High precision indoor positioning systems: challenges and research directions

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SensorNets, Barcelona, 19-21 February 2013

Motivation

Numerous technologies

- Radio-based positioning systems
  - WiFi localization (with / without fingerprinting)
  - Bluetooth Low Energy
  - RFID systems
  - Ground-based transmitters to extend GPS service indoors
- Inertial tracking
- Ultrasound-based positioning
- Visible light positioning
- Magnetic positioning
- Hybrid
  - sensing ambient magnetic and photo-acoustic signatures
  - WiFi+inertial positioning system

Key challenges

1. **Cluttered indoor spaces**
   - Non-Line-Of-Sight (NLOS) signal propagation
   - Corrupts distance measurements
   - Leads to inaccurate position estimates

2. **Sparse infrastructure**
   - Not all areas are covered by many anchors
   - The lower the anchor density the highest the position error

3. **Positioning accuracy depends on the environment**
   - Spatial and temporal variability
   - Hard to measure empirically
   - Challenge in selecting / fusing data from different positioning systems

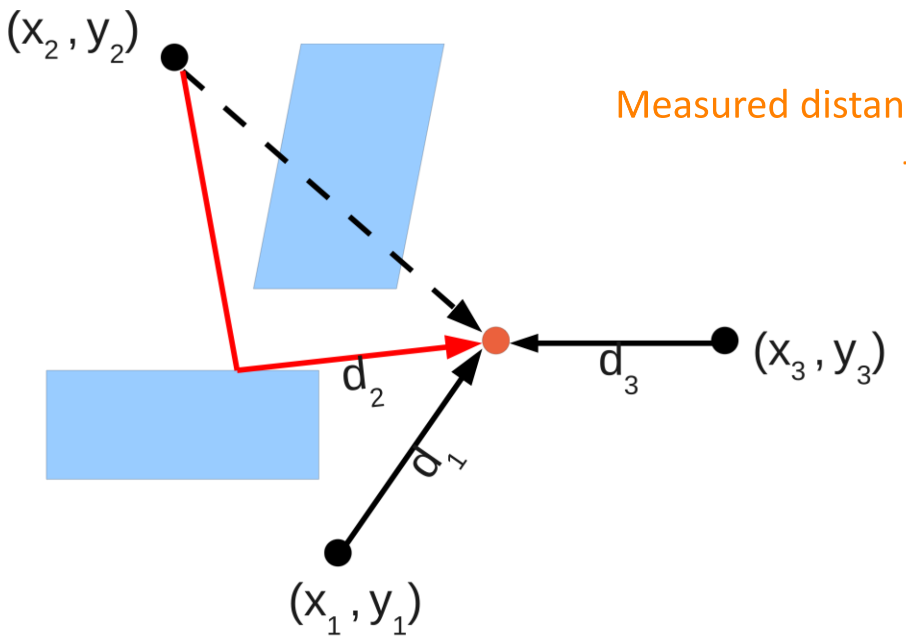
Challenge I

CLUTTERED INDOOR SPACES

Problem caused by clutter

Non Line Of Sight (NLOS) signals

$\Rightarrow$ inaccurate distance estimates



$$d_i = \bar{d}_i + \bar{n}_i + \bar{e}_i$$

Measured distance

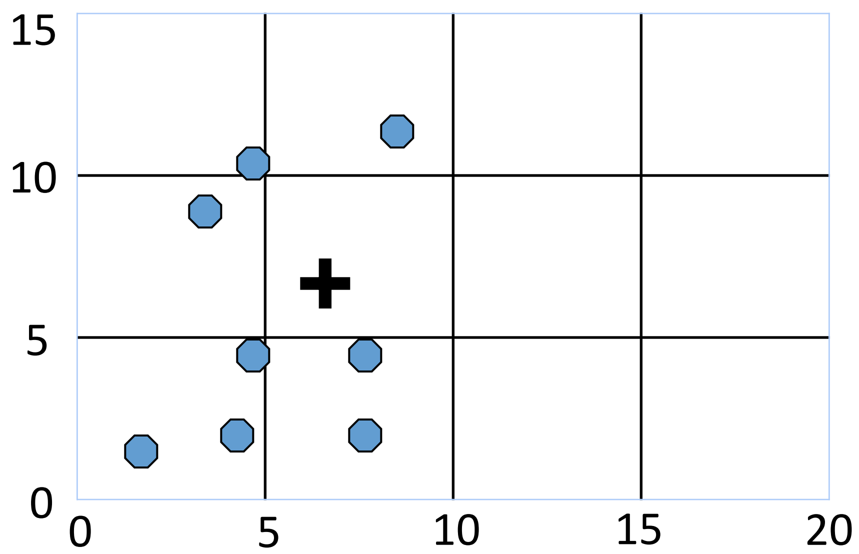
True distance

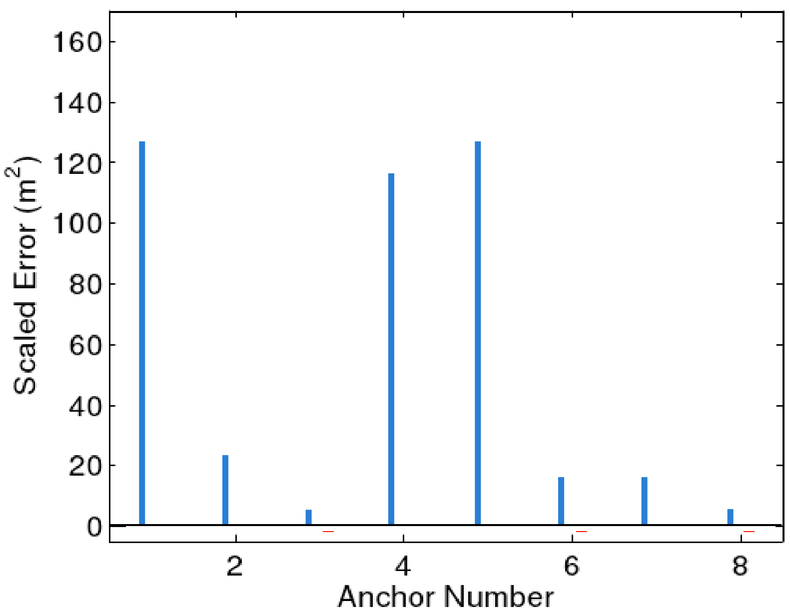
NLOS Error

LOS Error

Problem caused by clutter

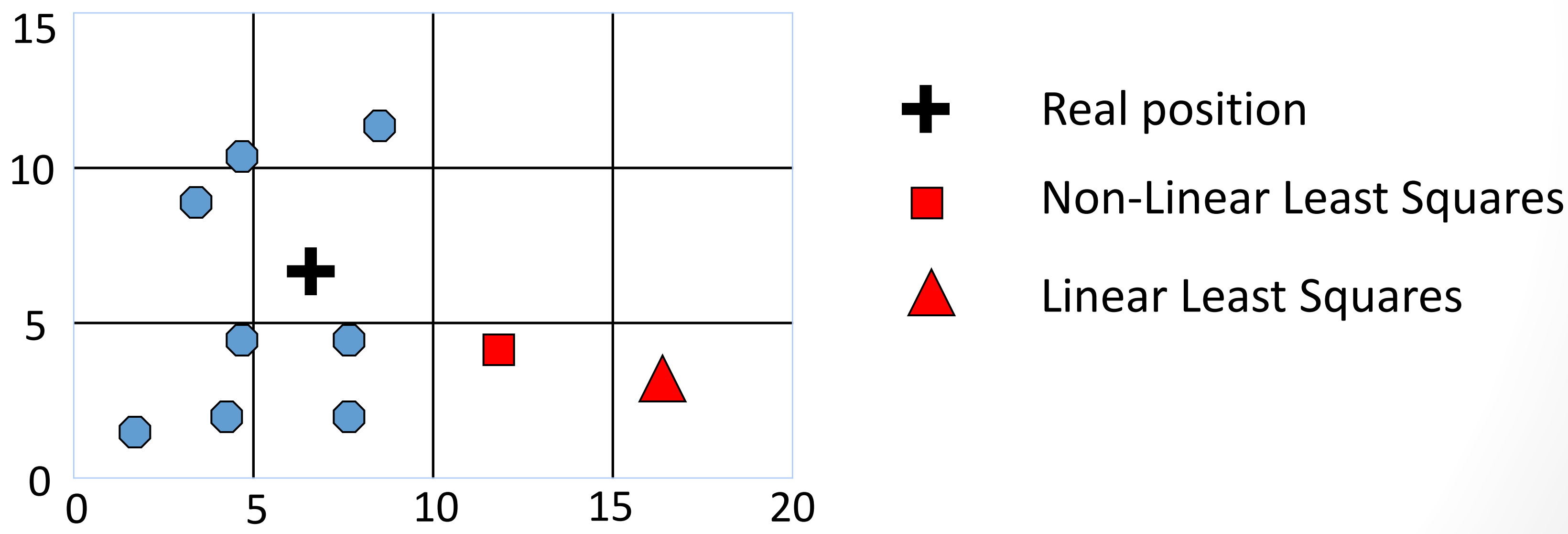
- Example of scenario with eight anchors:
  - Distances to five anchors have small LOS errors
  - Distances to three anchors have large NLOS errors





Problem caused by clutter

- A few large errors, if undetected, can lead to very inaccurate position estimates

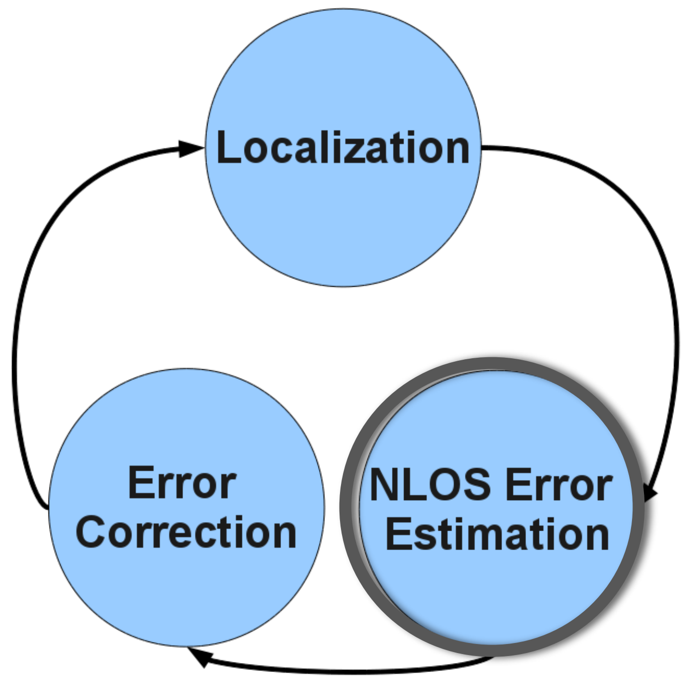


Approach 1: robust localisation

Key questions:

Can we find which measurements are NLOS?

Can we find how big are the positive NLOS errors?



Use the theory of compressed sensing

Convex Programming Based Robust Localization in NLOS Prone Cluttered Environments
Sarfraz Nawaz and Niki Trigoni --- IPSN 2011.

Approach 1: robust localisation

$$(x_i - x)^2 + (y_i - y)^2 = d_i$$

$$\cancel{\mathbf{Ax}} + \mathbf{n} + \mathbf{e} = \mathbf{b}$$

unknown node coordinates

Unknown NLOS errors

Multiplying both sides by C, such that CA=0

$$\mathbf{Cn} + \hat{\mathbf{e}} = \mathbf{y}$$

scaled NLOS errors

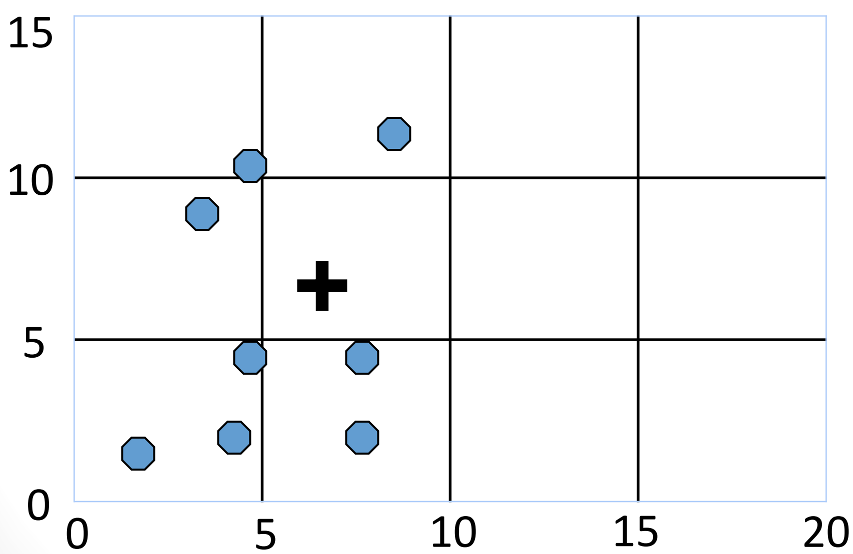
- **under-determined system**
- **n is sparse (most elements are 0)**

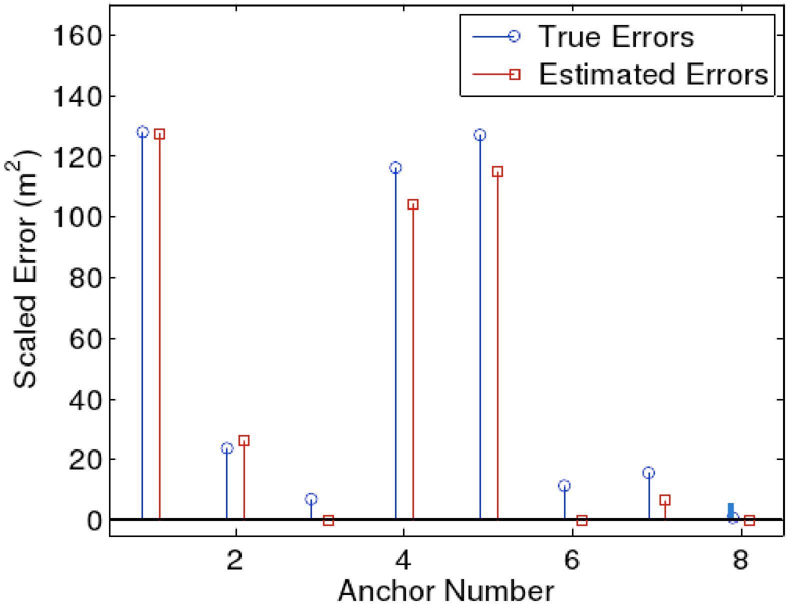
Convex Programming Based Robust Localization in NLOS Prone Cluttered Environments
Sarfraz Nawaz and Niki Trigoni --- IPSN 2011.

