



# Signal processing: a networking perspective

## Part 2 – option B

Andrea Zanella



[zanella@dei.unipd.it](mailto:zanella@dei.unipd.it)



**SIGNALS processing &  
NETWORKING research group**

## □ **Part 3: QoE-oriented networking**

- Mixing up PHY and application-layer signals
  - smart environments
- Context awareness from signal processing
  - SSIM characterization of video content
  - Handover optimization
- Bye bye!

# Exploiting complementarities

## Wireless Sensor Nodes (WSN)

- Pros
  - ▣ Low cost
    - Large networks with many devices
  - ▣ Low energy consumption
    - Possibility to power with small batteries or energy-scavenging
- Cons
  - ▣ Limited computing capabilities
  - ▣ Limited memory
  - ▣ Limited transmission range/speed

## Autonomous Mobile Robots (AMR)

- Cons
  - ▣ High cost
    - Single or few units
  - ▣ High energy consumption
    - Need for large batteries and/or recharging stations
- Pros
  - ▣ High computational capabilities
  - ▣ Large memory
  - ▣ Large energy capacity
  - ▣ Large transmission range/speed
  - ▣ Advanced mobility

# Application scenarios

## Application Scenarios

- Smart Environments
  - ▣ AMRs may catalog, localize and retrieve objects upon request
  - ▣ Libraries: AMRs may put back books on the shelves after closure
- Assisted Living
  - ▣ A portable device may drive a visual-impaired person through a partially unknown environment by vocally describing the smart objects that recognizes along the way
  - ▣ A personal robot may display to a motion-impaired user the list of smart objects that it discovers
    - remote controls, mobile phones, books, ...

## Limit of existing solutions

- Dataset of object-models stored on the robot
  - ▣ Low flexibility: new objects shall be included in the directory to be recognized
  - ▣ Similar objects are indistinguishable
- RFID-based communication
  - ▣ Cheaper, but requires physical proximity and does not support sophisticated algorithms nor multi-hop communication



# Target application: autonomous exploration of unknown “smart” environments

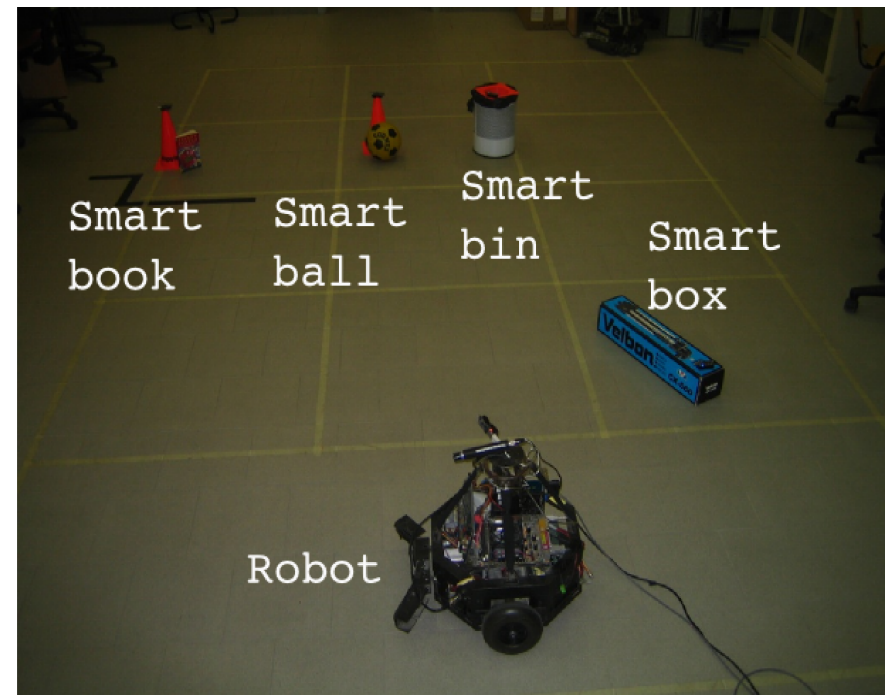
## Vision

- AMR equipped with
  - ▣ odometers for self-localization
  - ▣ on-board camera
  - ▣ RF transceiver
- Smart Objects (SOs), i.e., common objects tagged with WSNs that provide
  - ▣ Computational/communication capabilities
  - ▣ data storage
  - ▣ self-management features



## Goal

- Autonomous **exploration** of **unknown environments** and **interaction** with SOs
  - ▣ No prior info about the number or kind of SOs



# Experimental Set up

## TmoteSky sensor nodes

- 250 kbps @ 2.4 GHz
- Ultra low current consumption
- Light, temperature, RSSI sensors
- TinyOS



TmoteSky connected to ATX  
via USB + MoteService class  
added to Miro

## AMR Bender

- Home-made, based on Pioneer 2 ActivMedia platform
- Linux OS with Miro middleware
- ATX motherboard
  - ▣ 1,6 GHz Intel Pentium 4, 256 MB RAM, 160 GB HD
- On-board camera
- Odometers



# System's building blocks

## 1. Smart Object Identification

- The AMR gets a list of close by SOs, but does not know their location

## 2. Smart Object Mapping

- The AMR builds a map of the area estimating SOs' location

## 3. Smart Object Recognition

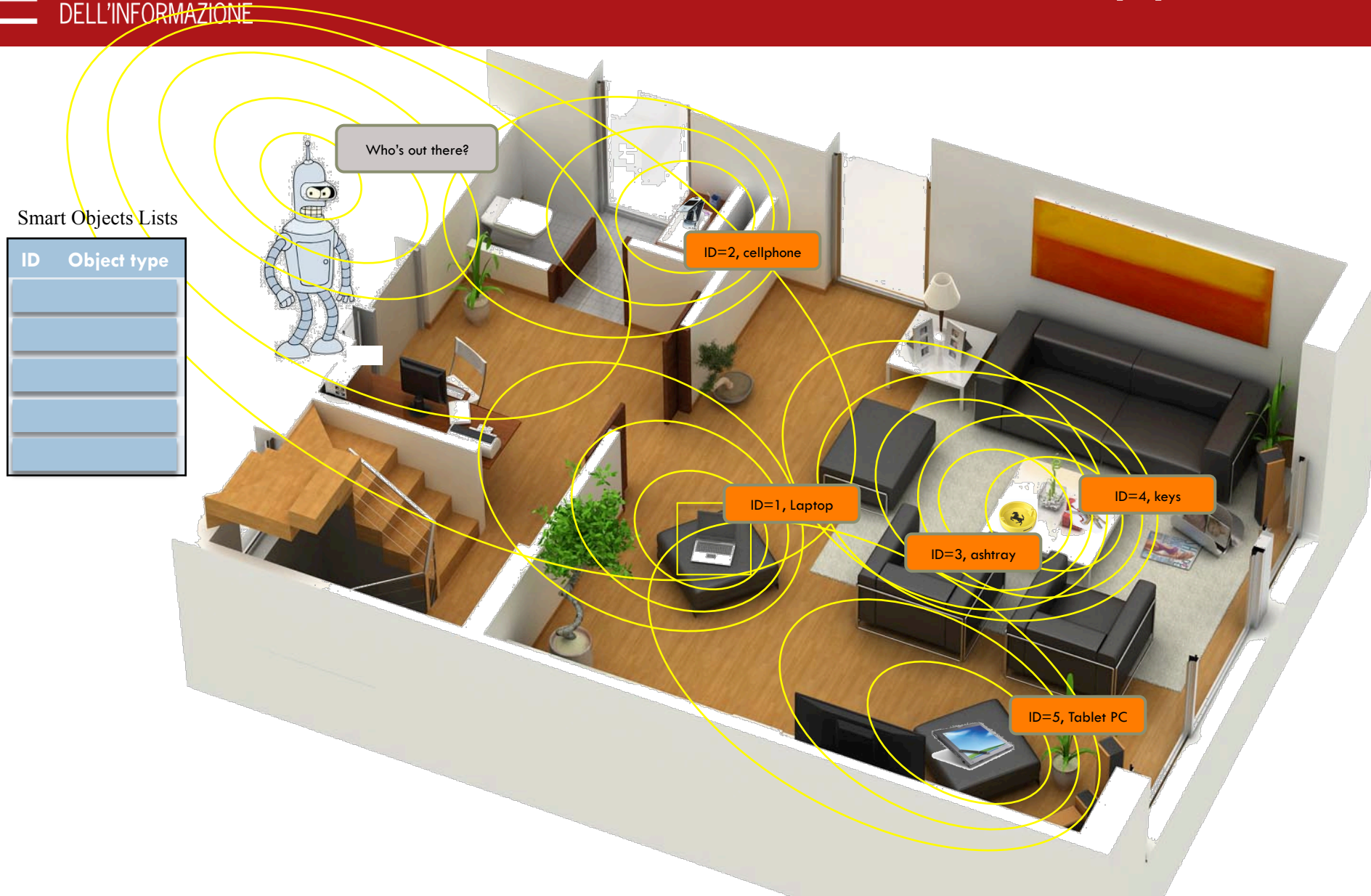
- The AMR gets close to a selected object and, then, visually recognizes it in the image taken by the on-board camera



