ΕΛΛΗΝΙΚΗ ΔΗΜΟΚΡΑΤΙΑ
ΠΑΝΕΠΙΣΤΗΜΙΟ ΚΡΗΤΗΣ

Ασύρματα Δίκτυα και Κινητοί Υπολογισμοί

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Τμήμα Επιστήμης Υπολογιστών
Πανεπιστήμιο Κρήτης

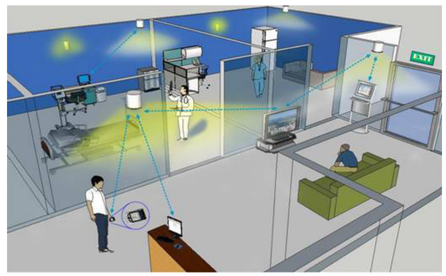
Χρηματοδότηση

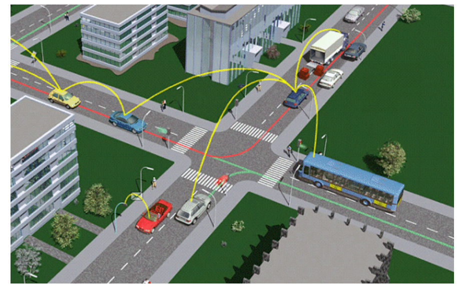
- Το παρόν εκπαιδευτικό υλικό έχει αναπτυχθεί στα πλαίσια του εκπαιδευτικού έργου του διδάσκοντα.
- Το έργο «**Ανοικτά Ακαδημαϊκά Μαθήματα στο Πανεπιστήμιο Κρήτης**» έχει χρηματοδοτήσει μόνο τη αναδιαμόρφωση του εκπαιδευτικού υλικού.
- Το έργο υλοποιείται στο πλαίσιο του Επιχειρησιακού Προγράμματος «Εκπαίδευση και Δια Βίου Μάθηση» και συγχρηματοδοτείται από την Ευρωπαϊκή Ένωση (Ευρωπαϊκό Κοινωνικό Ταμείο) και από εθνικούς πόρους.

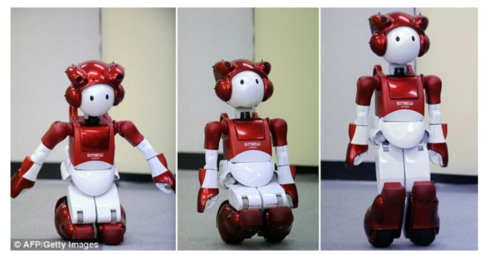
Με τη συγχρηματοδότηση της Ελλάδας και της Ευρωπαϊκής Ένωσης

Σημείωμα αδειοδότησης

Plethora of social networking location-based applications







Fast growth of location-based services

e.g., 74% of US smartphone owners use location-based services

Several positioning systems have been proposed

Taxonomy of Positioning Systems

- Infrastructure & hardware
- Signal modalities
- Models & algorithms for estimating distances, orientation, position
- Coordination system, scale and position description
- Localized or remote computations
- Mechanisms for **device identification, classification** or **recognition**
- **Cost, accuracy** & **precision** requirements

Taxonomy of Positioning Systems

- Radio (*Radar, Ubisense, Ekahau*)
- Infrared (*Active Badge*)
- Ultrasonic (*Cricket, Active Bat*)
- Bluetooth
- Vision (*EasyLiving)*
- Physical contact with pressure (*smart floor*) or touch sensors

The main points of our research in positioning.

- Use fingerprinting & design various statistical fingerprints
  Not all fingerprints are created equal !

- Getting real!
  Challenges when experimenting under real-world scenarios

- The power of compressive sensing

Received Signal Strength Indicator

No standardized relationship of any particular physical parameter to RSSI
No defined relationship between RSSI value & power level in mW or dBm
Vendors provide their own accuracy, granularity, and range for the actual power (measured as mW or dBm) and their range of RSSI values (from 0 to RSSI_Max).

