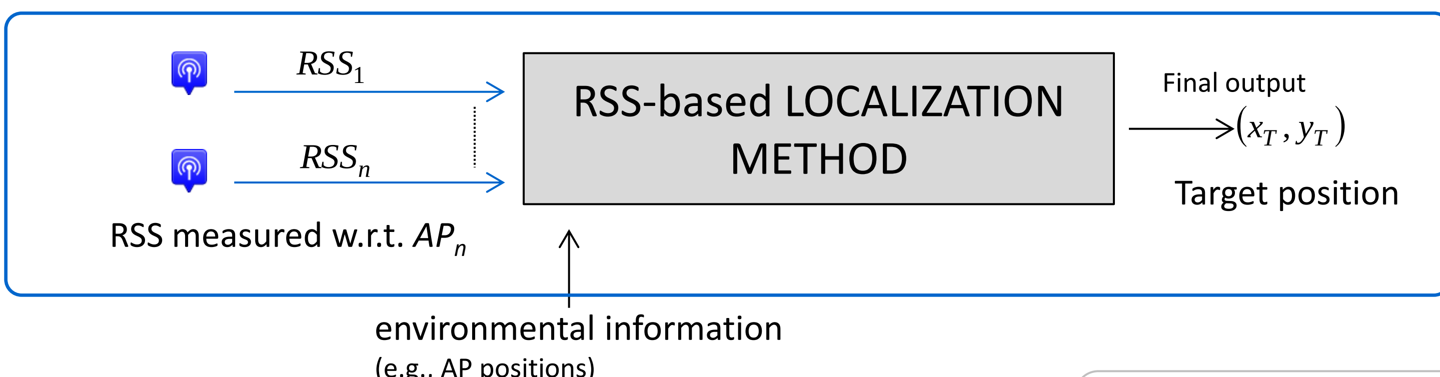
[1] F. Viani, F. Robol, A. Polo, P. Rocca, G. Oliveri, and A. Massa, "Wireless architectures for heterogeneous sensing in smart home applications – Concepts and real implementations," Proceedings of the IEEE – Special Issue on 'The Smart Home,' Invited Paper, vol. 101, no. 11, pp. 2381-2396, November 2013 (DOI 10.1109/JPROC.2013.2266858).

opportunistic approach?..

system architecture?..

RSS-based System Architecture

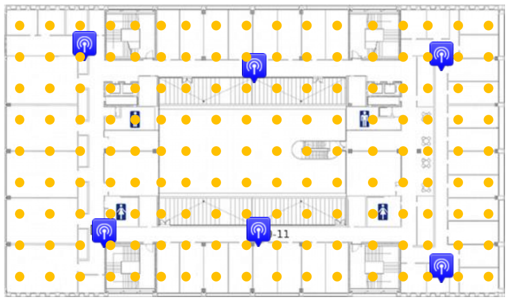




how to estimate position from RSS measurements?..

RSS-based Methodologies

Fingerprinting

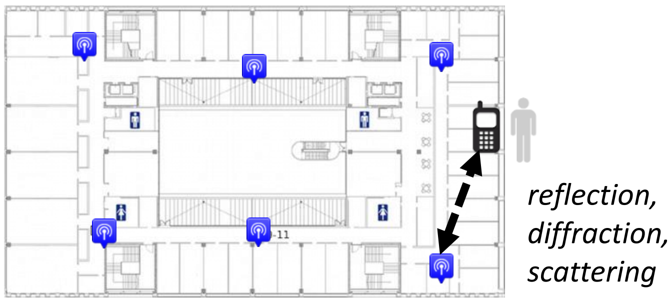


RSS signature map

→ **Which cell has the <u>best-matching signature</u>?**

↑ Accuracy
↓ Long offline training
↓ Prone to environment changes

Propagation Based



Numerical EM model

→ **<u>What is the estimated distance</u> between AP and target?**

↑ Scalability, No Training
↓ Prone to EM model accuracy
↓ Complex propagation in indoor

proposed method..

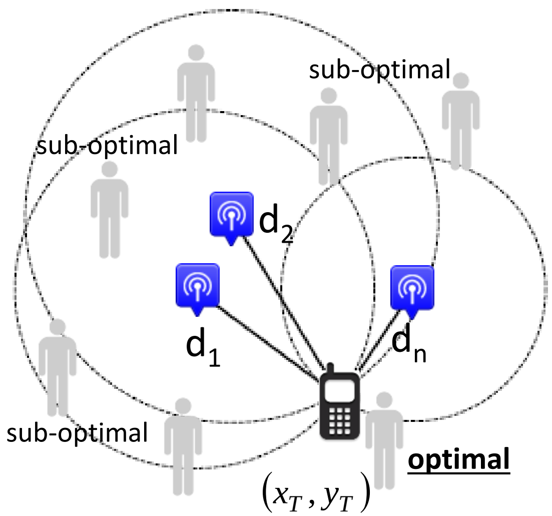
Proposed Localization Method

PROPOSED METHOD

Recast the location problem as an optimization problem

Find the optimal position (x_T, y_T)

that minimizes the two-terms function Ω



weighting coefficients

$$\Omega\left(x, y, \bar{\gamma}\right) = \alpha\,\Theta\left(x, y, \bar{\gamma}\right) + \beta\,\Delta\left(x, y\right)$$

RSS Propagation based | **Probabilistic based**

Exploit different information sources

solved by:
Particle Swarm Optimizer [1]

[1] P. Rocca, M. Benedetti, M. Donelli, D. Franceschini, and A. Massa, "Evolutionary optimization as applied to inverse problems," *Inverse Problems* – 25th Year Special Issue of Inverse Problems, Invited Topical Review, vol. 25, pp. 1-41, December 2009.

propagation term..

Propagation-based Term

WIRELESS PROPAGATION Minimize difference between estimated and measured RSS

$$\Theta\left(x,y,\overline{\gamma}\right)=\frac{\sum_{n=1}^{N}\left\{\left[RSS_n\left(x,y,\overline{\gamma}\right)-RSS\left(\zeta\left(x_n,y_n\right)\right)\right]^2\right\}}{\sum_{n=1}^{N}\left\{\left[RSS\left(\zeta\left(x_n,y_n\right)\right)\right]^2\right\}}$$

where

$RSS\left(\zeta\left(x_n,y_n\right)\right)$ **RSS measured** by *n*-th AP, proportional to the EM field

$$\zeta\left(x_n,y_n\right)=\int_{D^T} J^T\left(x',y'\right)G\left(x',y'\middle|x_n,y_n\right)dx'dy'$$

EM field measurements by WI-Fi APs

$$RSS_n\left(x,y,\overline{\gamma}\right)=P_0-10\lambda\log\left(\frac{\sqrt{\left(x-x_n\right)^2+\left(y-y_n\right)^2}}{d_0}\right)-\rho$$

RSS estimated by the EM propagation model (log-shadow path loss)

$\overline{\gamma}=\left[P_0,\lambda,\rho\right]$ EM channel parameters vector used in the propagation model

N Number of APs at $\left(x_n,y_n\right)$

propagation model..

Propagation-based Term

WIRELESS PROPAGATION Minimize difference between measurements and estimation

$$\Theta\left(x,y,\bar{\gamma}\right)=\frac{\sum_{n=1}^{N}\left\{\left[RSS_n\left(x,y,\bar{\gamma}\right)-RSS\left(\zeta\left(x_n,y_n\right)\right)\right]^2\right\}}{\sum_{n=1}^{N}\left\{\left[RSS\left(\zeta\left(x_n,y_n\right)\right)\right]^2\right\}}$$

Numerically estimated Received power

Path-loss exponent

TX-RX distance

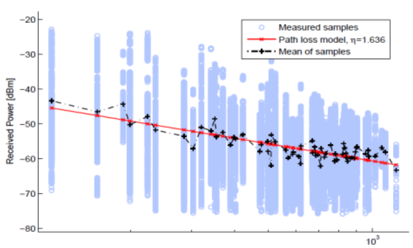
$$\boxed{RSS_n\left(x,y,\bar{\gamma}\right)}=\boxed{P_0}-10\boxed{\lambda}\log\left(\frac{\boxed{\sqrt{\left(x-x_n\right)^2+\left(y-y_n\right)^2}}}{\boxed{d_0}}\right)-\boxed{\rho}$$

$$\bar{\gamma}=\left[P_0,\lambda,\rho\right]$$

Transmitted power, measured at d_0

Reference distance from transmitter

Gaussian random variable (noise)



<u>Log-shadow path loss</u> model

- ↑ Simple
- ↑ Computationally efficient
- ↓ Accuracy in indoor environment

probabilistic term..

Probabilistic-based Term

PRESENCE PROBABILITY Exploit a-priori probabilistic information

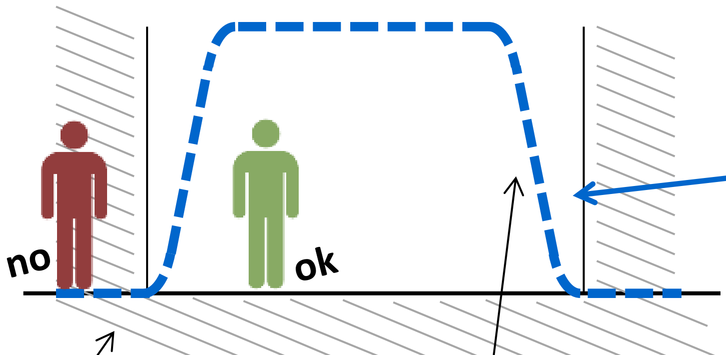
$$\Delta(x,y) = 1 - \Pr(x,y)$$

Concept:

Target presence probability $\Pr(x,y)$

is not uniform in the domain

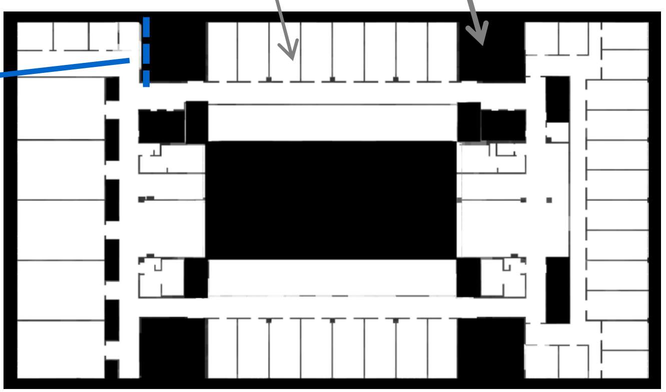
$\Pr(x',y') = 0$ $\Pr(x,y) = 1$



concrete material

smooth step for improving optimization convergence

Target cannot be in obstructed areas nor inside walls (x',y')

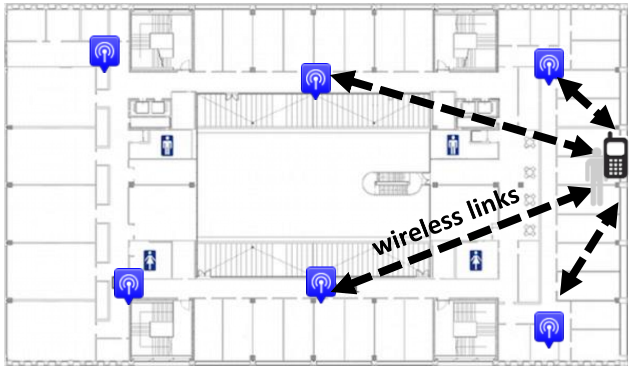


information available from blueprint

experimental validation..

Experimental Validation

LOCALIZATION FRAMEWORK Multi-client (App) / server software framework



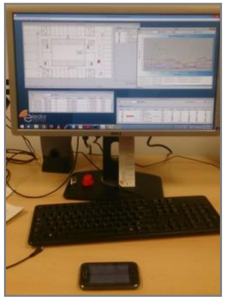
RSS measurements

estimated position

Wi-Fi or 3G channel

Localization Server

- Run & compare algorithms
- Replay logs
- Interactive map & tools



SW App

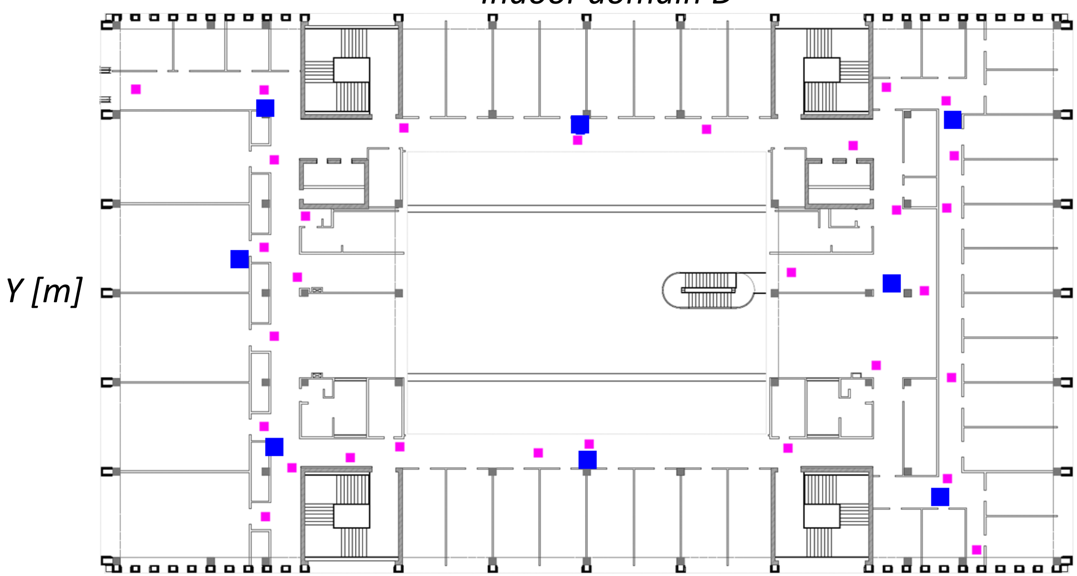
- Scan Wi-Fi networks (RSS)
- TX RSS to remote server
- Show position on device

validation scenario..

Experimental Validation

SCENARIO Office facility with standard Wi-Fi infrastructure

Indoor domain D



■ Access points (AP) ■ Test positions (U) at (x_u, y_u)

Test site parameters

X = 80.690 m
Y = 46.290 m

U = 35 (test positions)
N = 8 (APs)

Ceiling-mounted Wi-Fi AP

considered dataset

in each test position ■

- 15 RSSI set (≈1 min. Wi-Fi scan)
- 2 different smart-phones
- 2 different users

total: **2100 test problems**

Optimization parameters

$P_0 = [-48, -44]\, dBm \quad d_0 = 1m$

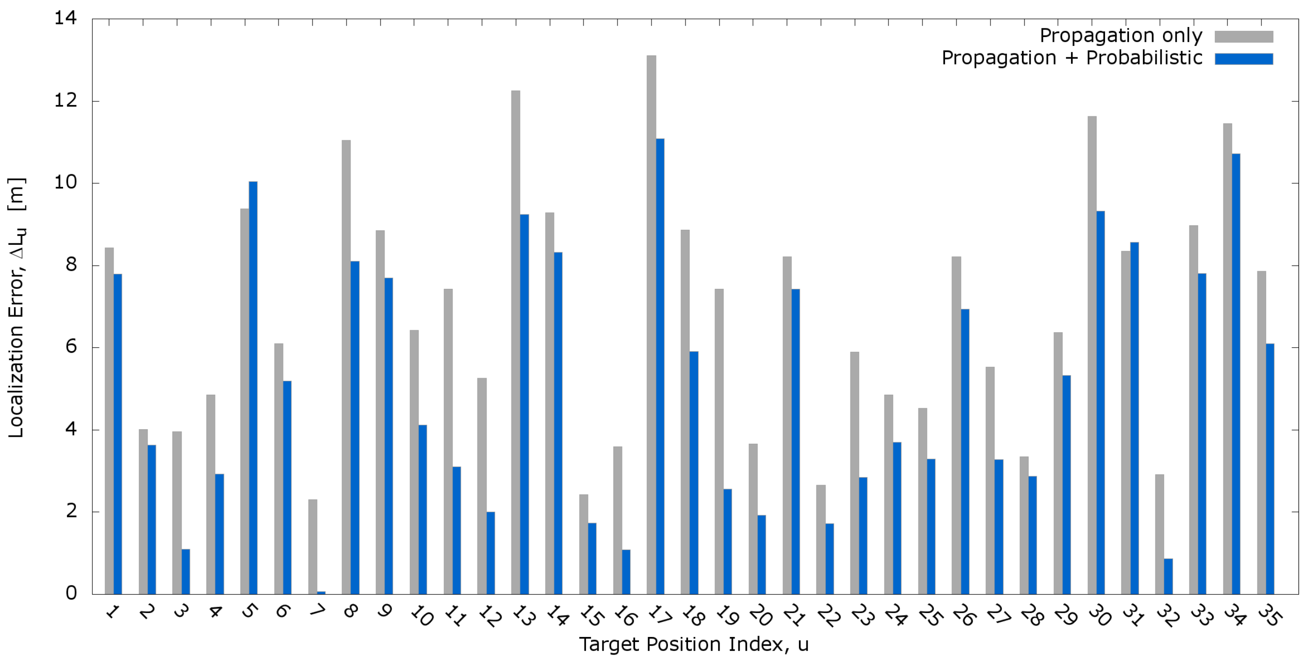
$\lambda = [2.2, 4.8]$

Max-Iterations = 1000
Population = 30

statistical assessment..

Experimental Validation

STATISTICAL ASSESSMENT Improved accuracy considering also probabilistic term



Aggregated mean localization error

Propagation only

$$\Delta L^{wo} = 7.15\ m$$
$$\delta^{wo} = 5.45\ m$$

Propagation + Probabilistic

$$\Delta L^{wp} = 6.49\ m$$
$$\delta^{wp} = 4.35\ m$$

$$\Delta L = \frac{1}{U}\sum_{u=1}^{U}\left\{\sqrt{(x-x_u)^2+(y-y_u)^2}\right\}$$

Mean localization error (Euclidean distance)

$$\delta = \sqrt{\frac{1}{N}\sum_{u=1}^{U}\left\{\sqrt{(\Delta L_u - \Delta L)^2}\right\}}$$

Standard deviation of localization error

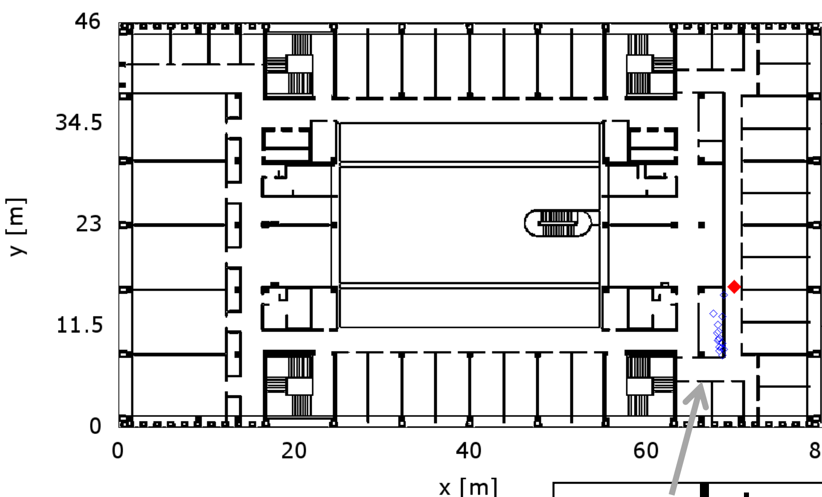
representative example..

Experimental Validation

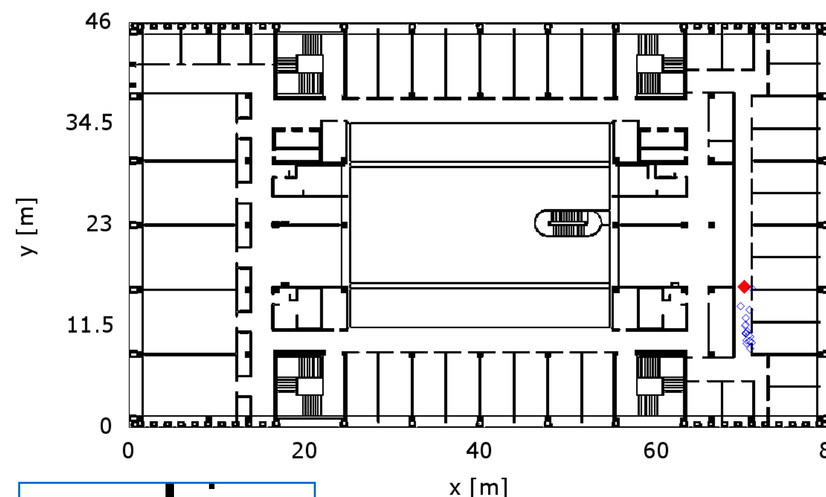
REPRESENTATIVE EXAMPLE

Improved accuracy by considering also probabilistic term

Propagation only

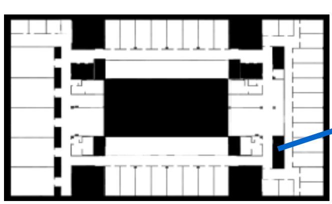


Propagation + Probabilistic

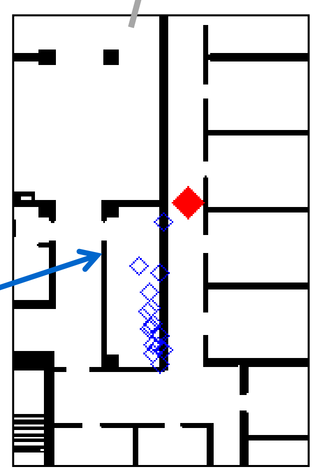


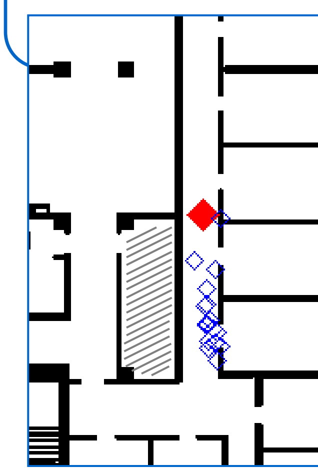
◆ Real target position

◇ Estimated positions



(maintenance room)

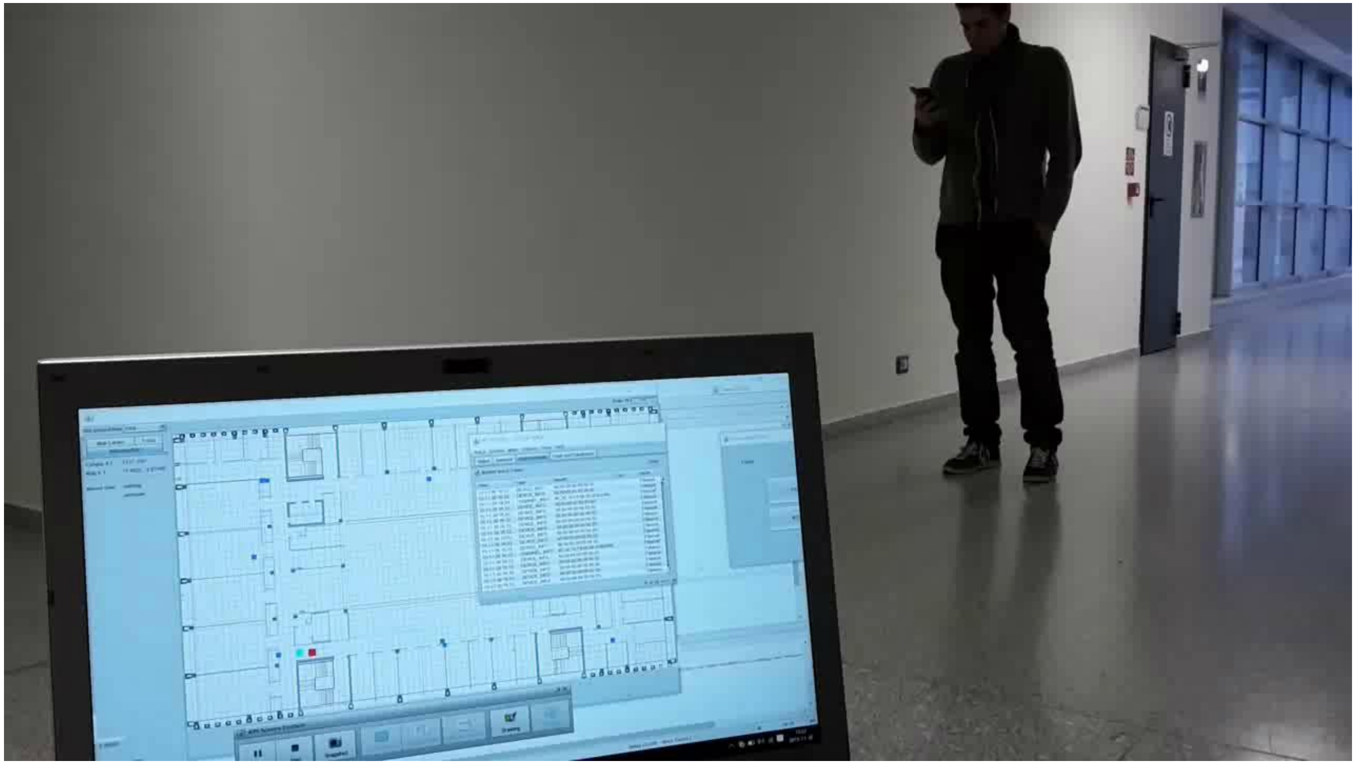


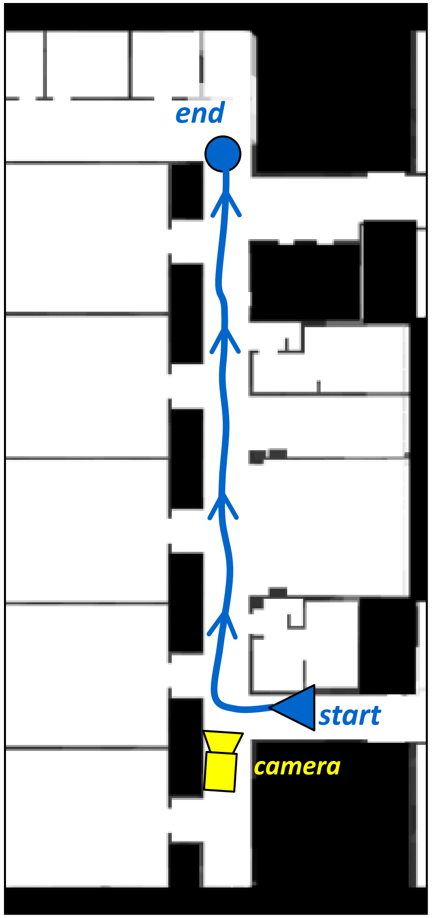


optimization convergence..