DIPARTIMENTO  
DI INGEGNERIA  
DELL'INFORMAZIONE

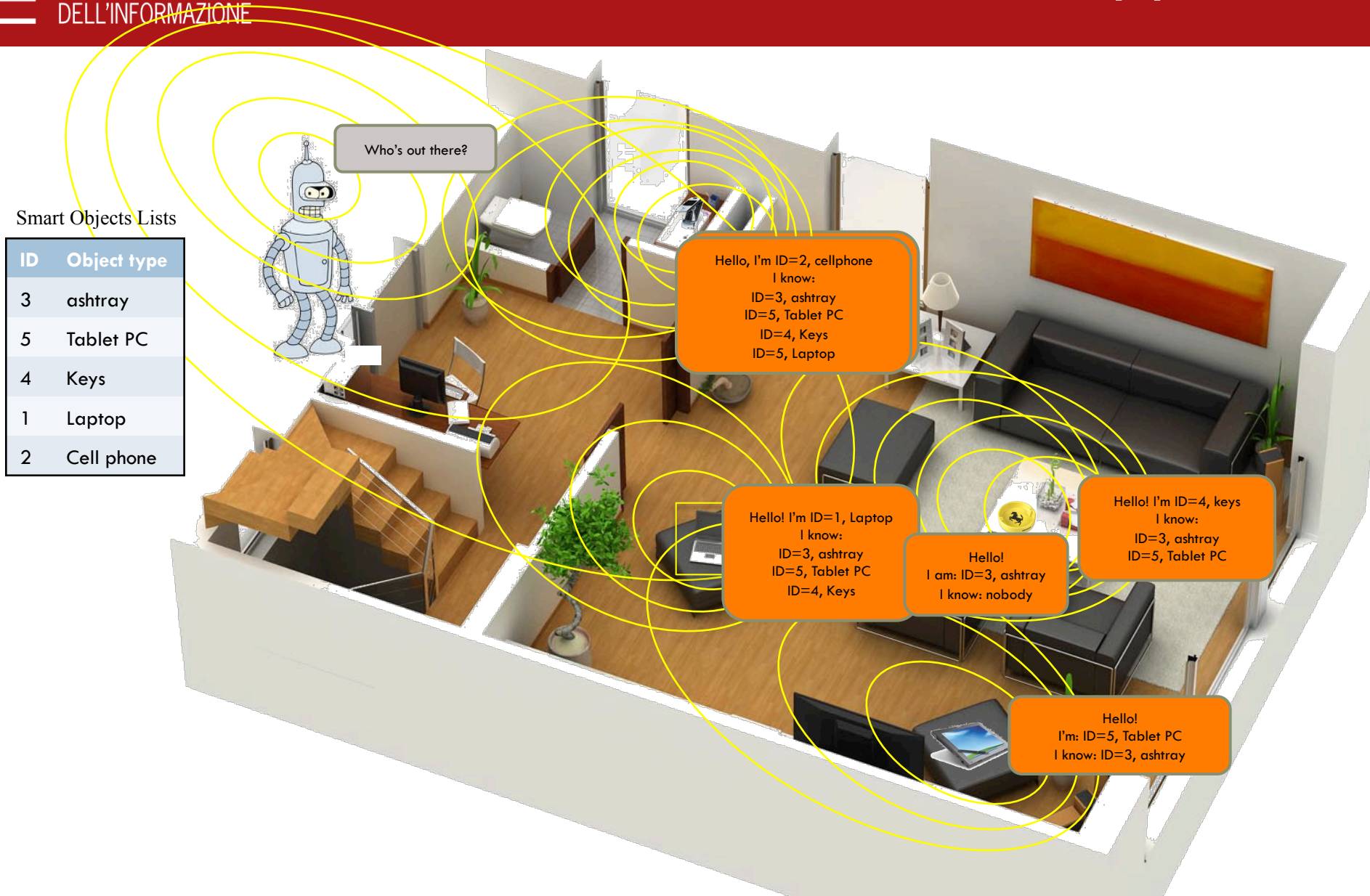
## Step 1. Smart Objects Identification

# Identification: centralized approach





# Identification: distributed approach





DIPARTIMENTO  
DI INGEGNERIA  
DELL'INFORMAZIONE

## Step 2. Smart Objects Mapping

# Mapping: still a challenge

- GPS works pretty well... outdoor...
  - ▣ Not that well indoor though!
  - ▣ Hungry for energy (& money): not suitable for SOs
- Cricket-like systems work fine, but require dedicated hw
  - ▣ Impact on device size, cost, location, energy efficiency...
- RF-based localization techniques are very attractive...
  - ▣ if you're not too picky about performance!
    - Radio Signal Strength Indication (RSSI) is natively provided by all WSN platforms
    - However, RSSI-based ranging is usually VERY noisy!



# Mapping: our solution

## WSN-wise

- Improve RSSI-based ranging by using the communication capabilities of WSNs
  - ▣ Multi-channel RSSI averaging

## AMR-wise

- Use on-board odometers of the AMR and its computational capabilities to perform sophisticated localization algorithm
  - ▣ SLAM: Simultaneous Localization (of the AMR) And Mapping (of the SOs)

# RSSI-based ranging: basics

## □ Path loss channel model

- ▣ received power  $P_i$  @ distance  $d_i$

$$P_i [dBm] = P_{Tx} + K - 10\eta \log_{10} \left[ \frac{d_i}{d_0} \right] + \underbrace{(\Psi_i)}_{\text{Shadowing}} + \underbrace{(\alpha_i(t))}_{\text{Fast Fading}}$$

environmental constant      transmitter-receiver distance

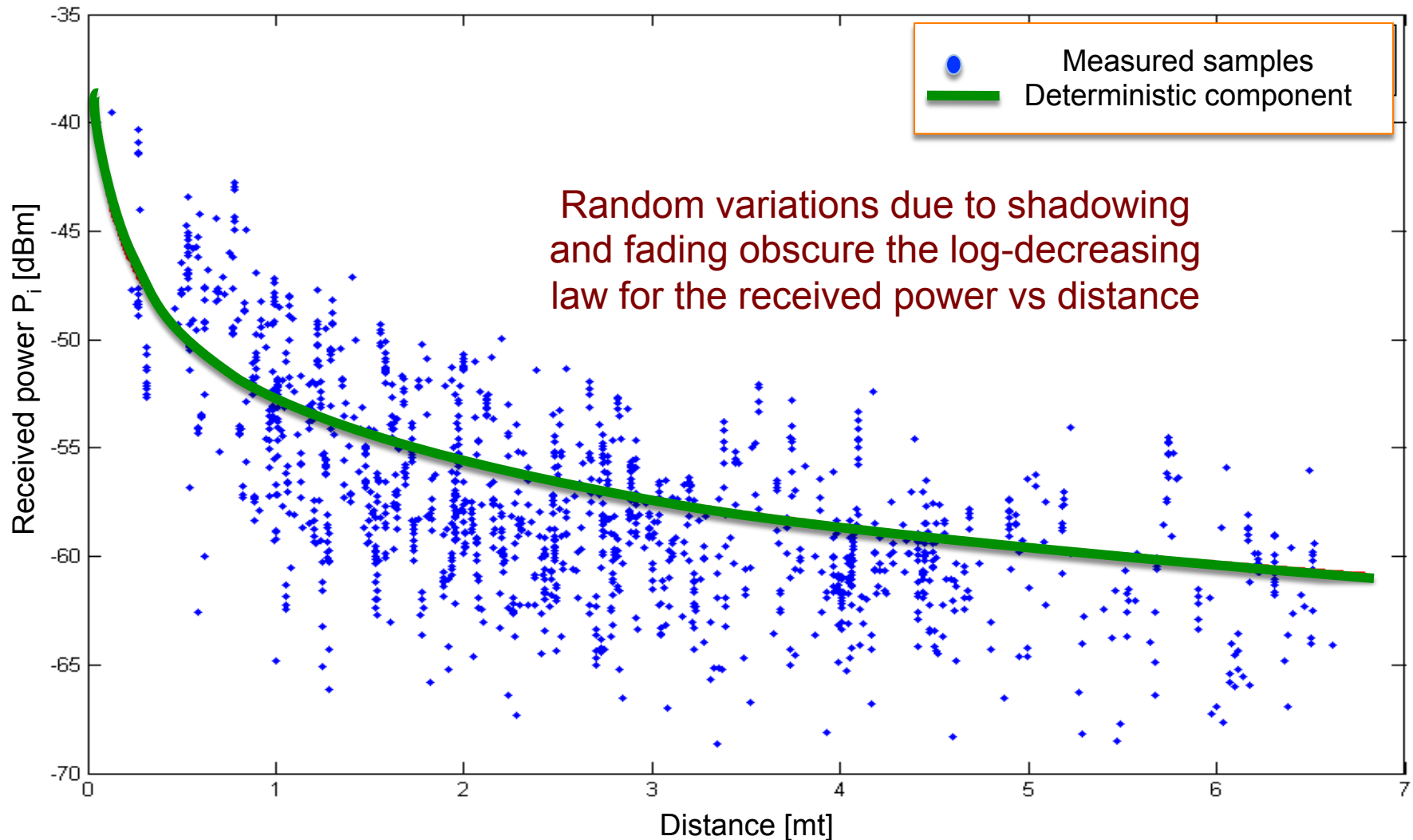
Received power      Transmit power      Path loss coefficient      reference distance

Deterministic component      Random term

Propagation-based ranging

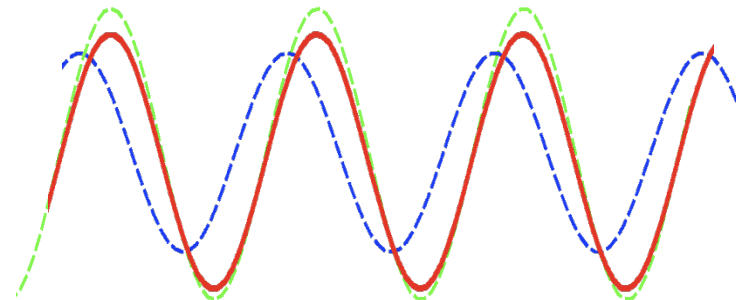
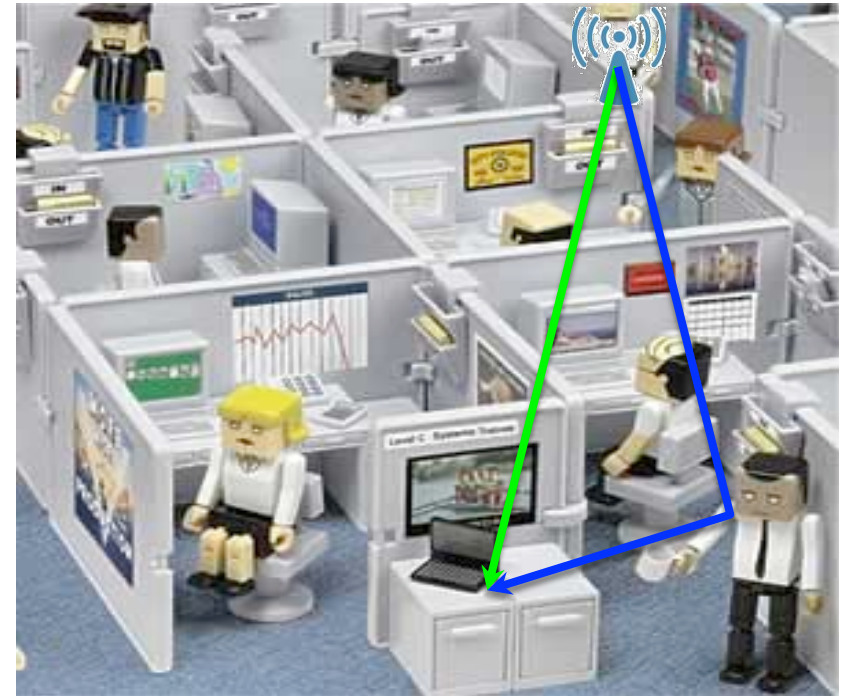
$$\hat{d}_i = 10^{\frac{P_{Tx} + K - P_i [dBm]}{10\eta}} = d_i \underbrace{10^{-\frac{\psi_i}{10\eta}}}_{\text{Ranging error}}$$