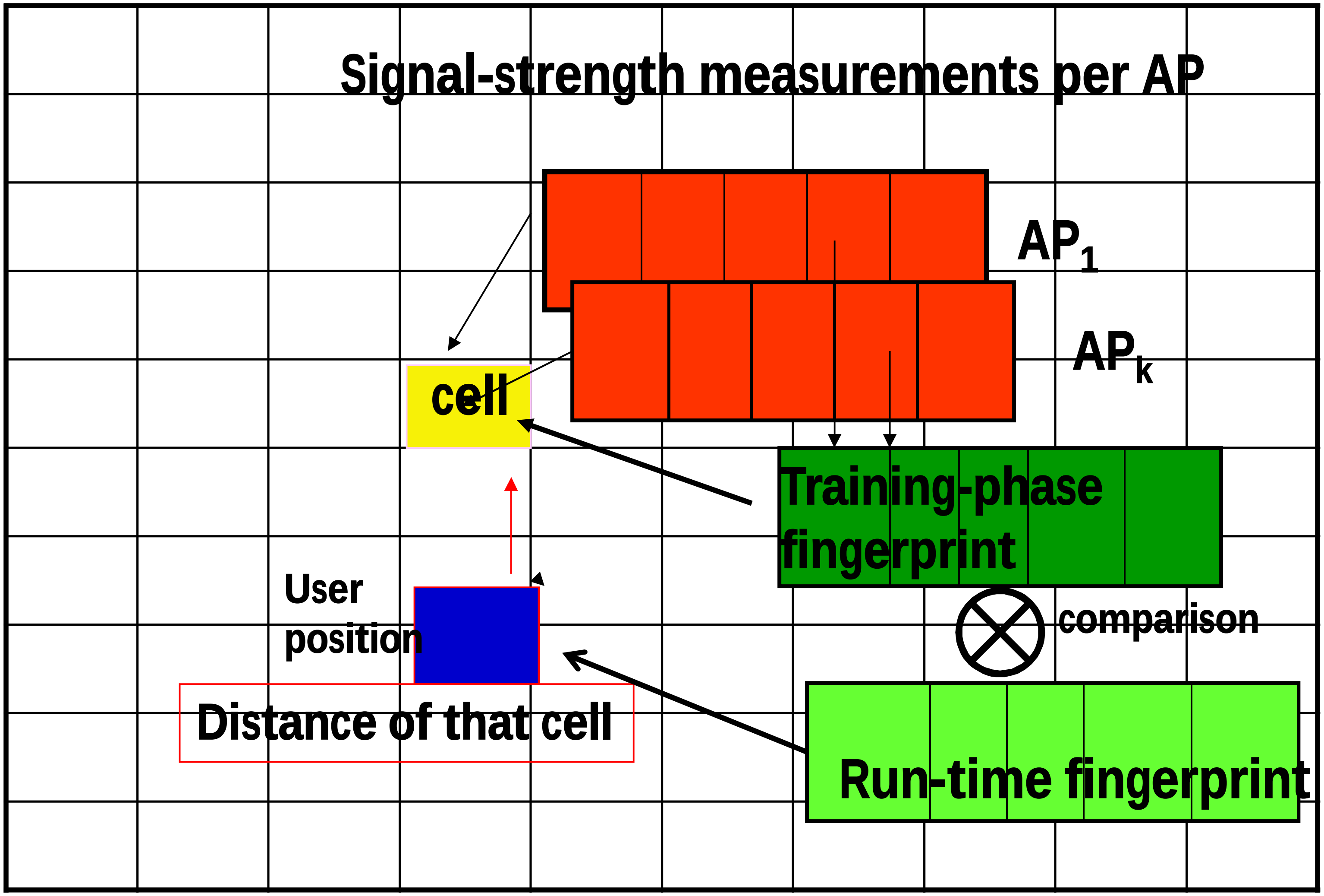
RSSI is acquired **during only the preamble stage** of receiving an 802.11 frame, not over the full frame

Received Channel Power Indicator(**RCPI**) measures the received RF power in a selected channel over the **preamble *and* the entire received frame**, and has defined absolute levels of accuracy and resolution

The simplicity of RSSI Fingerprinting

- **Grid-based** representation of physical space (cells)
- **RSSI measurements** collected from various APs @ **cells** of the space
- Design of the fingerprint
- Two phases: the **training** and the **runtime**
  - Generation of fingerprints based on measurements collected at each phase
- Estimated position: the cell whose **training** fingerprint has the minimum **distance** from the **runtime** one

RSSI Statistical Fingerprinting for Positioning



Examples of RSSI Statistical Fingerprints

- Confidence intervals
- Percentiles
- Empirical distribution of the RSSI measurements
- Theoretical distributions (e.g., ***Multivariate Gaussian*)**
- Compressive sensing

Fingerprint based on Percentiles

$T_j^i(c)$: vector with the percentiles based on the RSSI measurements collected during the training phase from i-th AP at cell c

Euclidian distance [redacted]

[redacted]

[redacted]

Distance of cell *c*

$$w(c) = \sum_{i=1}^{\square} \sqrt{\sum_{j=1}^{\square} (R_j^i - T_{\square}(c))^2}$$

[redacted]

Alternatively, K-Top weighted percentiles:
Weighted centroid of the K cells with the *smallest* distance

Fingerprint based on Empirical Distribution

- A vector whose entries correspond to **APs**
- Each entry composed by **all** the RSSI measurements collected **per AP**
- Only APs that appear in **both** training and runtime are used

- Distance: average **Kullback-Leibler Divergence** (KLDs)

- Reported position: the cell with the smallest distance

Statistical Fingerprint based on Confidence Interval

Each AP assigns a weight to cells based on the **relative "placement"** of the training vs. runtime confidence intervals

AP ***i*** assigns weight ***w(t)*** to cell ***t*** $[T_i^-(t), T_i^+(t)]$ $[R_i^-, R_i^+]$

$$w(t) = \begin{cases} \frac{T_i^+(t) - R_i^-}{R_i^+ - T_i^-(t)} & \text{if } T_i^-(t) < R_i^- < T_i^+(t) < R_i^+ \\ \frac{R_i^+ - T_i^-(t)}{T_i^+(t) - R_i^-} & \text{if } R_i^- < T_i^-(t) < R_i^+ < T_i^+(t) \\ 1 & \text{if } R_i^- \leqslant T_i^-(t) < T_i^+(t) \leqslant R_i^+ \\ & \text{or } T_i^-(t) \leqslant R_i^- < R_i^+ \leqslant T_i^+(t) \\ 0 & \text{if } R_i^- < R_i^+ \leqslant T_i^-(t) < T_i^+(t) \\ & \text{or } T_i^-(t) < T_i^+(t) \leqslant R_i^- < R_i^+ \end{cases}$$

Fingerprint based on Multivariate Gaussian

- Multivariate Gaussian for RSSI measurements collected from APs
- Closed-form Kullback-Leibler Divergence (KLD) for distance estimation
- Exploits the *2nd order* **spatial correlations** between APs
- Improves accuracy by iterating in multiple spatial scales (regions)

Multivariate Gaussian Distribution

Signature of **cell *i*** in ***training phase***: $c_i \mapsto \mathcal{S}_i = \{\vec{\mu}_i, \boldsymbol{\Sigma}_i\}$

- $\vec{\mu}_i$ *mean values* of the received RSSI measurements **per AP**
- $\boldsymbol{\Sigma}_i$: *covariance matrix* (measure of **spatial correlation**)

$c_R \mapsto \mathcal{S}_R = \{\vec{\mu}_R, \boldsymbol{\Sigma}_R\}$

Signature of a cell in runtime phase:

$I_R^{i,T}$

APs from which measurements were collected at both training & runtime phases

Multi-layer Multivariate Gaussian Approach

Main idea:

- Divide physical space into **overlapping** regions
- Apply multivariate Gaussian model ***in each region***
- **Select the region** with the minimum distance

Iteratively

- Divide the selected region into sub-regions
- Repeat the process in that region

until the current region becomes a cell

The region-based aggregation and iterative process helps to

- **eliminate an incorrect** region
- **increase the weight** of the correct region

Experiment

and it will lead you to the light

Cole Porter, 1930

Getting Real: Deployment of Testbeds.