Approach 1: robust localisation

- Basis Pursuit Denoising

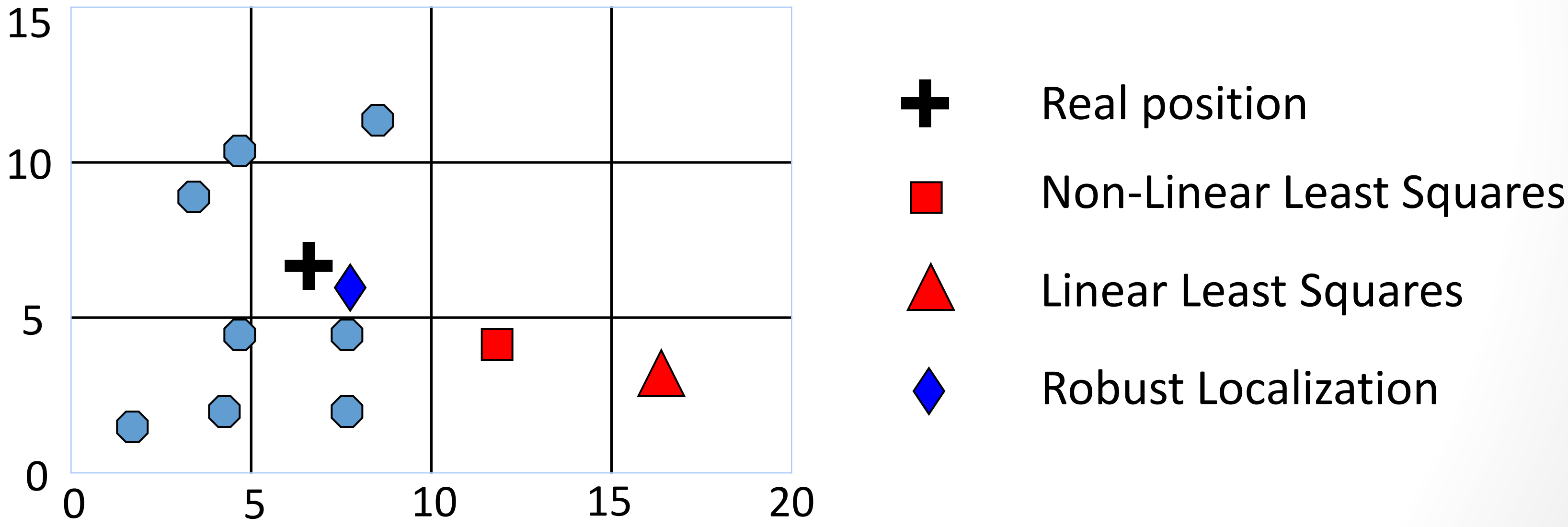
$$\text{minimize } \|\mathrm{n}\|_1 \quad \text{subject to} \quad \|\mathbf{Cn}-\mathbf{y}\|_2 \le \|\mathbf{e}\|_2, \quad \mathbf{n} \ge 0$$





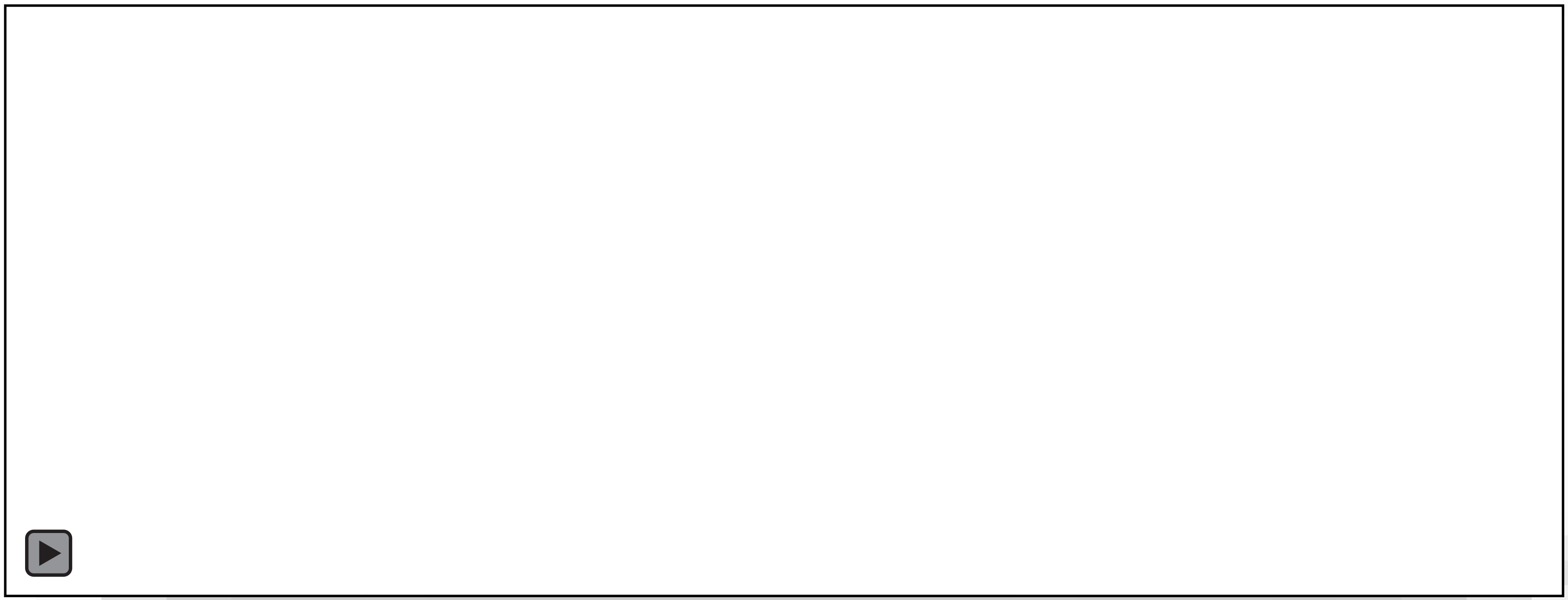
Approach 1: robust localisation

- Once we correct errors in distance estimates, we can accurately position the node



Approach 1: robust localisation

- In action!



Summary of first approach

- Robust localization technique based on the theory of compressed sensing
- It is agnostic to the sensing modality (radio, ultrasound, etc.)
- It evaluates large NLOS errors, and corrects them prior to localization

- However, it assumes more LOS than NLOS distance measurements

Need for second approach

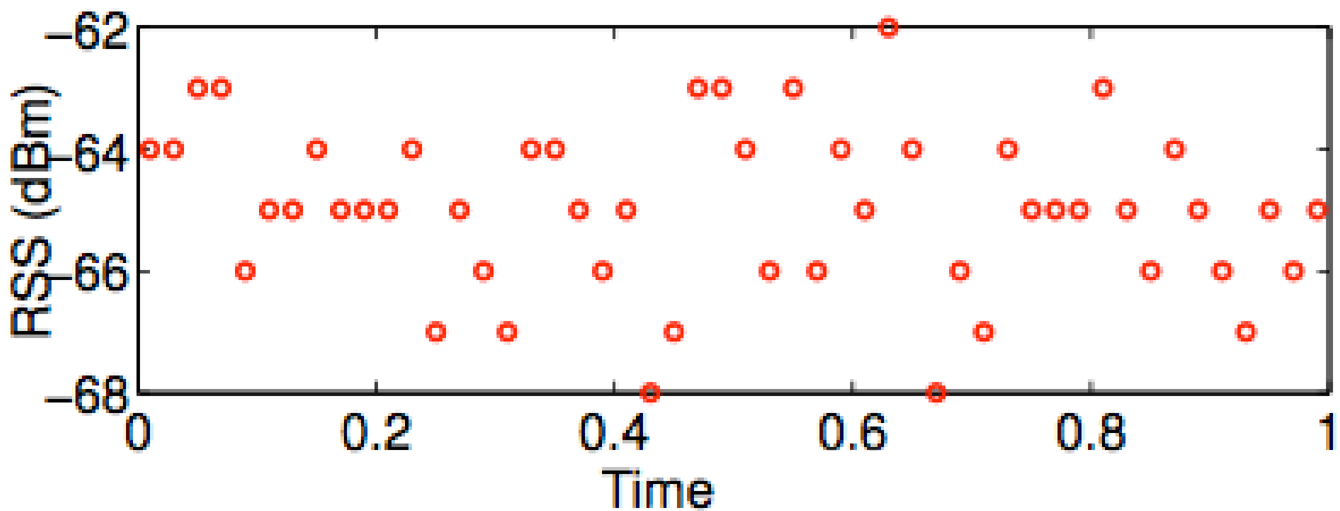
- The new approach should not require most distance measurements to be LOS

- Should be applicable to the widely available WiFi-based positioning systems

- These systems use RSS (Received Signal Strength) as an indicator of distance between two nodes
  - Advantage: infrastructure widely available
  - Disadvantage: notorious for inaccurate positioning

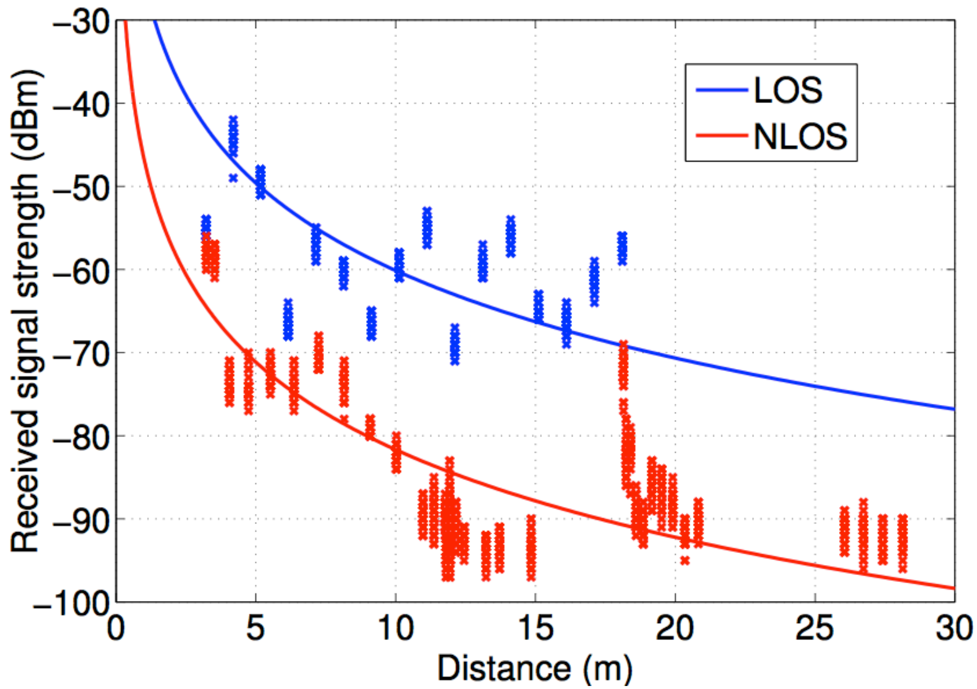
Approach 2

- Key idea: Look at multiple signal measurements over a short time period
- Can multiple measurements of radio RSS (Received Signal Strength) reveal if the measurements are taken in LOS or NLOS conditions?