Experimental Validation

REAL-TIME DEMONSTRATION Propagation only vs. Propagation + Probabilistic





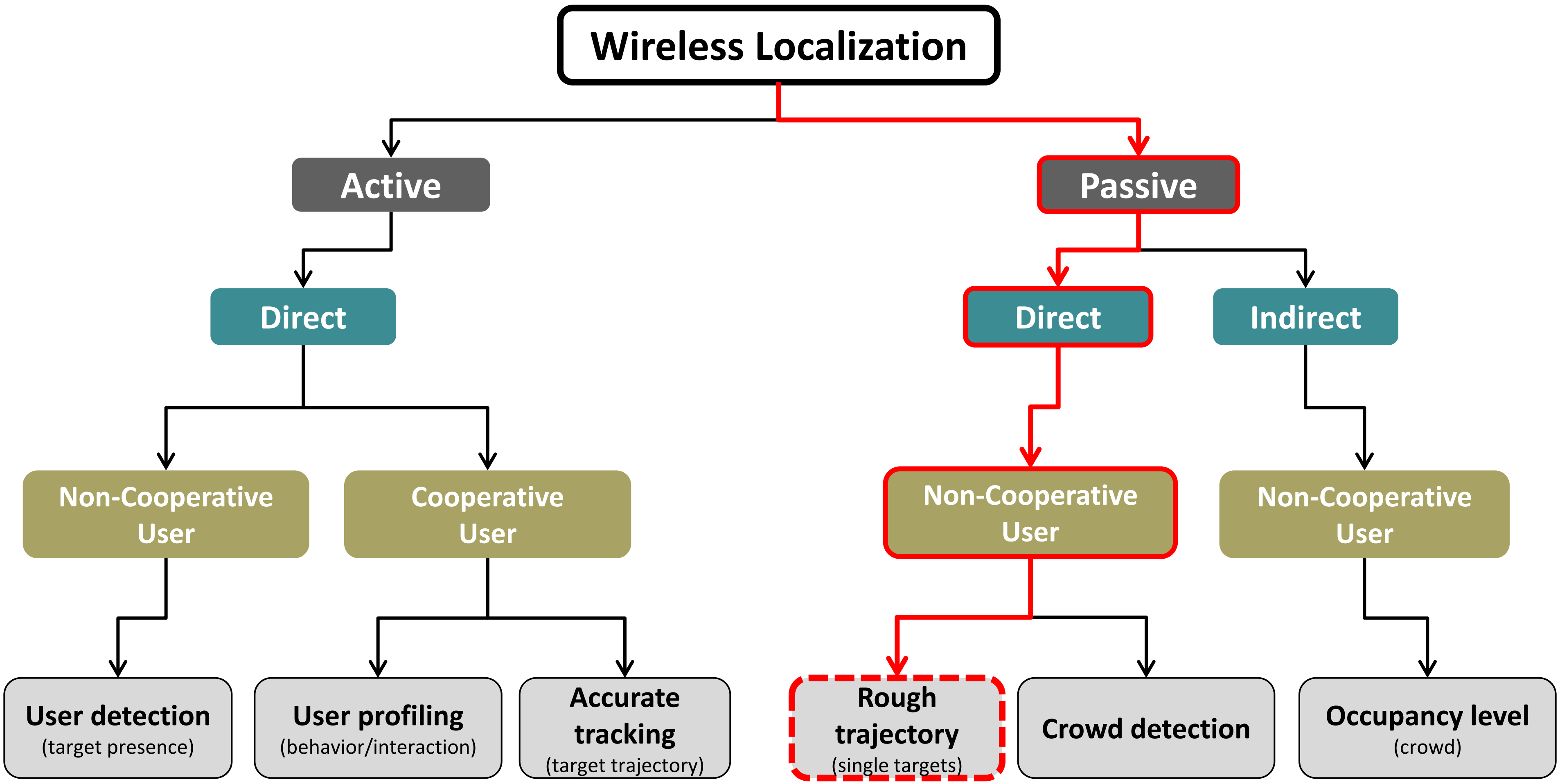
- **Propagation Only**
- **Propagation + Probabilistic**

Outline

- EM Positioning for IoT – Intro & Motivation
- Active Localization of Mobile Devices
  - Localization through optimization
  - Semantic-based probabilistic approach
- **Passive Localization of Transceiver-free Targets**
  - Target tracking
  - Crowd detection
  - Indirect occupancy estimation
- Conclusions and Actual Trends

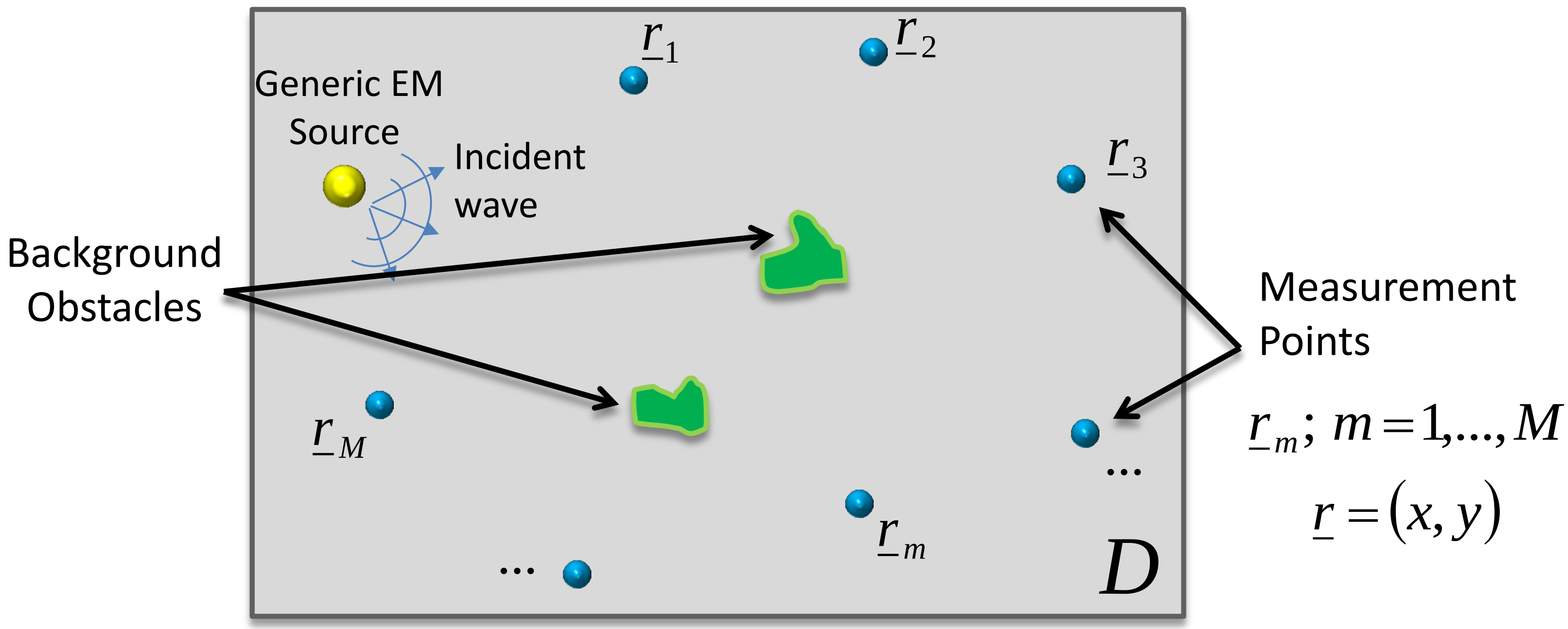
Passive Localization

Objective Passive tracking of wireless devices in indoor domains exploiting wireless propagation only



Problem Geometry

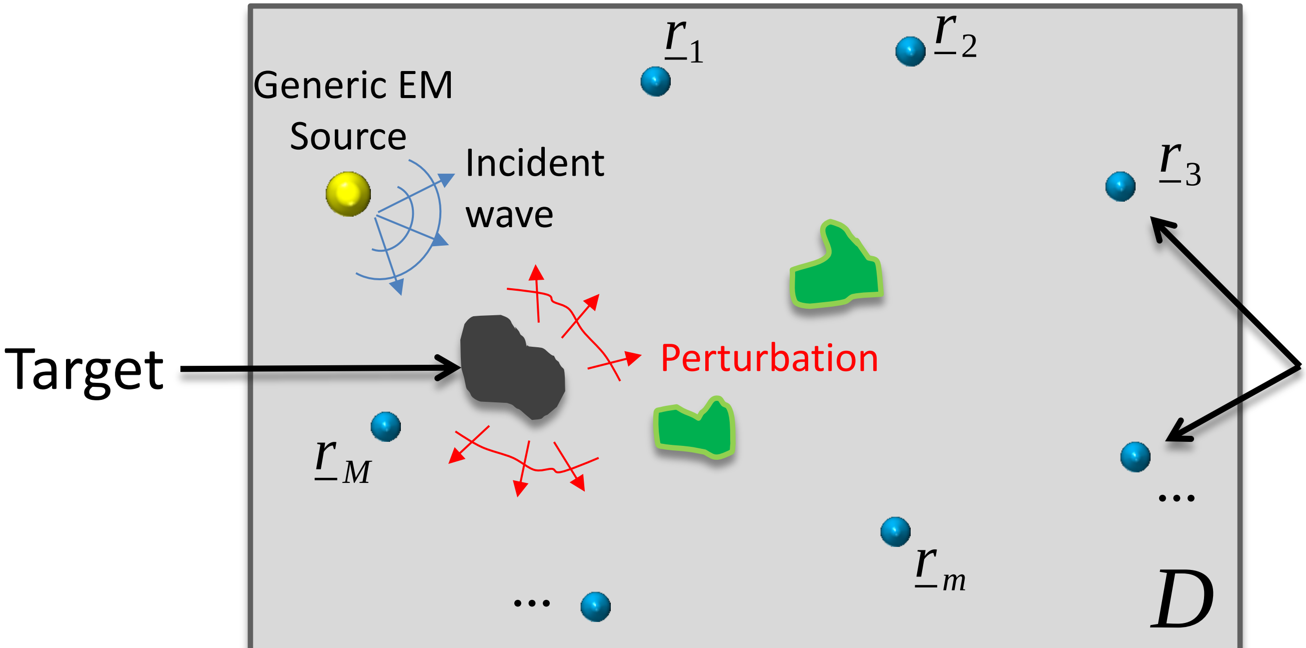
Background – Inhomogeneous Region



Field measured without the target $\zeta(\underline{r}_m)\quad m=1,\ldots,M$

Problem Geometry

Background with the Target



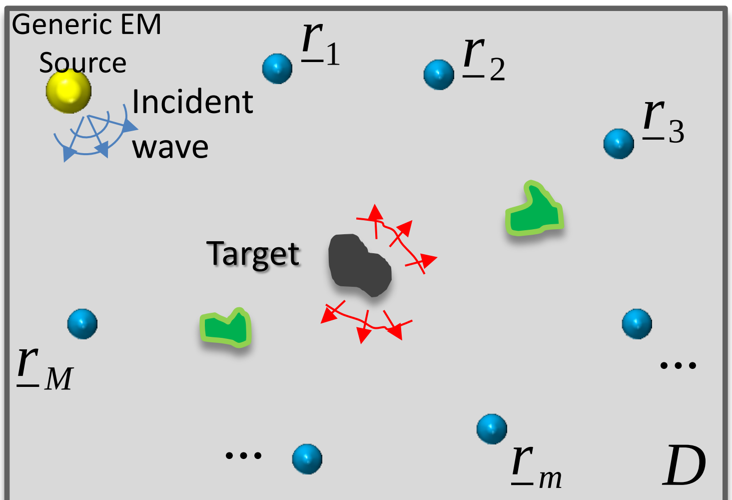
$$\underline{r}_m;\ m=1,\ldots,M$$

$$\underline{r}=(x,y)$$

Field measured with the target $\xi(\underline{r}_m)\ \ m=1,\ldots,M$

Field Equivalence Principle

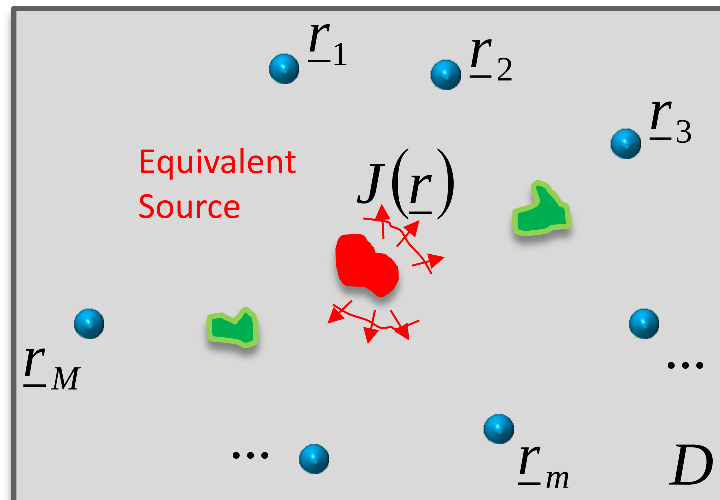
Background with the Target



Field measured with the target

$$\xi(\underline{r}_m) \quad m = 1, \ldots, M$$

Equivalent Source

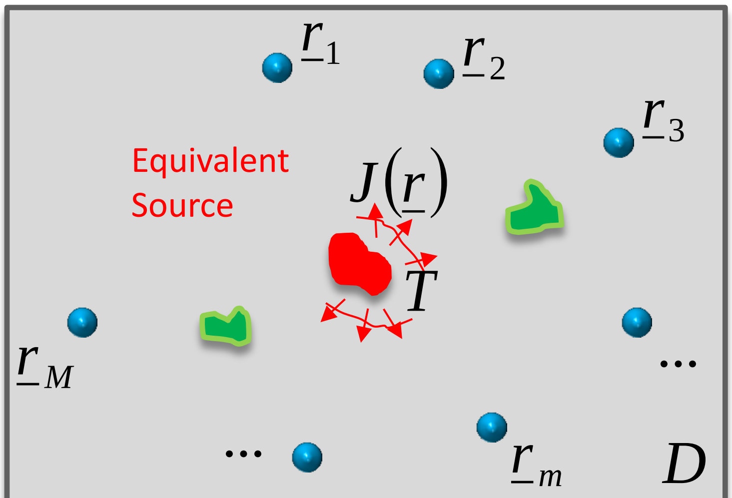


$$\xi(\underline{r}_m) = \Im\{J(\underline{r})\} \quad m = 1, \ldots, M$$

Inverse Scattering Problem

Field Equivalence Principle

Equivalent Source



$$\xi(\underline{r}_m) = \Im\{J(\underline{r})\} \qquad m = 1,\ldots,M$$

$$J(\underline{r}) = \tau(\underline{r})\,\xi(\underline{r}) \qquad \forall\, \underline{r} \in T$$

Material Properties

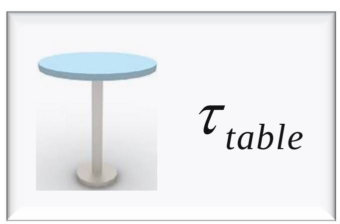
Field within the target

$$\tau(\underline{r}) = \varepsilon_r - 1 + j\,\frac{\sigma}{\omega\varepsilon_0}$$

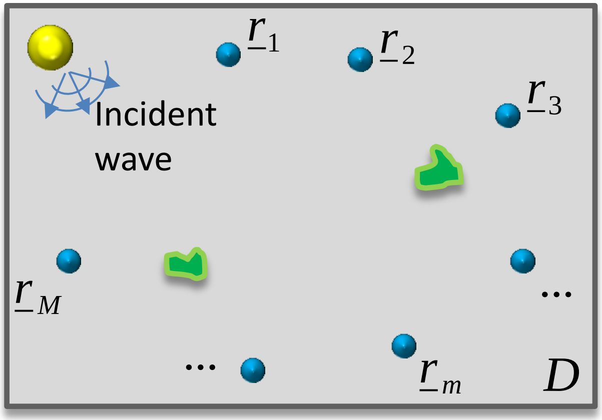
Conductivity

Relative Permittivity

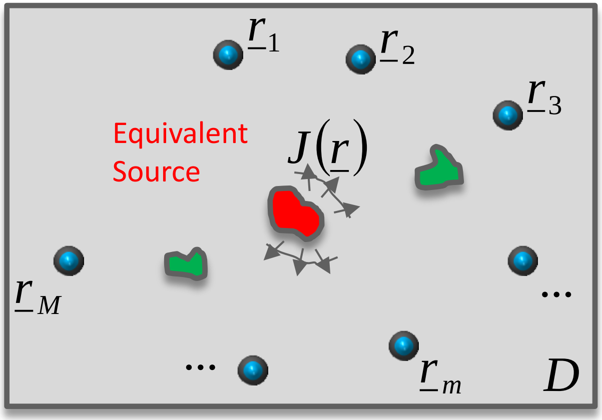
Vacuum Permittivity



Problem Formulation



+



$$\xi(\underline{r}_m) = \zeta(\underline{r}_m) + \int_T J(\underline{r}')G(\underline{r}_m / \underline{r}')d\underline{r}' \quad m = 1,\dots,M$$

Problem Redefinition:

Find position and occupation area of the target

Find $J(\underline{r})$ that satisfies the inverse scattering equation

$$\underline{E}_{m,v} = \frac{\xi_v(\underline{r}_m) - \zeta_v(\underline{r}_m)}{\zeta_v(\underline{r}_m)} \quad \begin{array}{ll} m = 1,\dots,M-1 & \textbf{RX} \\ v = 1,\dots,M & \textbf{TX} \end{array}$$

Localization Approach

How to solve the localization problem at hand?

Requirements:

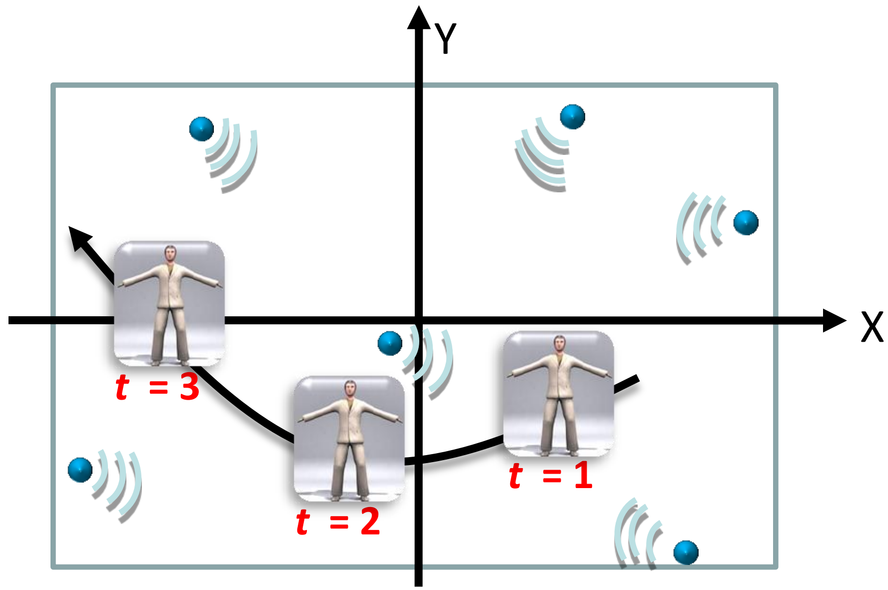
- **Simplicity**
- **Flexibility**
- **Real Time**

⬇

Learning by Example method

samples are needed…

Proposed Approach – Training Samples



Time	Target Position	Data
$t=1$ →	$\underline{r}_1$ →	$\underline{E}_{m,v}(t=1)$
$t=2$ →	$\underline{r}_2$ →	$\underline{E}_{m,v}(t=2)$
$t=3$ →	$\underline{r}_3$ →	$\underline{E}_{m,v}(t=3)$

$$\begin{pmatrix} \underline{r}_1 \\ \cdots \\ \underline{r}_2 \\ \cdots \\ \underline{r}_3 \end{pmatrix} \mapsto \begin{pmatrix} \underline{E}_{m,v}(0) \\ \cdots \\ \underline{E}_{m,v}(t) \\ \cdots \\ \underline{E}_{m,v}(T) \end{pmatrix}$$

Input/Output Relations

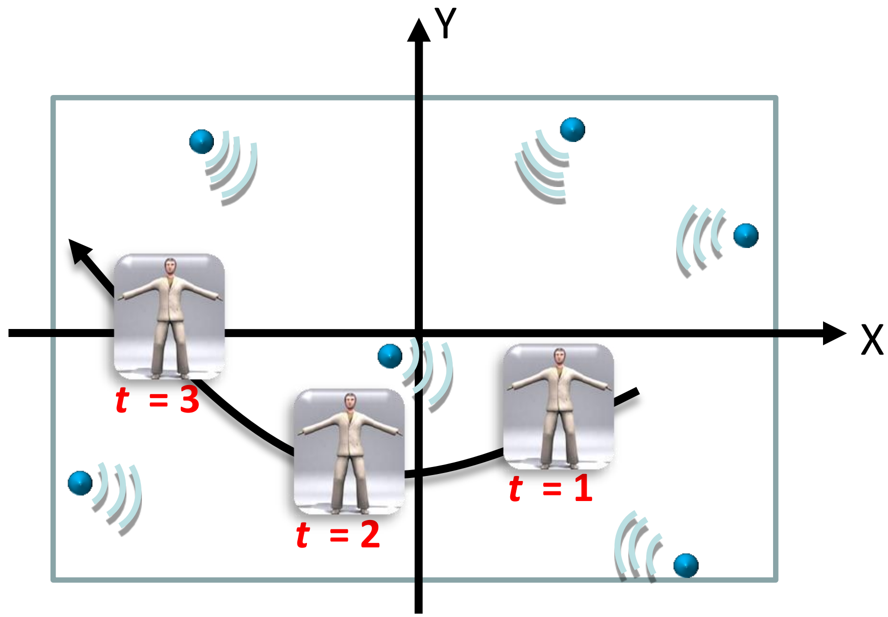
$t = 1, \ldots, T$

time steps

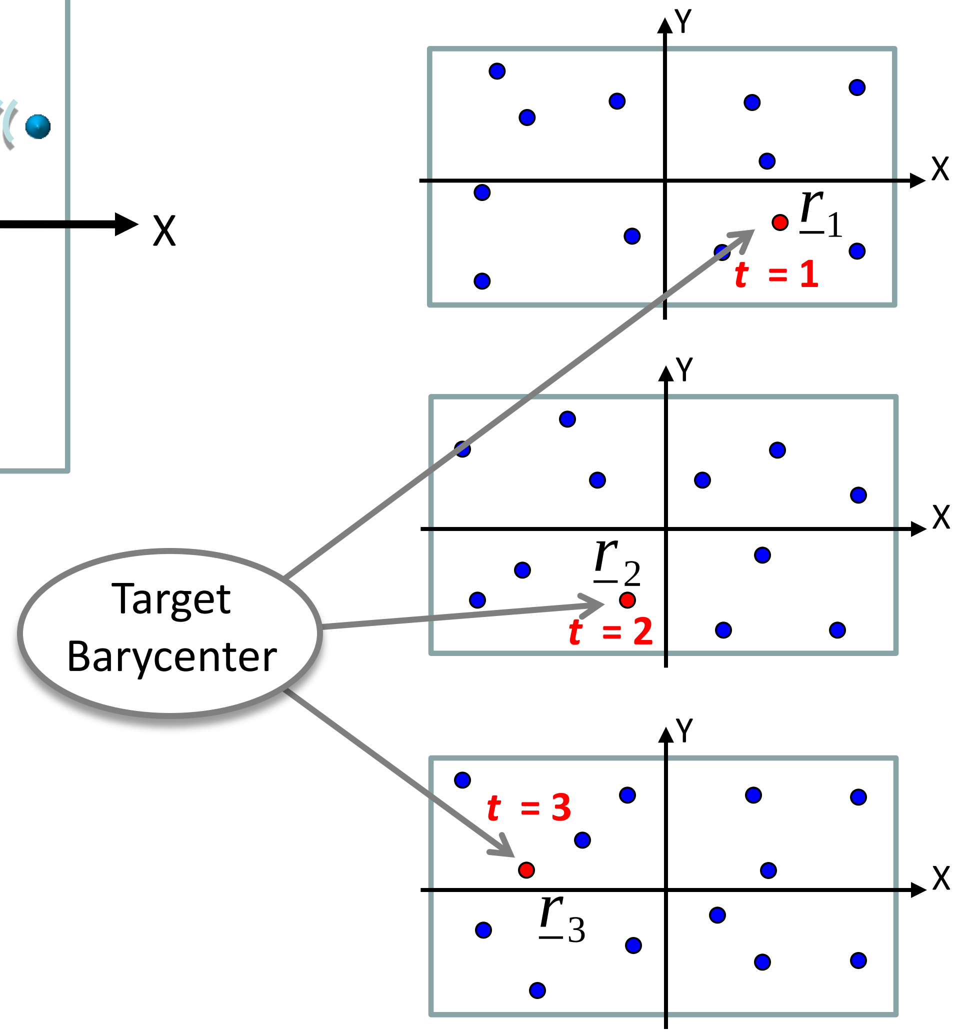
Samples exist

How can be used?