At different premises:

- Lab & hallway at **FORTH**: 7m x 12m
  10 APs (~ 5.4 on average @ cell)
  cell size 55cm x 55cm

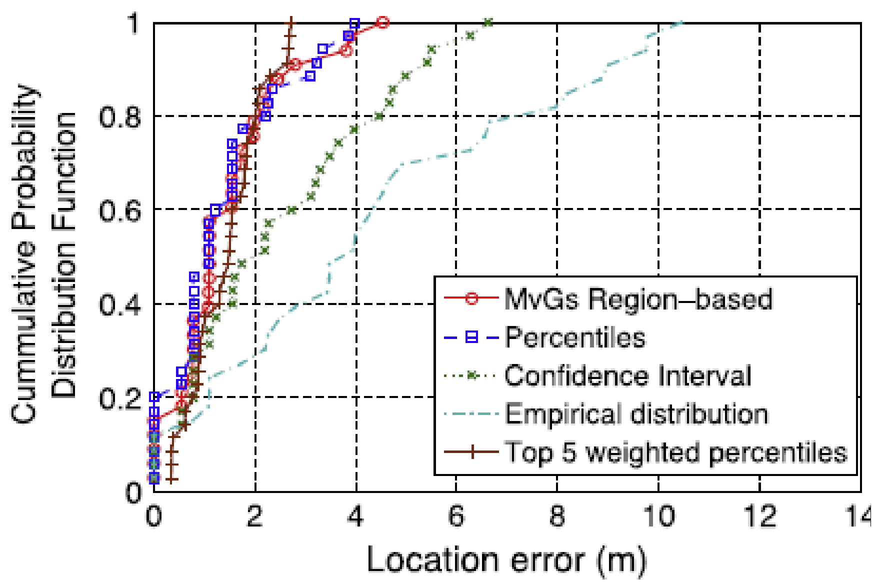
- **Aquarium**: 1760m^2, 40 tanks
  7 APs (~ 3.4 on average @ cell)
  cell size 1m x 1m

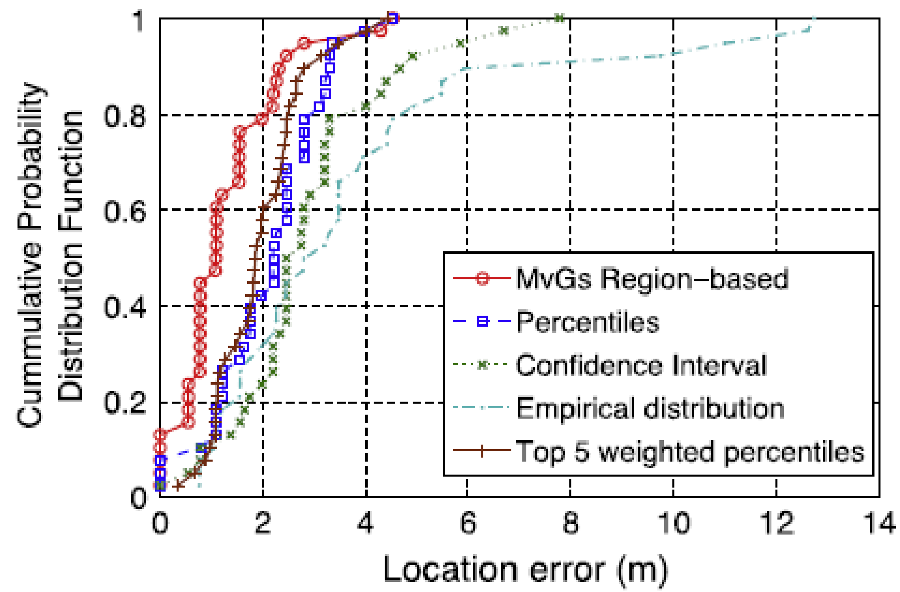
Under different conditions:

- Presence of people or visitors
  quiet vs. **busy** periods

- **Topological** layout

Evaluation of RSSI Fingerprint Approaches





But what do we REALLY learn from these experiments ?

Fingerprinting is nice, but the devil is in the detail.

- Pathologies in fingerprint comparisons
  Sensitivity to the variations in **RSSI measurements**

- **Large size** of data that need to be sent by energy-constrained devices
- When you suppress the noise-like features, do you still maintain the prominent information content?!

- Complexity and convergence issues

Robustness with respect to RSSI Variations

Not all fingerprints are created equal: some are less robust than others.

Pathology in the comparison of confidence interval fingerprints:

Sensitivity to the relative position of their endpoints (boundaries) :
Even a ***small “***displacement” may affect the value of the contribution assigned to a specific cell

Αι δεύτεραι πως φροντίδες σοφώτεραι.
Ευριπίδης, 480-306 π.Χ.