# RSSI-ranging: an example...



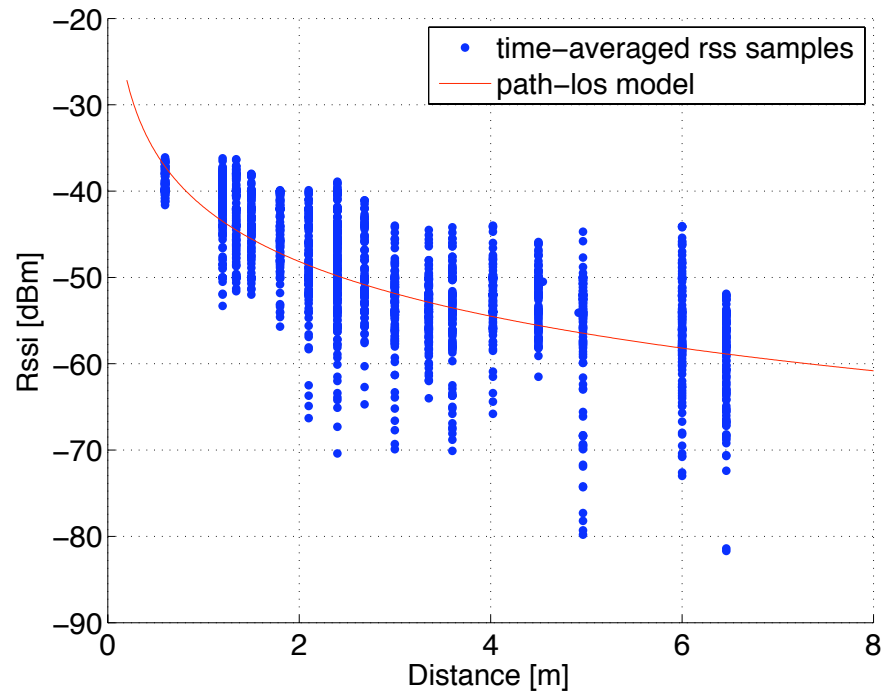
# Mitigating RSSI randomness

- Shadowing term is actually due to strong and slowly time varying multipath interference
- A shift in the carrier frequency will change the way reflected copies combine at the receiver

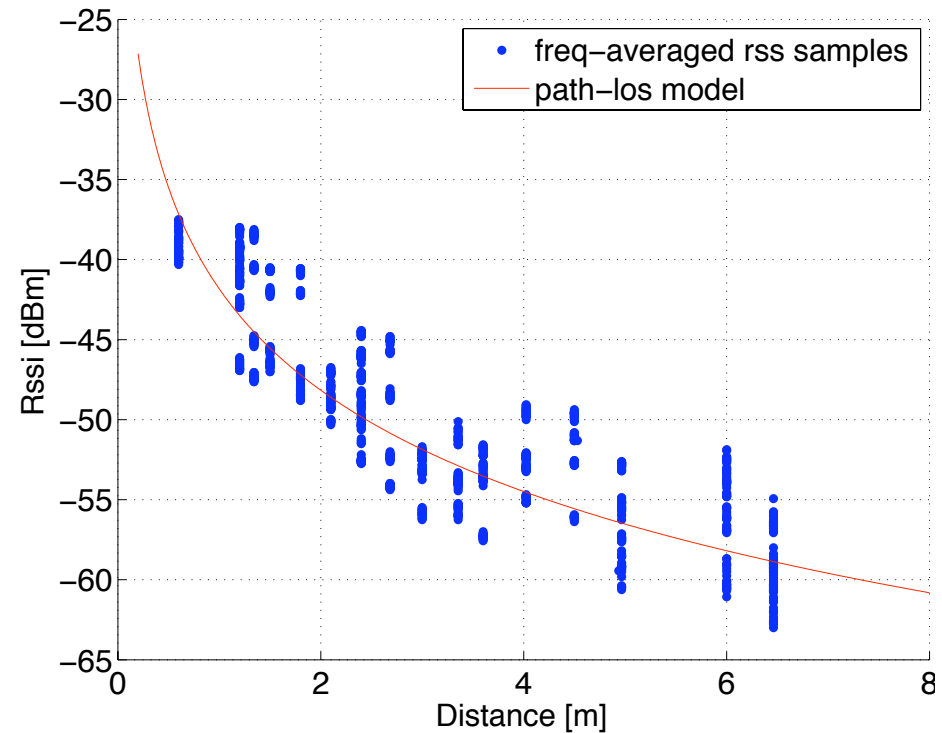


# Multi-channel RSSI: experimental results

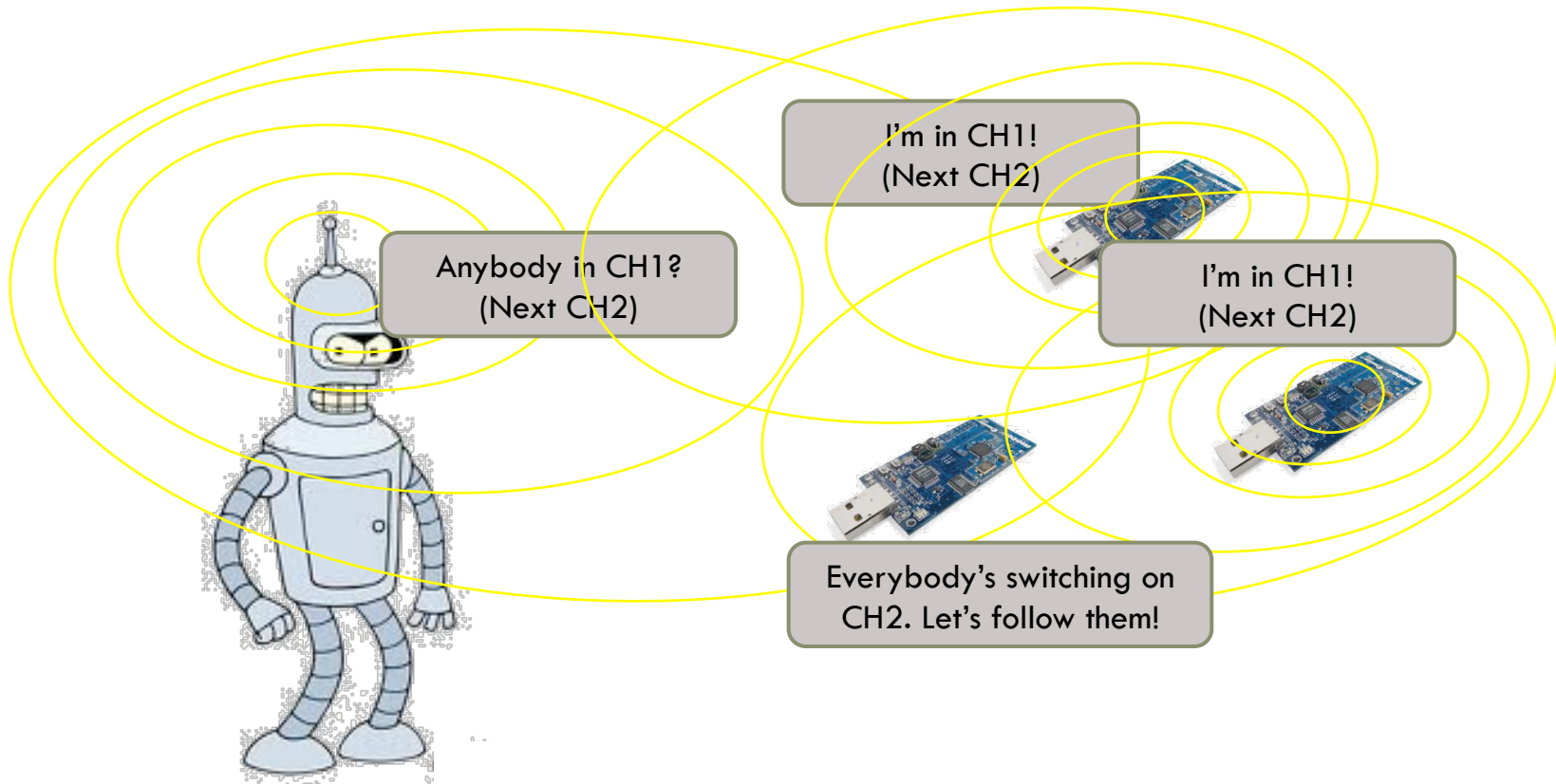
## Time Average



## Frequency average



# RF-jumping protocol in a nutshell!



# RF-jumping protocol

## AMR side

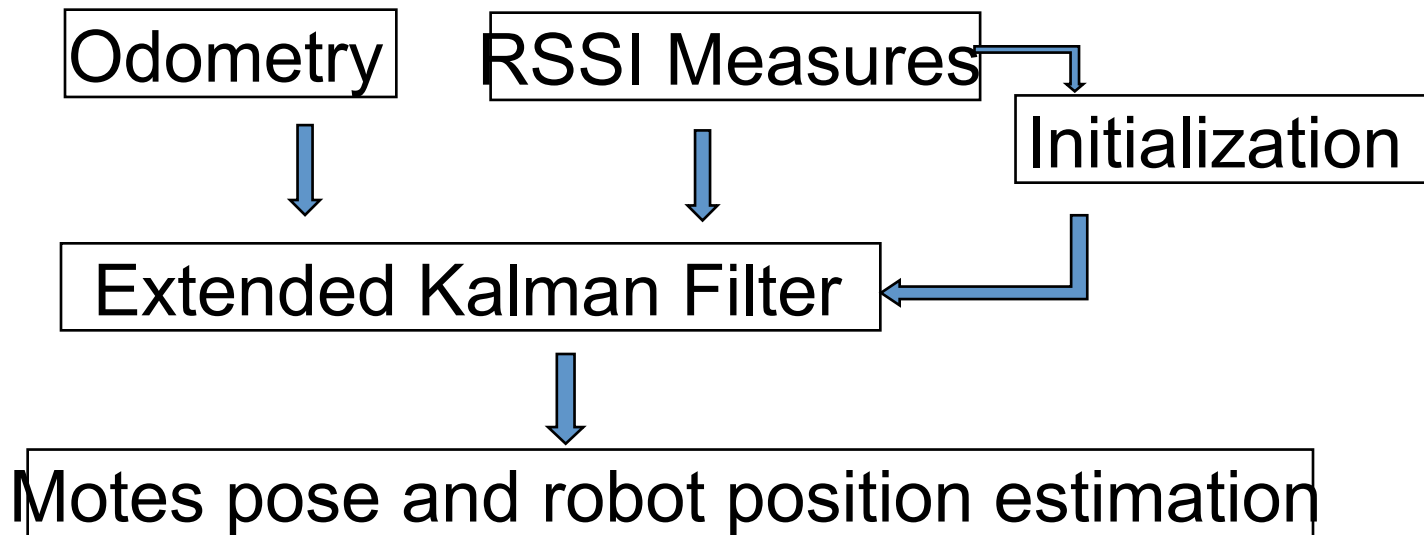
- Set TX Channel to default RF Channel
- FOR NextRFCh=1 TO 16 DO
  - Send REQUEST(NextRFCh)
    - Start REQ\_TO
  - WHILE NOT(REQ\_TO expired) DO
    - IF (REPLY pkt received)
      - Store RSSI sample
      - Restart REQ TimeOut
  - ENDWHILE
  - Set TX Channel to NextRFCh
- ENDFOR