Approach 2: RSS vs. Distance

- RSS does not map nicely to distance
- The mapping is different in LOS and NLOS conditions

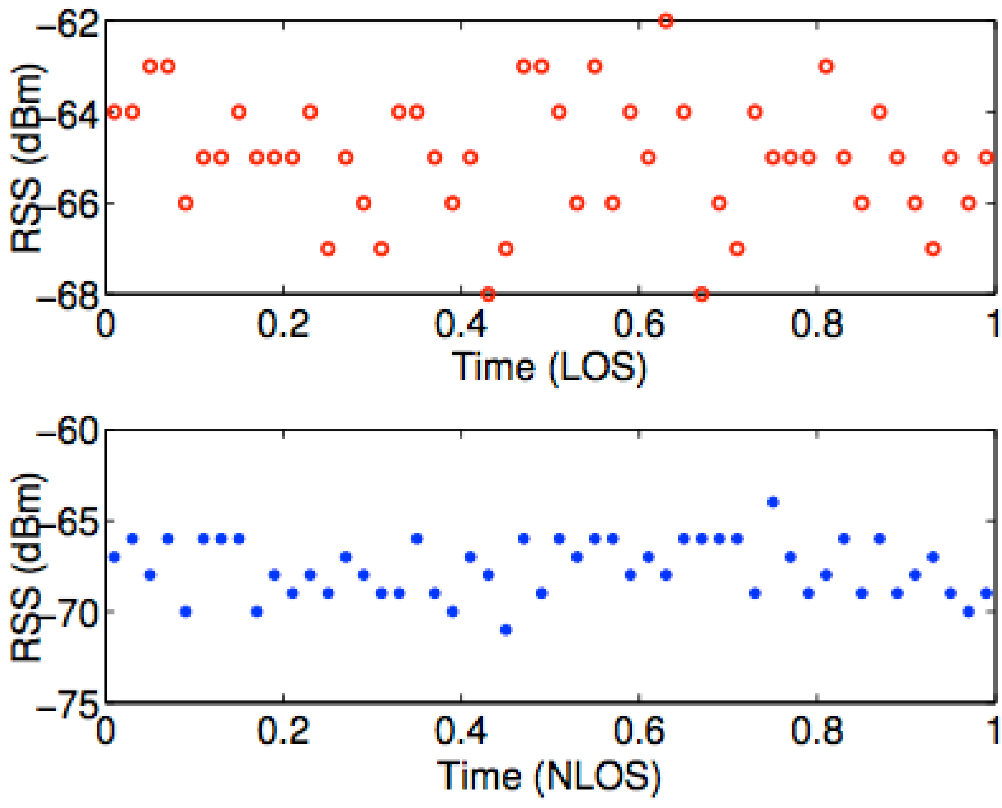


Approach 2: RSS is time-variant

- RSS from an anchor at a given position varies over time
- Variance alone is not enough to distinguish between LOS and NLOS

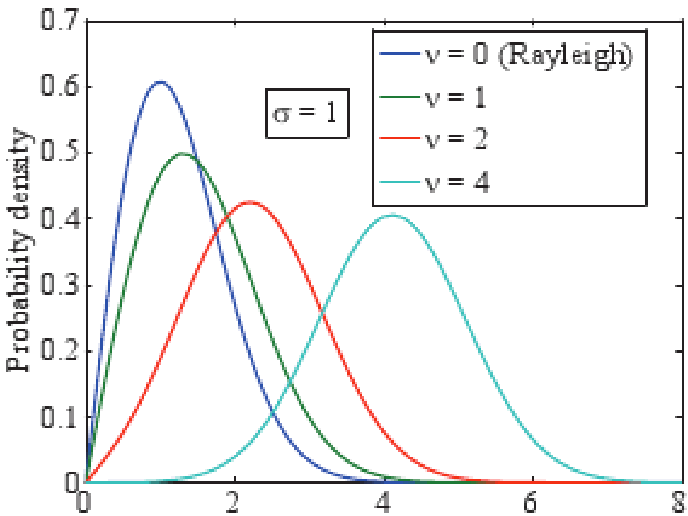
LOS

NLOS



Approach 2: NLOS identification

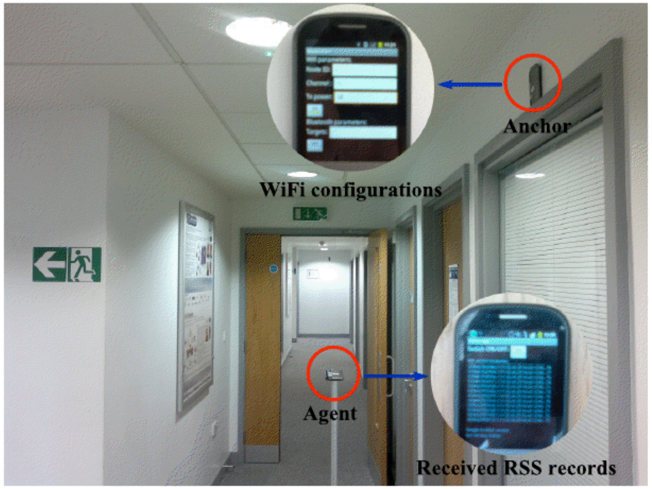
- We have tried various features:
  1. **Features of the samples** (mean, standard deviation, Kurtosis, skewness)
  2. **Shape of the estimated distribution** (Rician vs. Rayleigh)



  3. **Goodness-of-fit parameters between the samples and the estimated distribution** (e.g. Kolmogorov-Smirnov statistic, Chi-Squares, probability density difference)

Approach 2: Key results

- It is possible to distinguish between LOS and NLOS based on Received Signal Strength samples



- The accuracy depends on
  - on external interference conditions

    (night 94% - day 86%)
  - the number of RSS samples
    - (> 50 samples)

- Most indicative features (besides mean)
  - **low interference:** Rician K factor and variance are good indicators
  - **high interference:** skewness and curtosis (NOT variance)

Work in progress by Zhuoling Zhao and Niki Trigoni

Summary of second approach

- It is based on Radio Signal Strength (RSS) measurements
- It uses features of RSS samples to predict LOS / NLOS conditions
- It does not assume more LOS than NLOS distance measurements
- It has good classification accuracy particularly in low-interference conditions.

- However, it requires many RSS samples!

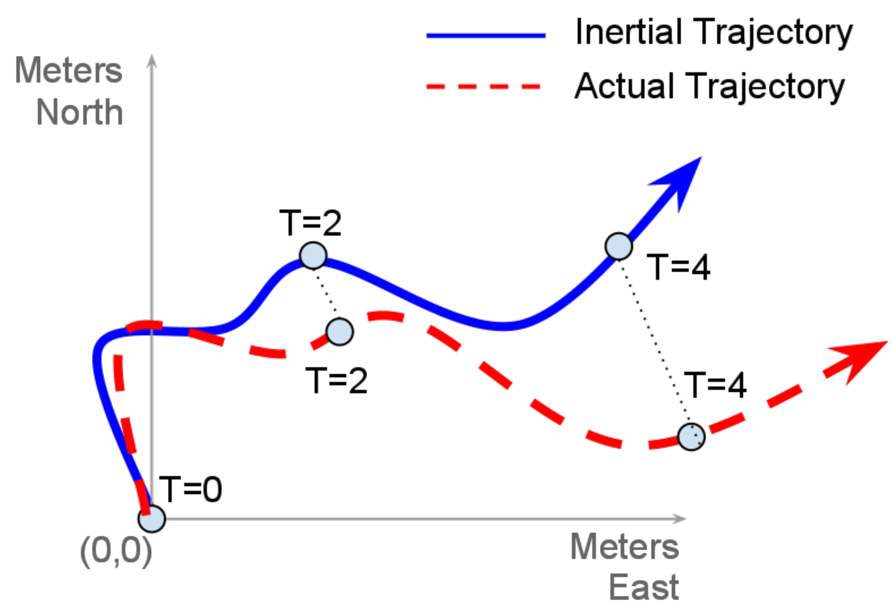
Work in progress by Zhuoling Zhao and Niki Trigoni

Challenge II

SPARSE ANCHOR INFRASTRUCTURE

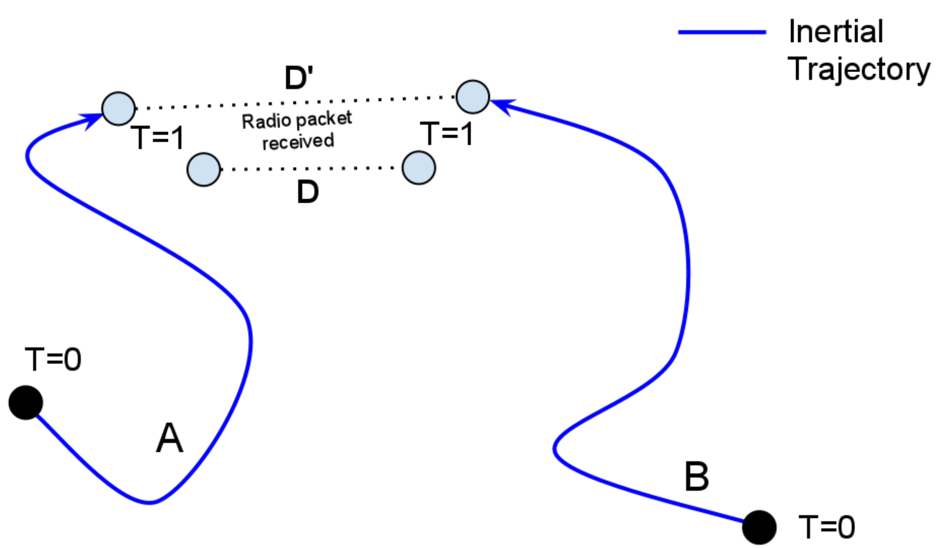
Sparse infrastructure problem

- Not all indoor spaces are covered by many anchors
- The lower the anchor density the highest the position error
- Inertial dead reckoning is a possible solution,
  - BUT the measurement error increases with time



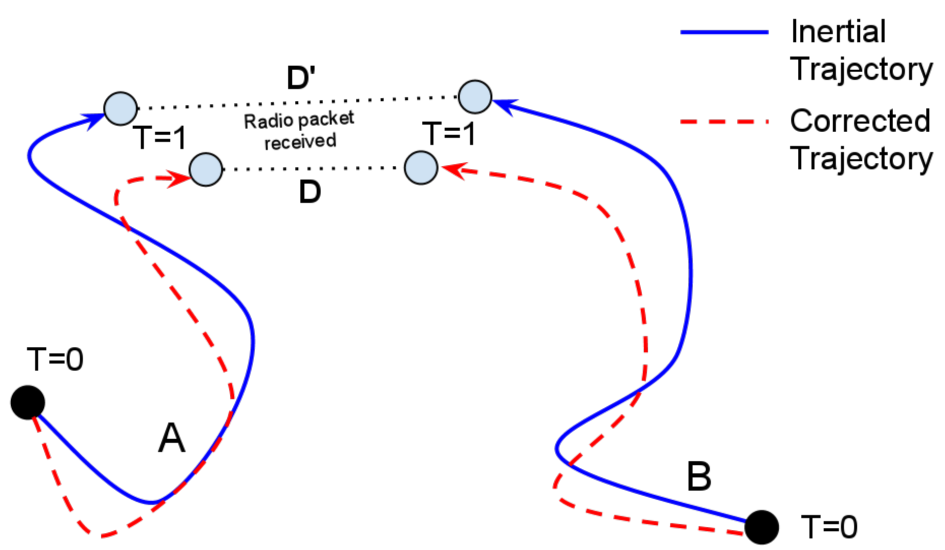
Exploit encounter constraints

- Node encounters:
  - What if nodes periodically emit radio beacons.
  - When they come close, they hear each other’s beacons.



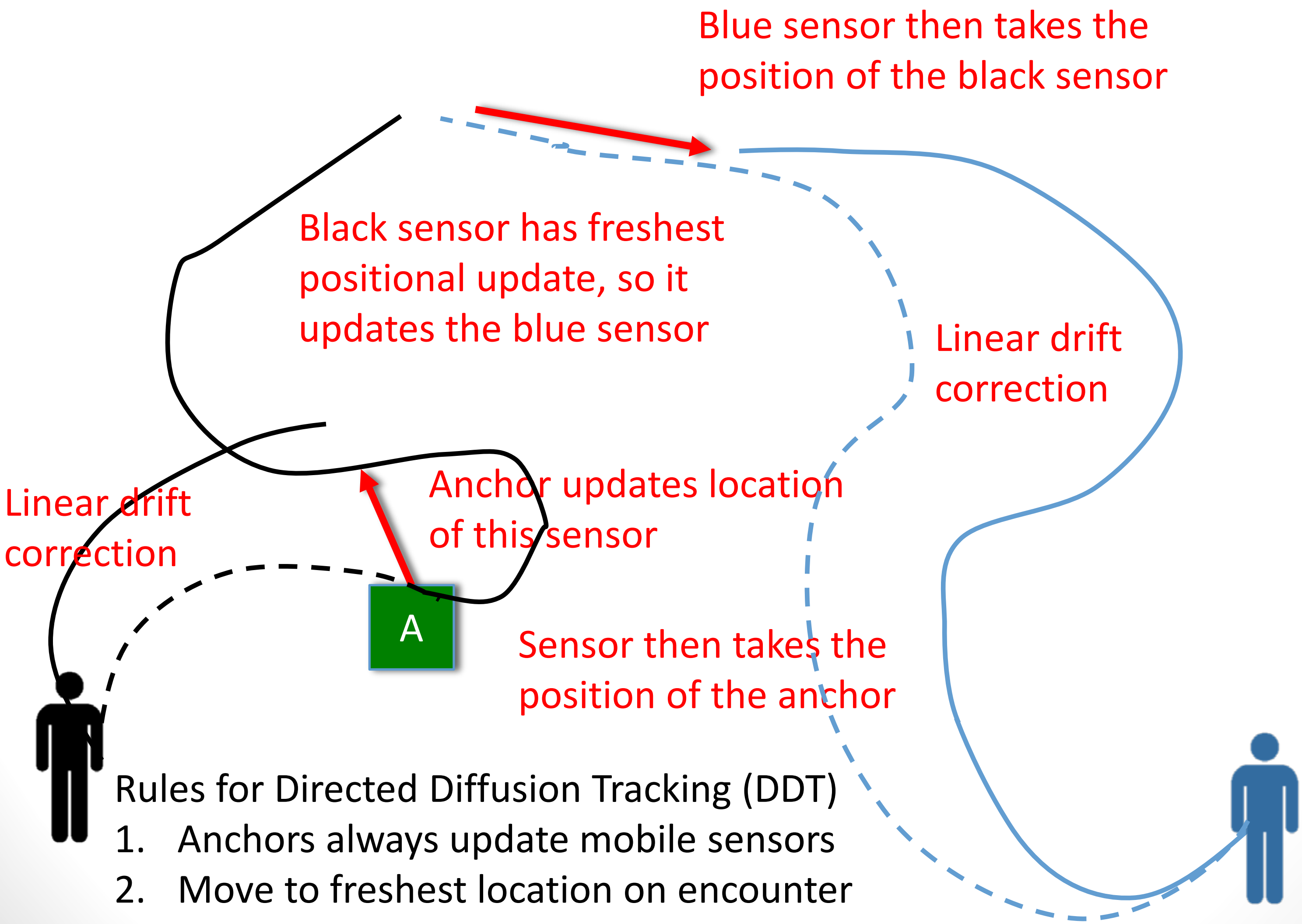
Exploit encounter constraints

- Encounter information relates them in space and time
- We exploit this information to correct positional error