Second thoughts are–in most cases–wiser.
Euripides, 480-306 BC

Lots of Measurements: Energy consumption vs. Accuracy

Sparsity: the transform coefficients vector has a small number of large amplitude coefficients and a large number of small amplitude coefficients

Several natural signals are often sparse in a discrete cosine transformation or in a Fourier basis

Example:
The 50 Hz powerline signal is sparse in the frequency-domain

Warming-up with Compressive Sensing

x: the vector with **measurements**

x : expressed in terms of the **Ψ basis** $x = \Psi w$, w: coefficients vector

x is **K-sparse in Ψ** if it can be represented by **K elements of this basis**

<u>Theorem:</u>
if x is K-sparse, it can be reconstructed from **M non-adaptive linear projections** onto a second measurement basis (**M = r K << N**)

Compressive sensing in context

x: the vector with the **RSSI measurements** – x is **not** sparse

x can be expressed in terms of the **Ψ basis**: $x = \Psi w$

w: indicator vector {0,1}
w is sparse

Ψ: created at training

compressed form of x

$$\mathbf{g} = \mathbf{\Phi x}$$

Φ: measurement matrix
Standard Gaussian
Fixed

$$\mathbf{g} = \mathbf{\Phi \Psi w}$$

Optimization problem: find the **w: indicator vector {0,1}**

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} \|\mathbf{w}\|_0, \ \ s.t. \ \mathbf{g} = \mathbf{\Phi \Psi w}$$

The compressive sensing positioning method

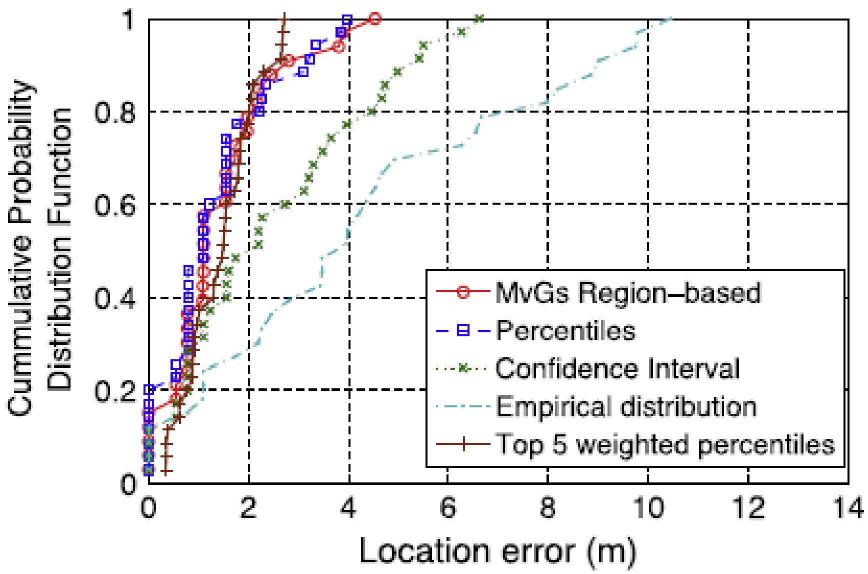
1. Training phase: collect RSSI measurements from all APs at each cell For each AP i, generate $\mathbf{\Phi}_T^i$ and $\mathbf{\Psi}_T^i$
2. Runtime phase: collect RSSI measurements from each AP at the unknown position [redacted]
3. At runtime perform the following steps:
   - Send the length of runtime RSSI measurements, $n_{c,i}$, to the server
   - From each $\mathbf{\Phi}_T^i$, extract the columns until line $n_{c,i}$ and send it to the wireless device
   - Compute the measurements vector $\mathbf{g}_{c,i}$ and send it to the server
   - $\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} (\|\mathbf{w}\|_1 + \tau\|\mathbf{g} - \mathbf{\Phi\Psi w}\|_2),$
4. Report the centroid of the individual estimates given by the CS reconstruction scheme per AP c^* as the estimated position

run-time RSSI measurements

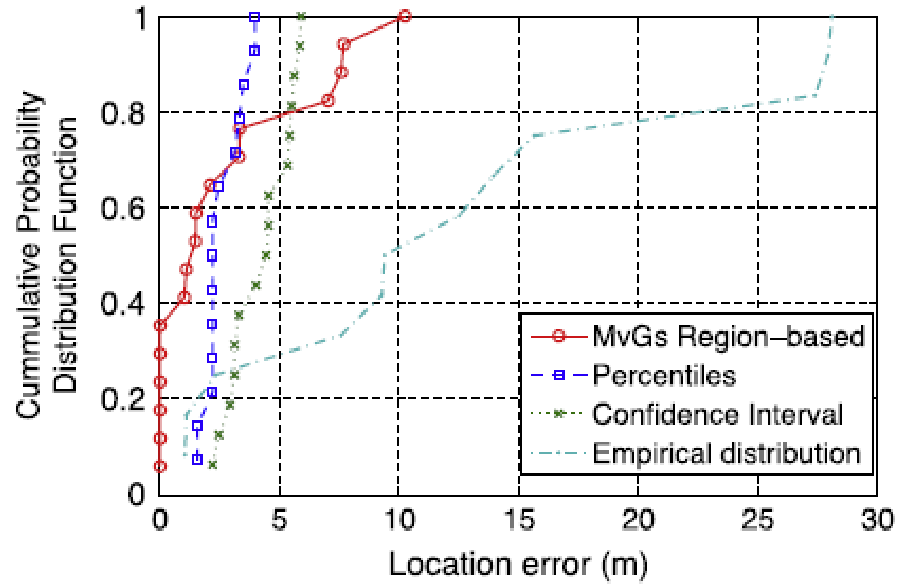
$$\mathbf{g}_{c,i} = \mathbf{\Phi}_R^i \mathbf{X}_{c,R}^i,$$