## SO side

- Set flag=false
- IF (REQUEST pkt received)
  - Get NextRFCh
  - Set flag=true
  - Set random REP\_TO in [0,REQ\_TO]
  - WHILE NOT(REP\_TO expired) DO
    - IF (REPLY pkt received) & flag THEN Restart REP\_TO
  - ENDWHILE
  - Send a REPLY pkt & switch to NextRFCh
- IF (REPLY pkt received) & NOT flag THEN
  - Get NextRFCh
  - Switch to NextRFCh

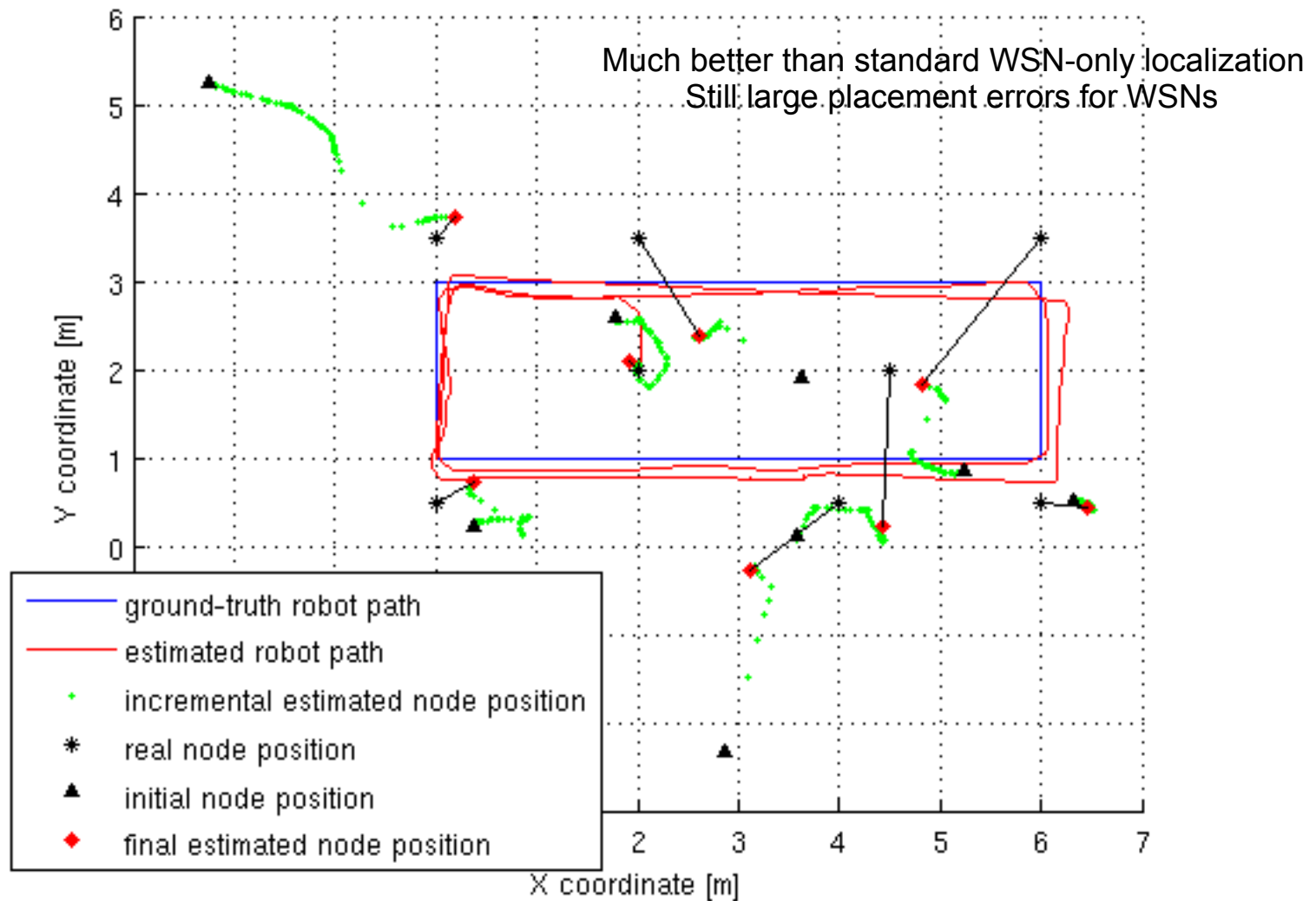
# Standard SLAM

Localization Algorithm:



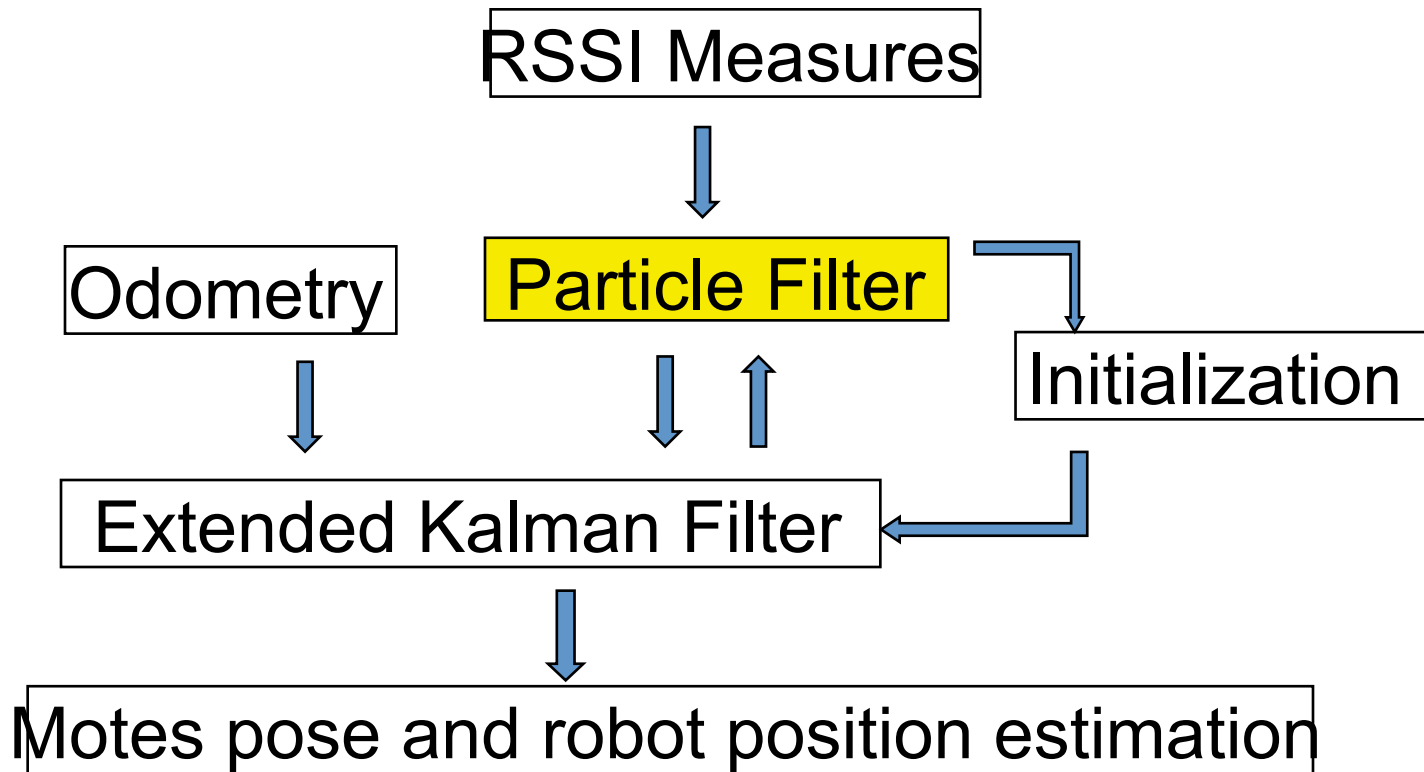


# Standard SLAM result

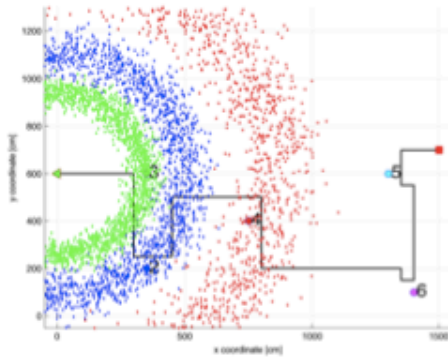


# SLAM with particle filter

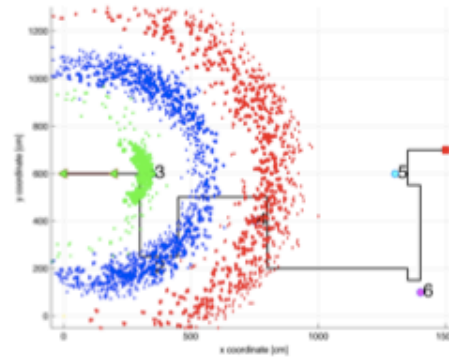
Localization Algorithm:



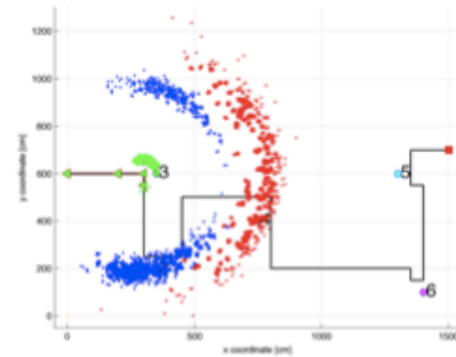
# Delayed Initialization based on Particle Filter