Existing approach

Directed Diffusion Tracking by Constandache et al, 2010



Rules for Directed Diffusion Tracking (DDT)

1. Anchors always update mobile sensors
2. Move to freshest location on encounter

Proposed approach

- Encounter-Based Tracking (EBT)

STEP 1 : Graph construction

↓

STEP 2 : Graph realization

↓

STEP 3 : Drift correction

↓

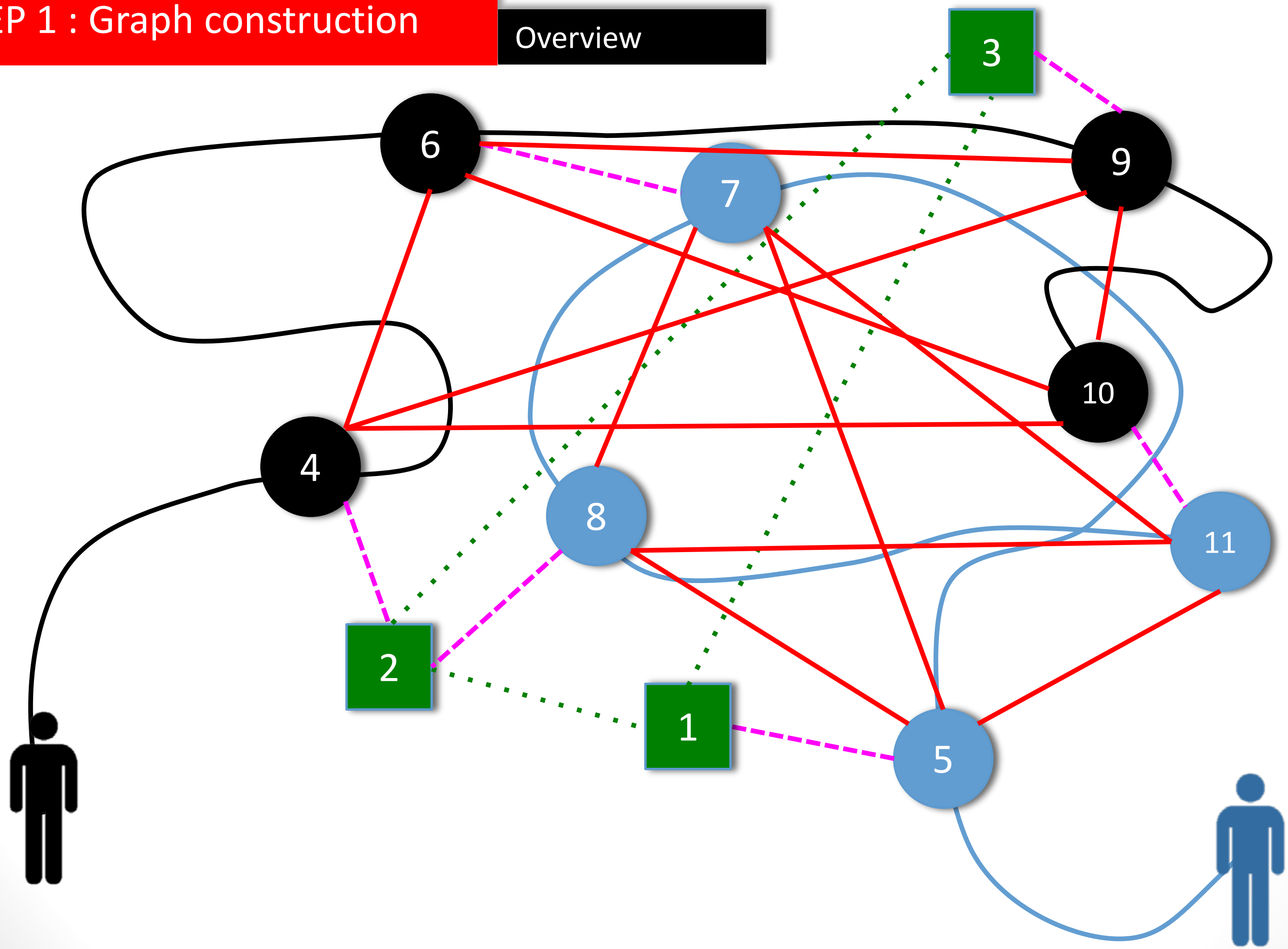
STEP 4 : Trajectory projection

Encounter Based Sensor Tracking. *Andrew Symington and Niki Trigoni, Mobihoc 2012.*

Encounter Based Tracking (EBT)

STEP 1 : Graph construction

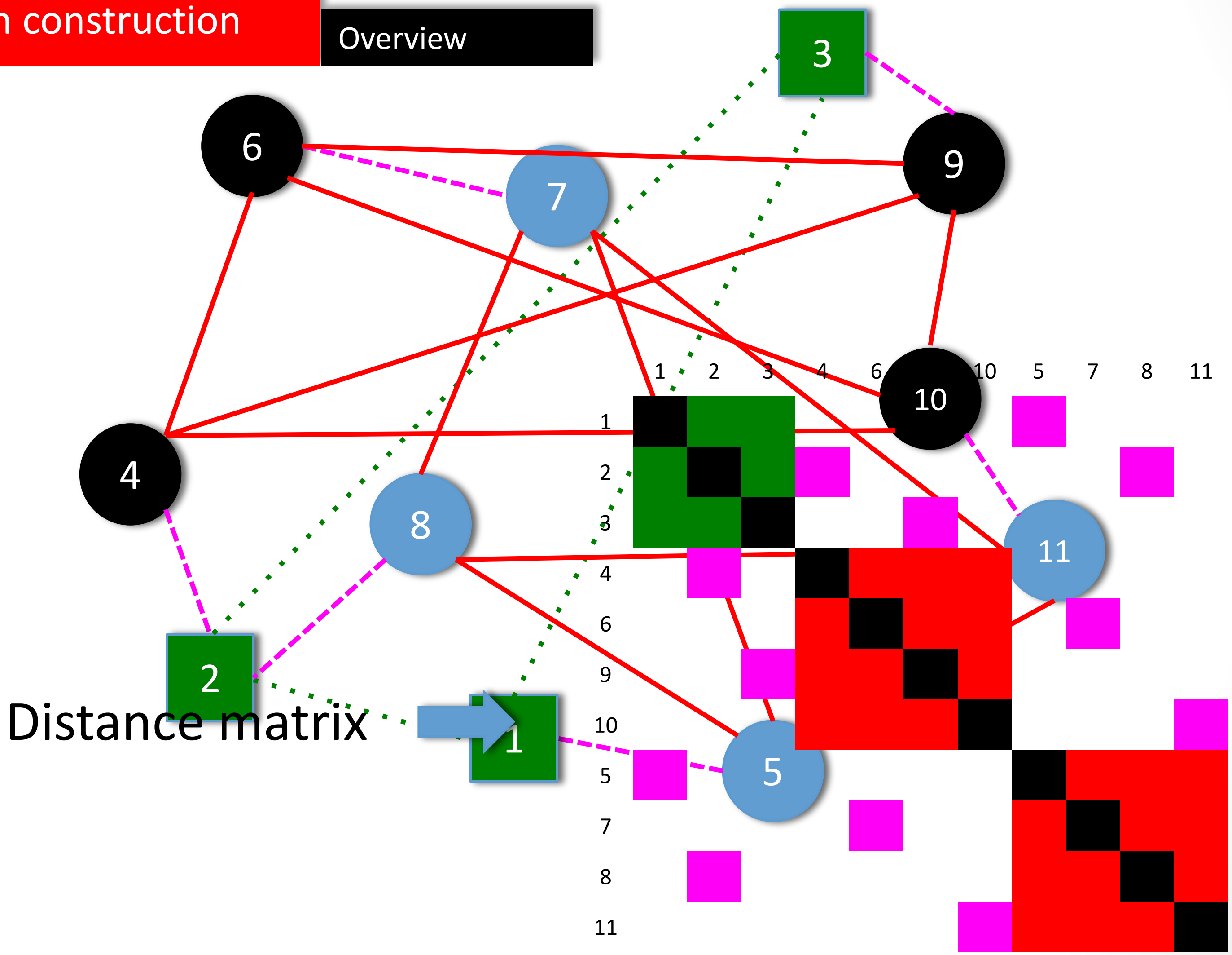
Overview



Encounter Based Tracking (EBT)

STEP 1 : Graph construction

Overview

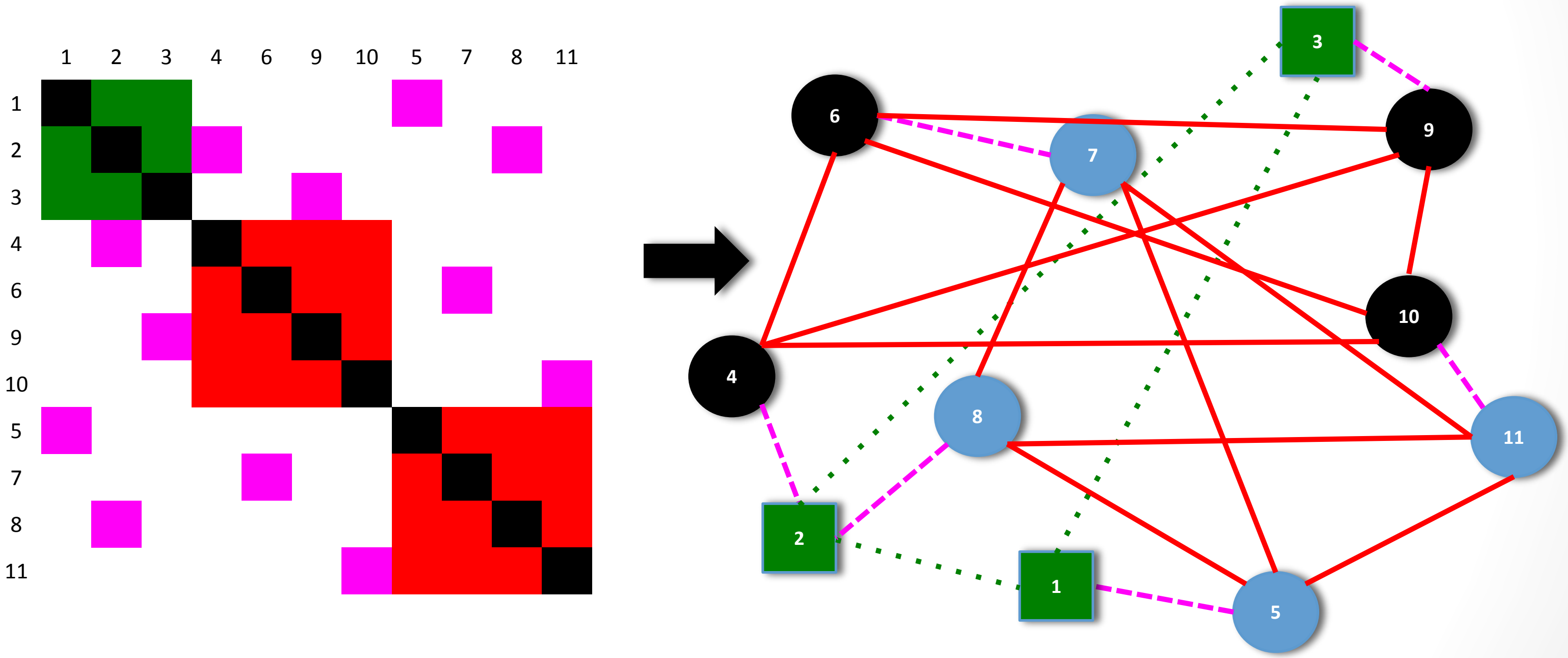


Encounter Based Tracking (EBT)

STEP 2 : Graph realization

Overview

Given the edges weights of a connected graph, find the 2D vertex positions



Is there exactly one 2D realization of this graph that satisfies the distances?