run-time measurement matrix

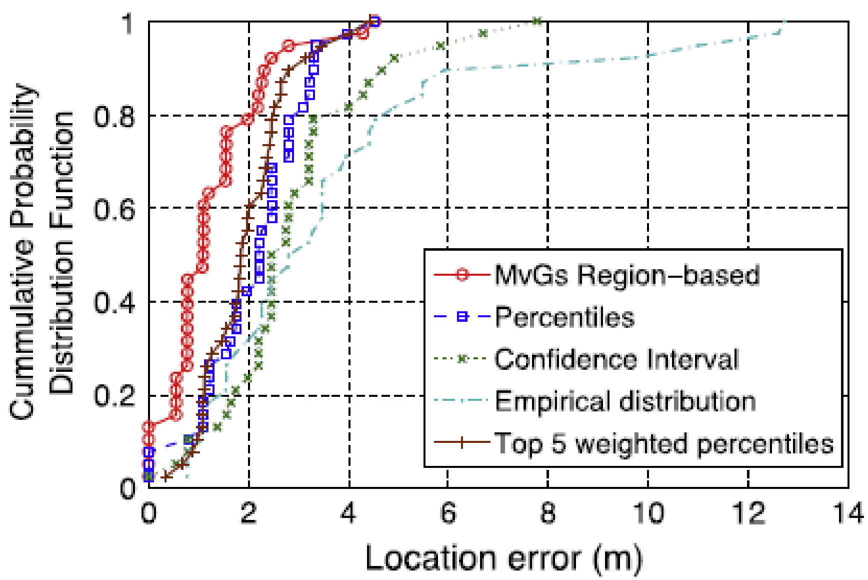
compressed form of run-time measurements