Proposed Approach – Binary Problem



$\underline{r}_c, c = 1, \ldots, C$ Positions



Target PRESENCE $\chi_c = +1$

Target ABSENCE $\chi_c = -1$

Available Informations:

- EM Field data
- Point Positions
- Binary States

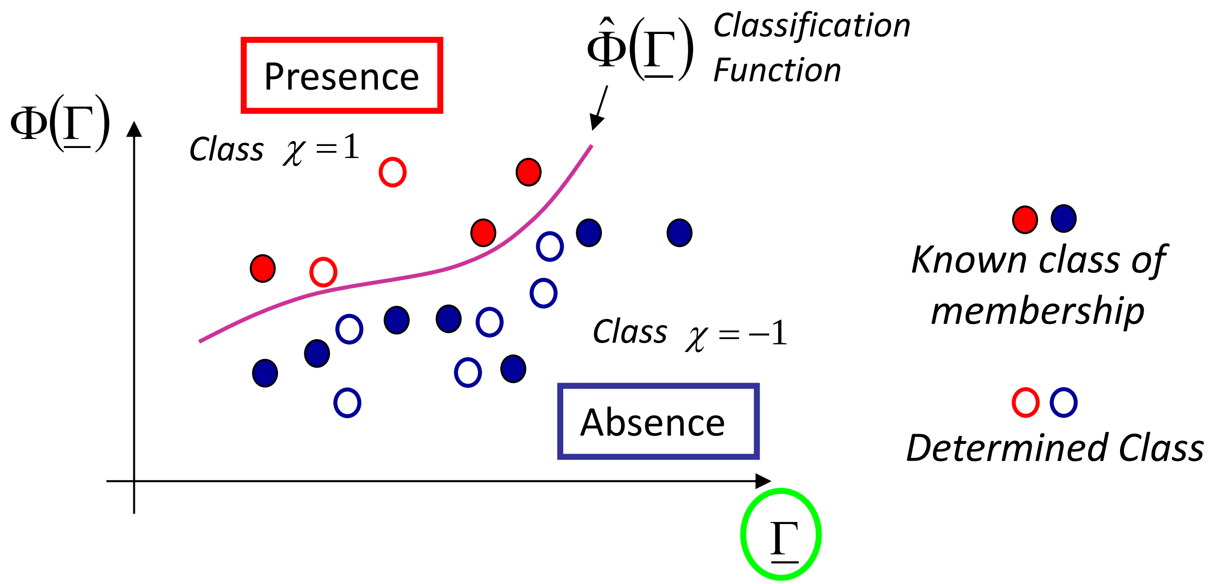
Proposed Approach - Classification

Training data set

$$\underline{\Gamma}_c^{(t)} = \left\{ \underline{E}_t ; \underline{r}_c , \chi_c ; c = 1,\ldots,C; t = 1,\ldots,T \right\} \qquad \chi_c \in [-1,1]$$

Objective

Determine the class of membership for each input data



<u>*Class of membership* is exactly determined for each input data</u>

Proposed Approach - Classification

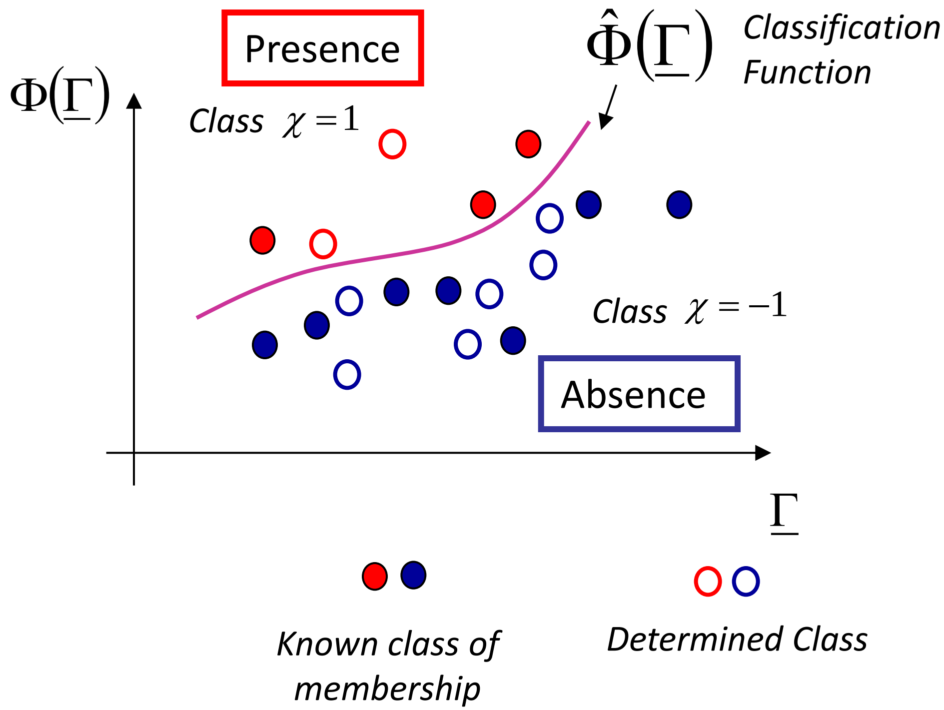
Drawbacks

(1) Unbalanced Additional Information

Usually the number of samples of class χ=-1 (i.e., Absence) is larger than that class χ=+1 (i.e., Presence)

↓

The classification function is biased towards the class with more samples



(2) Good/Bad Classification?

No information on the reliability of the classification is available since the output is of binary nature.

How to cope with these drawbacks?

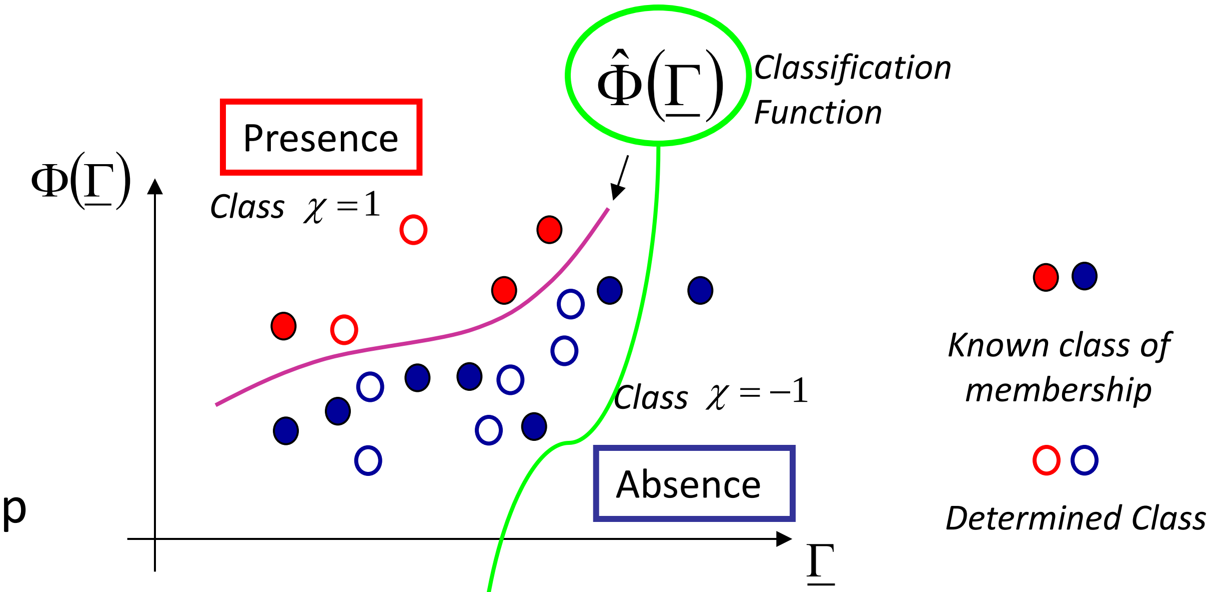
Two-Steps Procedure

Step 1

Binary Classification

↓

Determine the class membership

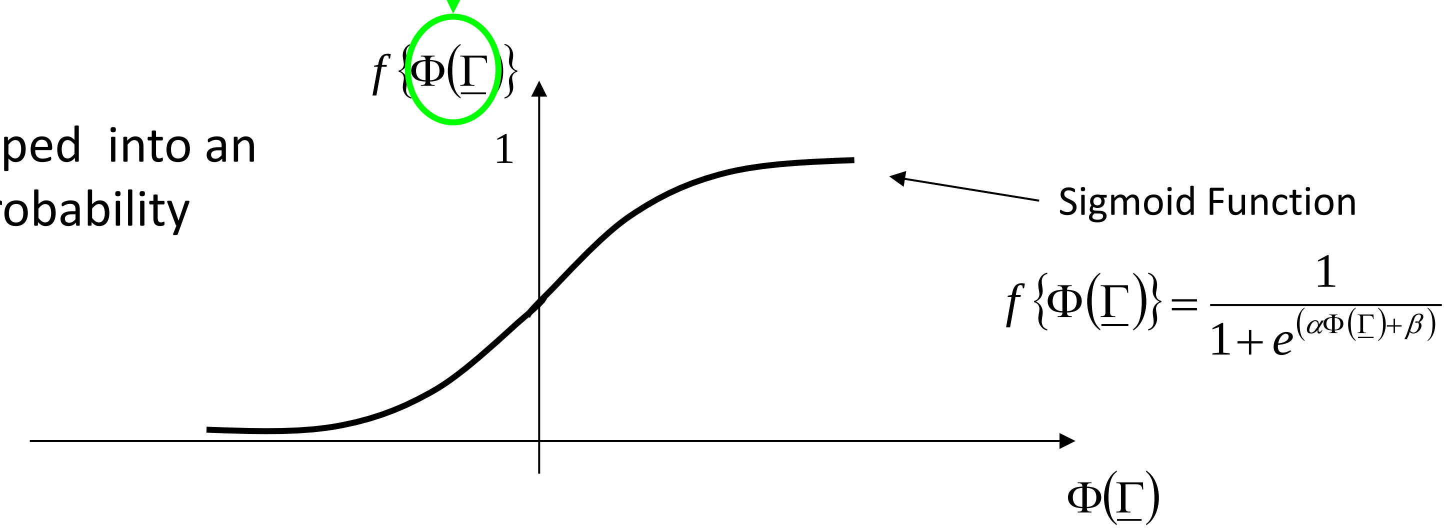


Step 2

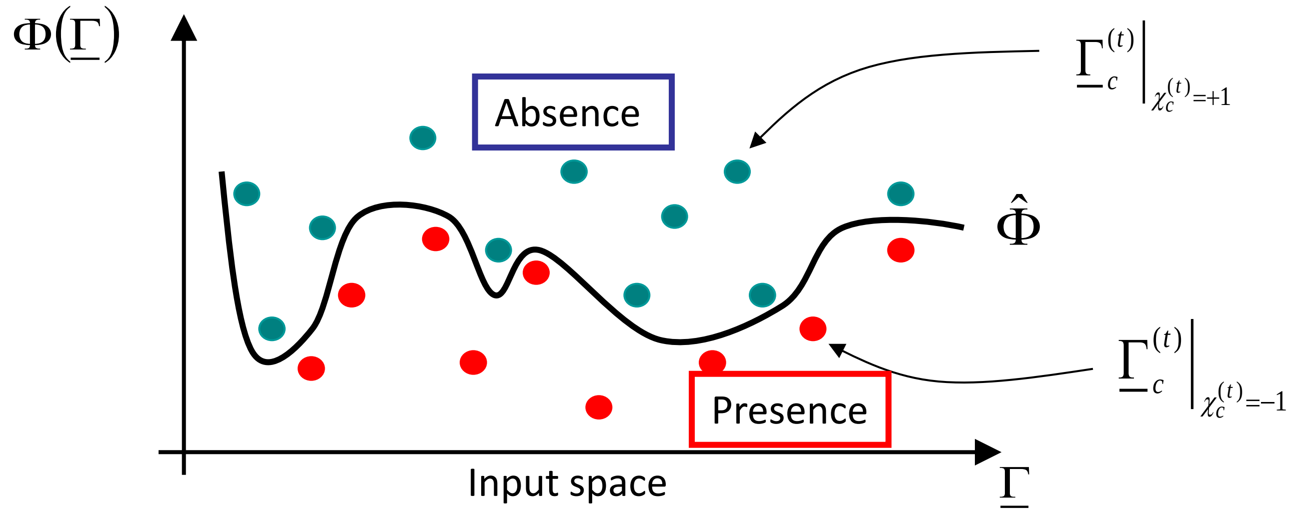
Binary Value Mapped into an A-posteriori Probability

↓

Determine the *degree of* class membership



Step 1 – Binary Classification



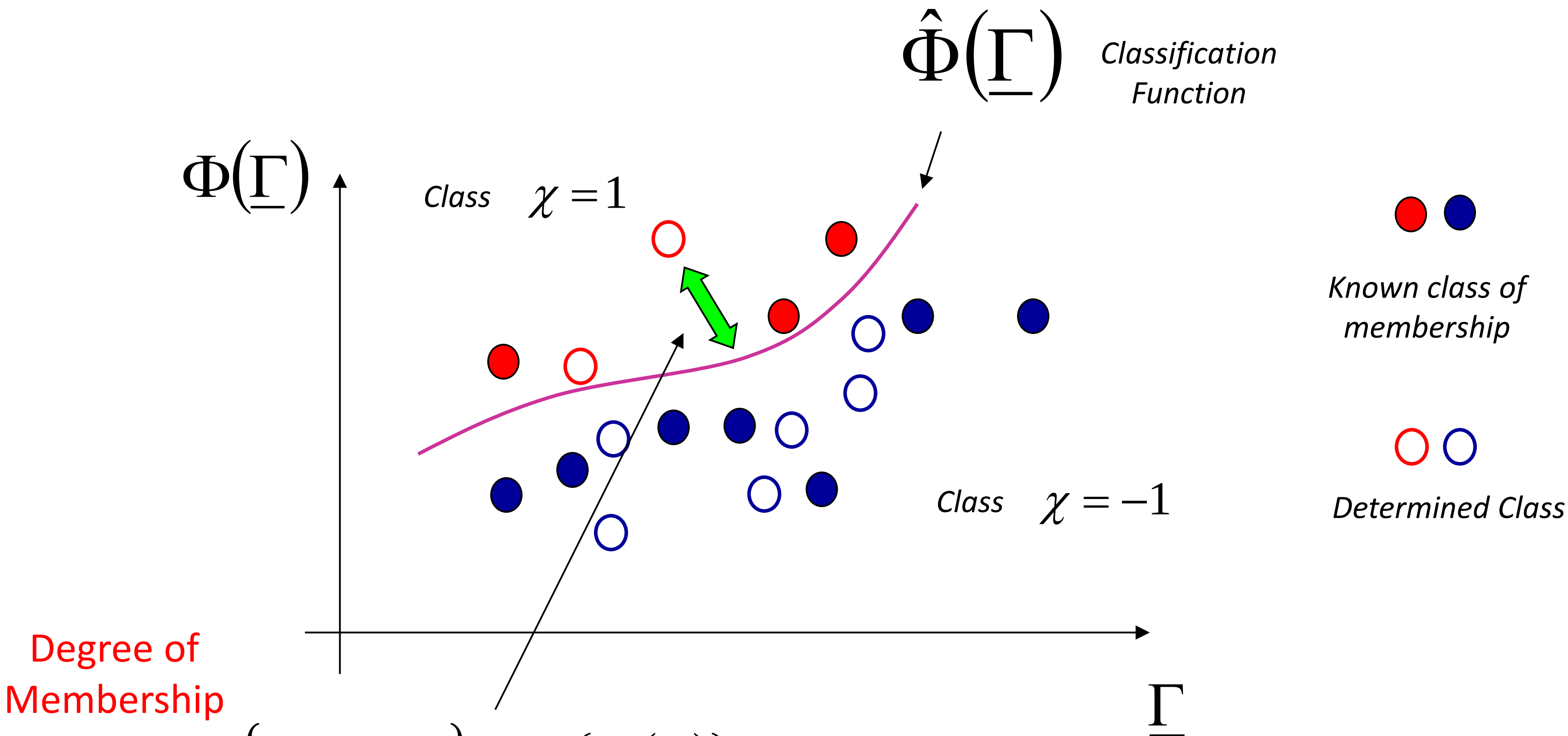
PROBLEM

non-linearly separable classes (in the input space)

PROPOSED SOLUTION

Non-linear SVM

Step 2 – A-posteriori Probability



$$\Pr\{\chi_c = 1 | \underline{\Gamma}\} = f\{\Phi(\underline{\Gamma})\}$$

Probabilistic approach gives information on the distance of the input samples from the classification function

A-Posteriori Probability:

$$\Pr\left\{\chi_c = 1 \mid \left(\underline{\Gamma}\right)\right\} = \frac{1}{1+\exp\left\{\gamma\hat{\Phi}\left(\underline{\varphi}\left(\underline{\Gamma}\right)\right)+\delta\right\}} \qquad c = 1,\ldots, C$$

with γ and δ estimated by the minimization of [*]:

$$\Upsilon\{\gamma,\delta\} = -\sum_{s=1}^{S}\sum_{c=1}^{C}\left\{\frac{\chi_c^{(s)}+1}{2}\log\left[\frac{1}{1+\exp\left(\gamma\hat{\Phi}_c^{(s)}+\delta\right)}\right]+\left(\frac{1-\chi_c^{(s)}}{2}\right)\log\left[\frac{\exp\left(\gamma\hat{\Phi}_c^{(s)}+\delta\right)}{1+\exp\left(\gamma\hat{\Phi}_c^{(s)}+\delta\right)}\right]\right\}$$

where

- $\hat{\Phi}_c^{(s)} = \hat{\Phi}\left(\underline{\varphi}\left(\underline{\Gamma}_c^{(t)}\right)\right)$
- $\left\{\left(\underline{E}, \underline{r}_c, \chi_c; c = 1,\ldots, c\right)^{(s)}; s = 1,\ldots, S\right\} \qquad S < T$

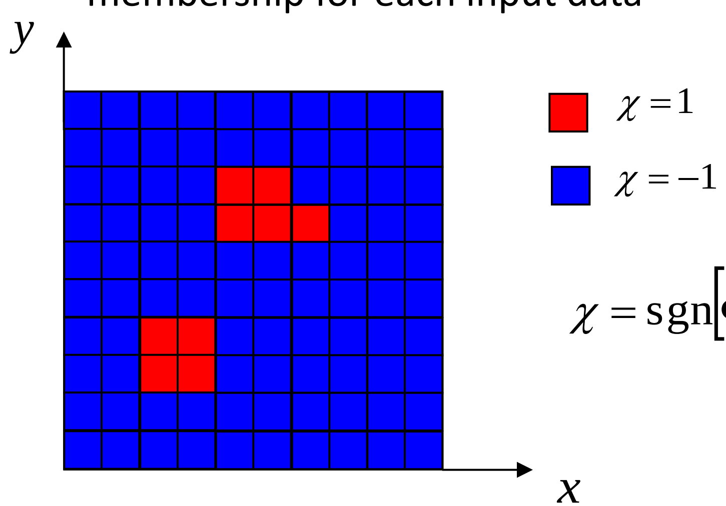
[*] J. Platt, "Probabilistic outputs for support vector machines and comparison to regularized likelihood methods," in *Advances in Large Marging Classifiers*, A. J. Smola , P. Barlett, B. Scholkopf, D. Shuurmans (Eds.), MIT Press, 1999