Assuming the above is true, can we find the graph embedding?

Encounter Based Tracking (EBT)

STEP 2 : Graph realization

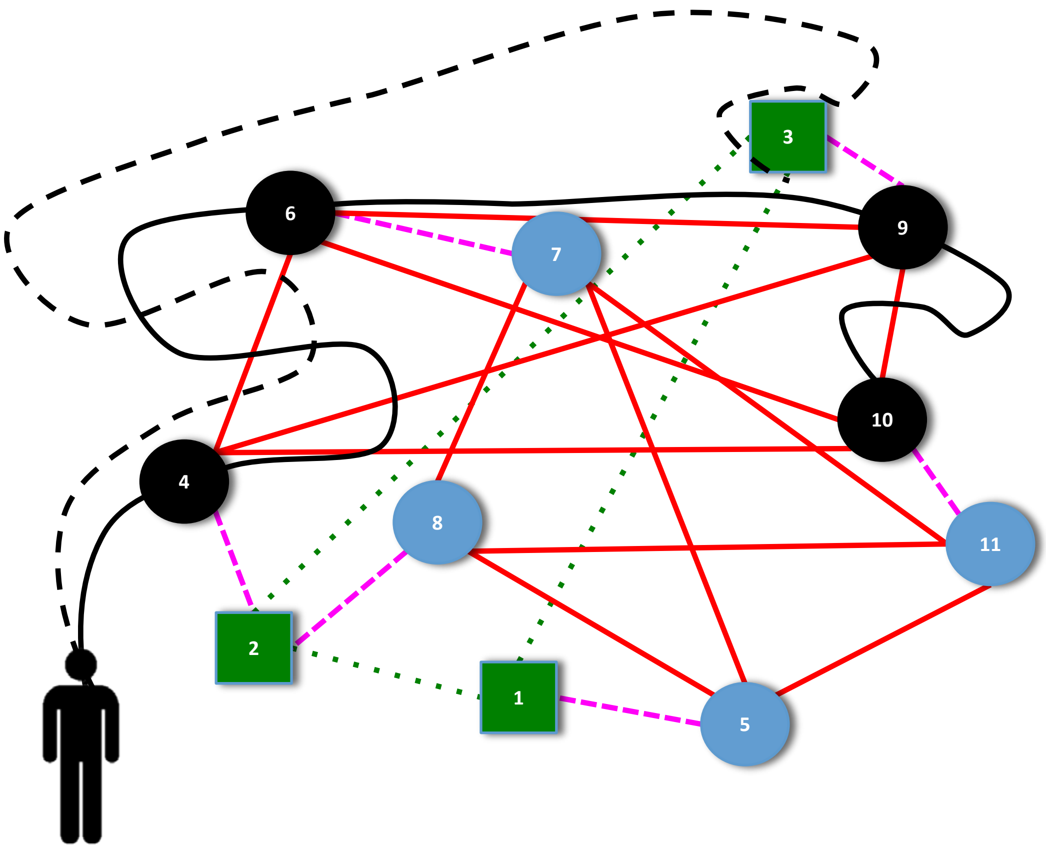
Overview of graph realization algorithms for static sensor localization

- Approaches from static localization literature
  - **Multidimensional scaling** (MDS) – *Shang et al., 2003.*
  - **Spectral graph drawing** (SGD) - *Broxton, 2006.*
  - **Semidefinite programming** (SDP) - *Biswas and Ye, 2004.*

Encounter Based Tracking (EBT)

STEP 3 : Drift correction

Overview



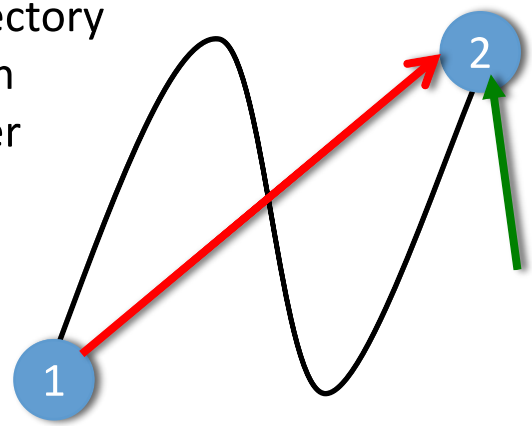
Encounter Based Tracking (EBT)

STEP 3 : Drift correction

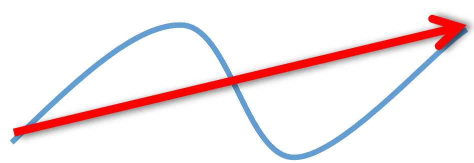
Linear drift correction (Constandache, 2010)

Observation
The shape of the curve is distorted when there is a large angle between the two red vectors

3. Spread error over time, so the trajectory ends aligned with second encounter



2. Calculate Error vector



1. Shift trajectory to begin at first encounter

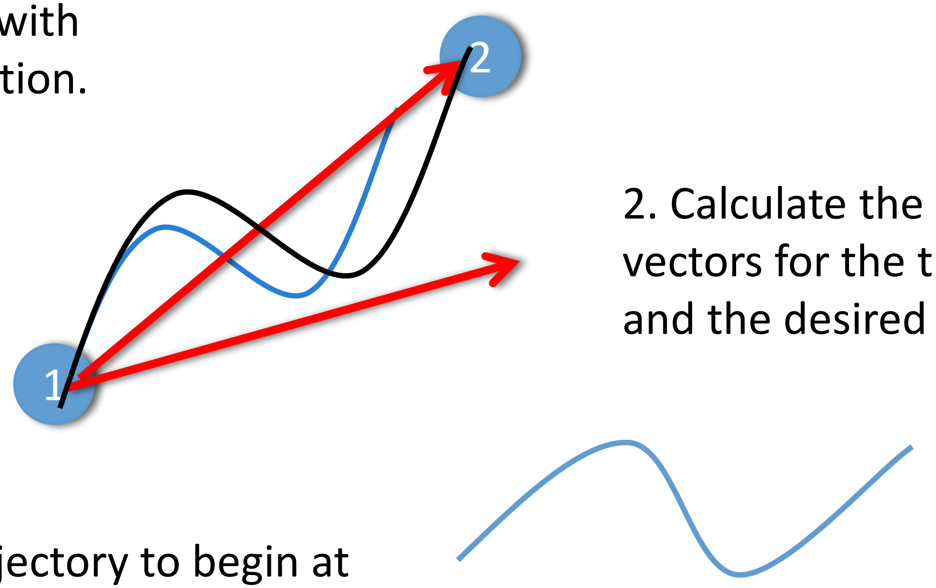
Encounter Based Tracking (EBT)

STEP 3 : Drift correction

Radial drift correction

4. Scale the trajectory, so that its end point is aligned with the second encounter.

3. Rotate trajectory so that it is aligned with the desired direction.



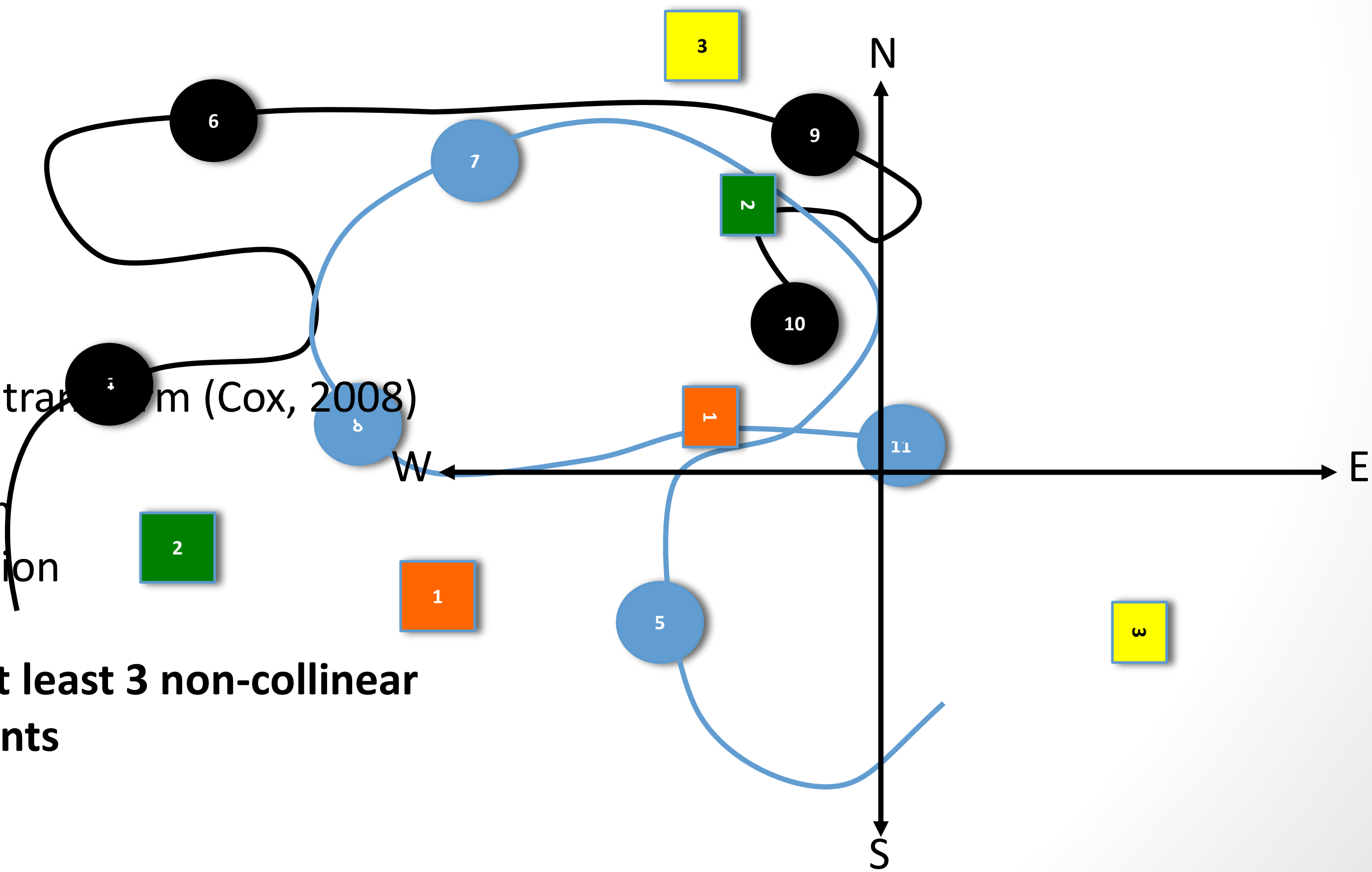
2. Calculate the direction vectors for the trajectory and the desired path.

1. Shift trajectory to begin at first encounter

Encounter Based Tracking (EBT)

STEP 4 : Trajectory projection

Overview



Procrustes transform (Cox, 2008)