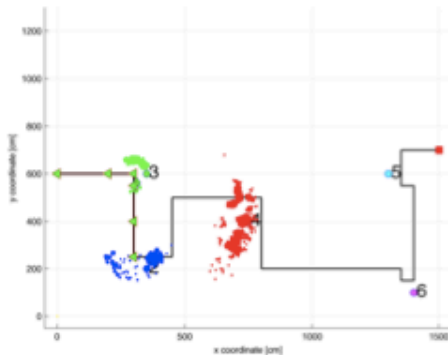
(a)



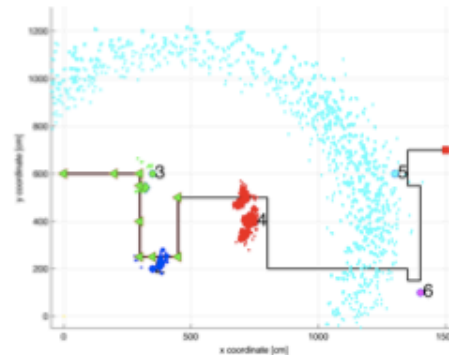
(b)



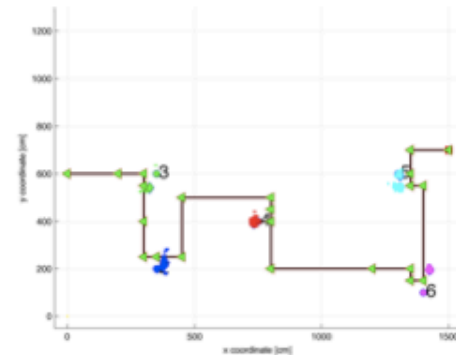
(c)



(e)



(f)



(g)



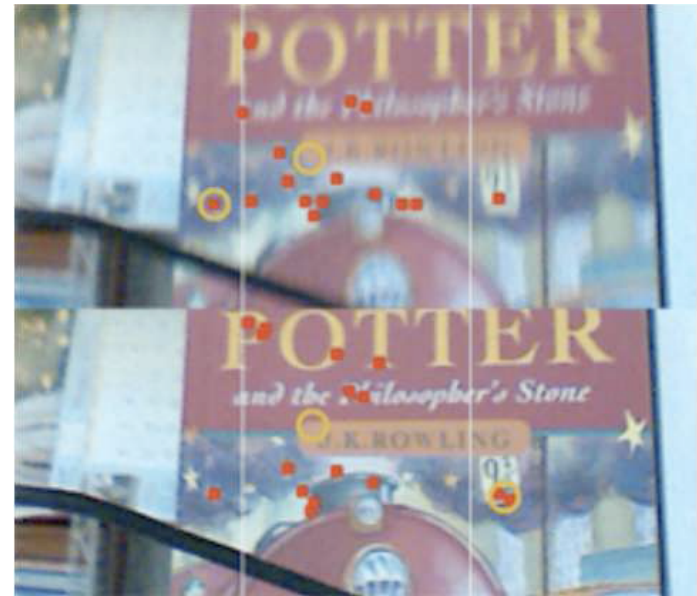
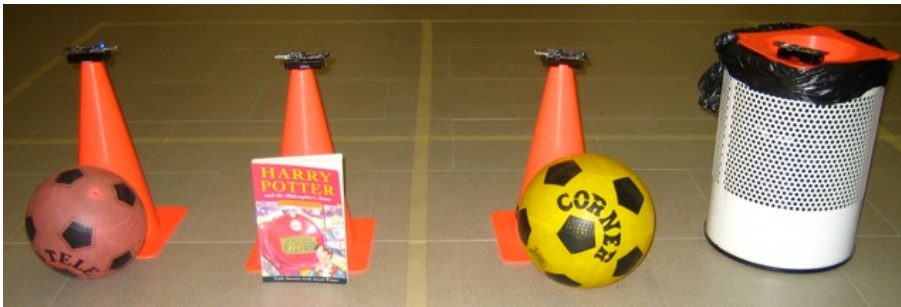
## Step 3. Smart Objects Recognition



DIPARTIMENTO  
DI INGEGNERIA  
DELL'INFORMAZIONE

# SO recognition by visual inspection

- The AMR should be able to recognize the objects from a description of the objects' appearance
- The object appearance is stored inside the object (in the notes)
- The appearance is coded by scale invariant feature descriptors robust also to motion blur (MoBIF)

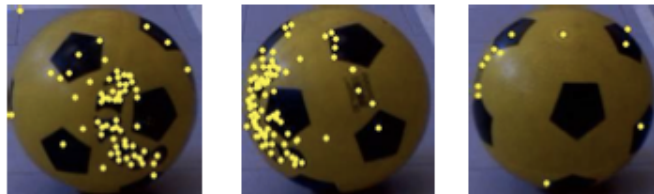


Feature matching under motion blur (Pretto et al. ICRA 2009)

# Storing the appearance

- Enhancing robustness to scale:
  - ▣ the object is imaged at different distances: near, medium, far
- Enhancing robustness to rotation:
  - ▣ the object is imaged every 20 deg.
- Limiting descriptors size
  - ▣ MoBIF descriptors extracted at different distances and angles are merged removing redundancy!

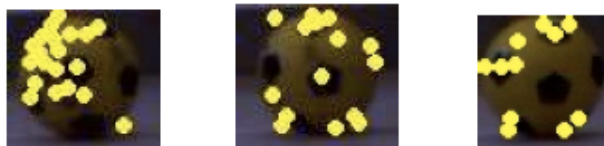
1 meter



2 meters



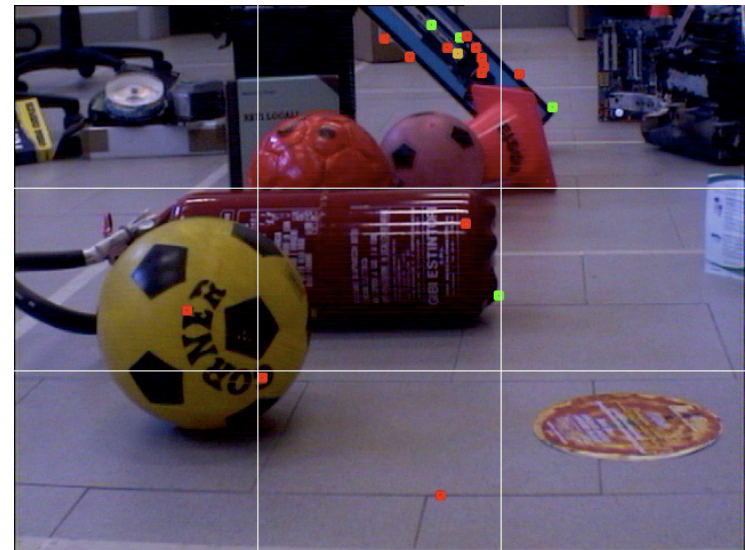
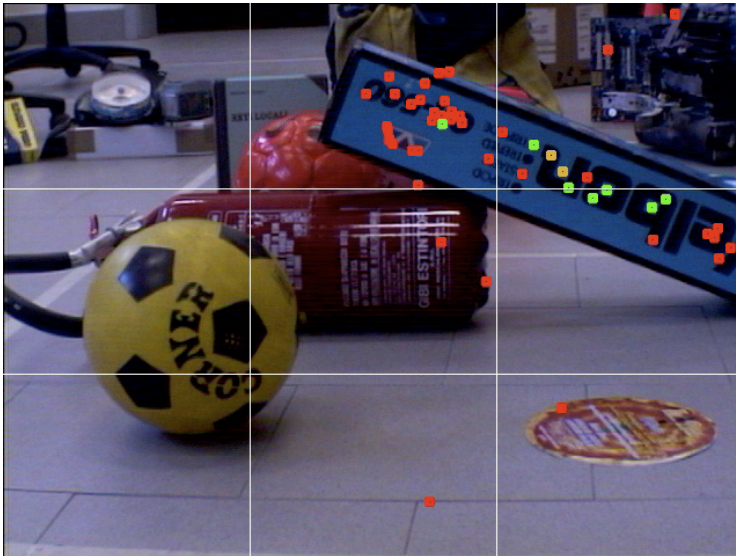
5 meters





# MoBIF Matching

- ❑ The AMR requires the selected SO to send its MoBIF descriptors
- ❑ The AMR dynamically extracts MoBIF descriptor from the image taken by onboard camera
- ❑ When MoBIF descriptors matching exceeds a threshold the SO is recognized
  - ▣ matching is robust to scale, occlusion, illumination and rotation



# Conclusions

- Synergetic combination of WSN and AMR:
  - ▣ AMR helps WSN nodes localization
  - ▣ WSN helps object recognition and handling by AMRs
  - ▣ AMR & WSN together delivers new services
- Future work:
  - ▣ Improve localization by using also images taken by onboard camera into the SLAM algorithm
  - ▣ Include smart navigation algorithms to the framework
  - ▣ Adding object-handling algorithms to the system



# bibliography

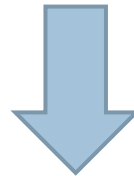
- E. Menegatti, M. Danieleto, M. Mina, A. Pretto, A. Bardella, S. Zanconato, P. Zanuttigh, and A. Zanella, "Autonomous discovery, localization and recognition of smart objects through WSN and image features" in the proceedings of the IEEE Globecom 2010 Workshop on Towards SmArt COmmunications and Network technologies applied on Autonomous Systems, 6 december 2010, Miami, Florida, USA.