Step 2 – A-posteriori Probability

Deterministic Classification

Objective

Determine the class of membership for each input data



$$\chi = \mathrm{sgn}\left[\hat{\Phi}(\underline{\Gamma})\right]$$

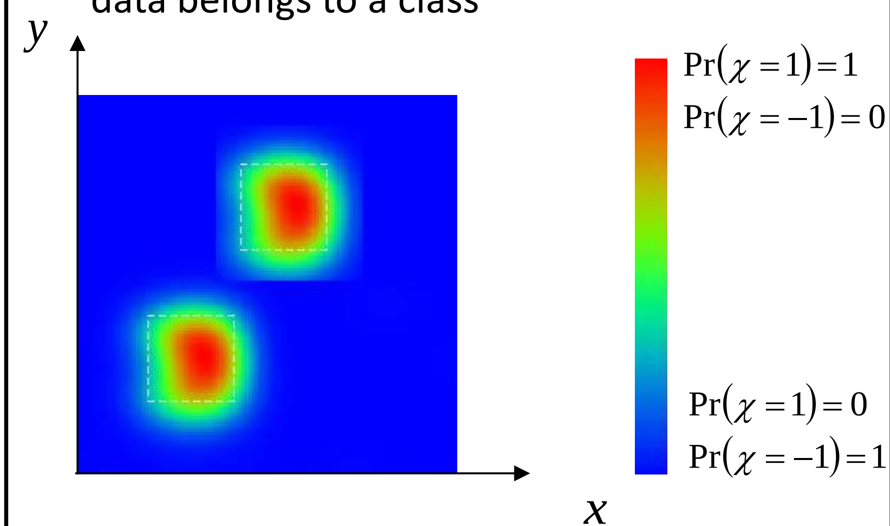
⬇

Binary knowledge on the class of the input data

Probabilistic Classification

Objective

Determine the probability that an input data belongs to a class

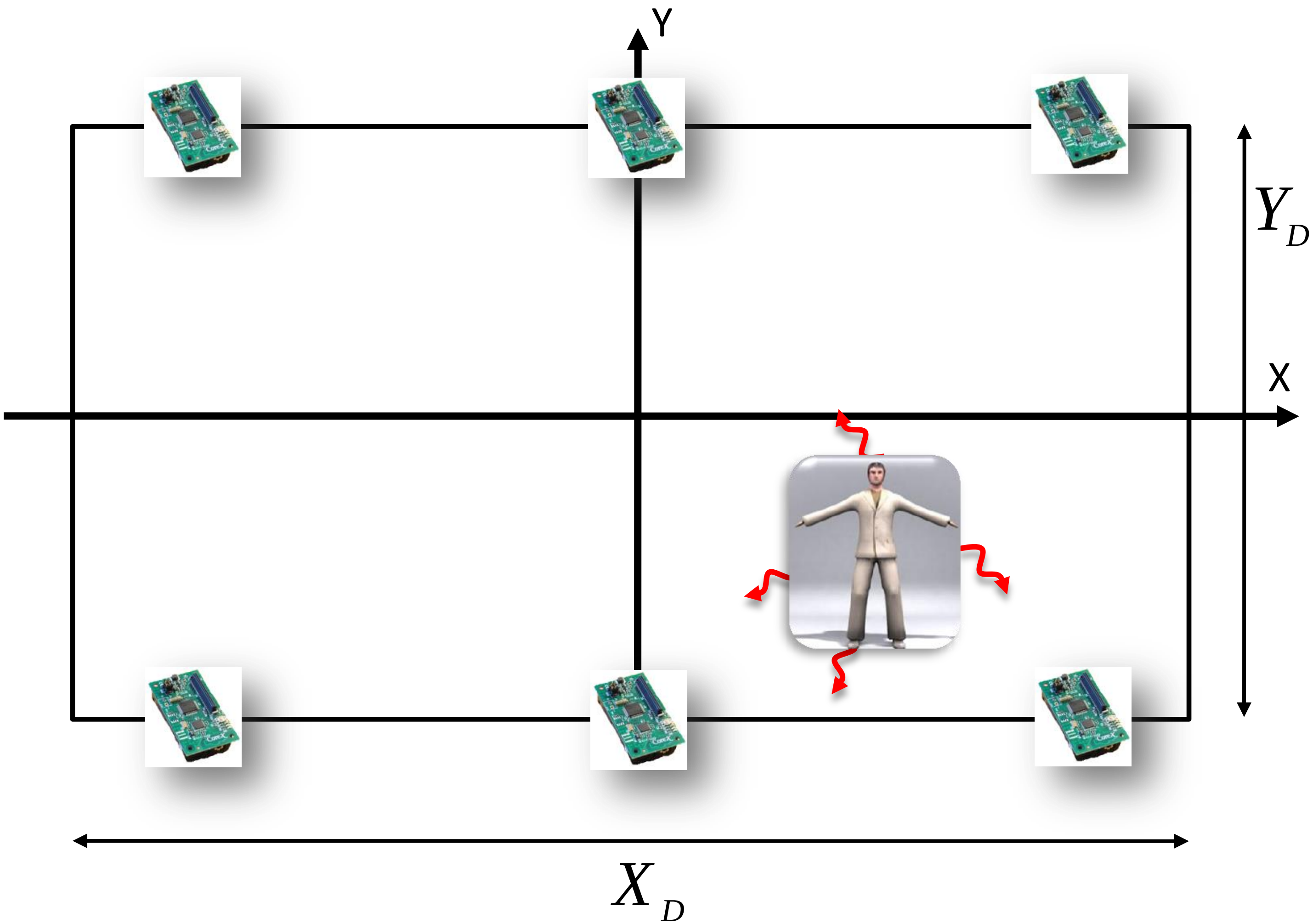


⬇

Knowledge on the degree of membership of the input data to the class

Additional Information

Experimental Validation - Outdoor



Scenario

- *rural area*
- *no obstacles*

Sensor Nodes

$$M = 6$$

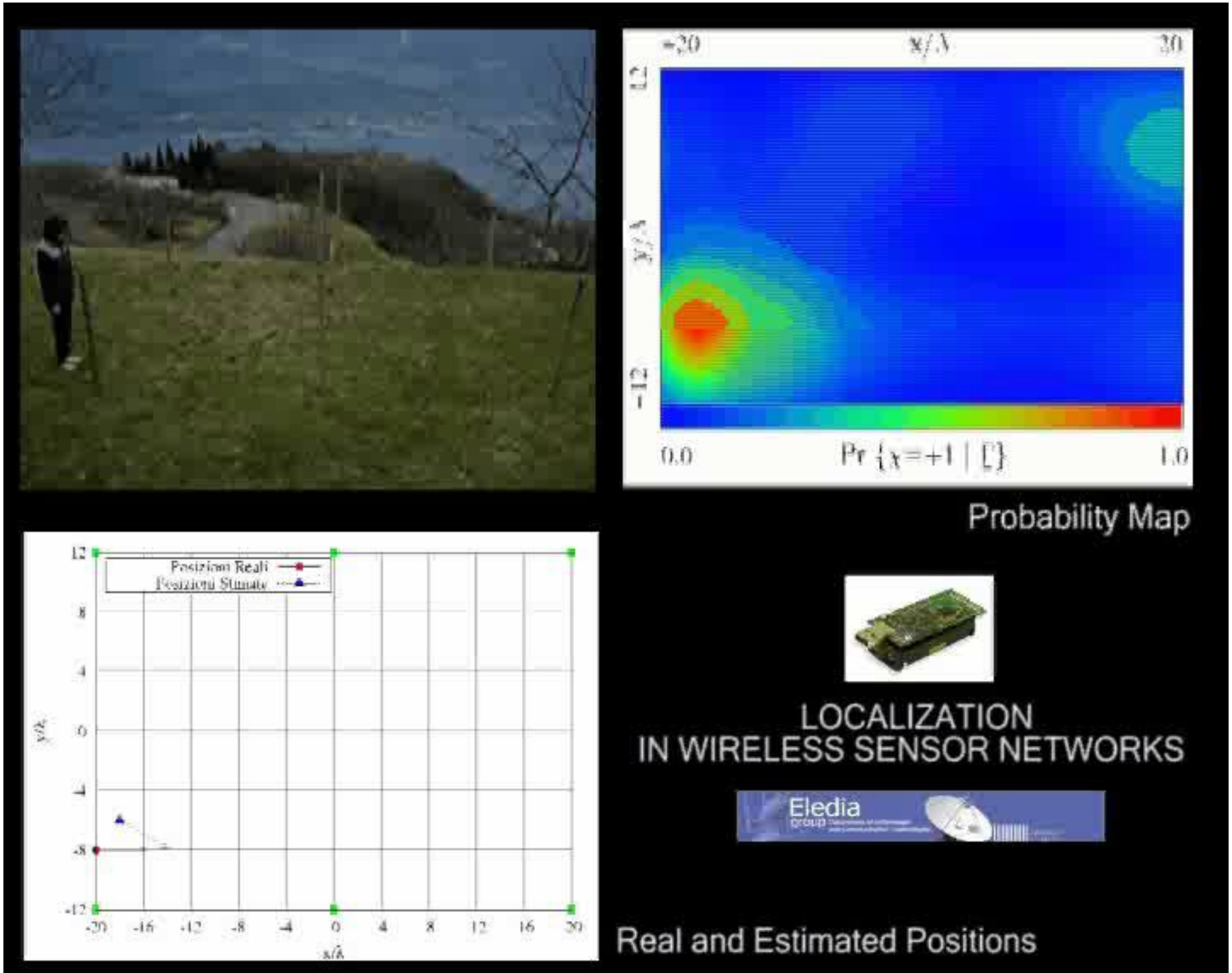
Domain Size [m]

$$X_D = 5$$
$$Y_D = 3$$

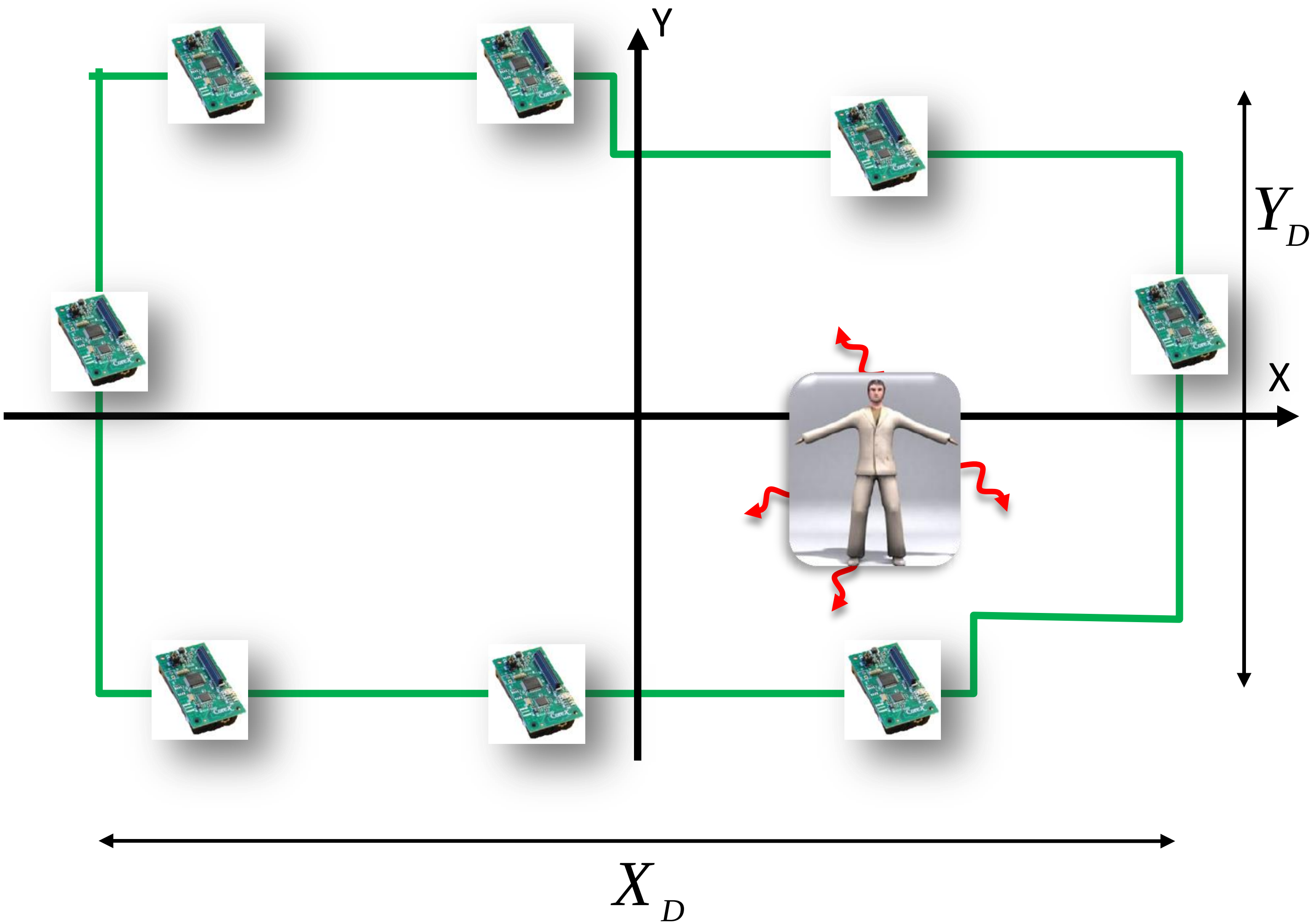
Frequency [GHz]

$$f = 2.4$$

Demo – Outdoor Scenario



Experimental Validation - Indoor



Scenario

- *standard office*
- *obstacles*

Sensor Nodes

$$M = 8$$

Domain Size [m]

$$X_D = 7$$

$$Y_D = 4$$

Frequency [GHz]

$$f = 2.4$$

Demo – Indoor Scenario (1/3)

Absence/Presence/Movement of Targets

Maximum
of Probability

Estimated Position
(Kalman filtered)

Demo – Indoor Scenario (2/3)

Heterogeneous Movements

Maximum of Probability

Estimated Position (Kalman filtered)

Demo – Indoor Scenario (3/3)

Unknown Obstacle

Maximum of Probability

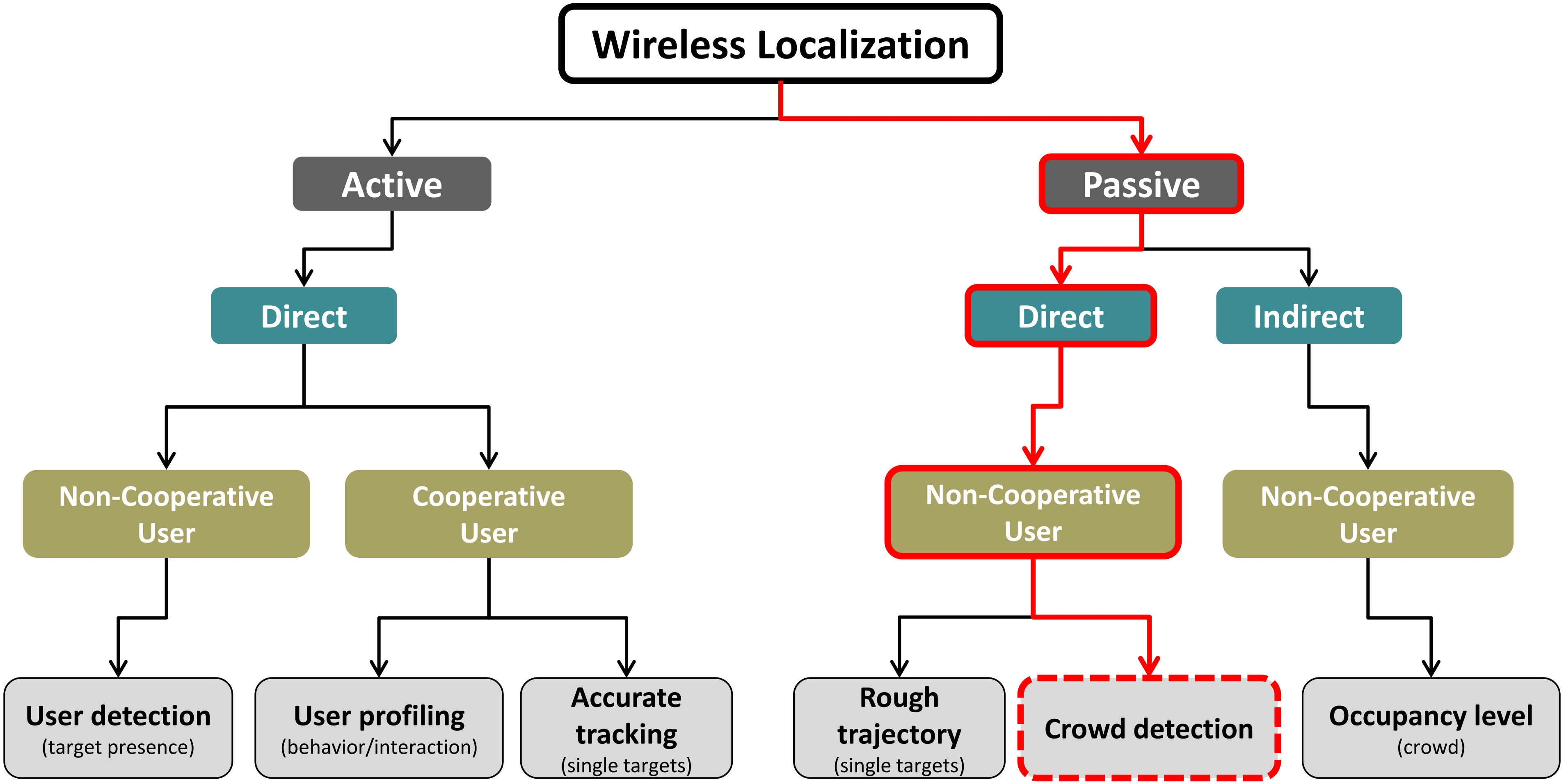
Estimated Position (Kalman filtered)

Outline

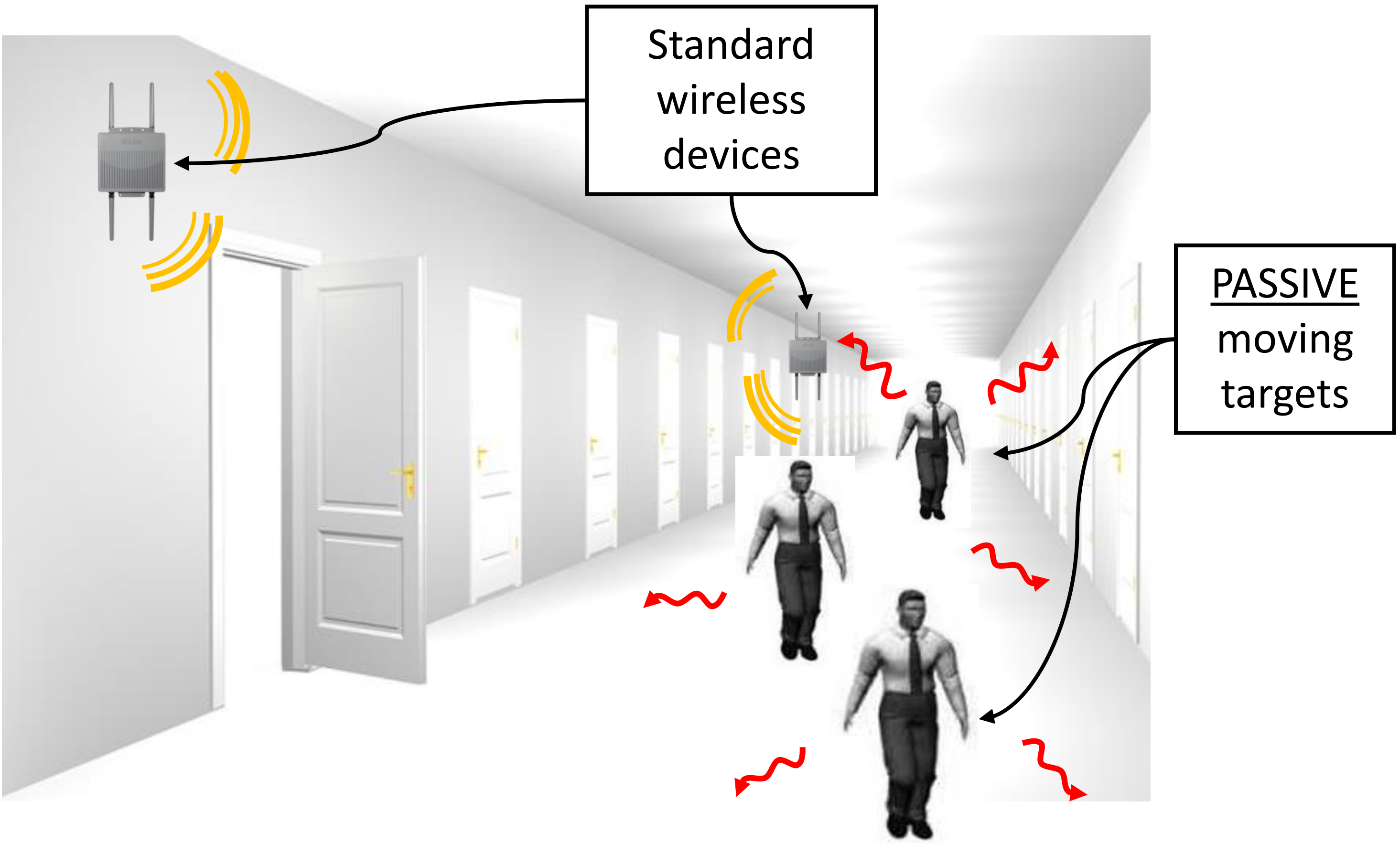
- EM Positioning for IoT – Intro & Motivation
- Active Localization of Mobile Devices
  - Localization through optimization
  - Semantic-based probabilistic approach
- Passive Localization of Transceiver-free Targets
  - Target tracking
  - **Crowd detection**
  - Indirect occupancy estimation
- Conclusions and Actual Trends

Passive Crowd Detection

Objective Detection of crowd presence in indoor areas exploiting standard wireless networks already deployed



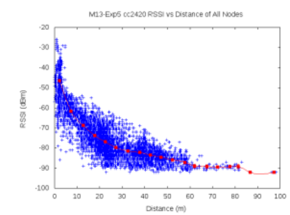
Passive Crowd Detection - Scenario



Principle Crowd perturbs the EM propagation of standard wireless devices: **Opportunistic Localization**

Challenges of “*Opportunism*”

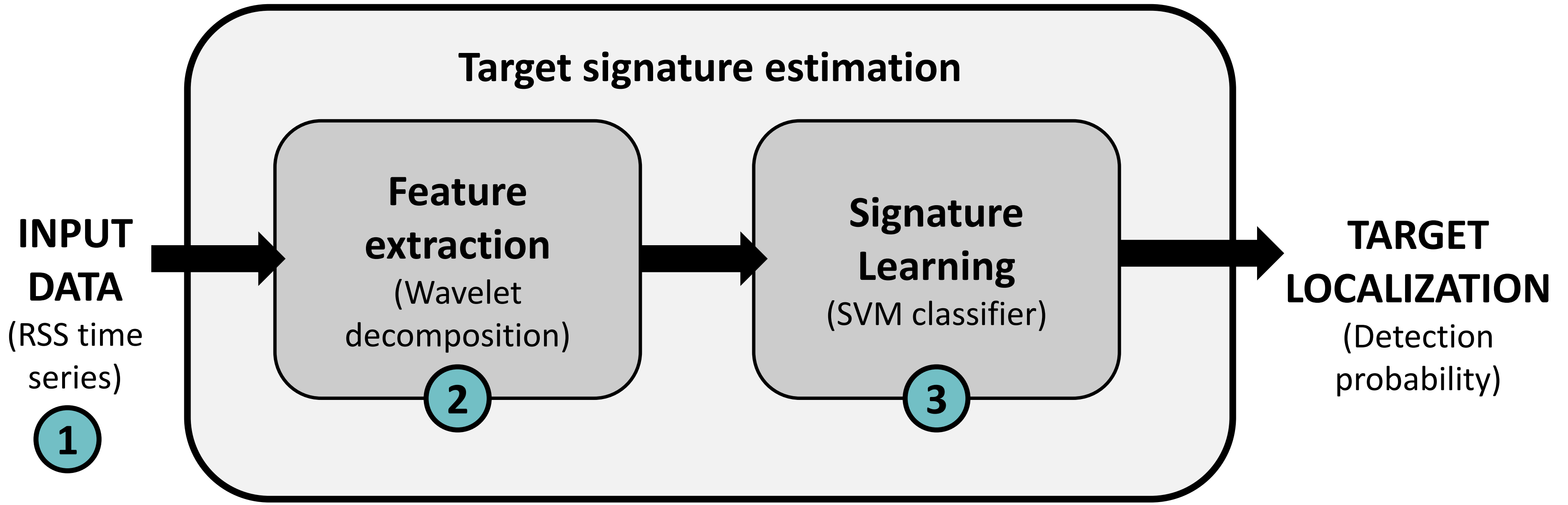
- **<u>Signal stability</u>**. Standard wireless devices are designed to minimize effects of undesired perturbations:
  - Adaptive power control
  - Frequency hopping strategies
  - Jamming reduction procedures
  - …
- **<u>Limited information</u>**. EM propagation is represented by simplified/rough quality indicators (e.g., RSSI, LQI)



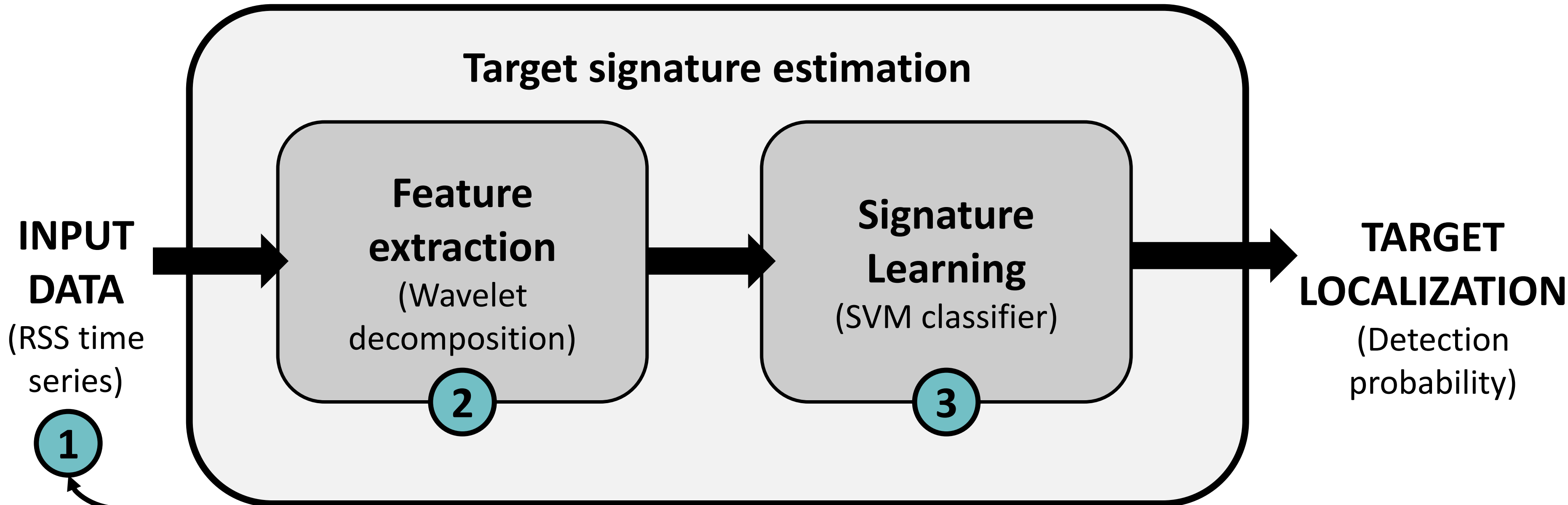
- **<u>Standardization</u>**. Data acquisition method is regulated by standards (e.g., IEEE802.11)

«Target signature extraction» is very complex without dedicated hardware/systems!