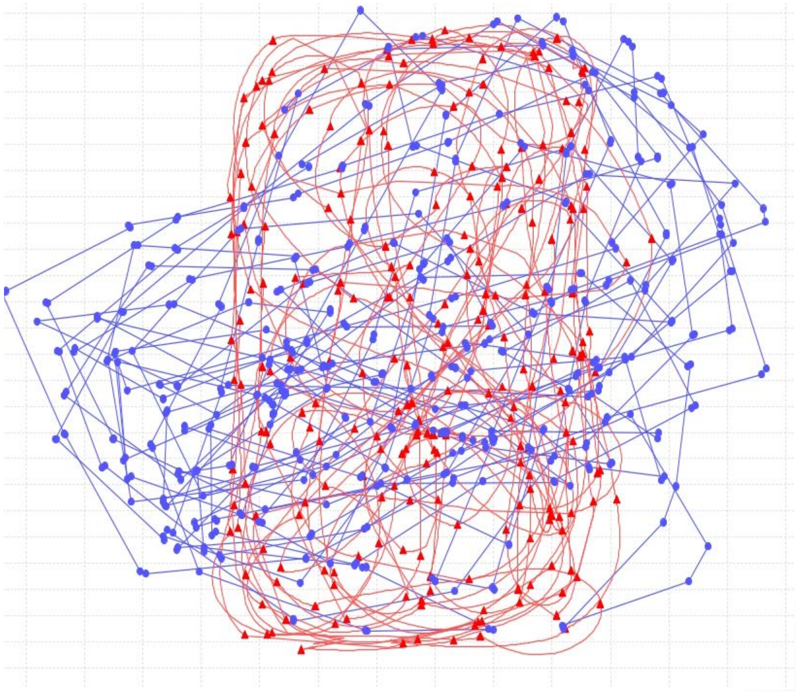
- Scale
- Rotation
- Translation

Requires at least 3 non-collinear anchor points

Experimental setup

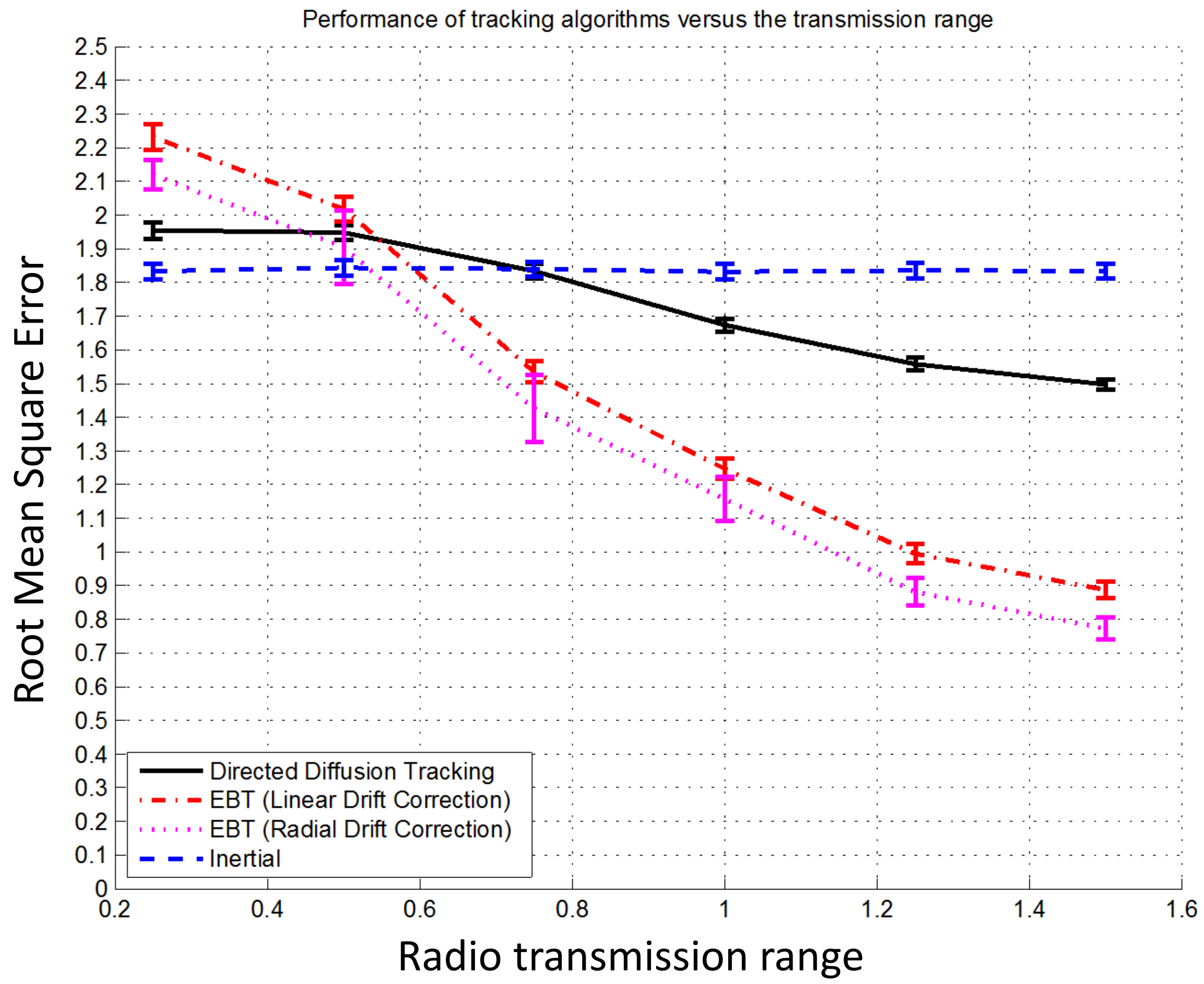
Mobility data

- IPIN2010 pedestrian data set from Angermann et al, 2010.
  - 260s random walk
  - 7m x 7m room
  - Available data streams
    - Inertial trajectory
    - Ground truth trajectory
- How we used the data
  - 30s random subsample
  - 5 sensors
  - Time synchronisation
  - Synthetic encounters



Results: Transmission range

Effect of radio transmission range on tracking error



Summary of EBT

- Combines anchor-based localization with inertial tracking
- Exploits wireless encounters between mobile nodes
- Significantly improves localization accuracy (up to 46%) compared to competing approaches

- However, it is not applicable to all scenarios
  - Is cooperative in nature
  - Raises trust / privacy concerns
  - Does not estimate location undertainty

    Unlike robotics approaches
    (based on pose graphs)

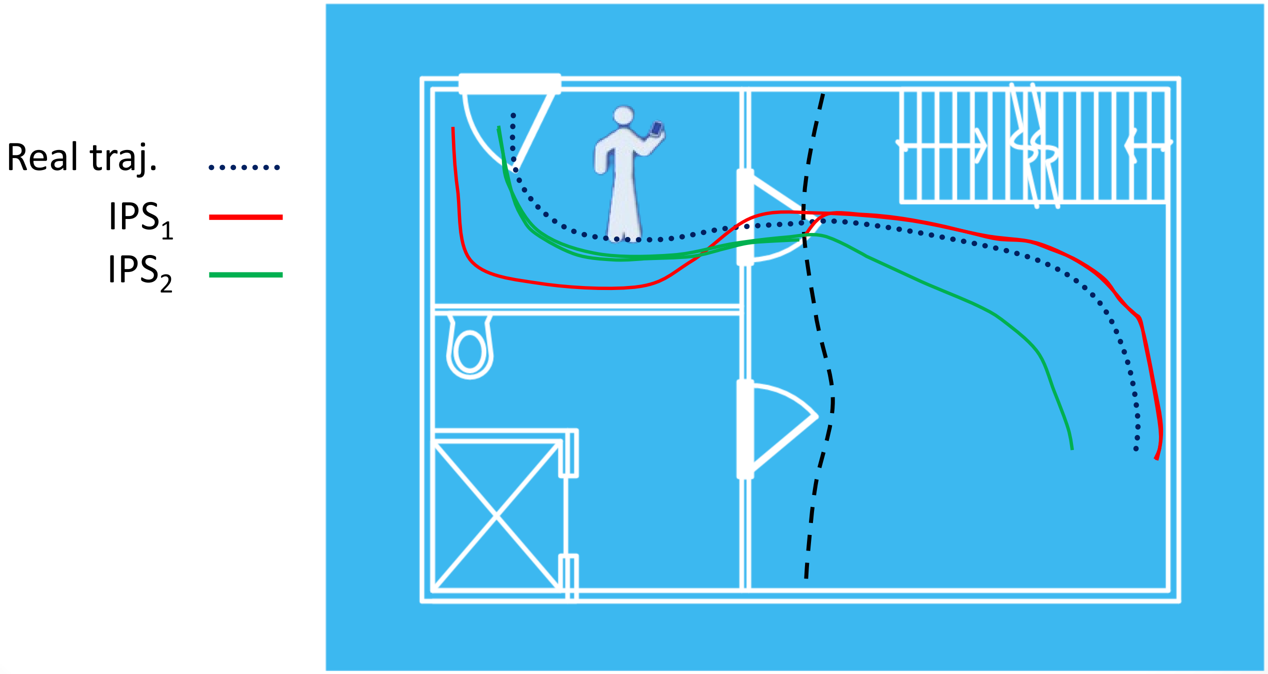
Encounter Based Sensor Tracking. *Andrew Symington and Niki Trigoni, Mobihoc 2012.*

Challenge III

POSITIONING ACCURACY DEPENDS ON THE ENVIRONMENT

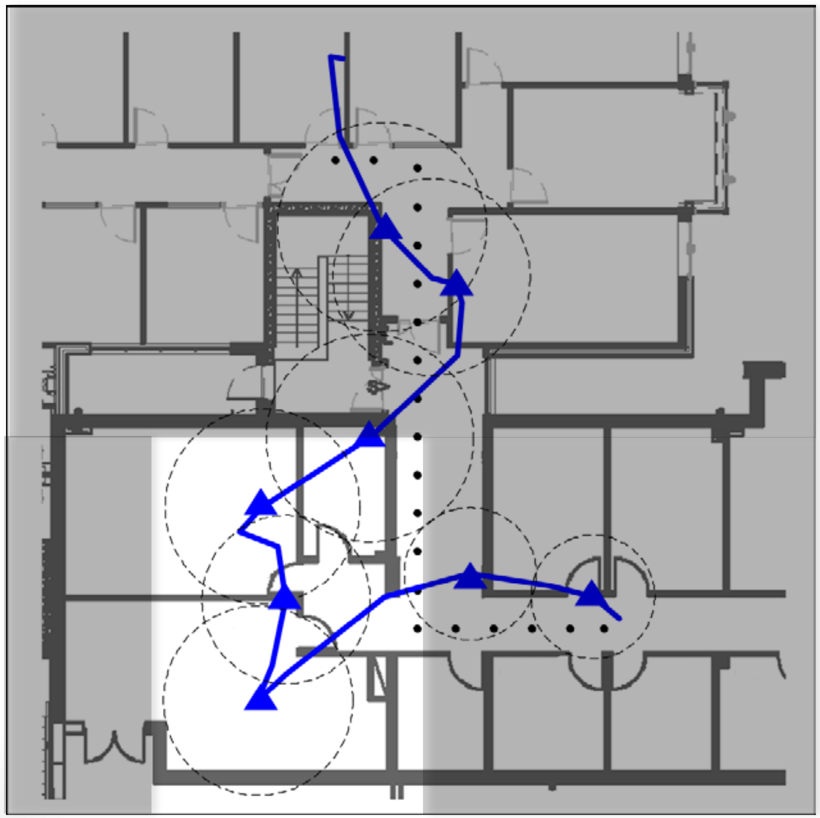
Variations in position accuracy

- The accuracy of an indoor positioning system (IPS) depends on the environment
  - dense vs. sparse sensing infrastructures
  - cluttered environment vs. open space
- Scenario with co-located IPSs: which one to choose?

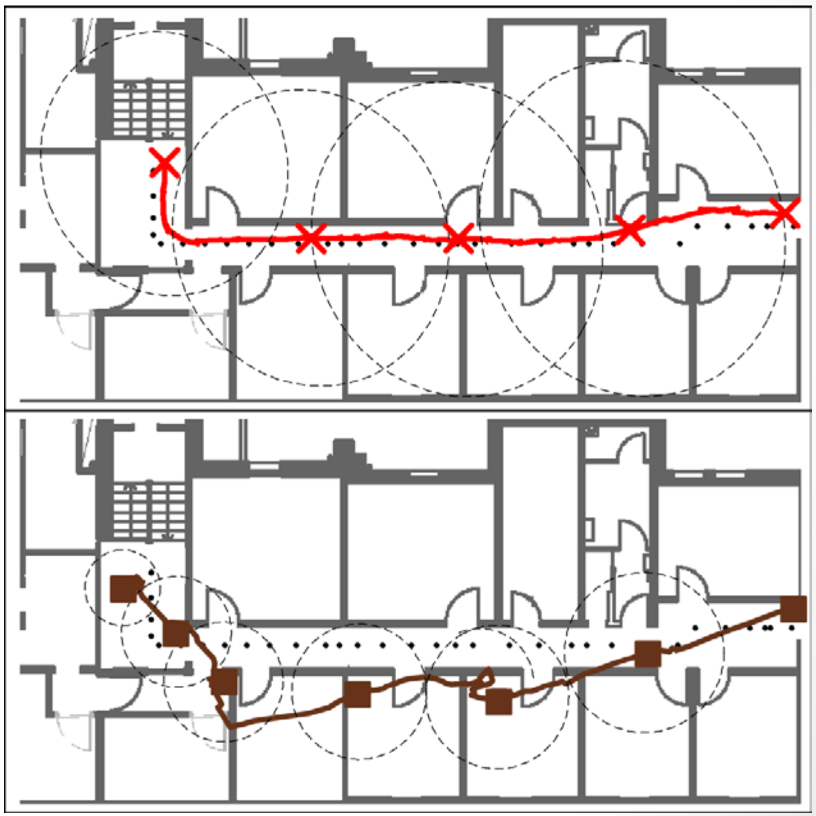


Variations in position accuracy

- Why not rely on reported accuracy?