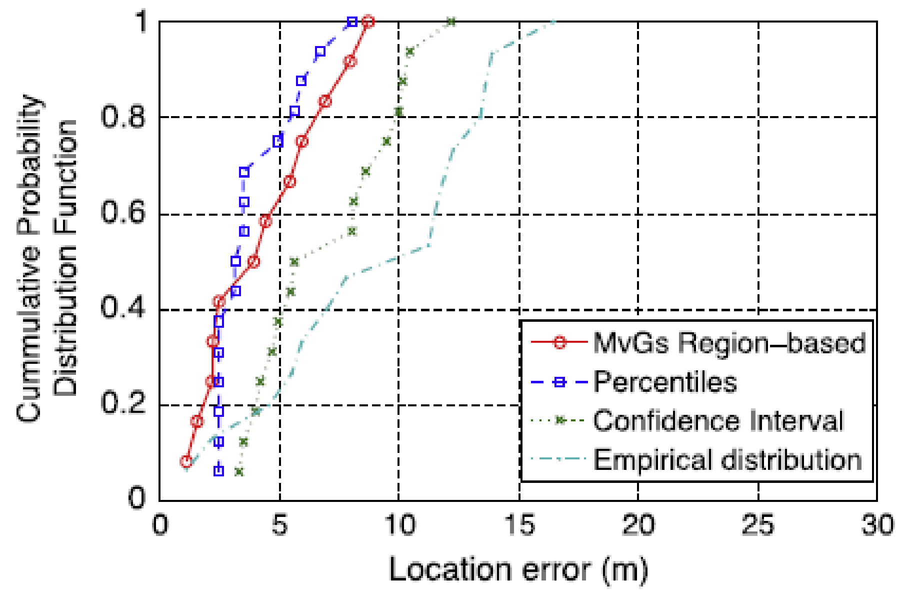
(a) Sc-A dataset



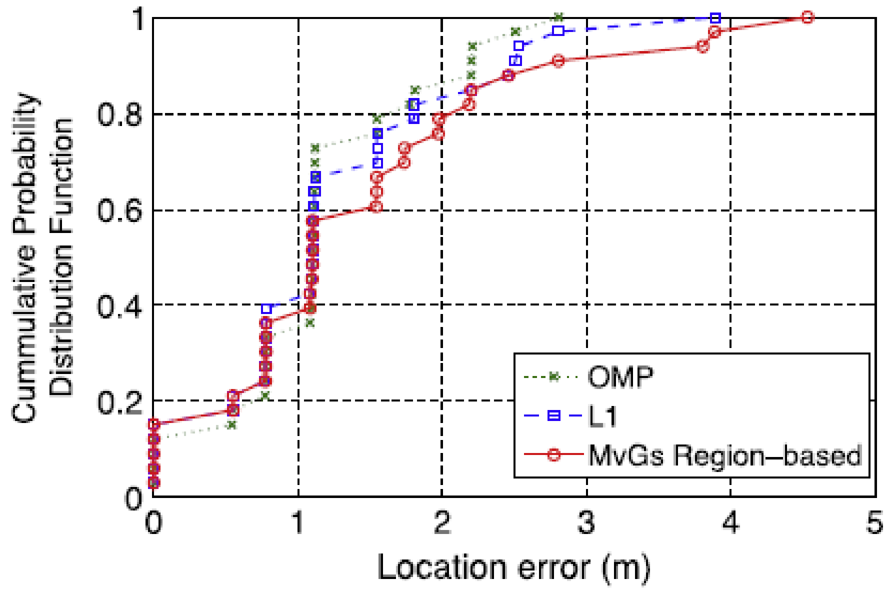
(a) Sc-C dataset



(b) Sc-B dataset



(b) Sc-D dataset



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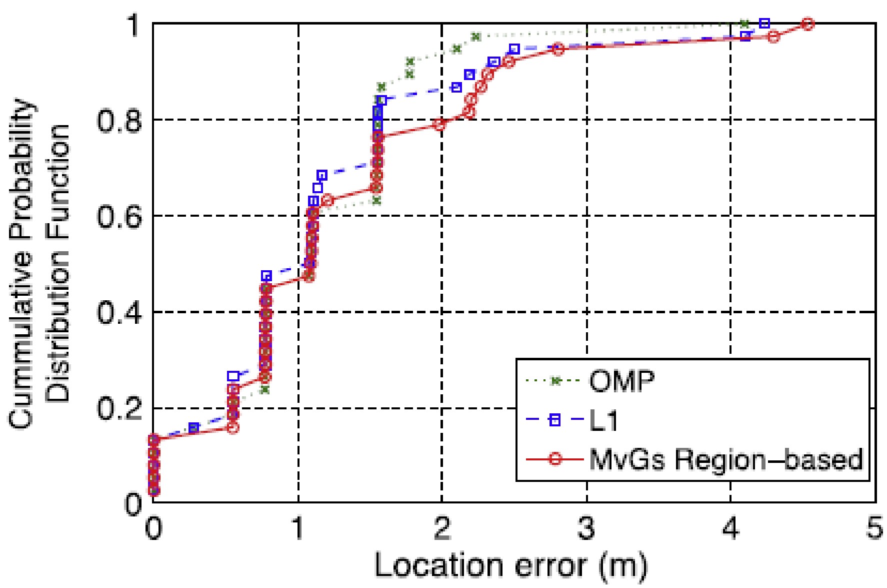
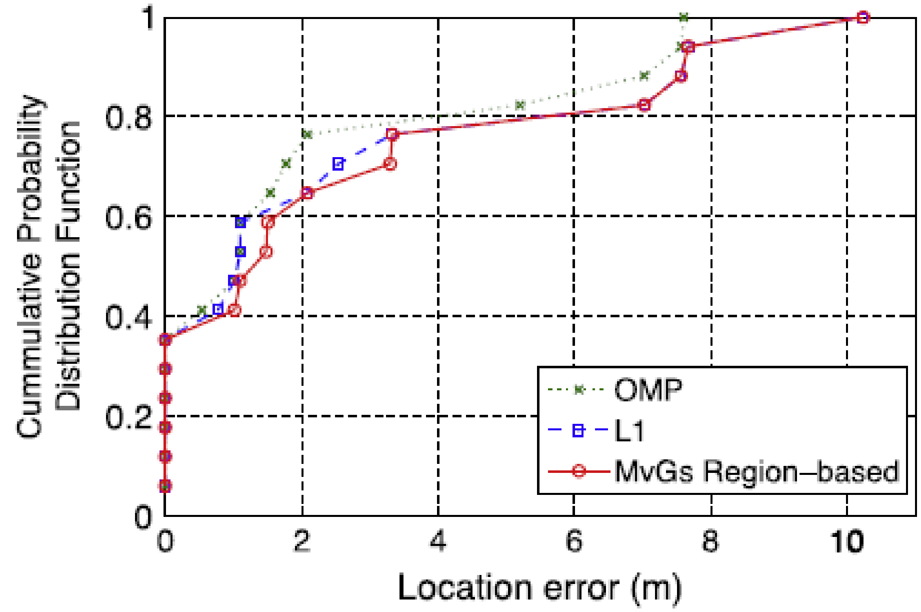


(b) Sc-B dataset



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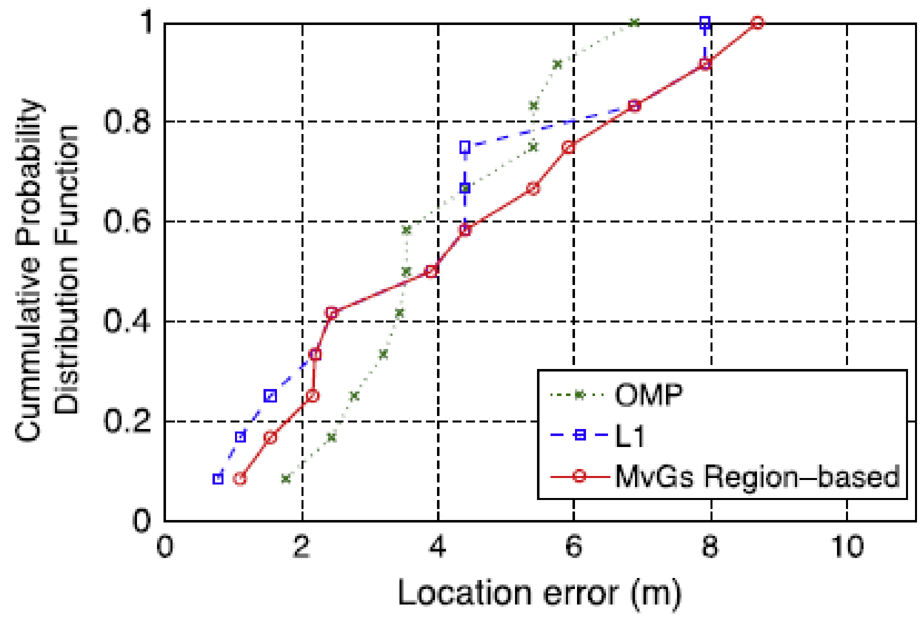

(b) Sc-D dataset

Lessons Learned; Thou shalt not ignore radio propagation.

- The prominent impact of the presence of people and AP placement on accuracy.

- A proper pre-processing of the RSSI measurements is required.

- The ability to suppress the noise-like features is important.

- Reduce the amount of data sent to suppress the noise-like features but maintain the prominent information content!

- The iterative multi-layer spatial approach improves the accuracy by
  - eliminating distant incorrect cells
  - considering the neighboring cells around the user position

Summarizing the performance results ...