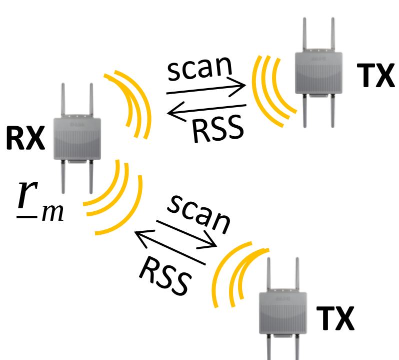
Crowd Detection Approach



① RSS Data Acquisition



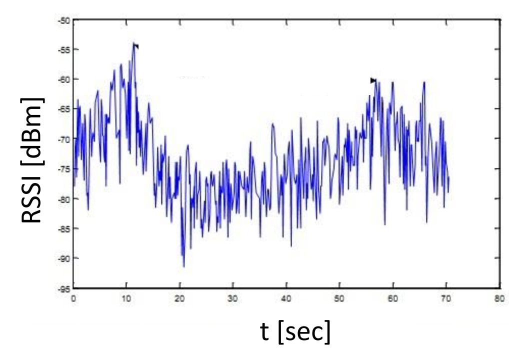
IEEE802.11
RSS scan procedure



- Each AP scans other active APs
- Every scan returns one RSS value $v(\underline{r}_m, t)$ for one transmitting AP
- The scan procedure is iterated K times to collect RSS time series

$$\{V(t)\} = [v(\underline{r}_m, t_0), \ldots, v(\underline{r}_m, (K-1)\Delta t)]$$

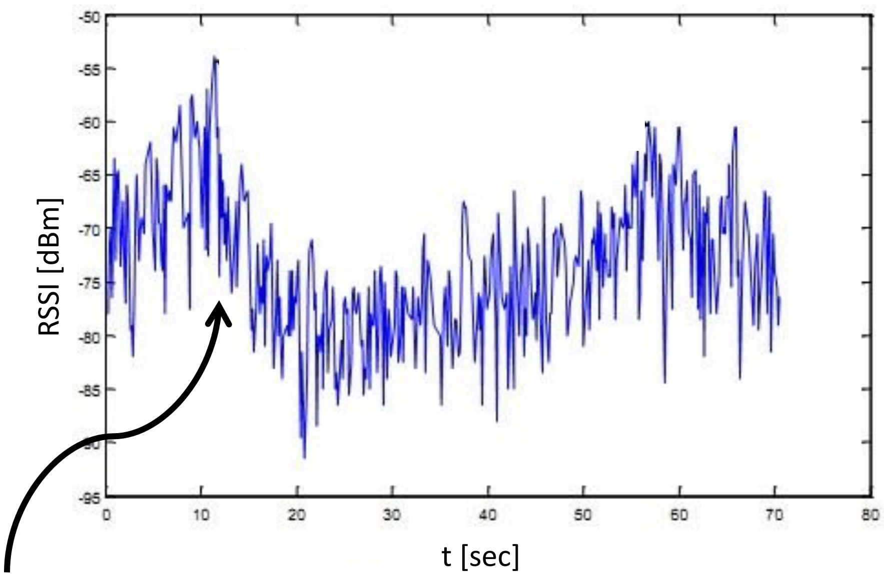
RSS time series



① RSS Data Acquisition

<u>RSSI is strongly affected by:</u>

- Metallic obstacles
- Objects and forniture
- In-band EM interferences
- (Low-cost) hardware inaccuracies
- Antenna orientations
- Human presence
- ...

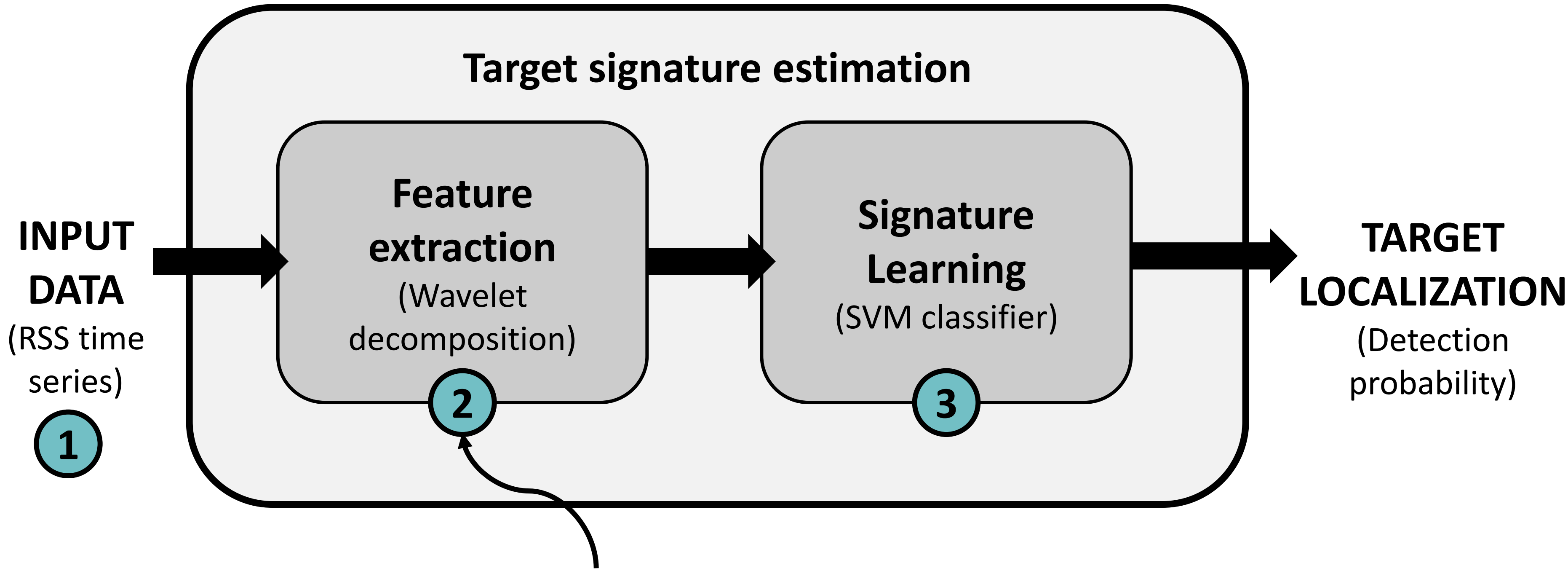


The fusion of such noise sources causes complex and umpredictable RSS pattern

- Multiple frequency content
- High time variability

Challenge Detect/extract/learn the «target signature» in complex RSS data

2 Feature Extraction



IDEA: analyze RSS in a <u>transformed domain</u>

② Wavelets: Introduction

Definition (1D) [*]

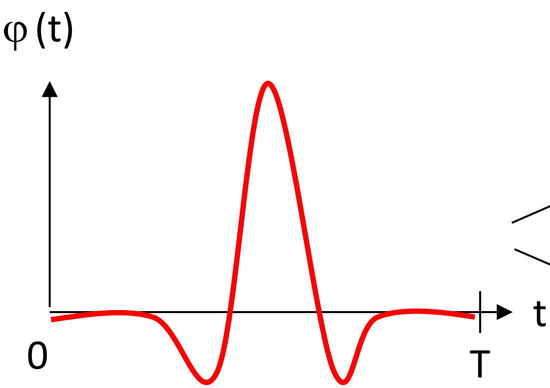
A wavelet basis $\varphi_{ls}(t)$ [$l=0,1,2\ldots,L$; $s=0,1,..,2^{l}-1$] is a family of functions generated by <u>dilations</u> and <u>translation</u> of a single seed function $\varphi(t)$ (with finite support T)

Wavelet basis

$$\varphi_{ls}(t)=\varphi\left(\underbrace{l\times t}_{\text{Dilation}}-\underbrace{\frac{s\times T}{2^{l-1}}}_{\text{Translation}}\right)$$

Example

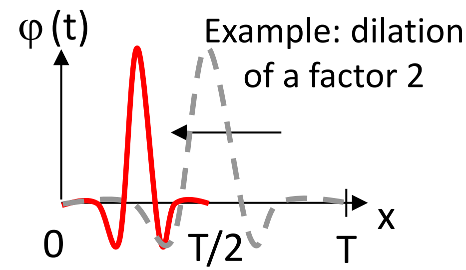
"Mexican Hat" Wavelet, 1D



Seed function (l=1, s=0)
["Mexican Hat"]

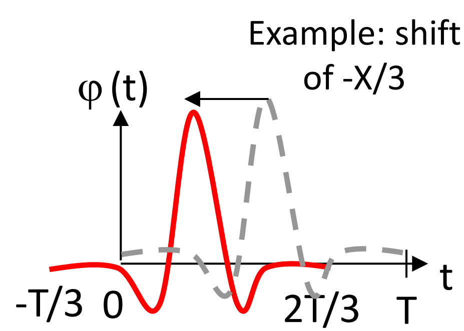
Dilation

Scaling of the function in time



Translation

Shift of the function in time

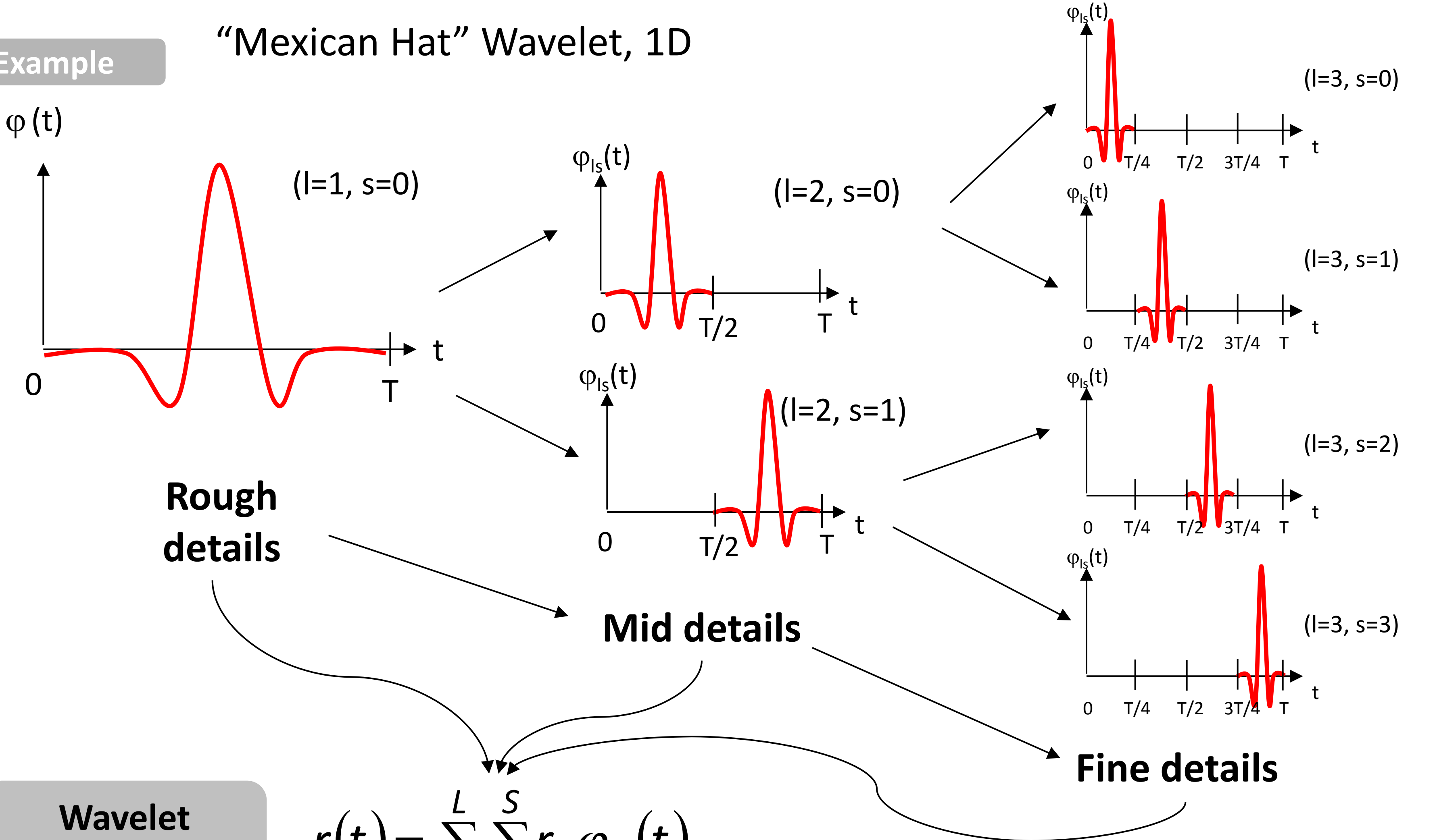


[*] I. Daubechies, "Orthonormal bases of compactly supported wavelets", Communications on Pure and Applied Mathematics, vol. 41, no. 7, p. 909–996, October 1988

② Wavelet Levels and Details

Example

"Mexican Hat" Wavelet, 1D



Wavelet Expansion (1D)

$$r(t)=\sum_{l=1}^{L}\sum_{s=1}^{S} r_{ls}\varphi_{ls}(t)$$

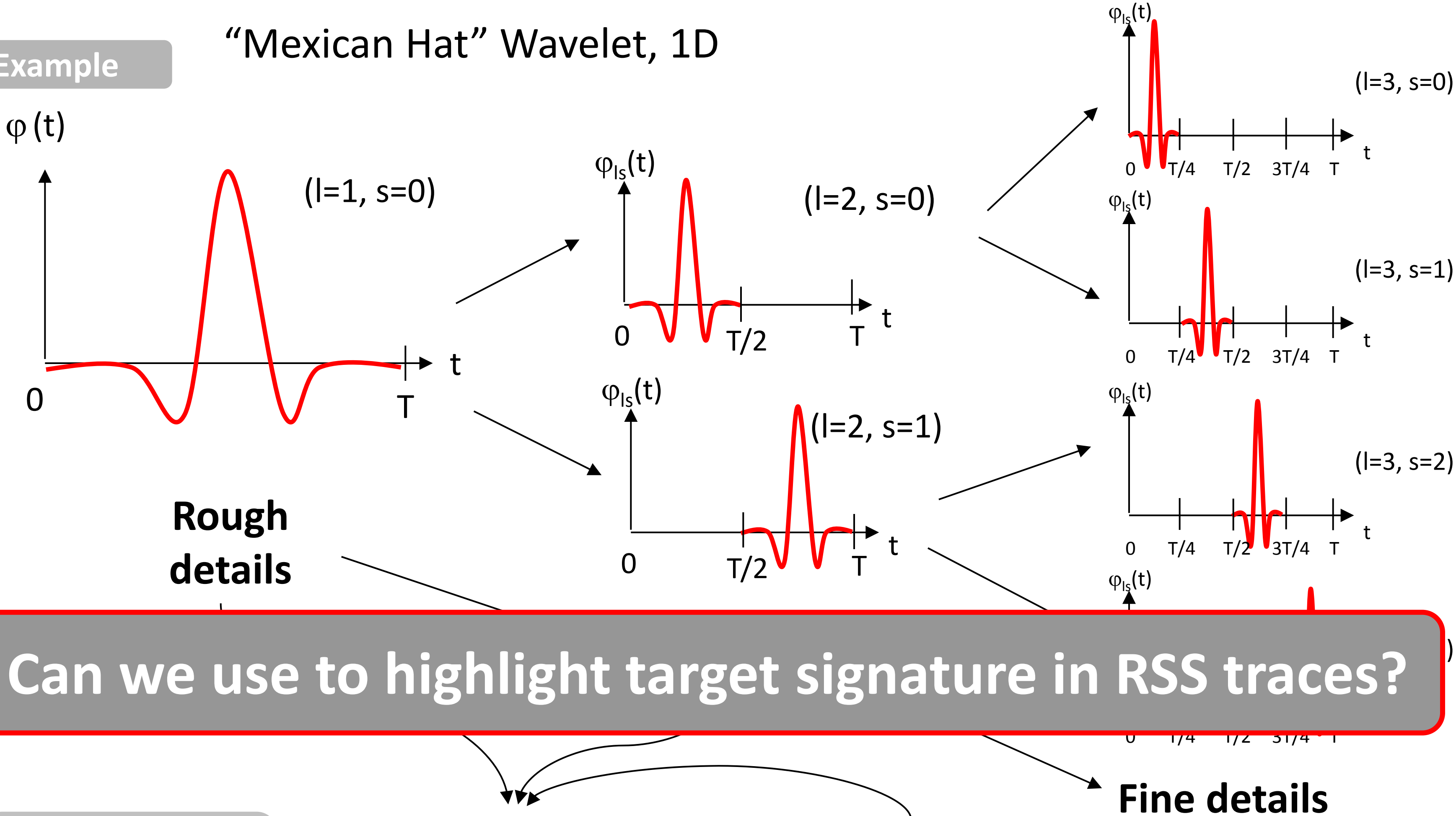
Wavelet of level *l* can be analyzed to understend information at that discretization detail

[*] I. Daubechies, "Orthonormal bases of compactly supported wavelets", Communications on Pure and Applied Mathematics, vol. 41, no. 7, p. 909–996, October 1988

② Wavelet Levels and Details

Example

“Mexican Hat” Wavelet, 1D



Can we use to highlight target signature in RSS traces?

Wavelet Expansion (1D)

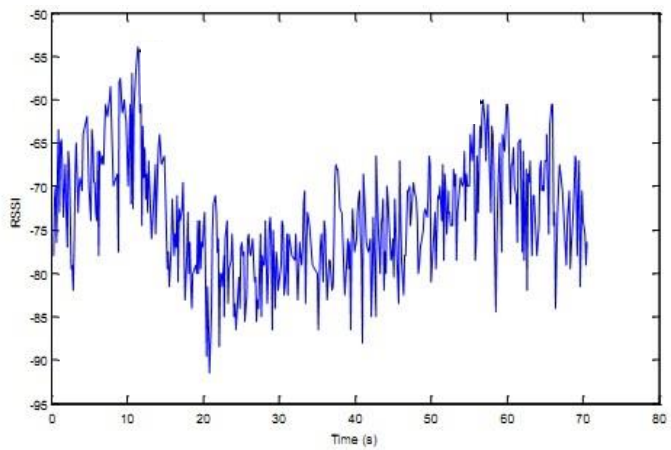
$$r(t)=\sum_{l=1}^{L}\sum_{s=1}^{S} r_{ls}\varphi_{ls}(t)$$

Wavelet of level *l* can be analyzed to understend information at that discretization detail

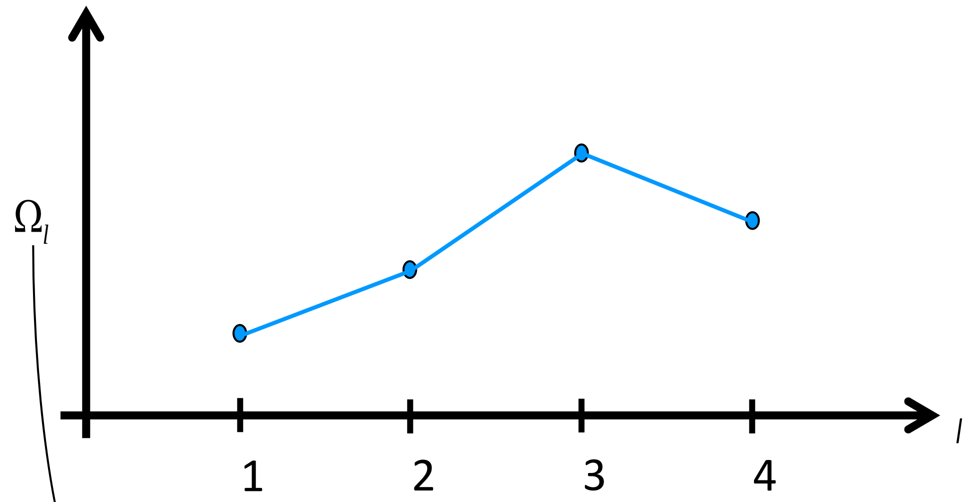
[*] I. Daubechies, “Orthonormal bases of compactly supported wavelets”, Communications on Pure and Applied Mathematics, vol. 41, no. 7, p. 909–996, October 1988

② Approach: Signatures in DWT

RSS in time domain



RSS in "aggregated" wavelet domain



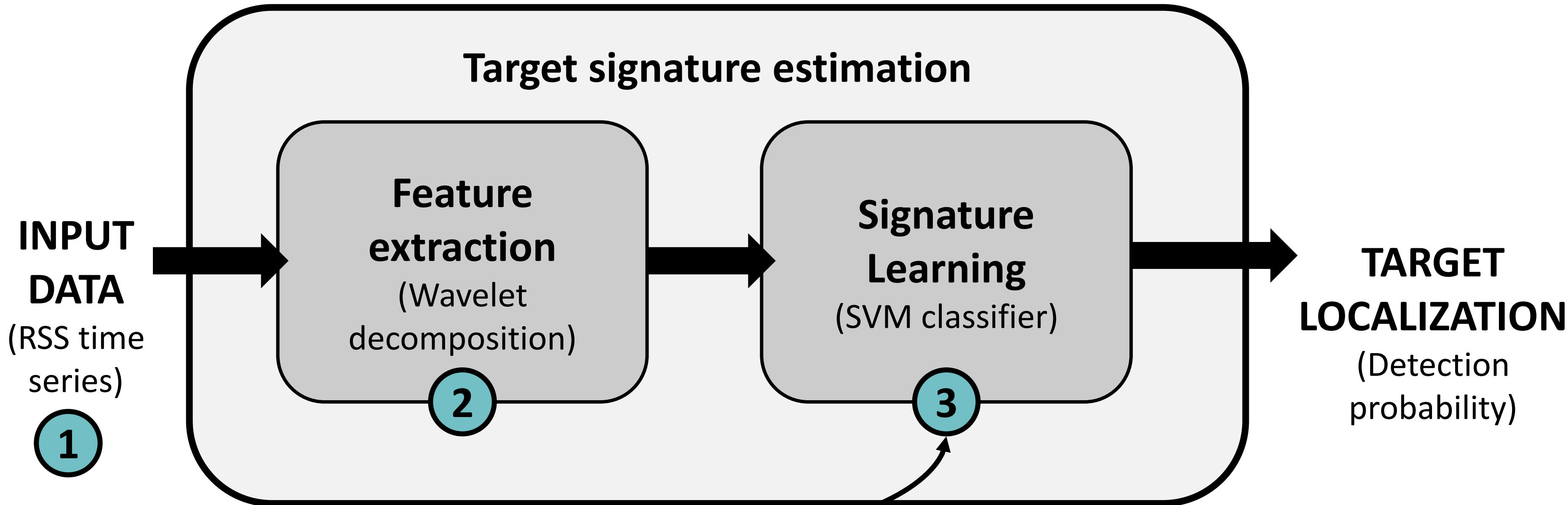
Detail Coefficients Indicator (DCI)

$$\Omega_l = \sum_{s=0}^{S-1} \left| r_{ls} \right|^2 \quad l = 1,\ldots,L$$

It represents the energy of the signal at each wavelet level *l=1,…,L*

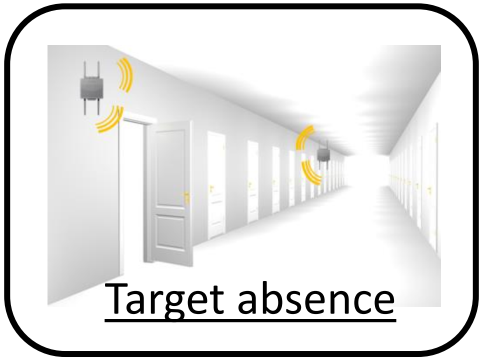
How to detect signatures from DCI behavior?