Ground truth
WiFi triangulation



Ground truth
Inertial Dead Reckoning
WiFi fingerprinting

Variations in position accuracy

Objectives

- Assess the accuracy of co-located Indoor Positioning Systems (IPSs) in different parts of the area

- Allow users to exploit this information to carefully choose which IPS to use where

Learning approach

Step 1:

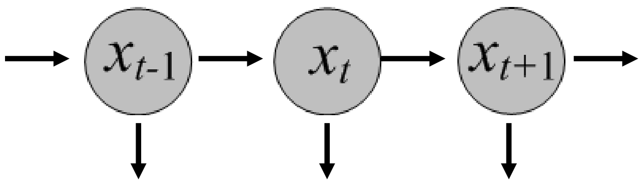
Cast the problem of accuracy assessment into that of learning the parameters of an augmented HMM

Step 2:

Use an Expectation Maximization algorithm to learn the HMM parameters

Augmented HMM

- Parameters of the augmented HMM $\lambda = (\pi, A, \mathbf{B})$



z_{t-1}

Loc	*Prob*
425	0.3
426	0.05
427	0.15
428	0
429	0
430	0
431	0
432	0
H1	0.5
H2	0
H3	0

z_t

Loc	*Prob*
425	0
426	0
427	0.2
428	0.1
429	0
430	0
431	0.1
432	0
H1	0
H2	0.4
H3	0.2

z_{t+1}

Loc	*Prob*
425	0
426	0
427	0
428	0
429	0
430	0
431	0.1
432	0.1
H1	0
H2	0.2
H3	0.6

Emission probabilities:
the *expected probability*
that the IPS reports $\boldsymbol{l_k}$
when the user is actually at l_j

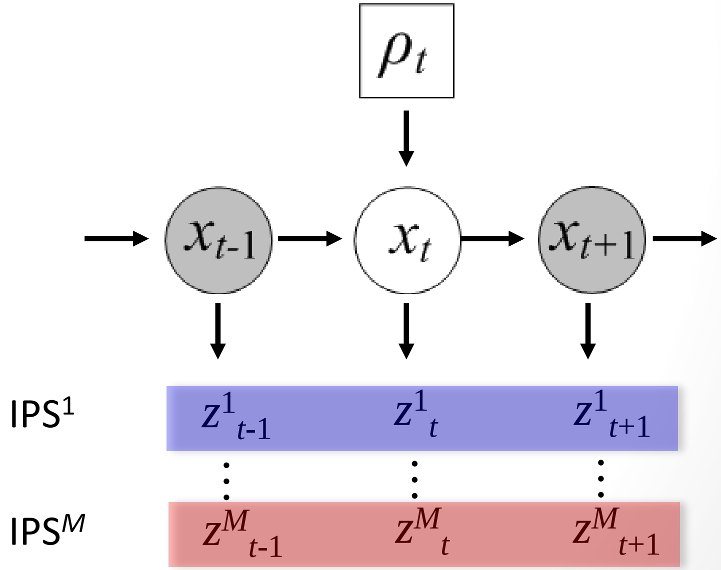
Observations:
Not scalars,
but probability distributions

Augmented HMM

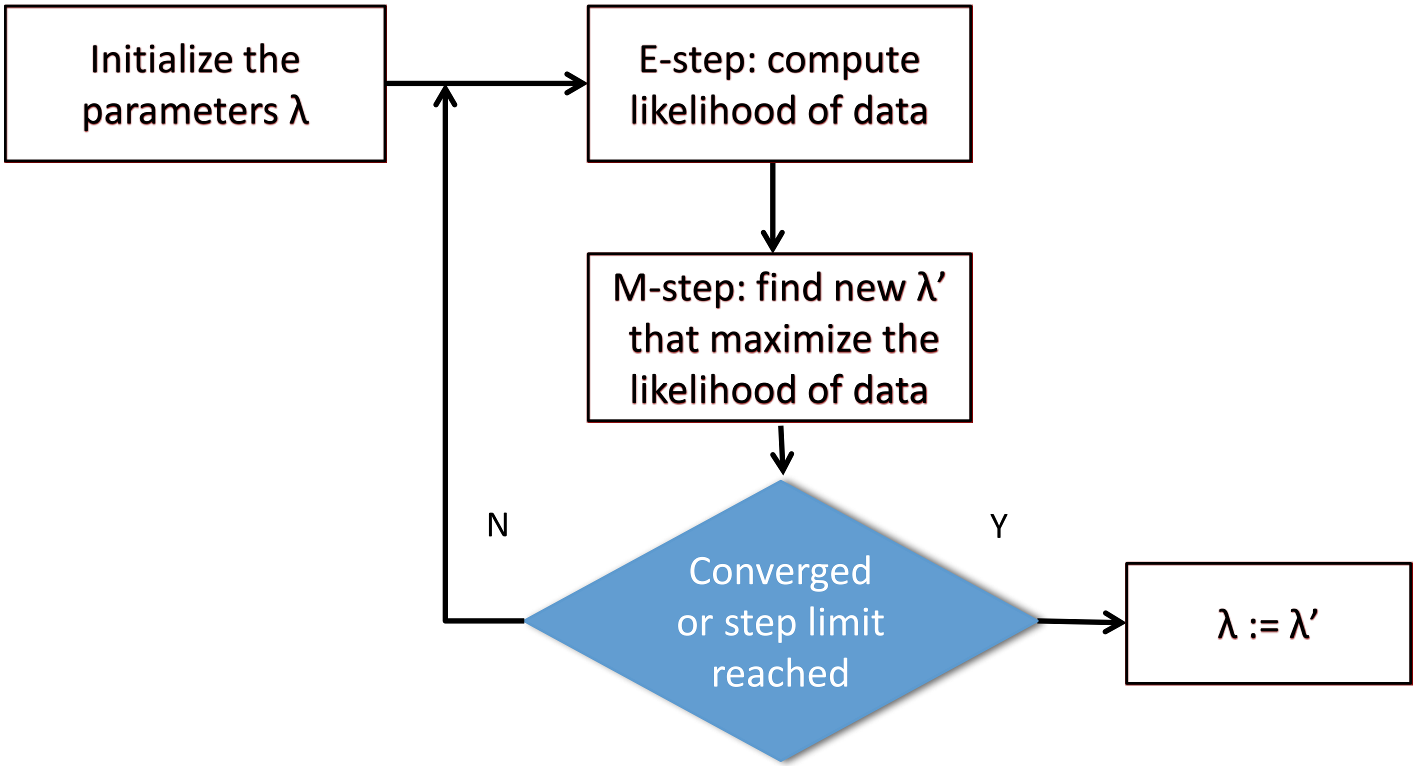
- Prior belief on the locations of the user
  - Comes from calendars, flight boarding times…

"Meeting in 430 on 3pm today"

$\rho_{3\text{pm}} = \{q_{3\text{pm}}(430) = 0.9, \text{ others } 0.1/(N\text{-}1)\}$



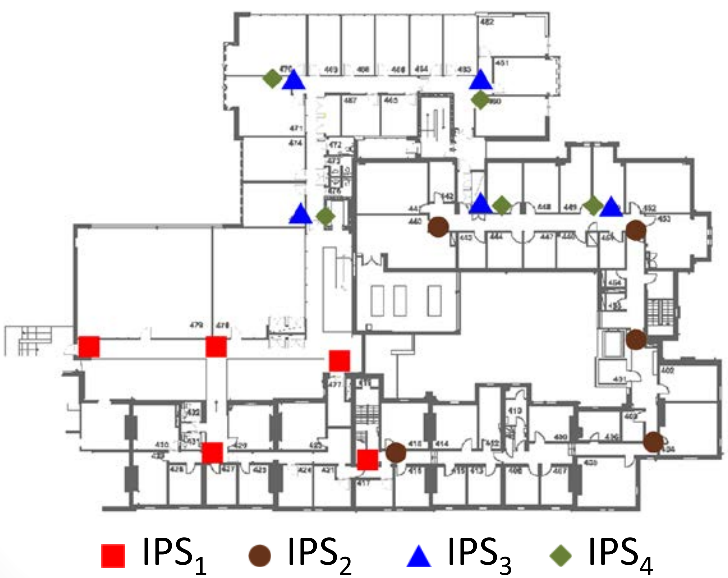
Expectation Maximization Alg.



- Extension of Baum-Welch algorithm to take into account probabilistic observations and priors

Experimental setup

- Indoor setting
  - The 4th floor of the CS department (20d)
- 4 WiFi-based IPSs with different basestations
- 2 users with different devices

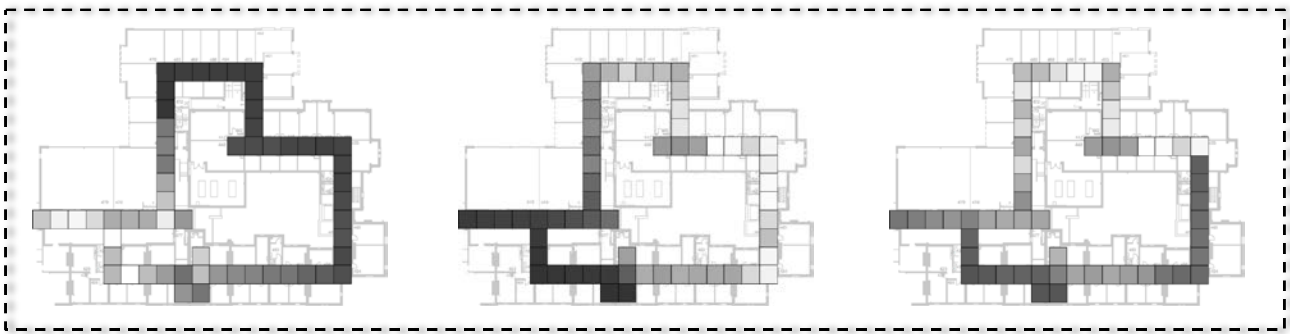


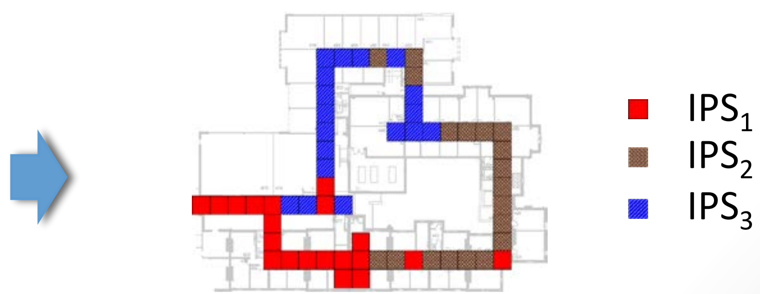
Accuracy varies across space

- Depends on infrastructure density

IPS_1 IPS_2 IPS_3

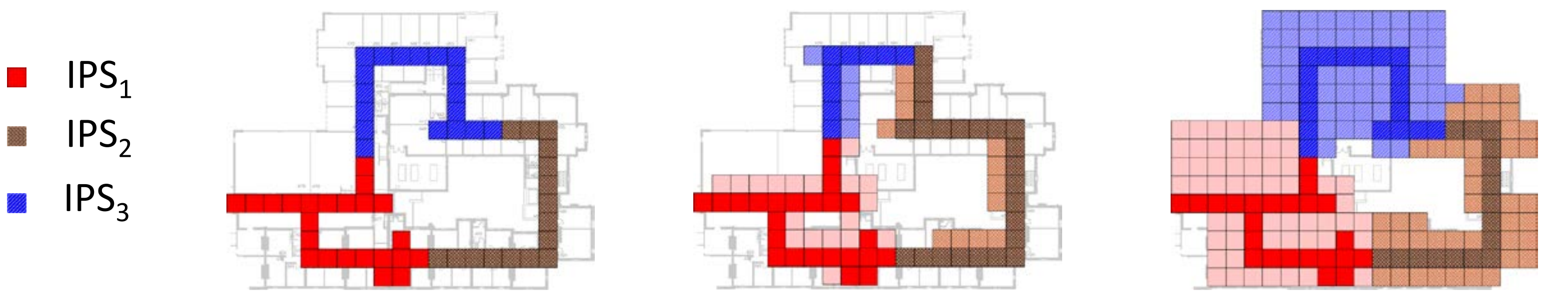
Real acc.





Learnt vs. Reported accuracy

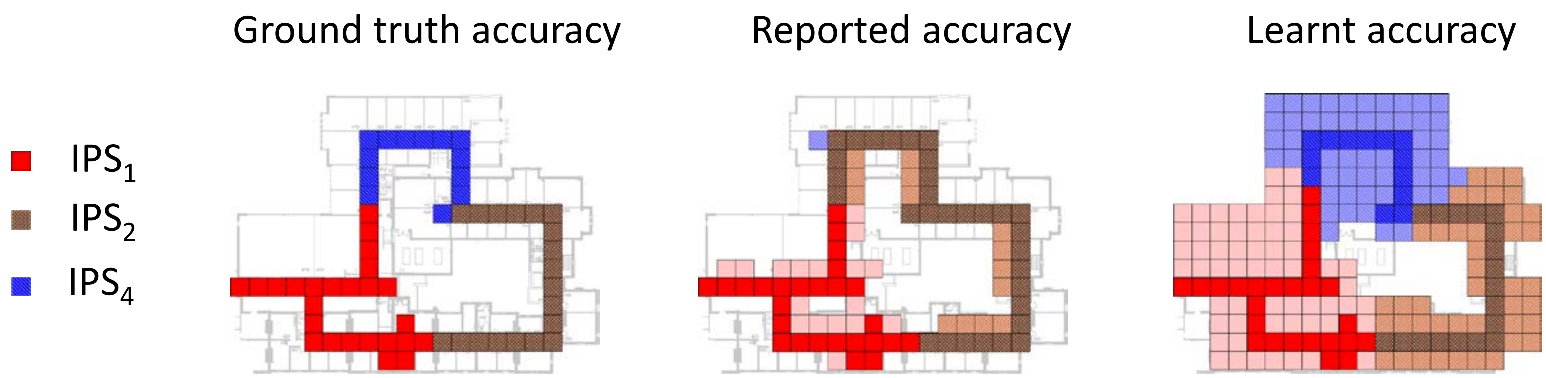
Ground truth accuracy | Reported accuracy | Learnt accuracy