## Context-awareness and reactivity

# Cognition-based Network

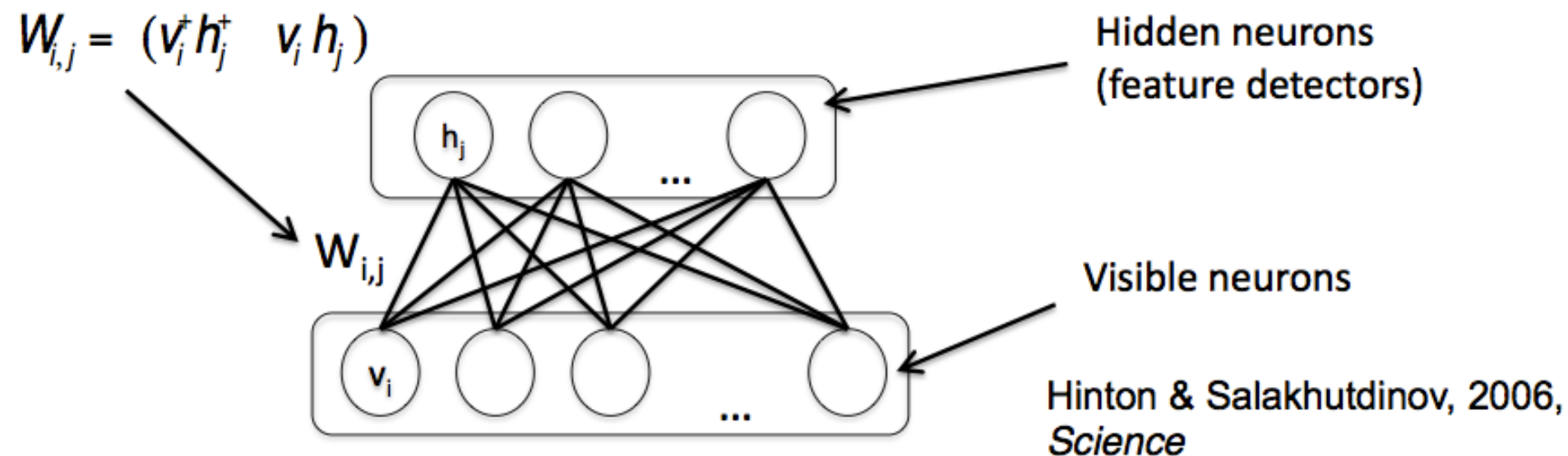
- Each node of the network:
  - ▣ exploits local information to achieve its goal
  - ▣ shares it with its neighbors



- Self-adaptation to the environment to achieve network wide goals
- Cognition applied to the entire network (not just at the PHY and MAC layers)

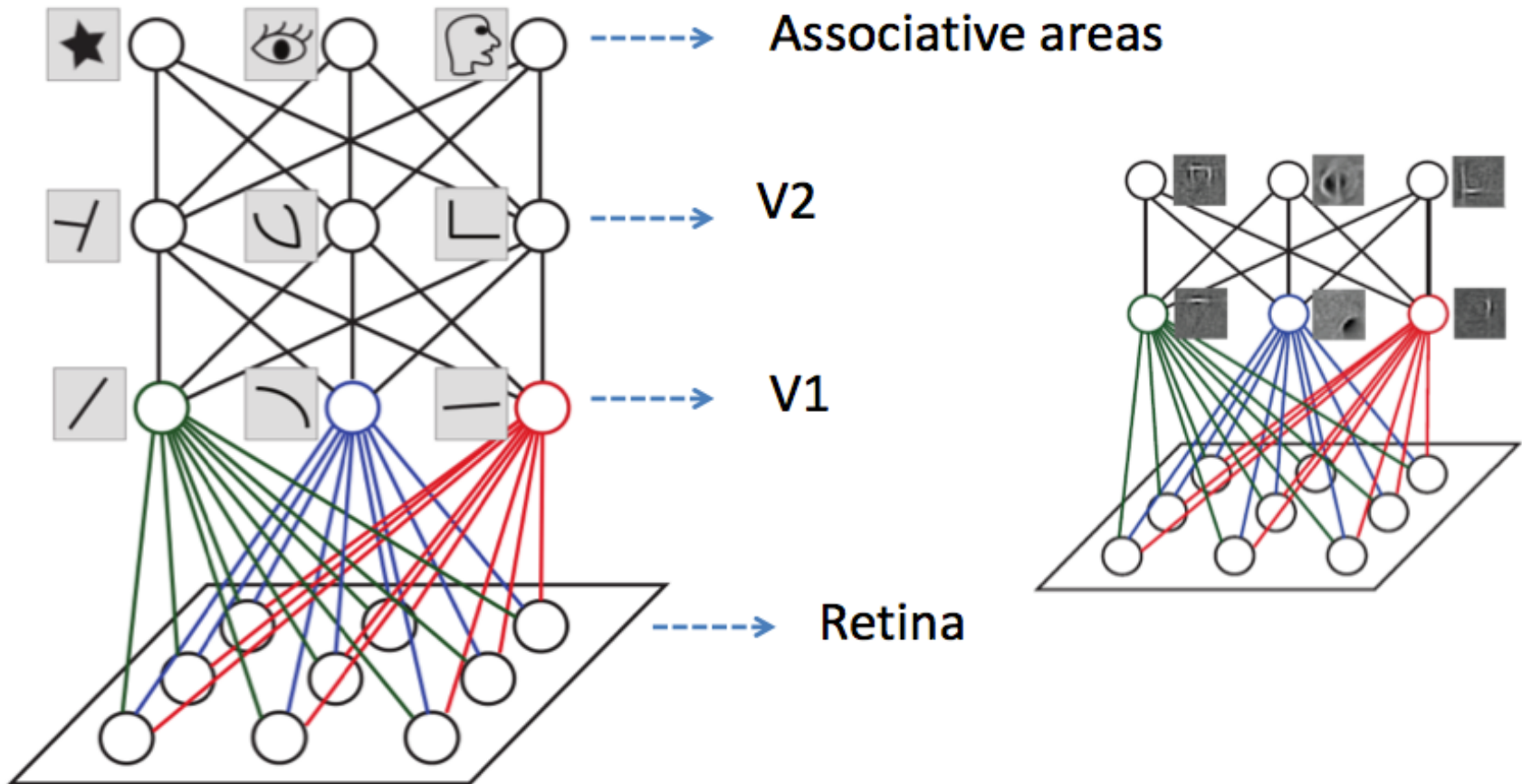
# Restricted Boltzmann Machines (RBM)

- Stochastic neural network
  - ▣ input layer symmetrically connected with a hidden layer of feature-detectors
- Unsupervised learning of an internal model of the data

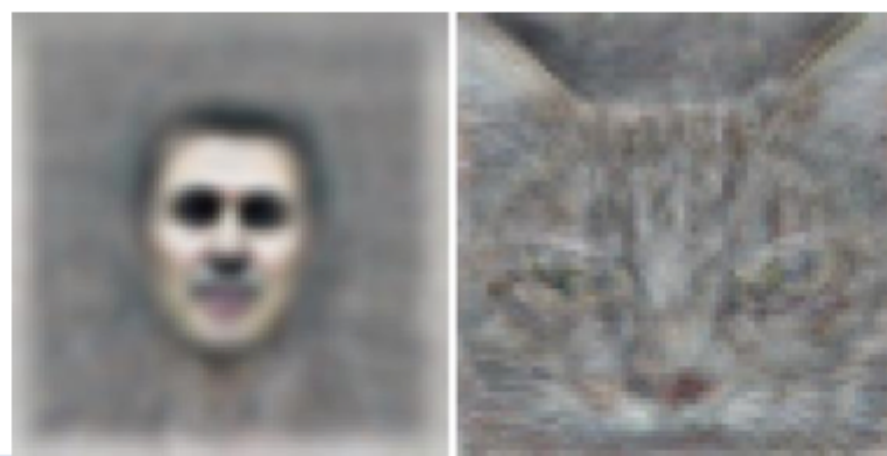


# Hierarchical processing

A key feature of cortical computation



# Example of learning/generation



Large scale simulation

Deep network 9 layers (1 billion connections)

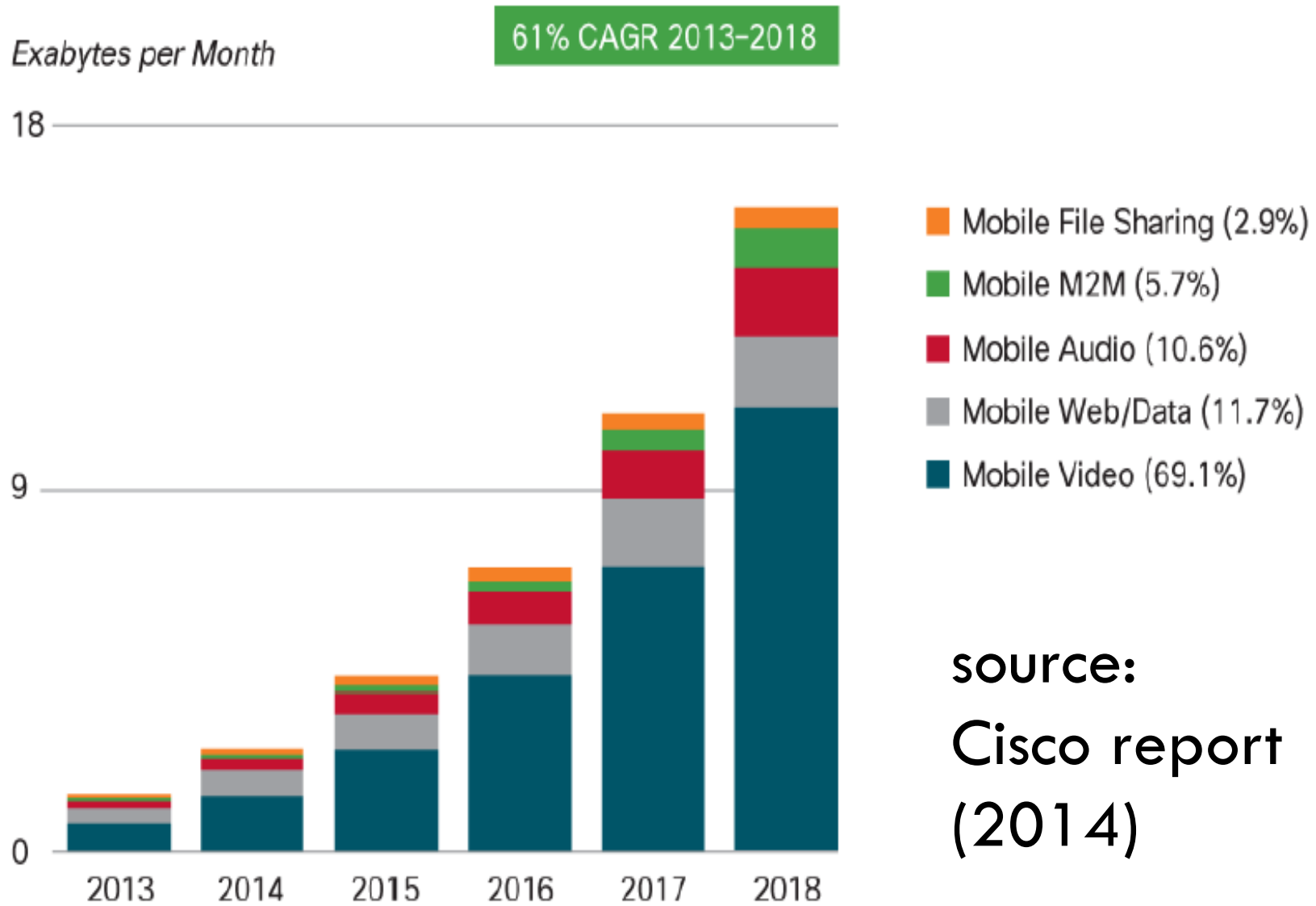
10 million (200x200) unlabeled images

(Le et al., 2012)

# Example of applications

- Content-based video management
- Context-dependent handover in HetNets
- Context-aware proactive content caching
- ...