- With less than 20% measurements, a reasonable accuracy can be achieved using compressive sensing (e.g., OMP)

	Quiet Period		Busy Period	
Premise	**MvG**	**OMP**	**MvG**	**OMP**
FORTH	1.09	1.08	1.10	1.08
Aquarium	1.48	1.09	4.15	3.59

- For the L1-norm optimization problem:
  Select an algorithm based on the convergence vs. accuracy tradeoff

Δεί τά μέλλοντα τοίς γεγενημένοις τεκμαίρεσθαι.
Ισοκράτης, 436-338 π.Χ.

Insight into future events is based on what happened in the past.
Isocrates, 436-338 BC

Exploring the Power of Compressive Sensing

- New transform & measurement bases that are **adaptive** to the specific characteristics of the RSSI data
- Exploit the random nature of the measurement vectors for **encryption without the extra computational cost** of a separate encryption protocol

Exploring other directions

- Employing various modalities to enhance the accuracy
- Reconsidering the problem of cooperative localization …

More information at
http://www.ics.forth.gr/mobile/

Thank you!

Who is afraid of real-life measurements?

At different premises:

- **FORTH**: 7m x 12m
  10 APs (~ 5.4 on average @ cell)
  cell size 55cm x 55cm
- **Aquarium**: 1760m^2, 40 tanks
  7 APs (~ 3.4 on average @ cell)
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	Quiet Period		Busy Period	
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Under different conditions:

- **Presence of people or visitors**
  relatively **quiet** vs. **busy** periods
- **Topological layout**

Lessons Learned;
How the estimations per AP are used

- CS-based approach is carried out for each AP separately, using the compressed RSSI measurements, and the final estimate is given by the centroid of the individual estimated positions
- The confidence interval, percentiles, and empirical distributions perform an averaging over all APs of the values of the corresponding distance function before the final location estimation
- E.g., in the case of empirical distribution:

Each cell is assigned a weight which corresponds to the average KLD of each AP (at that cell) from the runtime measurements collected at the unknown position from the same AP.

Two cells with different KLD values between the individual APs may be reported erroneously to be close to each other after taking the average KLD, since the average operator eliminates the distinct contribution of each separate AP

Fingerprinting based on Multivariate Gaussian (cnt'd)

- Mean sub-vectors $\vec{\mu}^s_R,\ \vec{\mu}^s_{i,T}$ and covariance sub-matrices $\mathbf{\Sigma}^s_R,\ \mathbf{\Sigma}^s_{i,T}$ are extracted according to $I^{i,T}_R$
- Multivariate Gaussian density function:

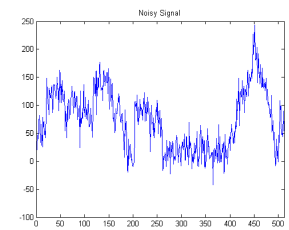
$$\boxed{p(\vec{x}|\vec{\mu},\mathbf{\Sigma}) = \frac{1}{(2\pi)^{K/2}|\mathbf{\Sigma}|^{1/2}}\exp\left(-\frac{1}{2}(\vec{x}-\vec{\mu})^T\mathbf{\Sigma}^{-1}(\vec{x}-\vec{\mu})\right)}$$

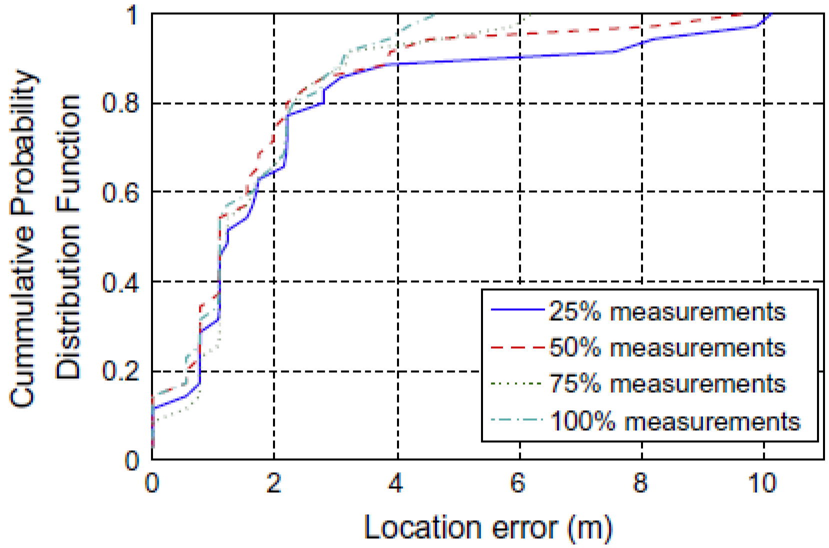
$$\boxed{\begin{aligned} D(p_R||p_{i,T}) \ &= \frac{1}{2}\Bigg((\vec{\mu}^s_{i,T}-\vec{\mu}^s_R)^T(\mathbf{\Sigma}^s_{i,T})^{-1}(\vec{\mu}^s_{i,T}-\vec{\mu}^s_R) \\ &\quad + \ tr\left(\mathbf{\Sigma}^s_R(\mathbf{\Sigma}^s_{i,T})^{-1}-\mathbf{I}\right) - \ln\left|\mathbf{\Sigma}^s_R(\mathbf{\Sigma}^s_{i,T})^{-1}\right|\Bigg) \end{aligned}}$$

Estimated position: cell with *minimum KLD*

- Design of new transform and measurement bases that are adaptive to the specific characteristics of the RSSI data.
- A new sparsifying basis being able to increase the degree of sparsity of an RSSI measurements vector, represented in terms of this basis, is critical in the framework of CS, since the reconstruction accuracy increases as the sparsity increases.
- An improved performance can be guaranteed with high probability by employing an appropriate measurement matrix, which is highly incoherent with the sparsifying basis.