3 Signature Learning

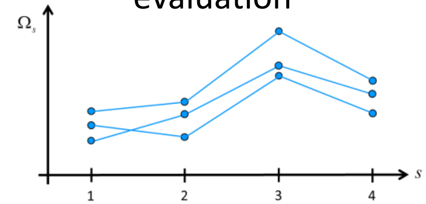


IDEA: Classify the **DCI** signatures with respect to target absence/presence

③ Learning by Example Strategy

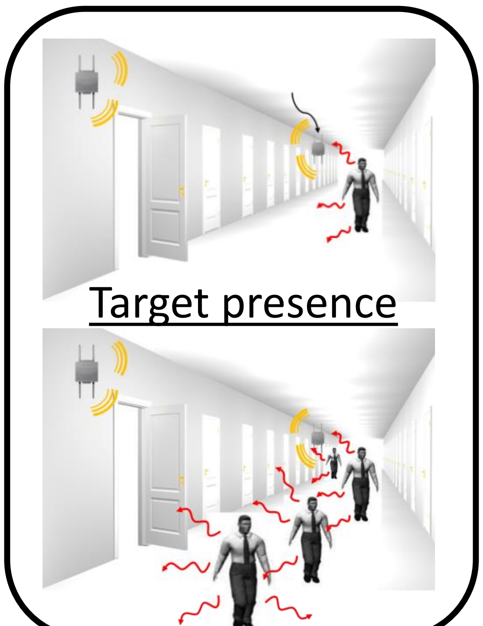


DCI evaluation

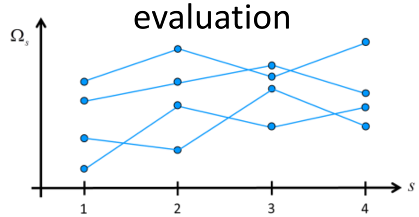


$\Omega_l^0,\ l=1,\dots,L$

Training features of Class *C=0*



DCI evaluation



$\Omega_l^1,\ l=1,\dots,L$

Training features of Class *C=1*

Binary SVM classifier[*]

Training of decision function $\Phi\left[\Omega_l^{0/1}\right]$

Test with unknown data $C=\mathrm{sgn}\{\Phi[\Omega_l]\}$

RESULT

Probability of Target presence

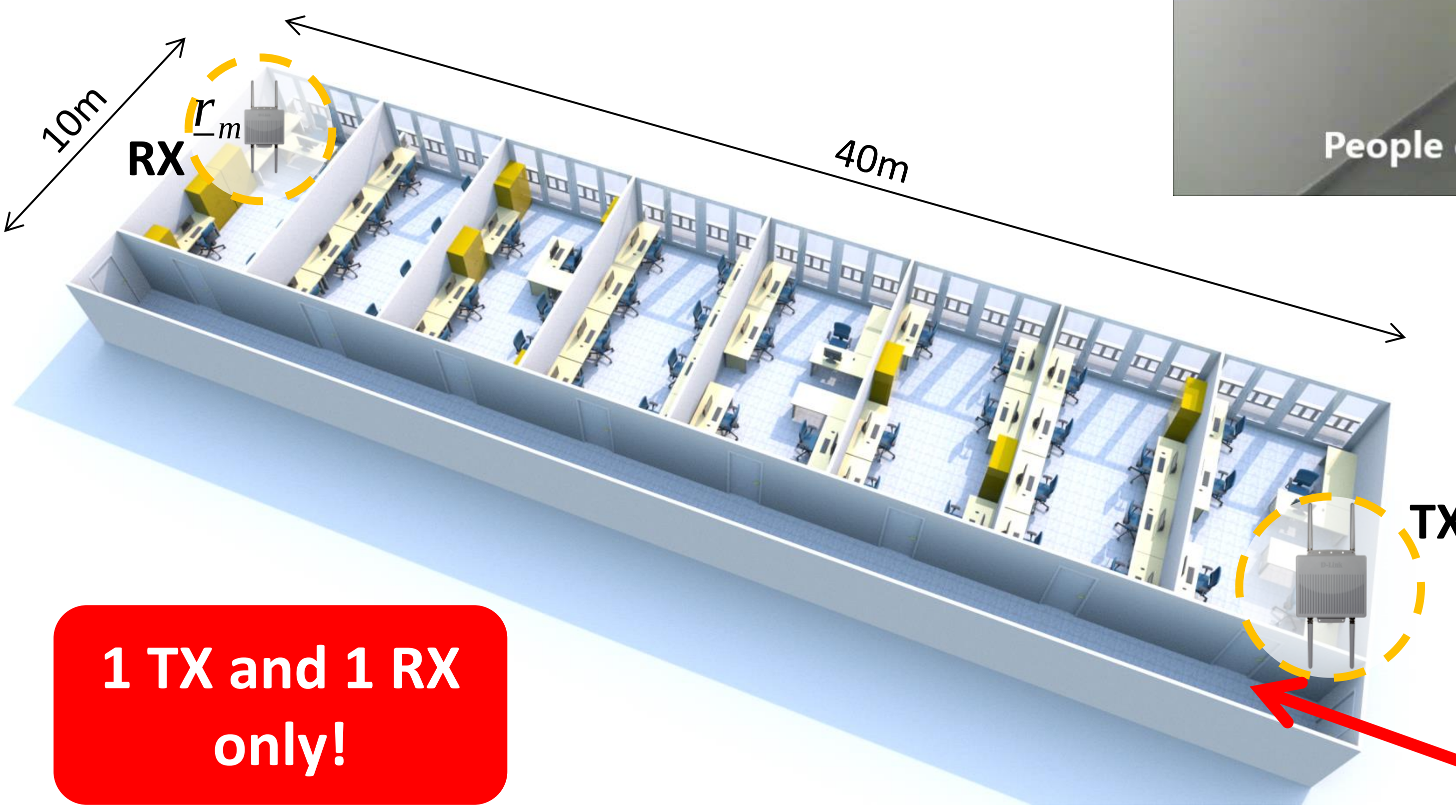
$\Pr\{C=1|\Omega_l\}$

[*] A. Massa, A. Boni, and M. Donelli, «A classification approach based on SVM for electromagnetic subsurface sensing,» *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 9, pp. 2084-2093, Sep. 2005.

Experimental Validation

Test site features:

- Real indoor area (40x10 mq)
- Presence of fornitures and obstacles
- *IEEE802.11g* wireless Access Points (16 dBm TX Power)
- Time-varying target presence (h24 monitored)



1 TX and 1 RX only!

Monitored corridor
(true in/out people counting)

Test Case 1 – Single Day

Test set acquisition

Date: 12/03/2015, Thursday

Duration: 24 hours

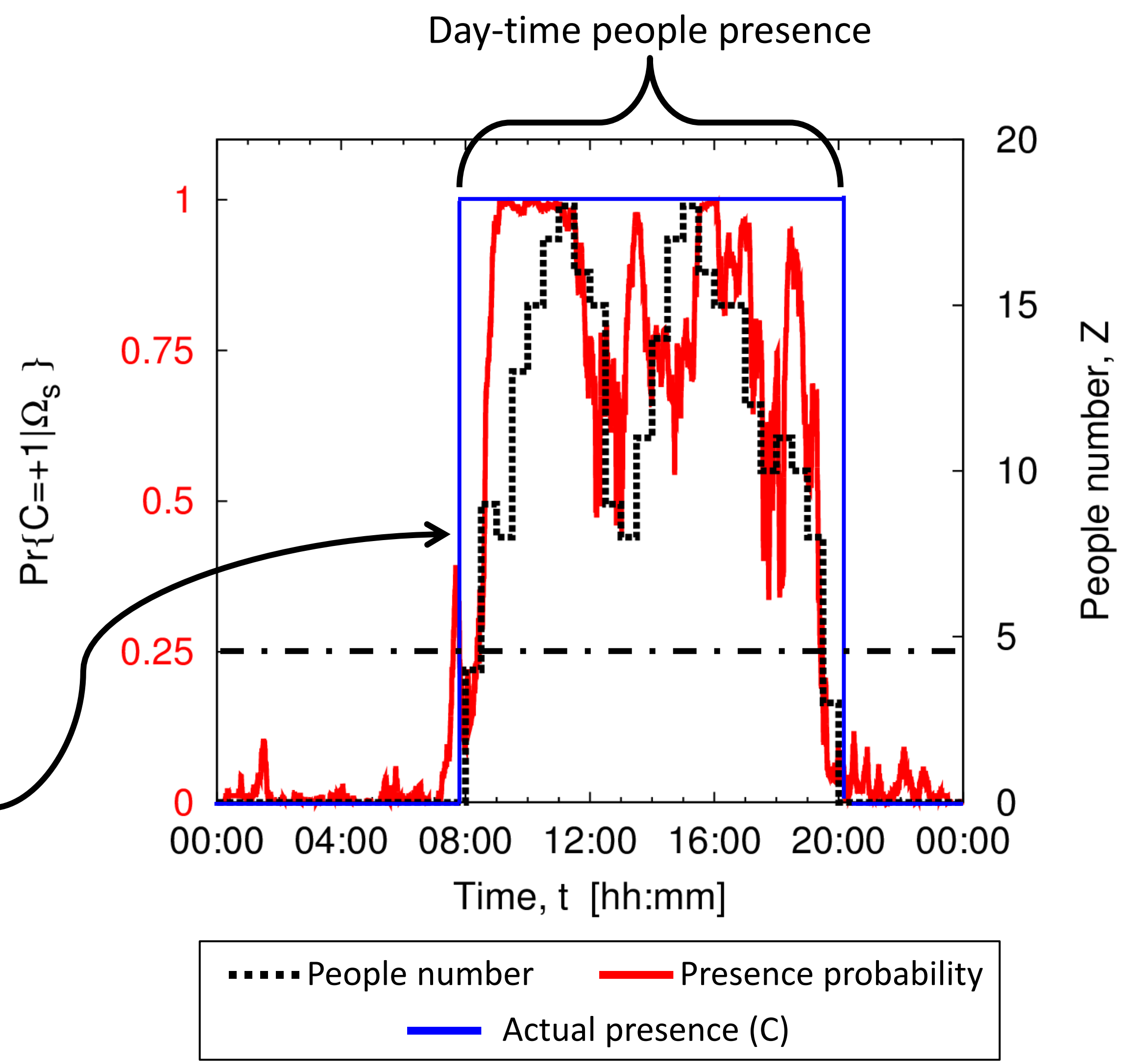
Test samples: 89711

Performance

- False positive detection: < 5%
- False negative detection: < 2%

With threshold probability $\Pr_{th}\{C=+1\}=0.25$

First morning entrance correctly detected
(first target at 07:50)



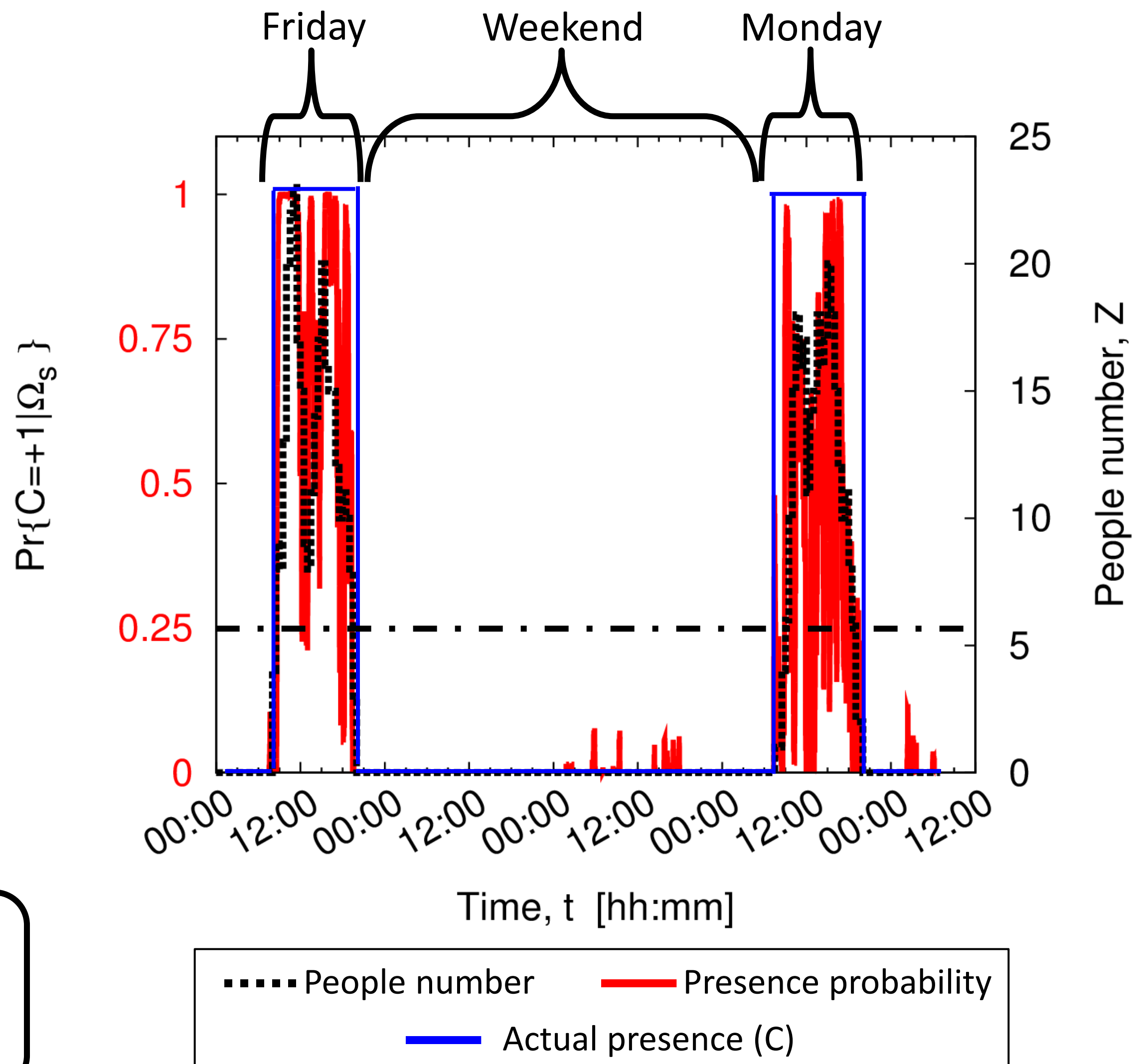
Test Case 2 - Weekend

Test set acquisition

Date: from 13/03/2015, Friday
to 16/03/2015, Monday

Duration: 108 hours

Test samples: 407551



Performance

- False positive detection: < 3%
- False negative detection: < 2%

With threshold probability $\Pr_{th}\{C=+1\}=0.25$

Empty state correctly estimated during the whole weekend

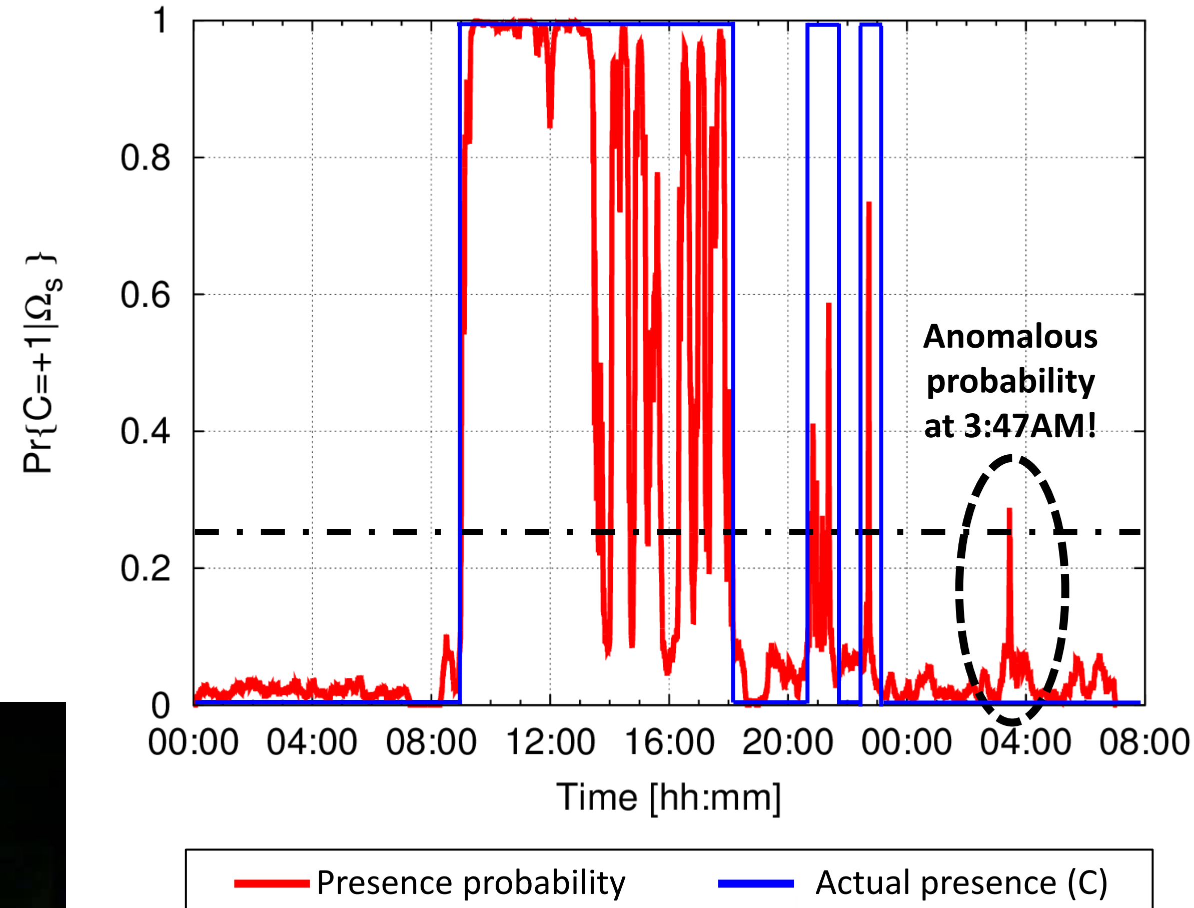
Test Case 3 – Intrusion Detection

<u>**Test set acquisition**</u>

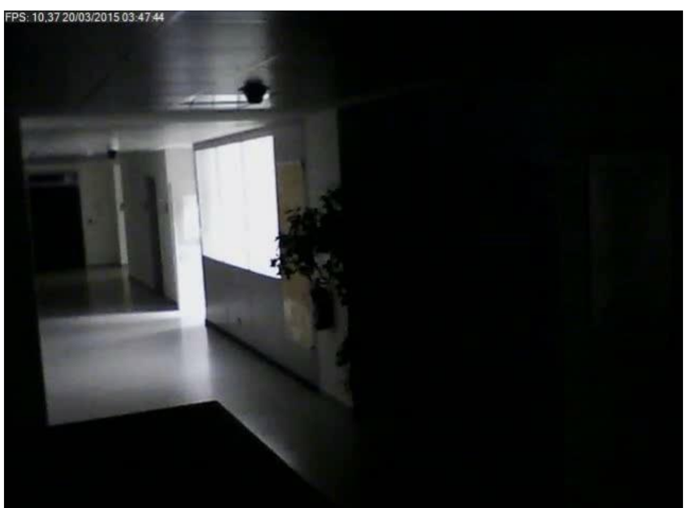
Date: 20/03/2015, Friday

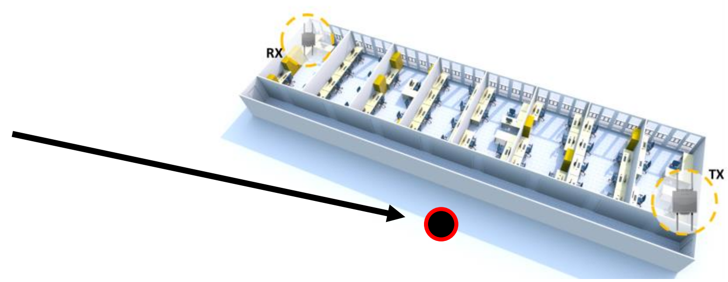
Duration: 32 hours

Test samples: 128740



Night (unexpected) movement detected <u>in the corridor close to the monitored one</u>!



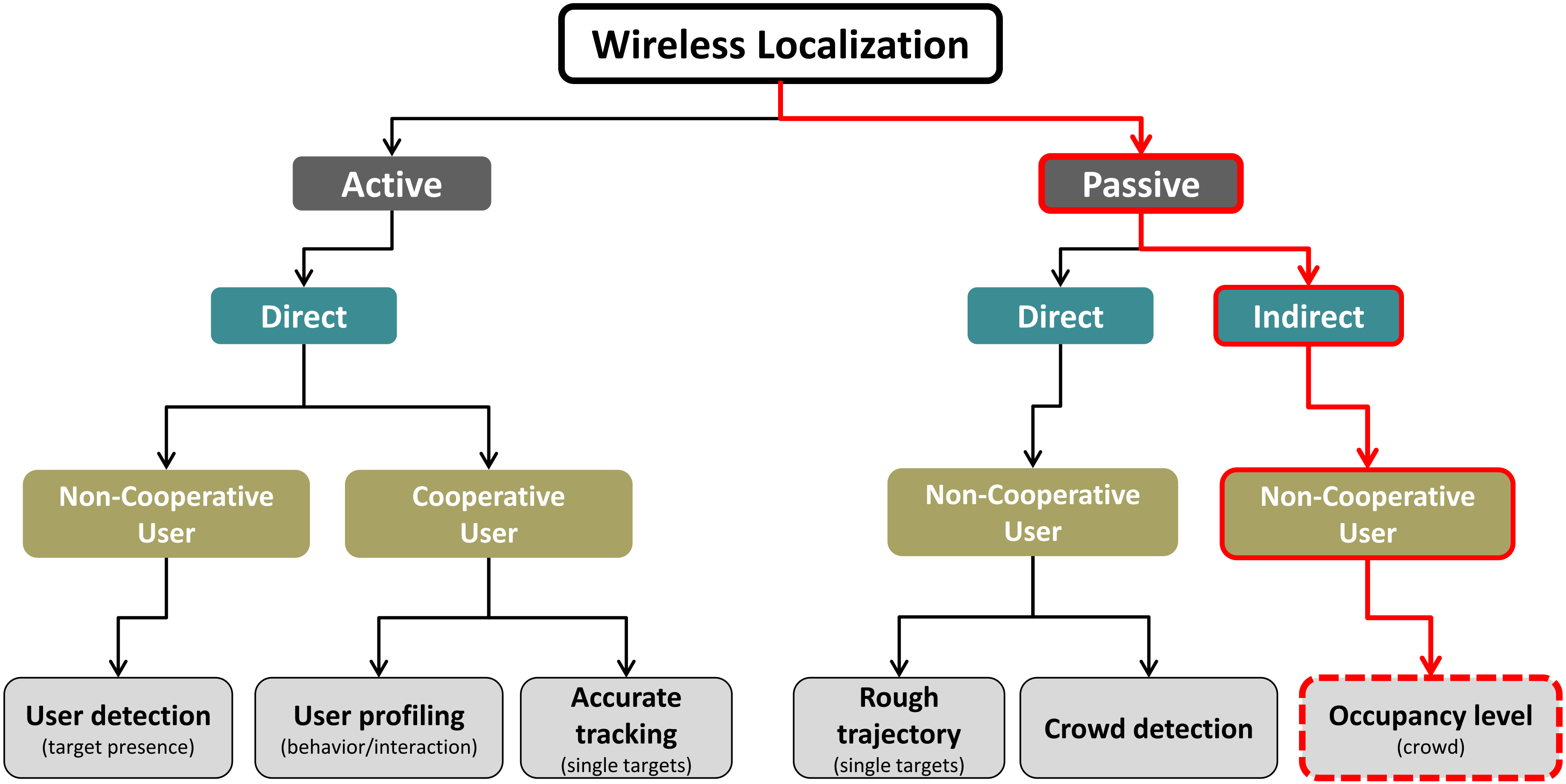


Outline

- EM Positioning for IoT – Intro & Motivation
- Active Localization of Mobile Devices
  - Localization through optimization
  - Semantic-based probabilistic approach
- Passive Localization of Transceiver-free Targets
  - Target tracking
  - Crowd detection
  - **Indirect occupancy estimation**
- Conclusions and Actual Trends