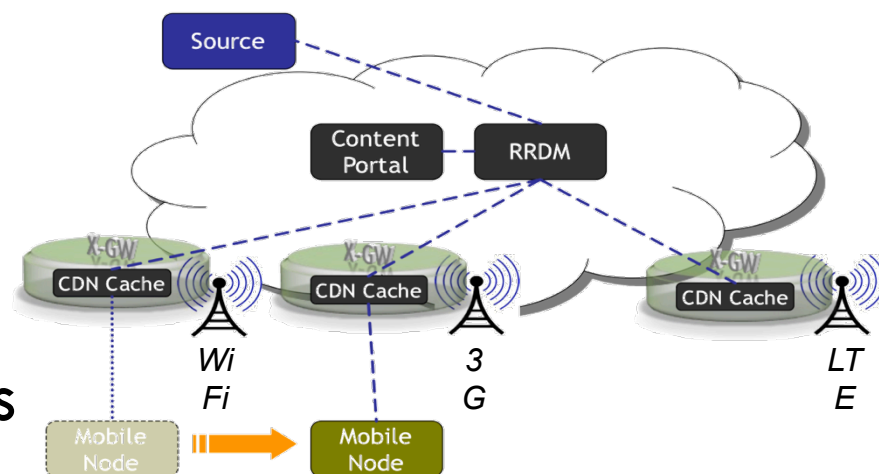
# Multimedia growth





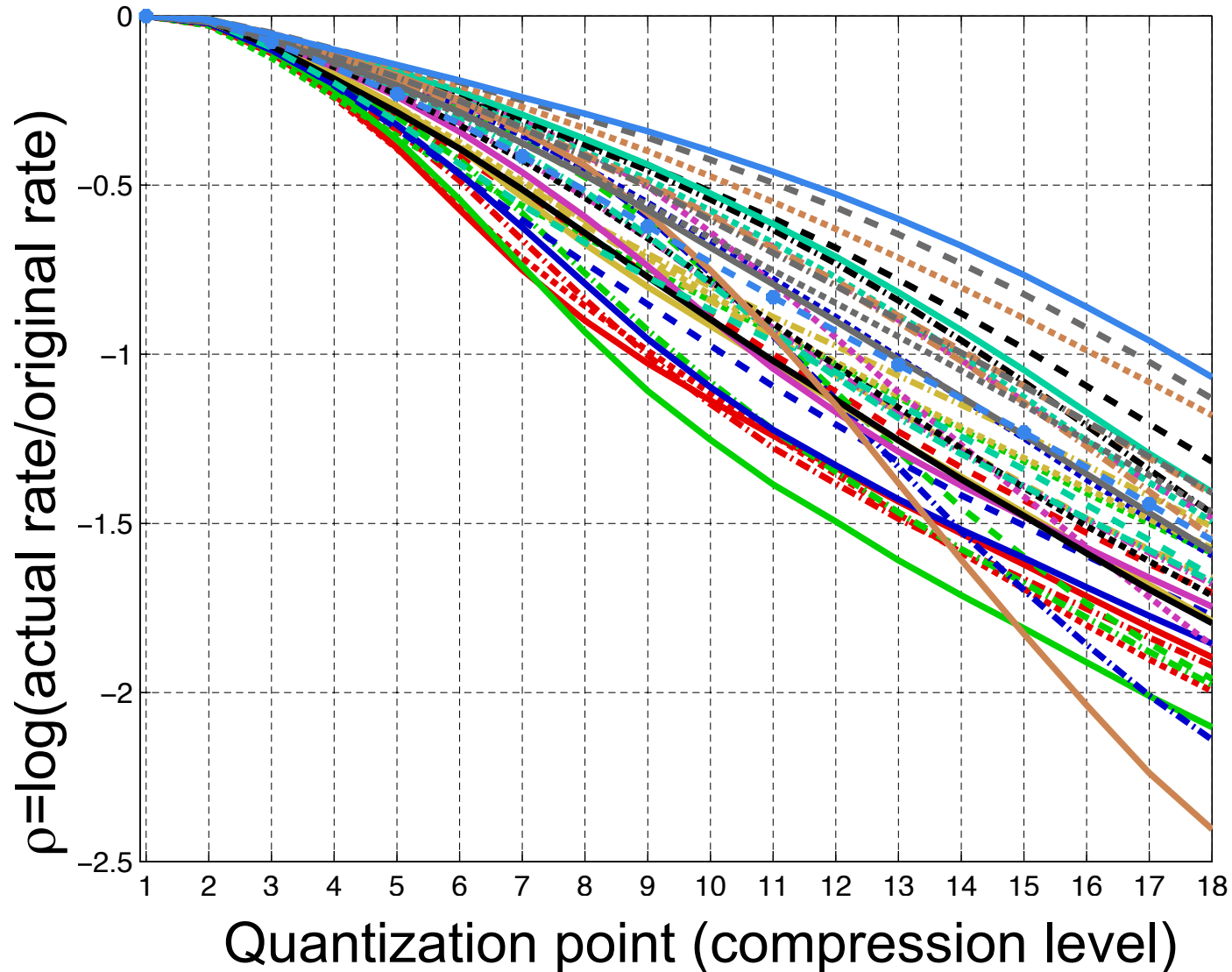
# Challenges for video systems

- ❑ Heavy data
- ❑ Hierarchical system
- ❑ Backhaul network capacity
- ❑ Must handle different access techniques
- ❑ Needs to account for video popularity, heterogeneous user terminals
- ❑ Quality-of-Experience of video is hard to capture

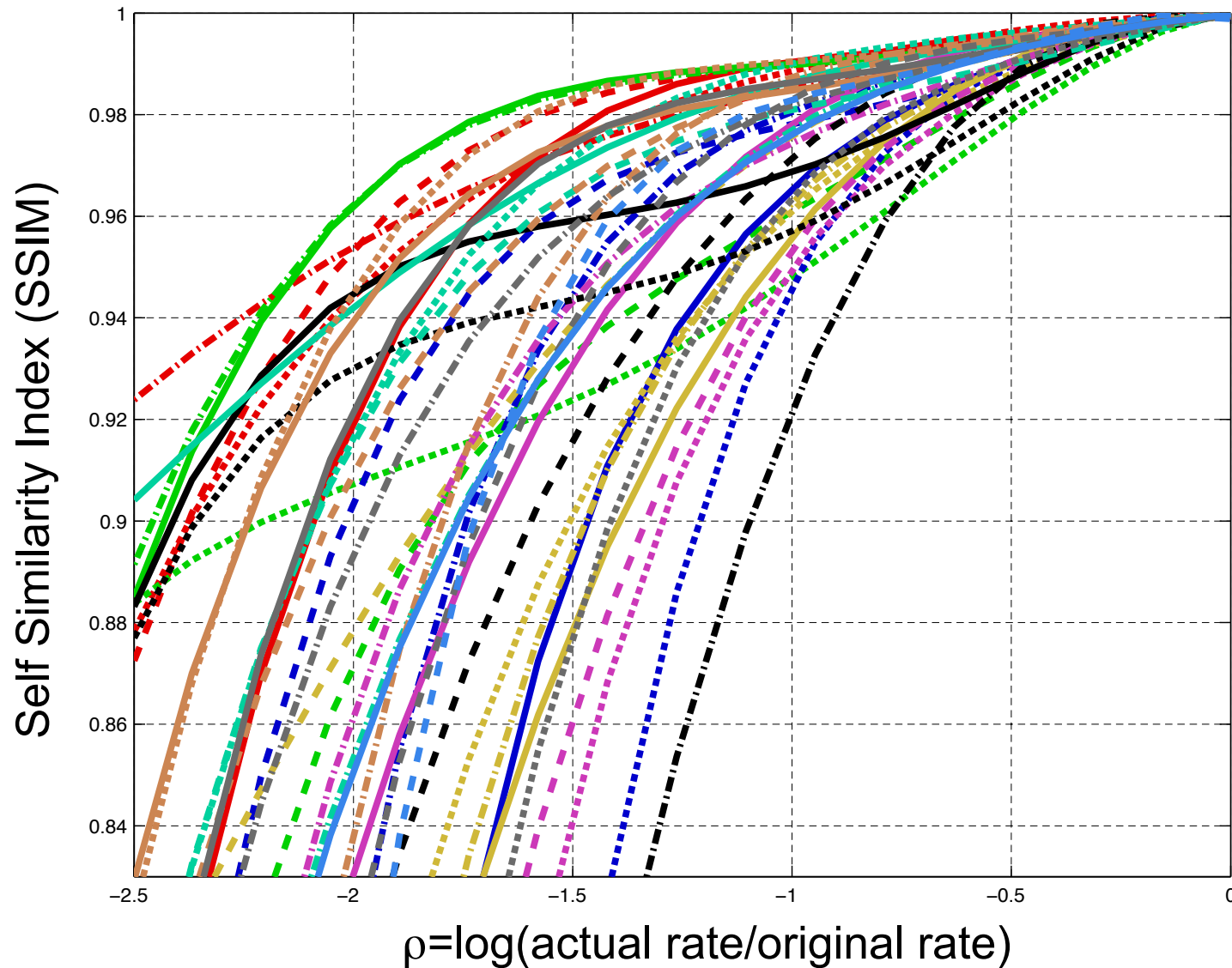


- We consider a test set of 38 video clips, all encoded in an H.264-AVC format
- All the videos are encoded with a 16-frame structure (1 I-frame, 15 P-frames) and compressed with 18 different rates
- Depending on the content, the perceived quality of a compressed version changes
  - ▣ We used the SSIM indicator to capture it