Who is afraid of real-life measurements?





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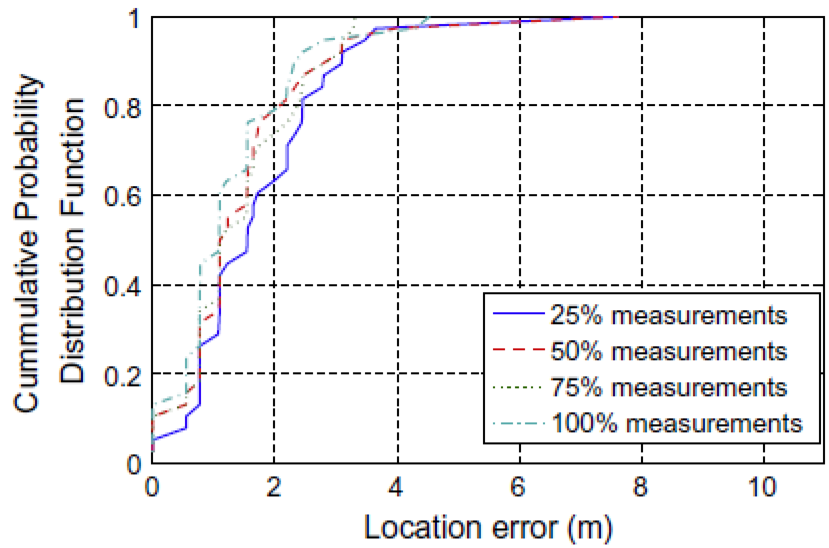

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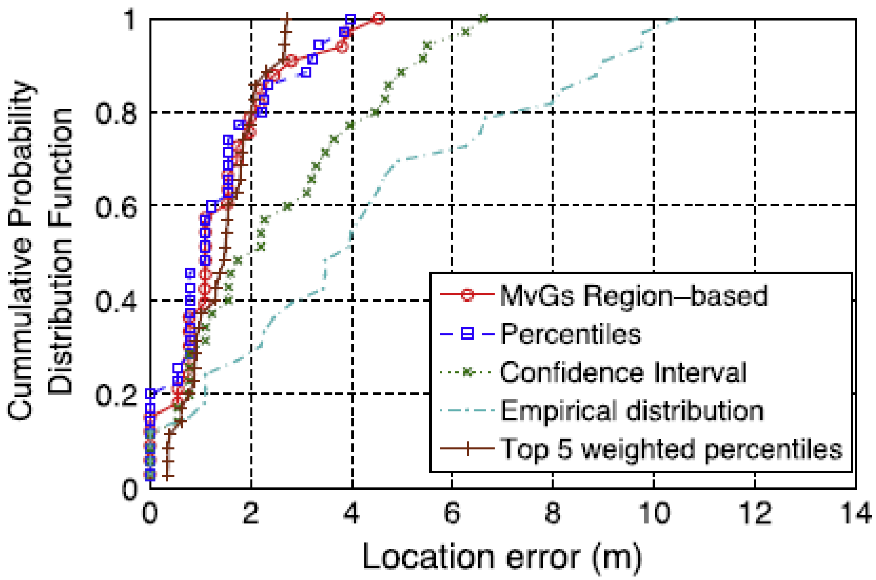
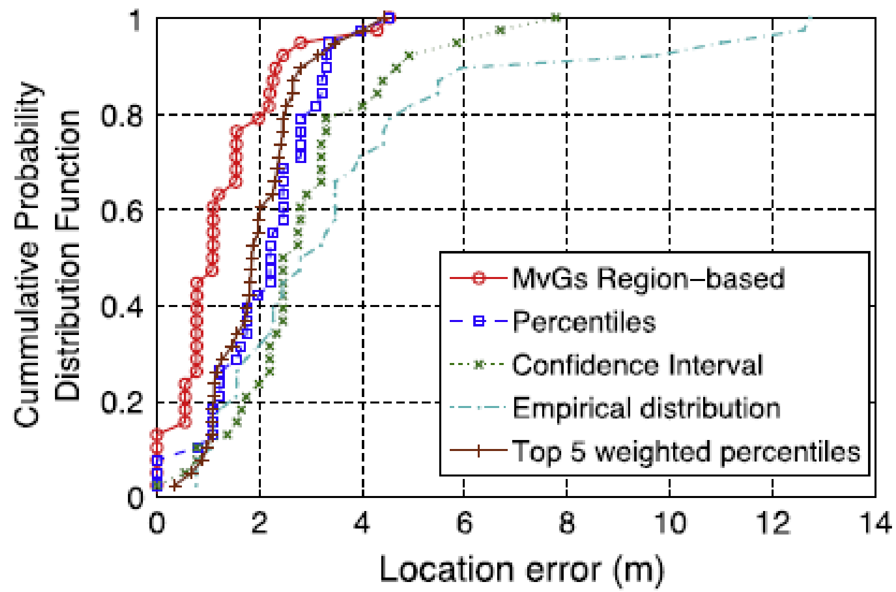
Evaluation of RSSI Fingerprint Approaches





Fingerprinting is nice, but the devil is in the detail.

- Pathologies in fingerprint comparisons
- **Sensitivity to the variations** in RSSI measurements
- **Size of data** that need to be exchanged!

    energy constraints of mobile devices

Τέλος Ενότητας

Ευρωπαϊκή Ένωση
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ΕΣΠΑ 2007-2013
πρόγραμμα για την ανάπτυξη
ΕΥΡΩΠΑΪΚΟ ΚΟΙΝΩΝΙΚΟ ΤΑΜΕΙΟ
Με τη συγχρηματοδότηση της Ελλάδας και της Ευρωπαϊκής Ένωσης