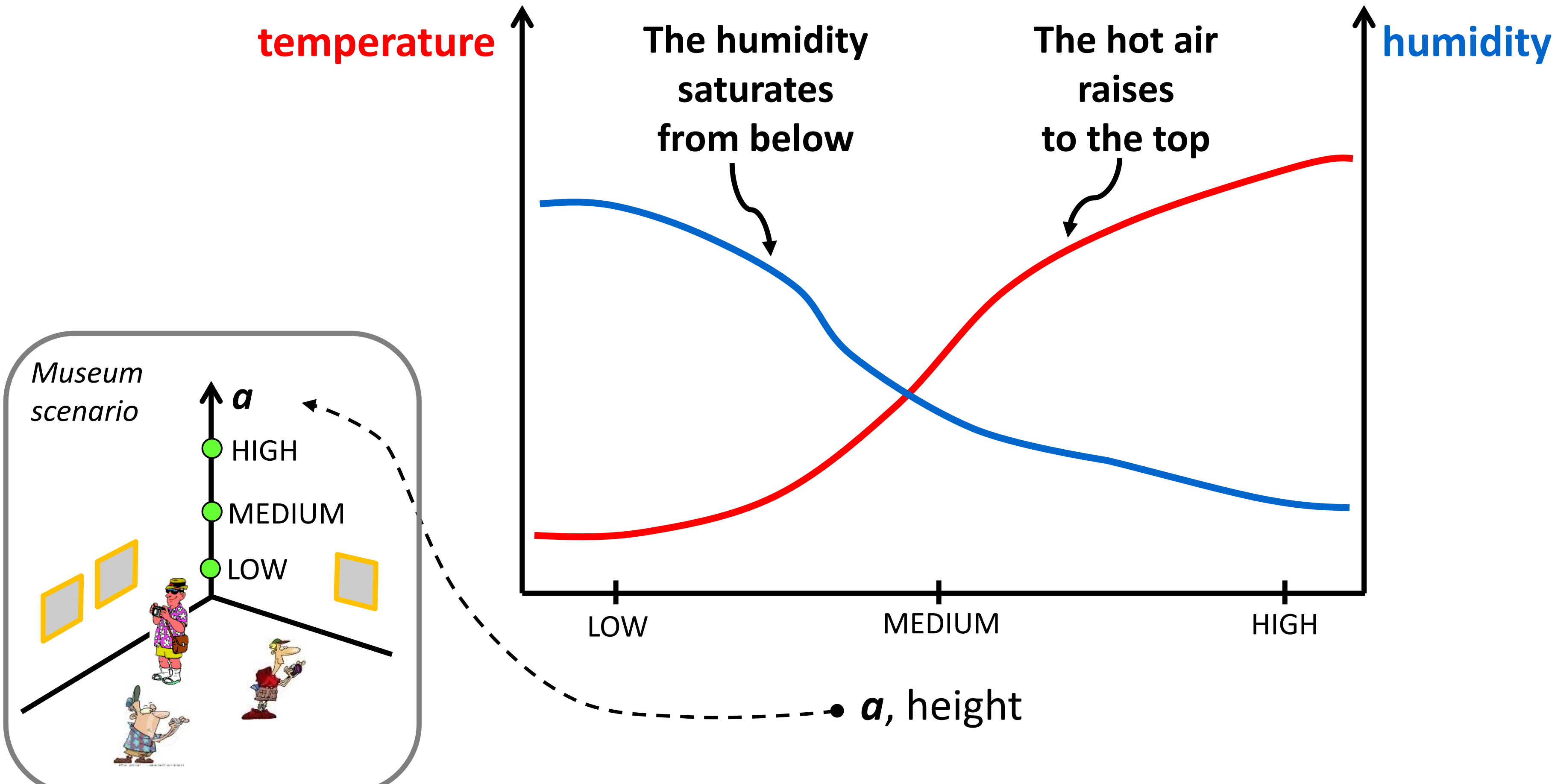
Indirect Occupancy Estimation

Objective Estimate indoor occupancy level only exploiting environmental data acquired by IoT devices



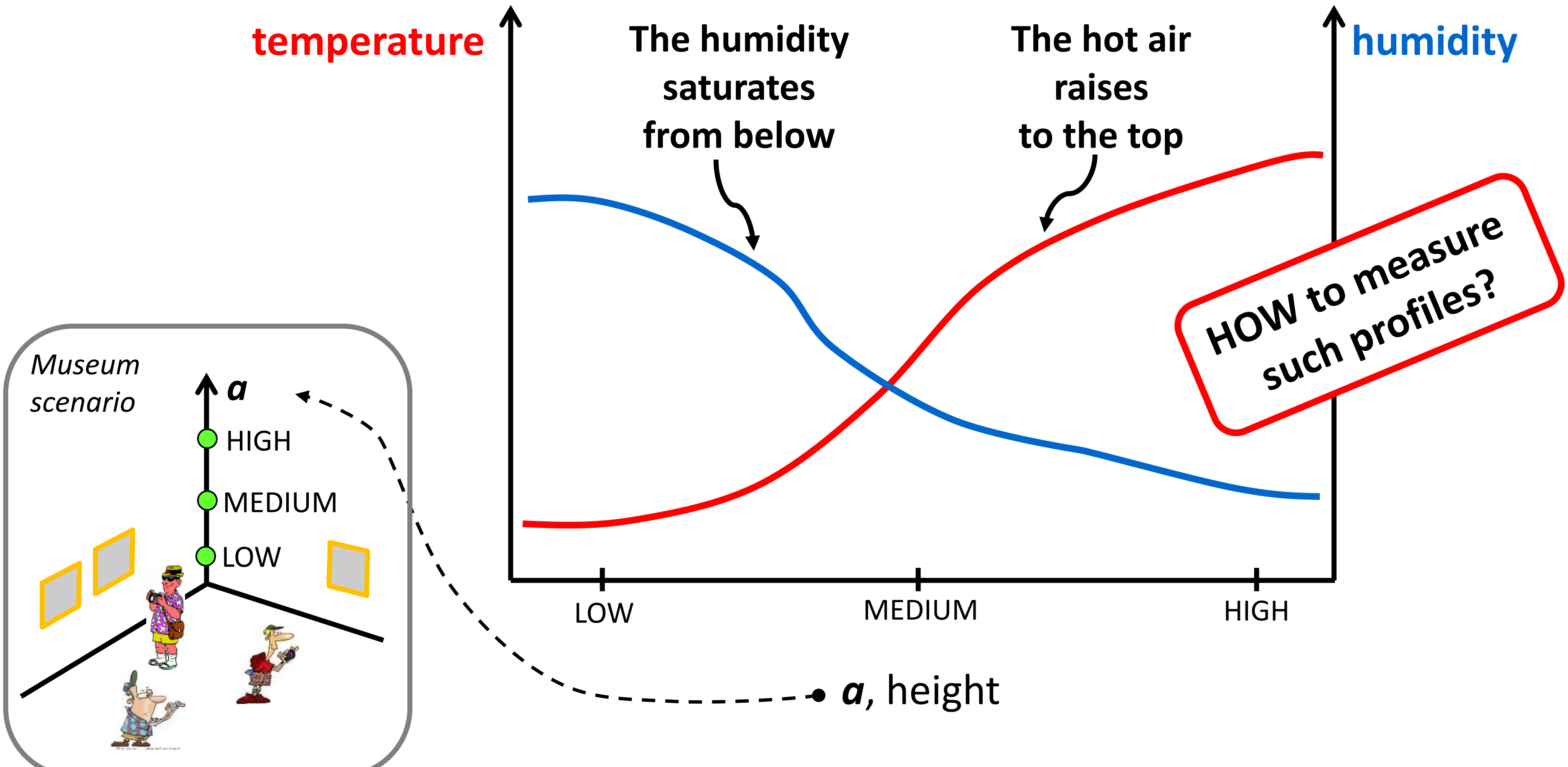
Occupancy Estimation: Basic Principle

PRINCIPLE People presence causes <u>two opposite vertical profiles</u> of temperature and humidity



Occupancy Estimation: Basic Principle

PRINCIPLE People presence causes <u>two opposite vertical profiles</u> of temperature and humidity



IoT Hardware Platform

SENSORS

- **Temperature** (°C) and **humidity** (%RH)
- Temperature Accuracy: ±0.3°C
- Humidity Accuracy: ±2%RH

FEATURES

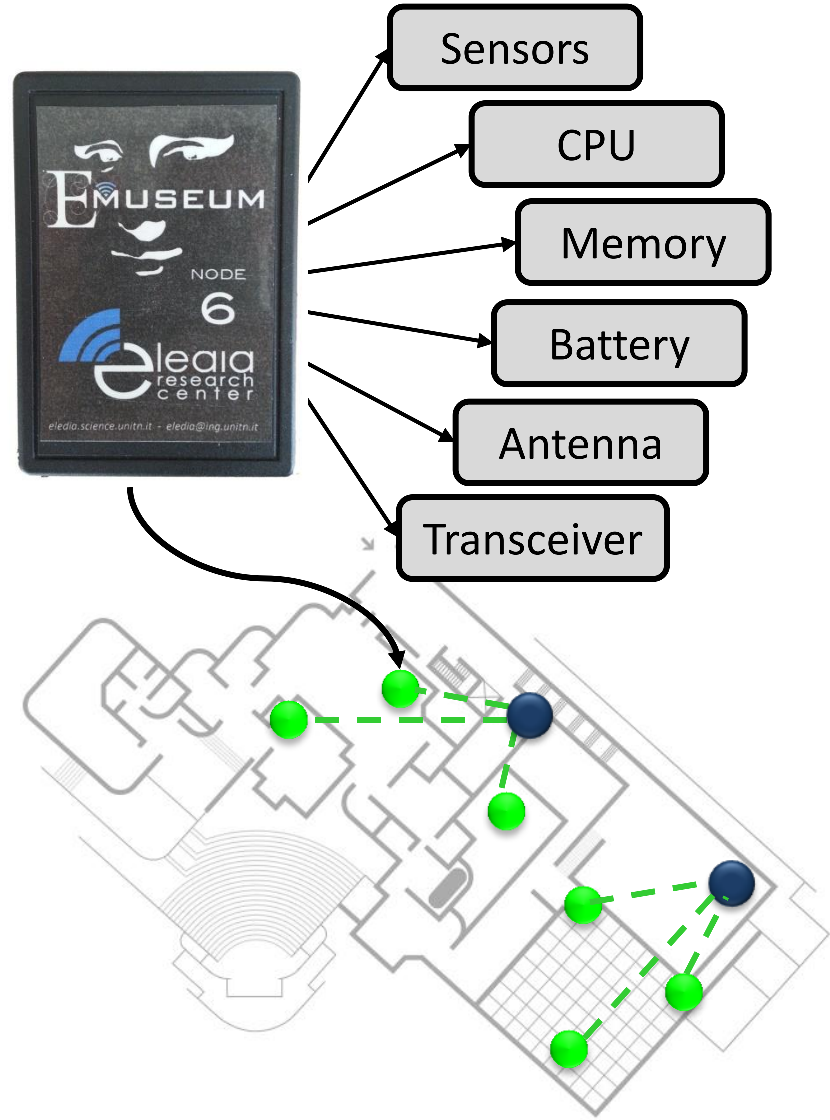
- **Real-time** data
- **Flexible** acquisition (periodic or on-demand)
- **Remote interaction** with sensors (user commands)
- **Low power** (<1.5mA in standby)
- **Sub-GHz** working frequency (868 MHz)

INSTALLATION

- Simple **deployment** (small, robust, battery-operated devices)
- System **lifetime** > 15 months

DEVICE

- Size: 85mm x 60mm x 20mm
- Consumptions: 0.9 mA (stand-by), 15 mA (tx/rx)
- Voltage: 3V
- Working frequency: 868 MHz



IoT Platform: Key Features

SENSORS

- **Temperature** (°C) and **humidity** (%RH)
- Temperature Accuracy: ±0.3°C
- Humidity Accuracy: ±2%RH

FEATURES

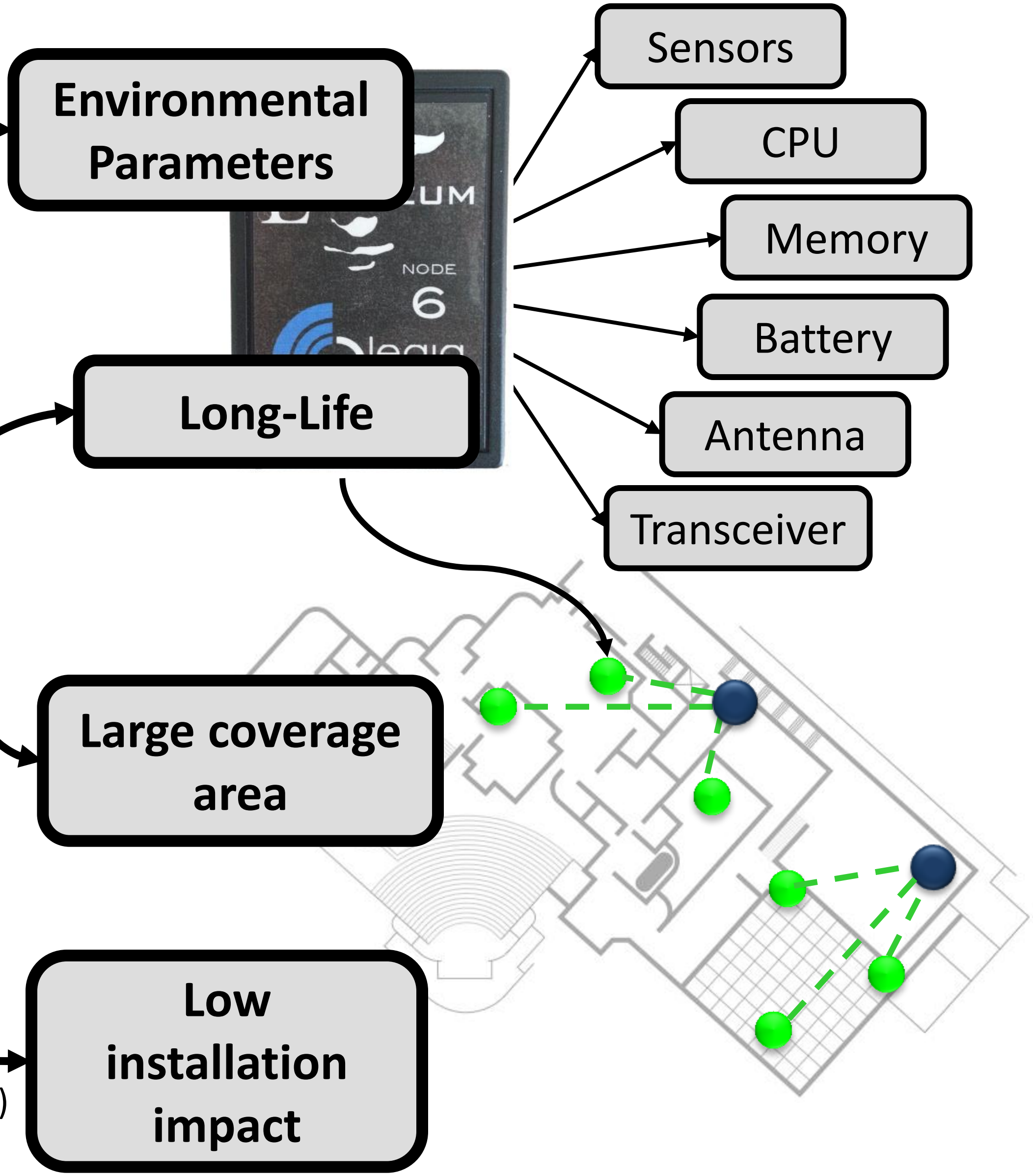
- **Real-time** data
- **Flexible** acquisition (periodic or on-demand)
- **Remote interaction** with sensors (user commands)
- **Low power** (<1.5mA in standby)
- **Sub-GHz** working frequency (868 MHz)

INSTALLATION

- Simple **deployment** (small, robust, battery-operated devices)
- System **lifetime** > 15 months

DEVICE

- Size: 85mm x 60mm x 20mm
- Consumptions: 0.9 mA (stand-by), 15 mA (tx/rx)
- Voltage: 3V
- Working frequency: 868 MHz



Occupancy Estimation: How?

1/4

METHOD Process the <u>slope of the vertical profiles</u> to identify an indicator of occupancy

Estimate the vertical profiles

↓

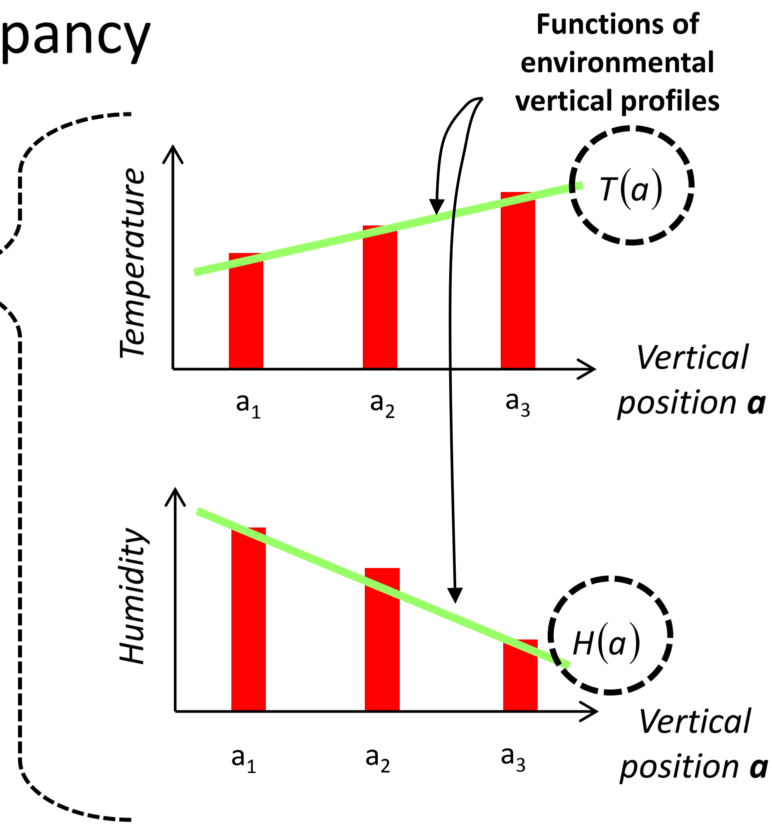
Calculate the slope of the profiles

↓

Aggregate derivative informations

↓

Learn relation between Ω and actual occupancy



where $a_1<a_2<a_3$

Occupancy Estimation: How?

2/4

METHOD Process the <u>slope of the vertical profiles</u> to identify an indicator of occupancy

Estimate the vertical profiles

↓

Calculate the slope of the profiles

↓

Aggregate derivative informations

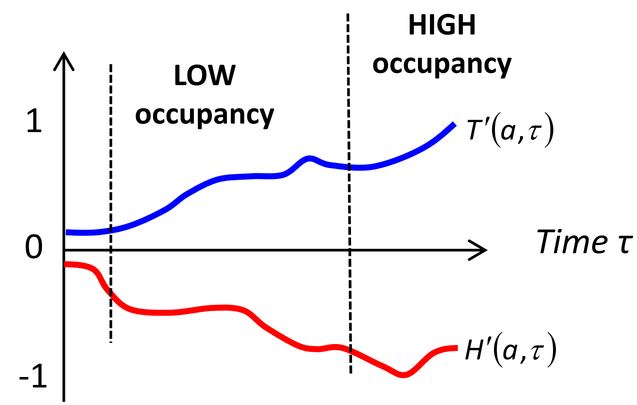
↓

Learn relation between Ω and actual occupancy

WHAT is the «intensity» of the occupancy-related pattern?

$$T'(a) = \frac{\partial T(a)}{\partial a}$$ Derivative of the Temperature vs. vertical profile

$$H'(a) = \frac{\partial H(a)}{\partial a}$$ Derivative of the Humidity vs. vertical profile



Higher the slope (positive or negative) higher the occupancy impact on the environment

Occupancy Estimation: How?

3/4

METHOD Process the slope of the vertical profiles to identify an indicator of occupancy

Estimate the vertical profiles

↓

Calculate the slope of the profiles

↓

Aggregate derivative informations

↓

Learn relation between Ω and actual occupancy

Positive Temperature derivative $T'(a,\tau)>0$

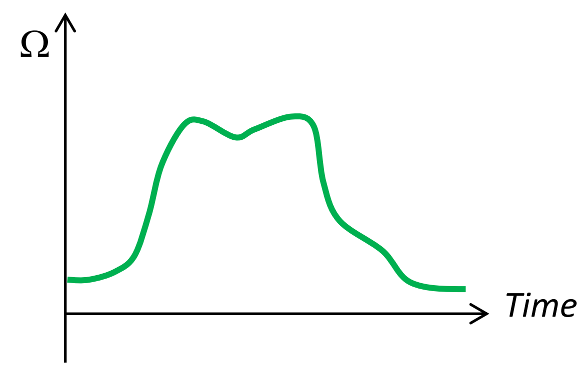
and **Negative** Humidity derivative $H'(a,\tau)<0$

indicate crowd presence

⬇

OCCUPANCY INDICATOR

$$\boxed{\Omega(\tau)\equiv\left[T'(a,\tau)-H'(a,\tau)\right]_{a=a_2}}$$



Occupancy Estimation: How?

4/4

METHOD Process the slope of the vertical profiles to identify an indicator of occupancy

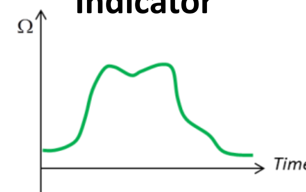
Estimate the vertical profiles

Calculate the slope of the profiles

Aggregate derivative informations

Learn relation between Ω and actual occupancy

Occupancy Indicator



Actual Occupancy
Percentage of tourists respect to maximum room capacity

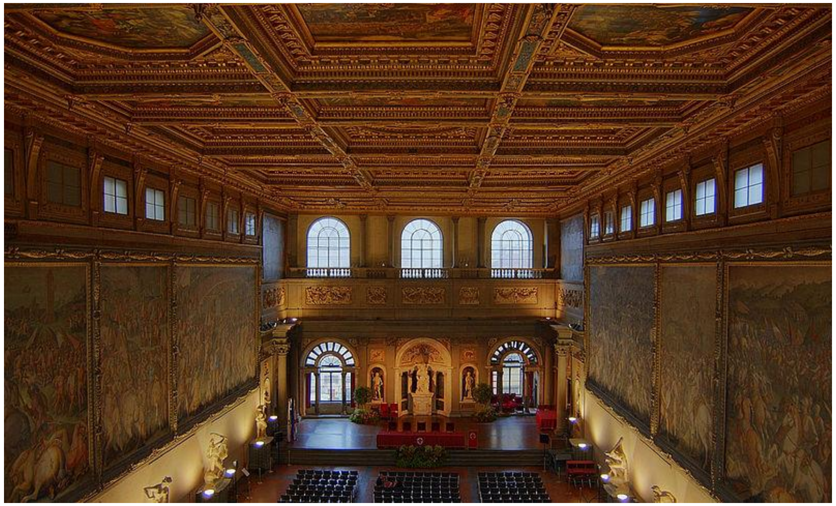
Support Vector Regression
(RBF Kernel Function)

Estimated Occupancy [%]

Practical Example?