# Rate versus compression



# SSIM versus rate

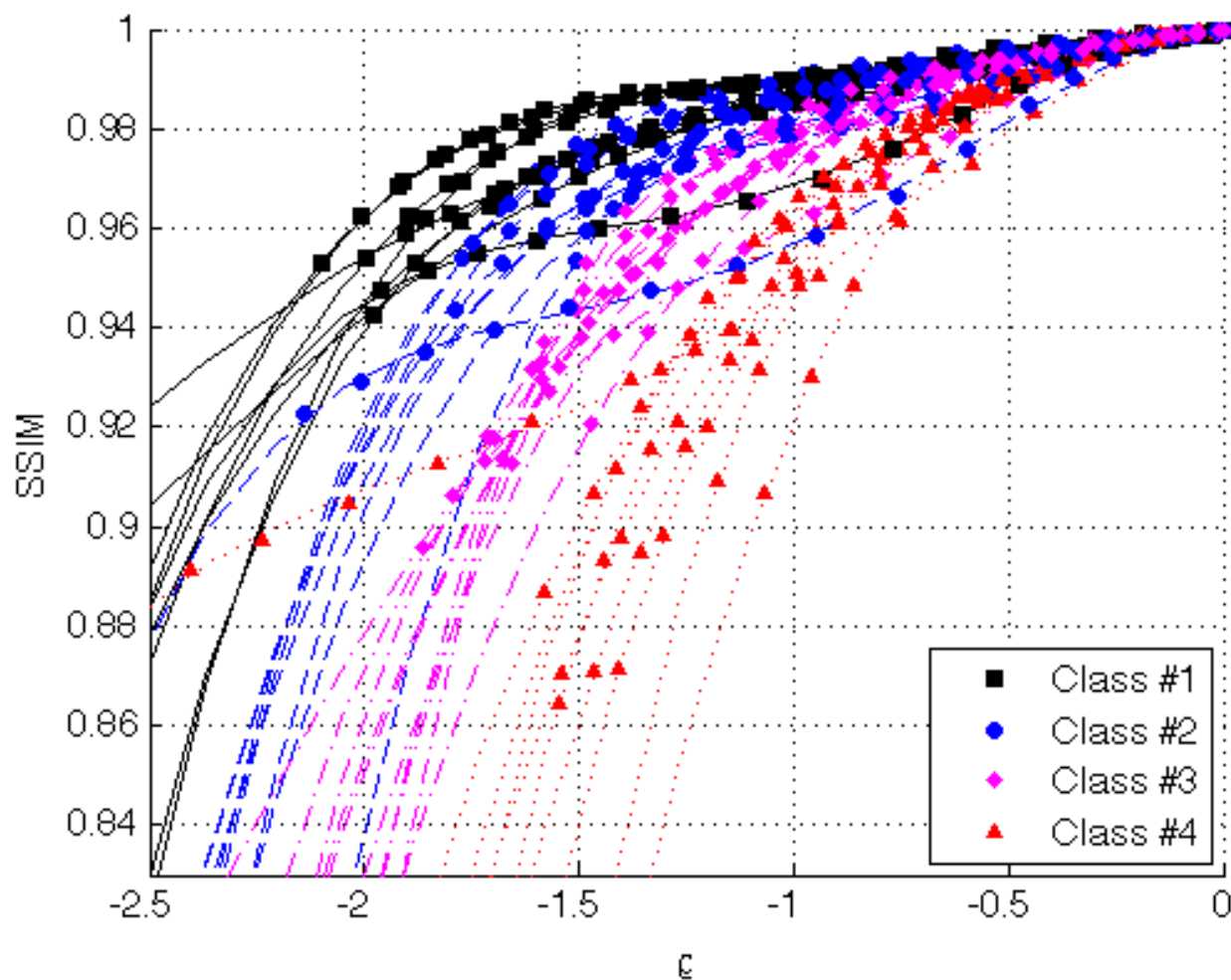


- All the video exhibit similar trends
  - ▣ monotonic descent
  - ▣ a steep “fall” after a threshold
- However, quantitative differences mean
  - ▣ different perceived end quality
  - ▣ different resource requirements
- These characteristics are more or less consistent within the same video

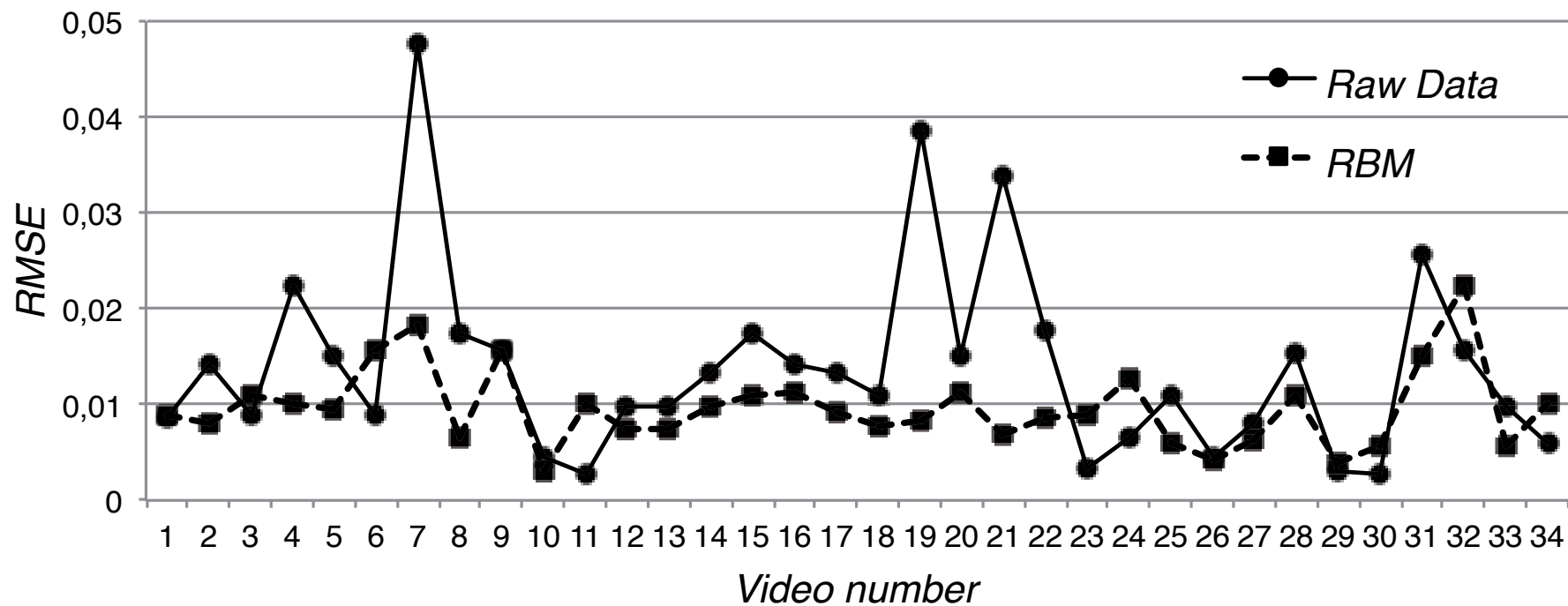
# Requirements for video delivery

- QoE-based and content-aware resource allocation
  - ▣ Rate-distortion curve depends on video content
  - ▣ Video content affects size of the encoded video frames
  - ▣ RBM can be used to infer rate-distortion curve of a video by observing the **size** (not the content) of video frames

# “Our” Video Classes

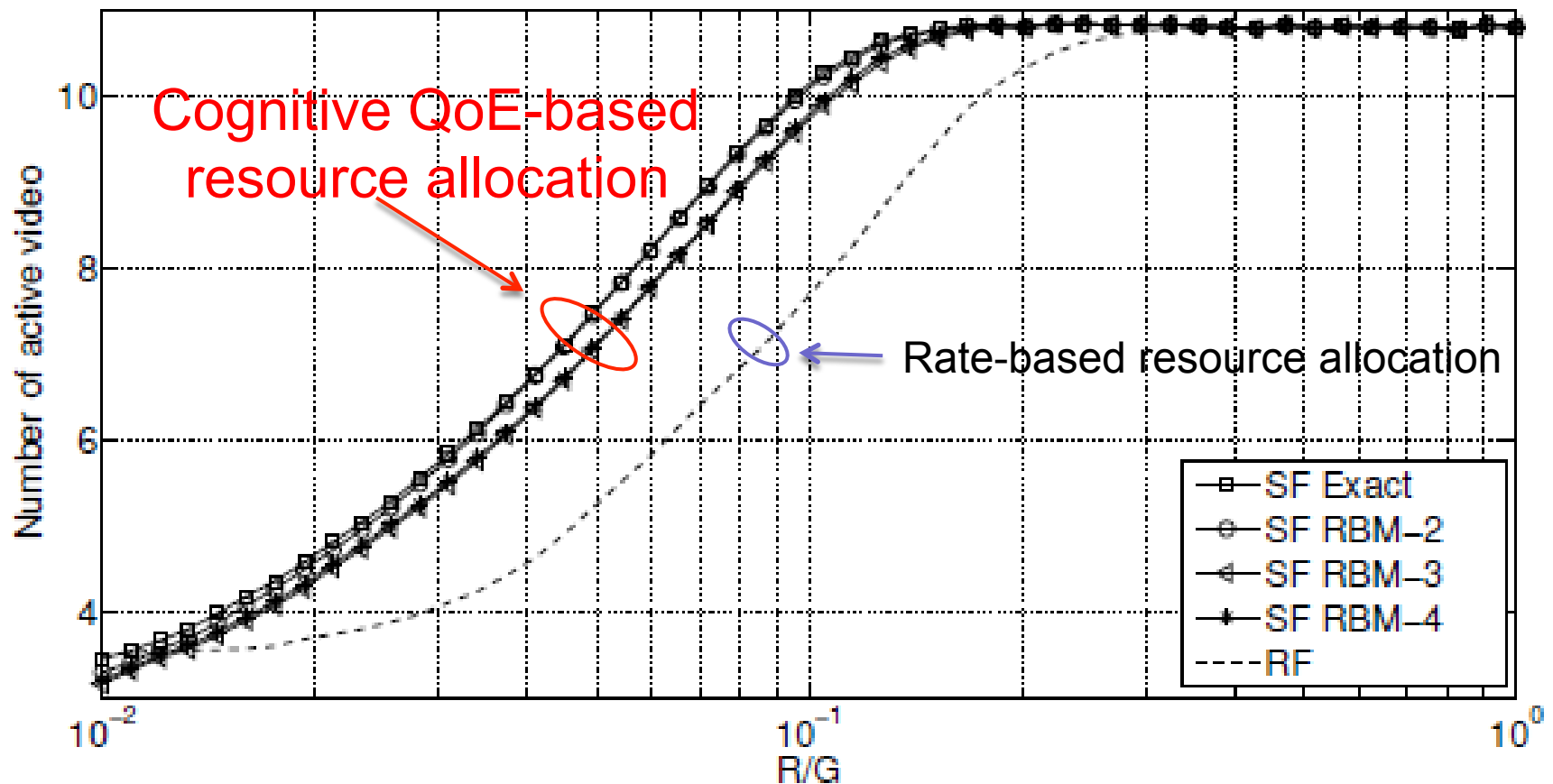


# RBM SSIM estimate





# Cognitive video admission control



Link rate over aggregate full-quality video rate

# Conclusions

- need for consolidated understanding of the fundamental limits for
  - ▣ massive access
  - ▣ short packets
  - ▣ extremely variable transmission patterns
- Need for developing cognitive optimization modules that seamlessly interoperate at system level

# That's all folks!