Deployment @ “Sala dei 500”

- Commissioned in 1494 by Girolamo Savonarola, expanded in 1555 by Cosimo I De’ Medici
- **Largest** and **most important** (historically and artistically) hall in “Palazzo Vecchio” in Florence
- Largest “civil power” hall in Italy
- Hosts sculptures and paintings made between 1490 and 1600 (including Michelangelo, Vasari, Giambologna, Ghirlandaio, Passignano, Francavilla,…)



Sala dei 500, Firenze

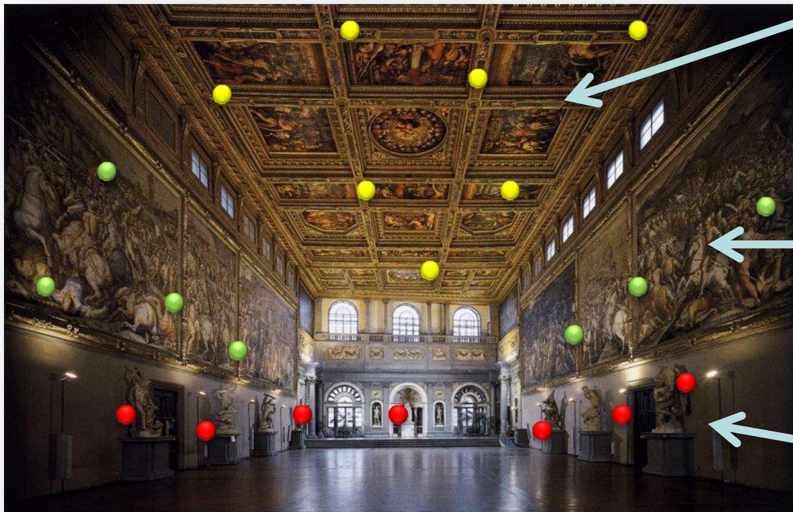
“Pisa attaccata dalle truppe di Firenze”, Giorgio Vasari

“Genio della Vittoria” Michelangelo Buonarroti

COMUNE DI FIRENZE

Deployment @ “Sala dei 500”

Dimensions: 54m[L] x 23m[W] x 18m[H]



Panelled ceiling
42 squares – woods and gold

Paintings
6 wall frescos

Sculptures
Pedestal statues

Monitoring campaign
Number of nodes: 22 indoor, 1 outdoor
Start date: 18 October 2012
Acquisition time interval: 10 minutes

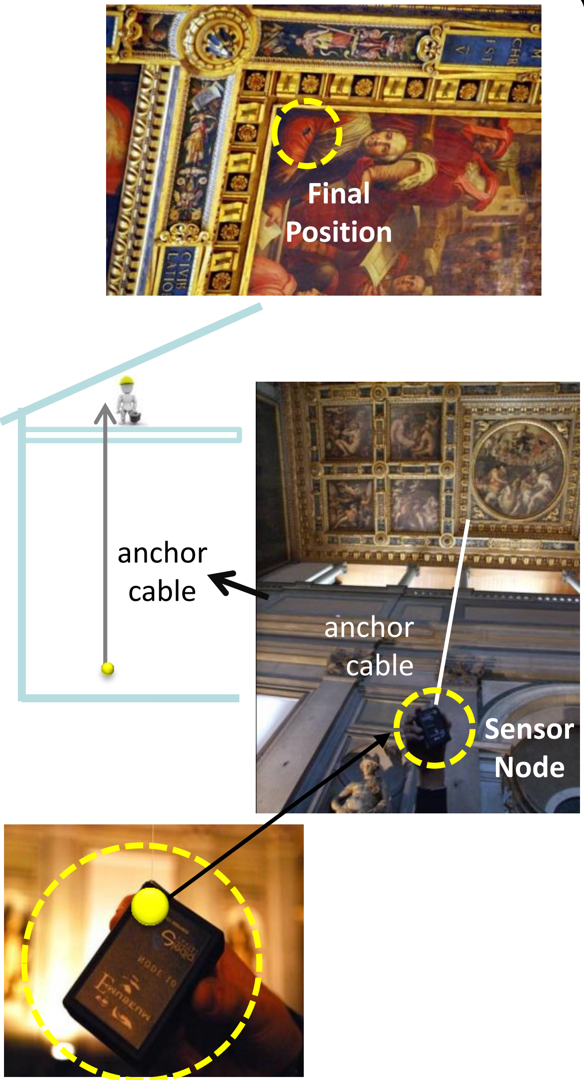
Three monitoring layers

Layer 3 [h=18m]

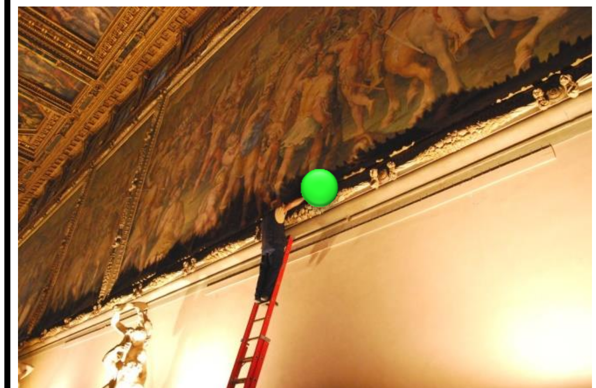
Layer 2 [h=5m]

Layer 1 [h=1.8m]

Deployment @ “Sala dei 500”



Layer 3 [a_3=18m]



Layer 2 [a_2=5m]

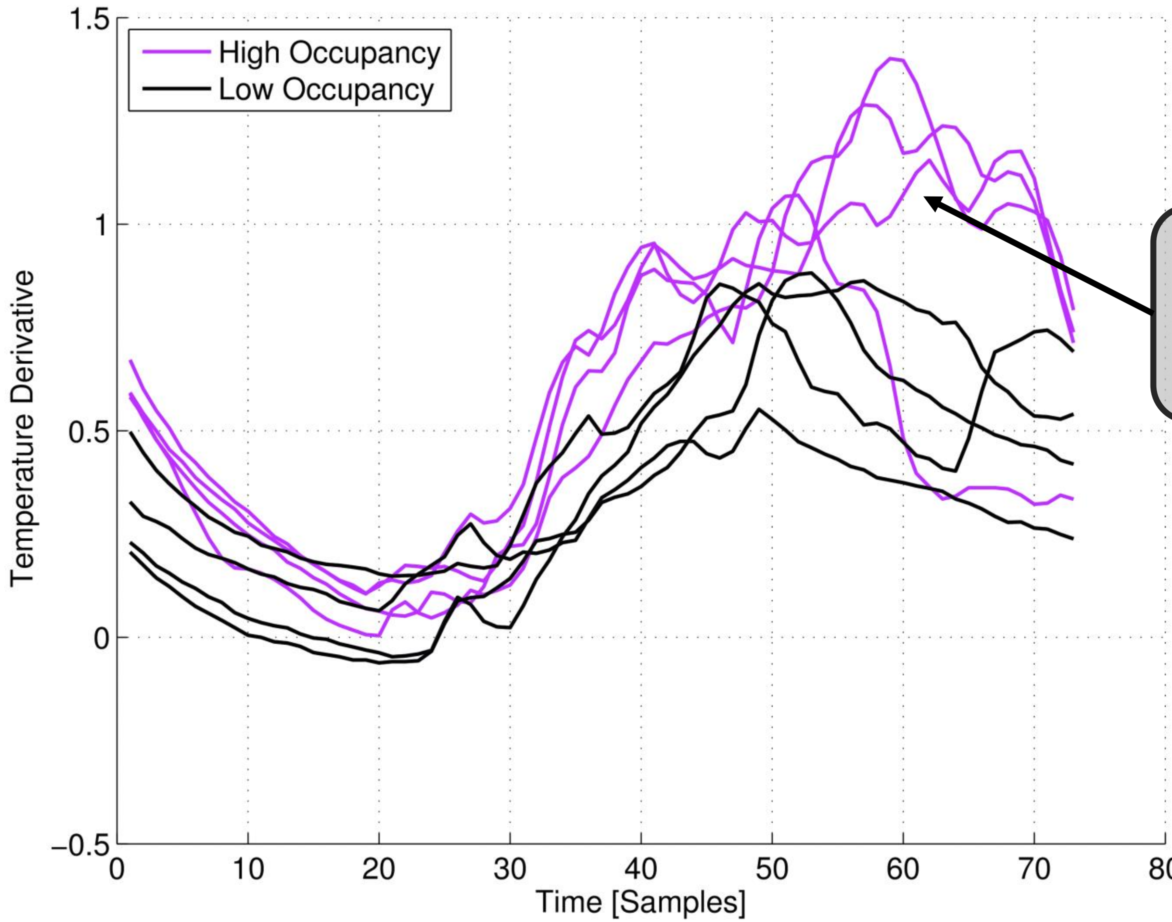
Layer 1 [a_1=1.8m]

Occupancy - Experimental Validation

OBJECTIVE Verify direct relation between OCCUPANCY level and the derivatives of vertical profiles

TEMPERATURE Derivative

$$T'(a) = \frac{\partial T(a)}{\partial a}$$



T' is higher for high occupancy

Temperature derivative $T'(a,\tau)$ – **Days with HIGH Occupancy**

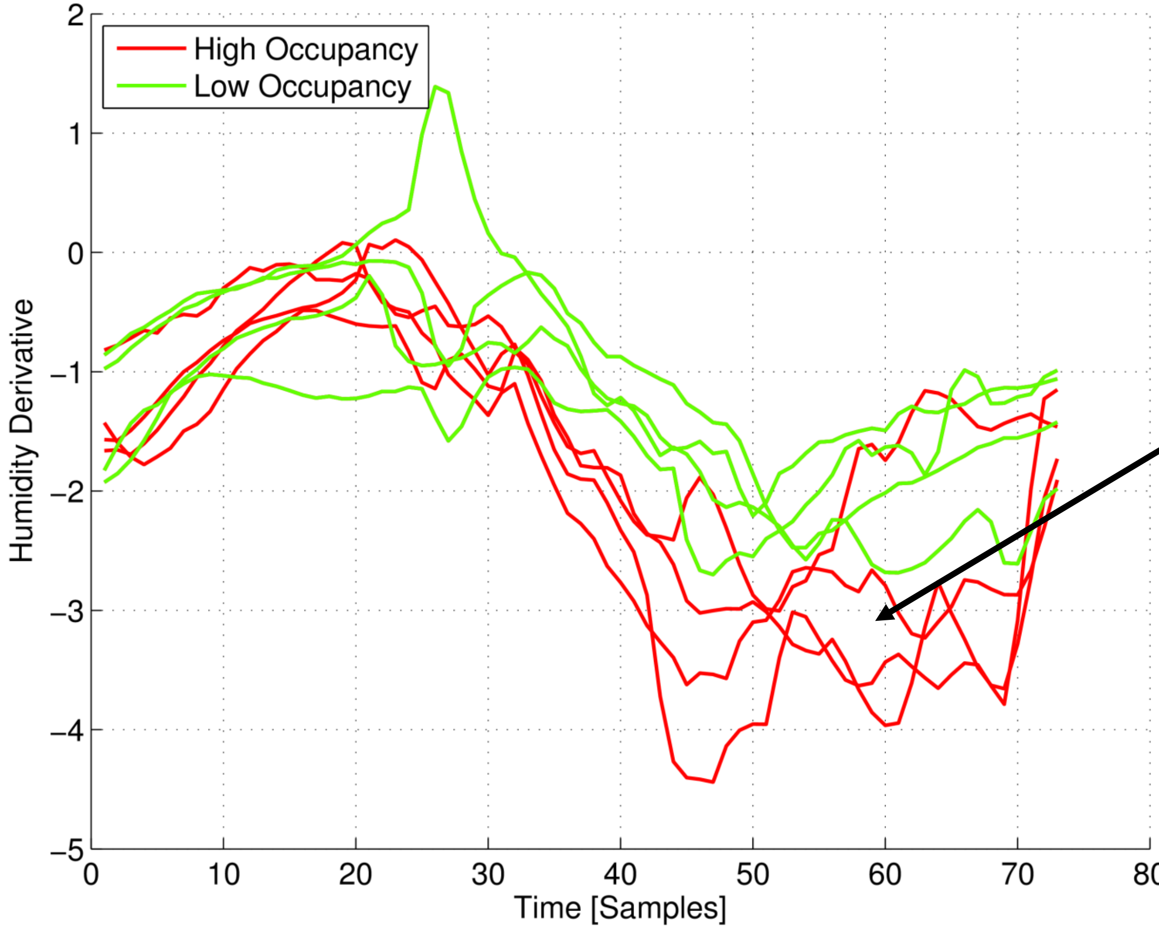
Temperature derivative $T'(a,\tau)$ – **Days with LOW Occupancy**

Occupancy - Experimental Validation

OBJECTIVE Verify direct relation between OCCUPANCY level and the derivatives of vertical profiles

HUMIDITY Derivative

$$H'(a) = \frac{\partial H(a)}{\partial a}$$



H' is lower for high occupancy

Humidity derivative $H'(a,\tau)$ – **Days with HIGH Occupancy**

Humidity derivative $H'(a,\tau)$ – **Days with LOW Occupancy**

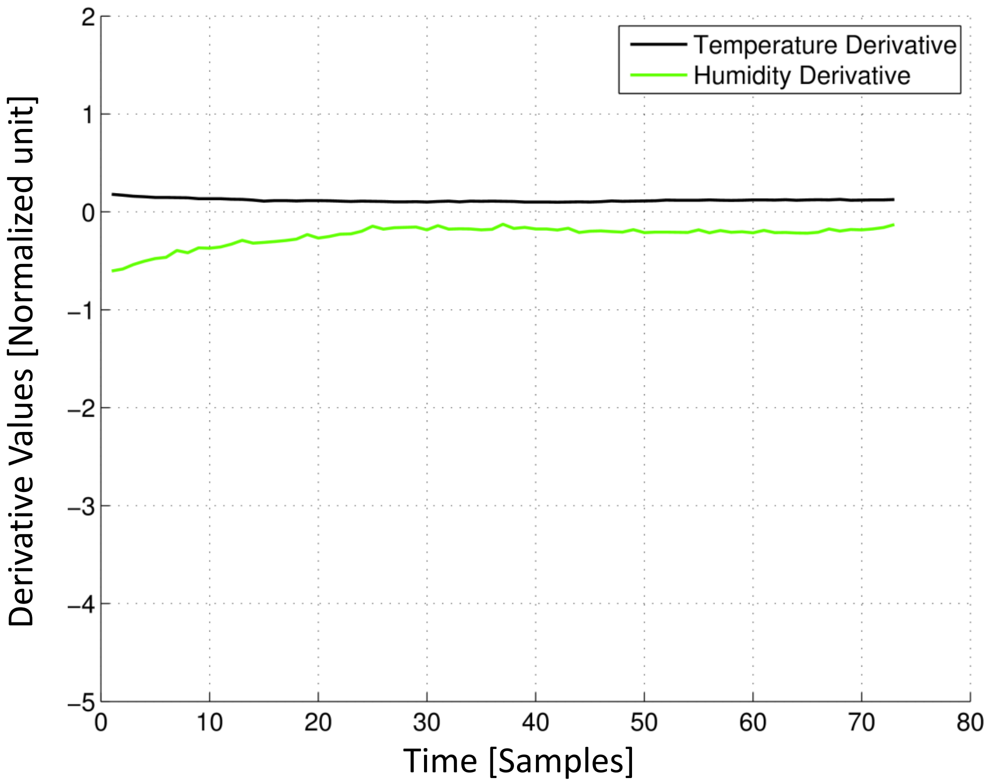
Low Occupancy Example

LOW OCCUPANCY

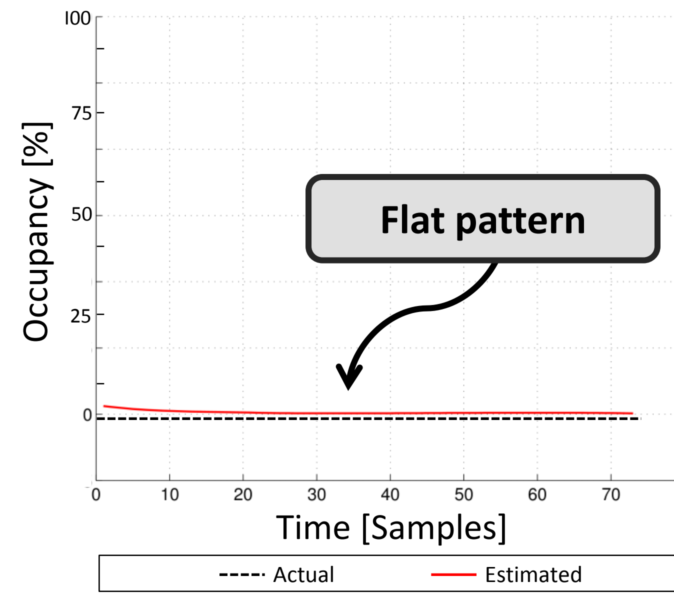
Museum is closed
(Christmas, 25 December 2013)

SVR parameters:
Training set size T=1008
Hyperparameter C=100
Gamma RBF G=0.1

Derivative Profiles



Estimated Occupancy [%]



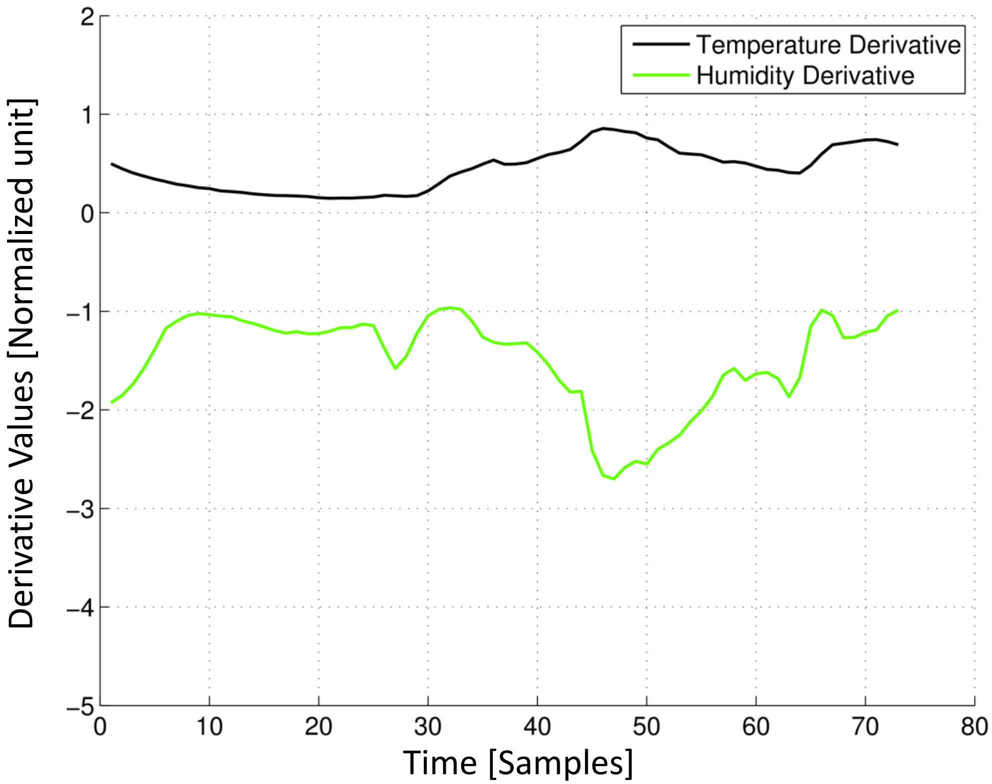
Standard Occupancy Example

STANDARD OCCUPANCY

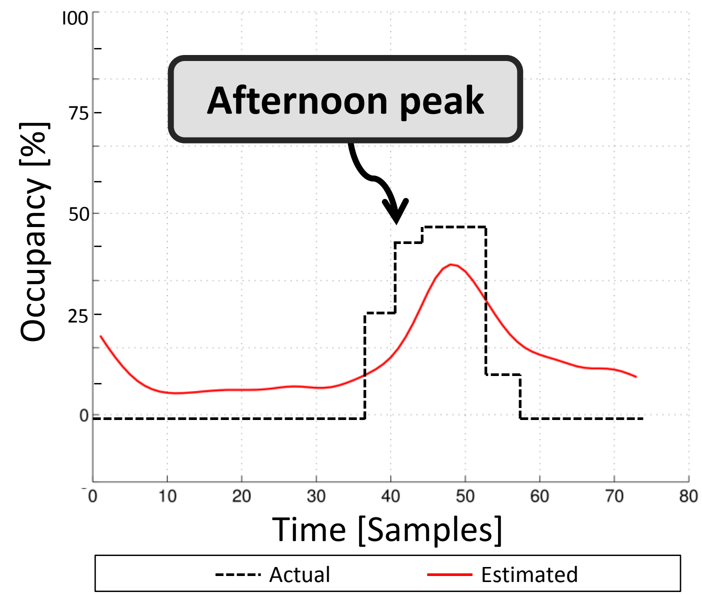
Museum is open
(Standard weekday, 24 October 2013)

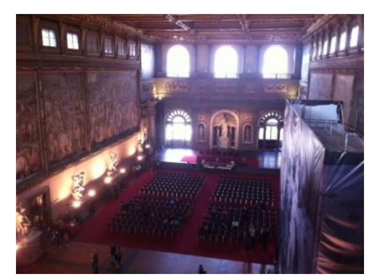
SVR parameters:
Training set size T=1008
Hyperparameter C=100
Gamma RBF G=0.1

Derivative Profiles



Estimated Occupancy [%]





High Occupancy Example

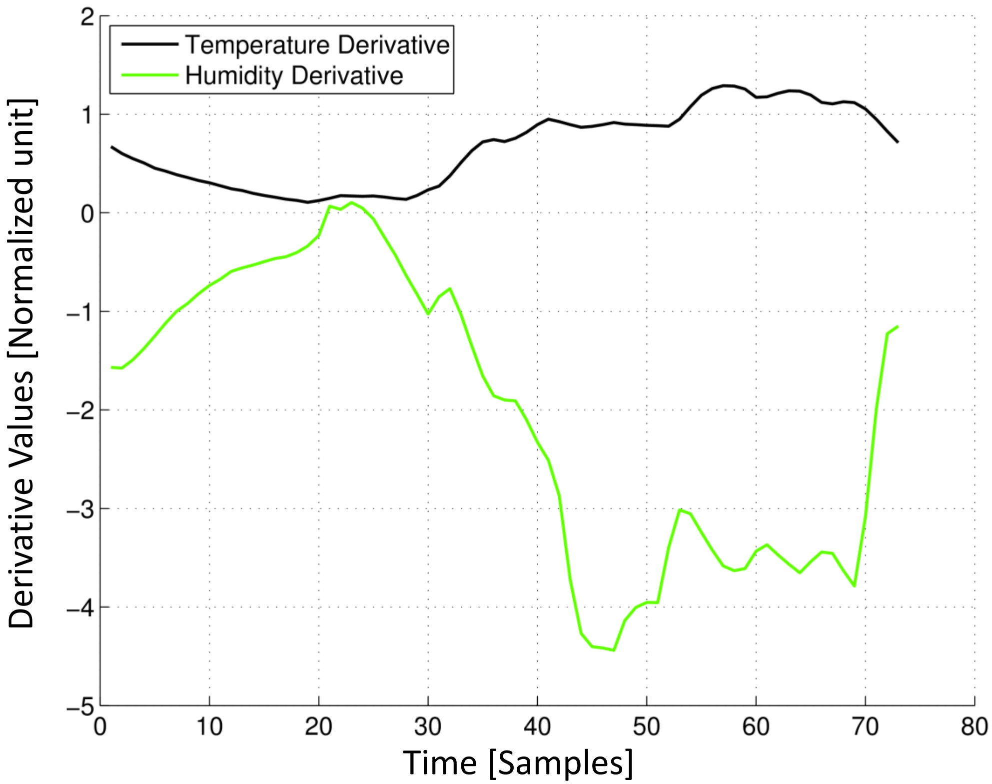
HIGH OCCUPANCY

Notte Bianca

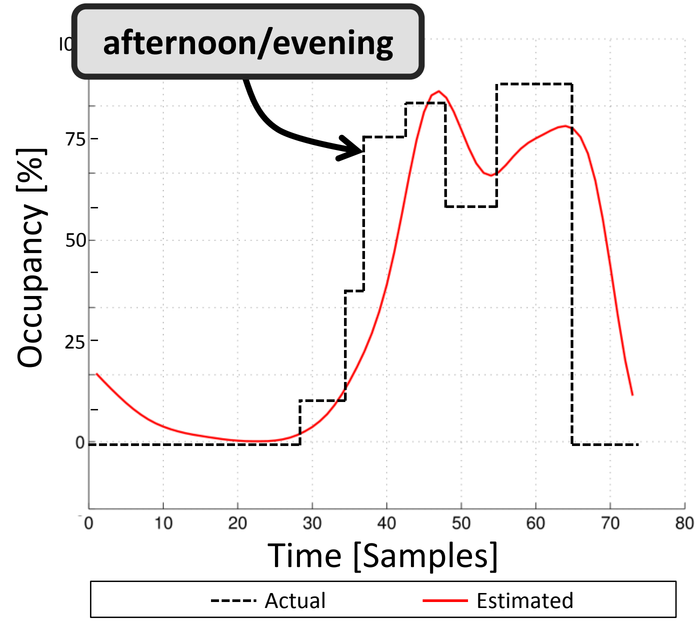
(Special Event, 30 April 2013)

SVR parameters:
Training set size T=1008
Hyperparameter C=100
Gamma RBF G=0.1

Derivative Profiles



Estimated Occupancy [%]



Conclusions

- Opportunistic Approaches for Wireless Localization
- EM information from IoT Devices can be Exploited for Localization
- Different Approaches for Different Scenarios and Requirements

Current Trends

- Sensor Fusion Strategies Exploiting Heterogeneous IoT Devices/Technologies (RFID, wearables, etc.)
- Investigation of Hybrid Solutions "*p-active*" (passive and active)

ELEctromagnetic DIAgnostics Research Center
ELEDIA@UniTN (University of Trento)
Via Sommarive 9, 38123 Trento, Italy
E-mail: andrea.massa@unitn.it
Web: www.eledia.org

EM Positioning for IoT

Fundamentals and Advances

Federico Viani, Alessandro Polo, Andrea Massa

IC1301 WIPE Cost Action – 2016 International Spring School
April 18-20, 2016 – Bologna, Italy