$EE = 0$ | $EE_R = 16.98$ | $EE_L = 2.02$

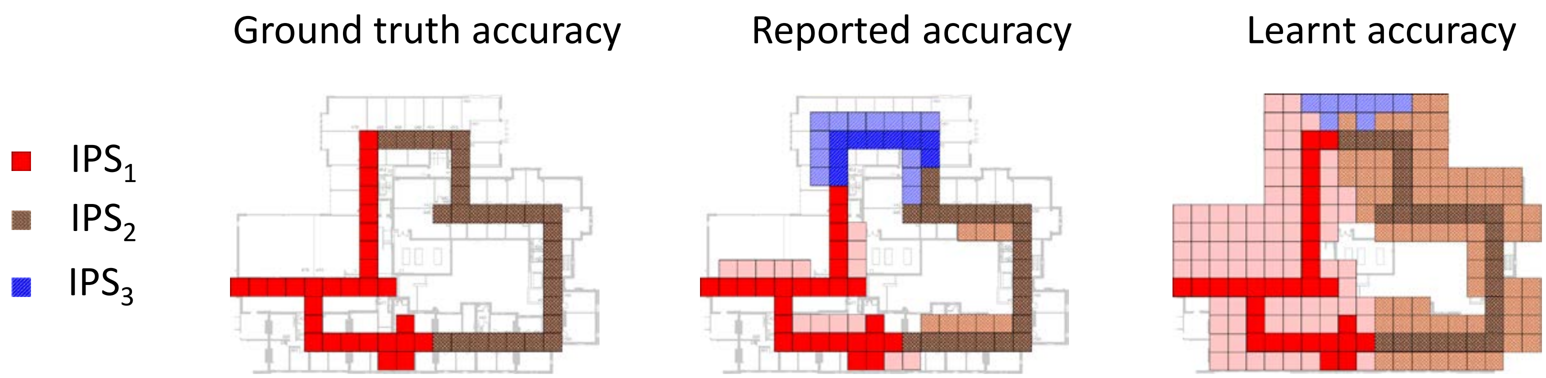
Learnt vs. Reported accuracy

- We replace IPS_3 with IPS_4, which overestimates its error
  - It has twice as high gyroscope and accelerometer variances



Learnt vs. Reported accuracy

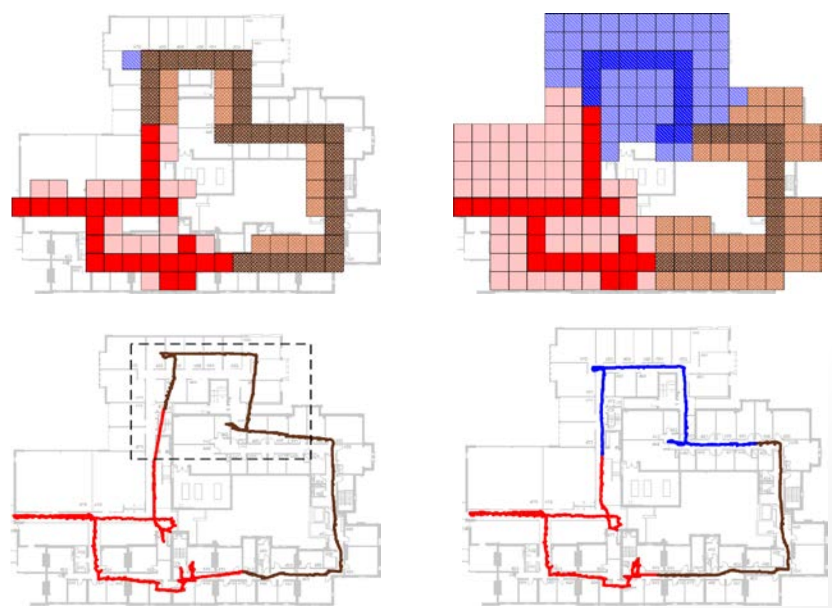
- We introduce a new user with different device
  - Holding a tablet rather than a phone
  - IPS_3 has not been tuned for such a device



Localization error

- Switch IPS according to different accuracy profiles
  - According to reported accuracy
  - According to learnt accuracy

Reported accuracy Learnt accuracy



$LE_R = 8.91$ $LE_L = 2.07$

Summary of learning approach

- Spatial variations in the accuracy of indoor positioning systems
- Estimating their accuracy is possible by using a HMM learning approach
- The learning-based approach outperforms the approach of relying on reported accuracy
- It can further be improved by exploiting prior information about people's locations, possibly drawn from their calendars

- Future work
  - More types of priors
  - More complex positioning systems

Work in progress by Hongkai Wen and Niki Trigoni

Challenges and Approaches Revisited

Challenge I: Clutter => NLOS

Robust localization

RSS-based NLOS identification

Challenge II: Infrastructure sparsity

Encounter-based tracking

Challenge II: Accuracy estimation

HMM-based learning approach

Thank you

Acknowledgements

- Dr Sarfraz Nawaz (Robust Localization)
- Zhuoling Zhao (RSS-based NLOS identification)
- Andrew Symington (Encounter based tracking)
- Hongkai Wen (Learning accuracy of positioning systems)

EPSRC
Engineering and Physical Sciences Research Council

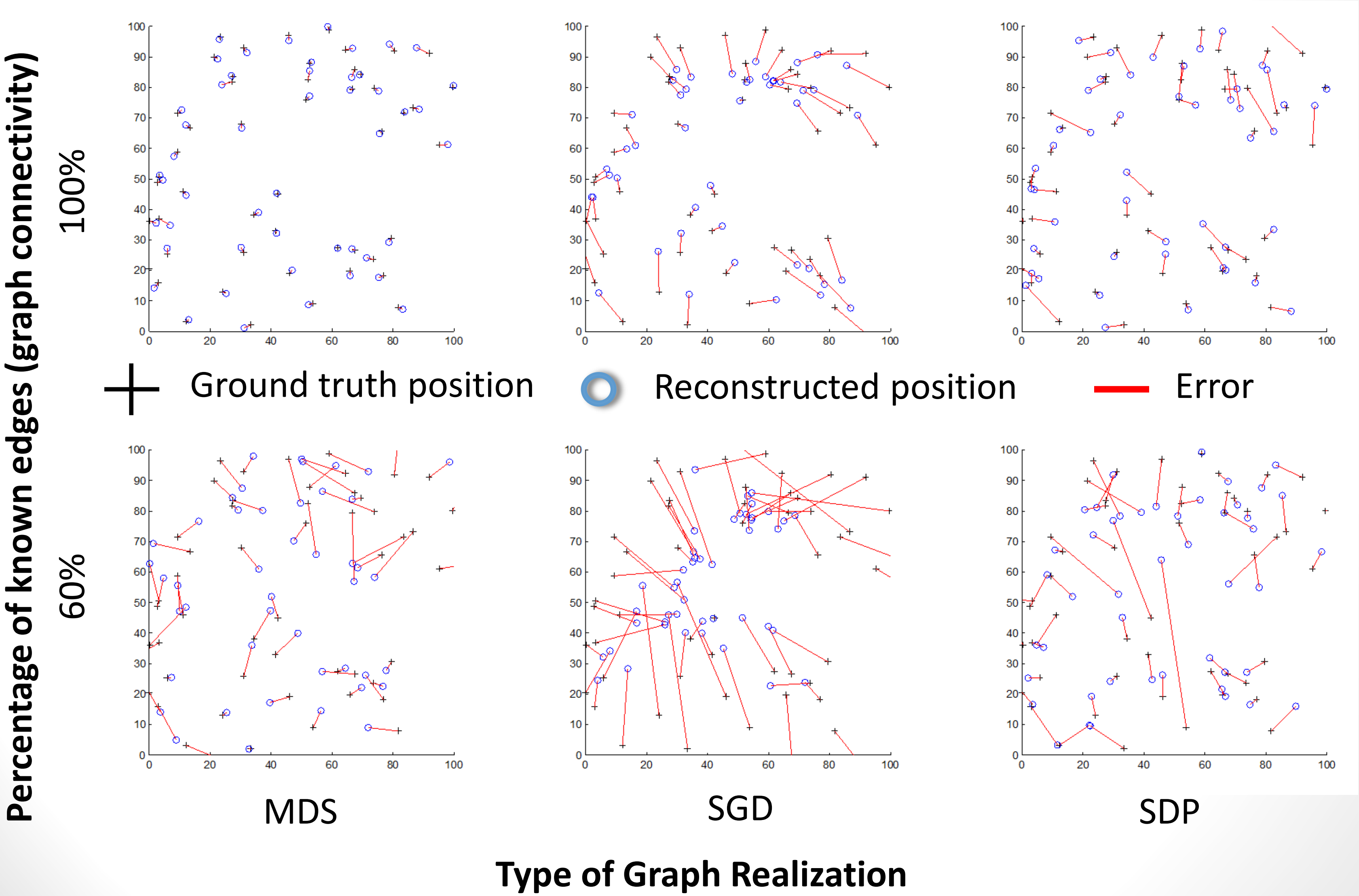
Encounter Based Tracking (EBT)

STEP 2 : Graph realization

Overview of graph realization algorithms for static sensor localization

- Approaches from static localization literature
  - **Multidimensional scaling** (MDS) – *Shang et al., 2003.*
    - MDS-MAP(P) – *Shang and Ruml, 2004.*
  - **Spectral graph drawing** (SGD) - *Broxton, 2006.*
    - **Degree normalised SGD** (DN-SGD) – *Koren, 2003.*
  - **Semidefinite programming** (SDP) - *Biswas and Ye, 2004.*
    - Exploiting matrix sparsity – *Kim et al, 2008.*
- We implemented the four bolded approaches above
  - MDS-MAP too computationally expensive
  - SGD and DN-SGD performance similar

Encounter Based Tracking (EBT)

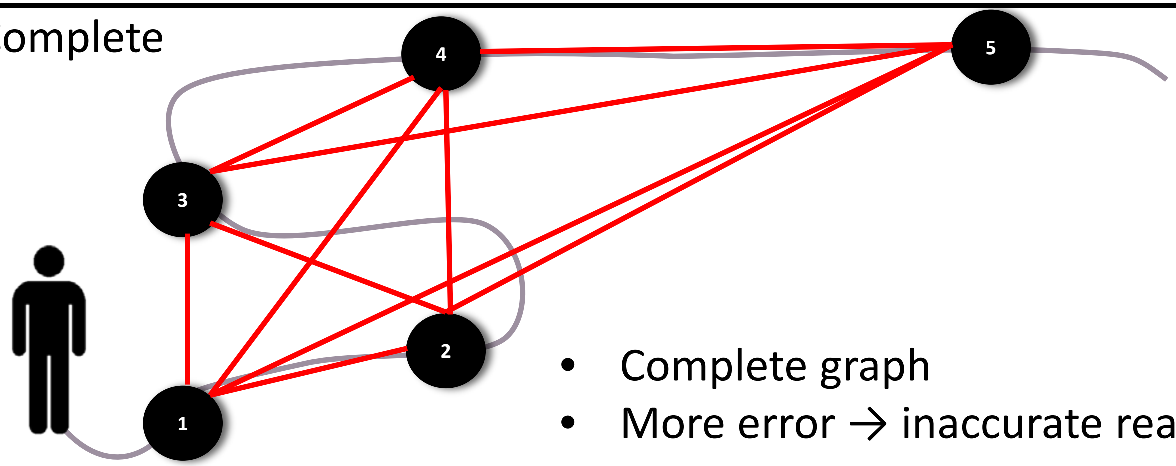


Encounter Based Tracking (EBT)

STEP 1 : Graph construction

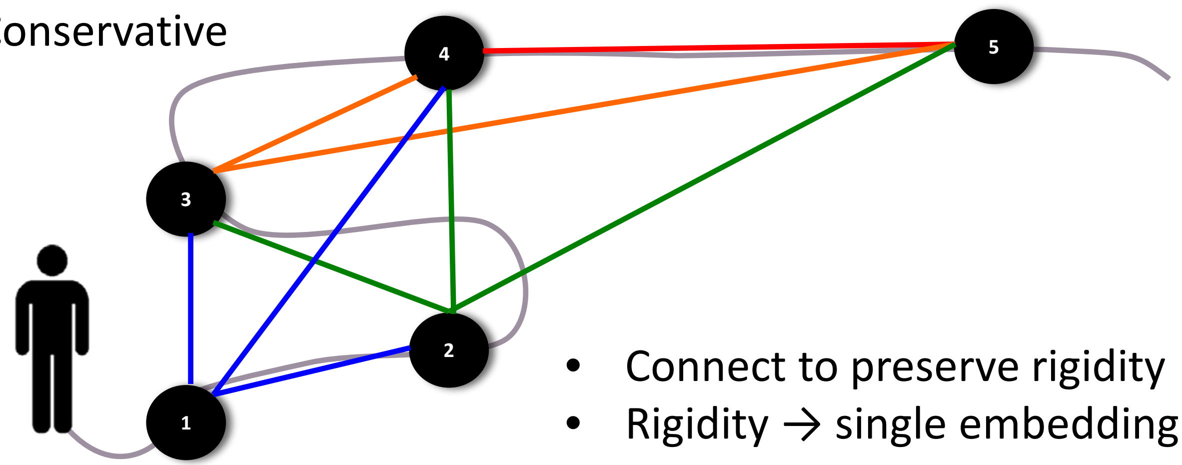
Edge selection

Complete



- Complete graph
- More error → inaccurate realizations

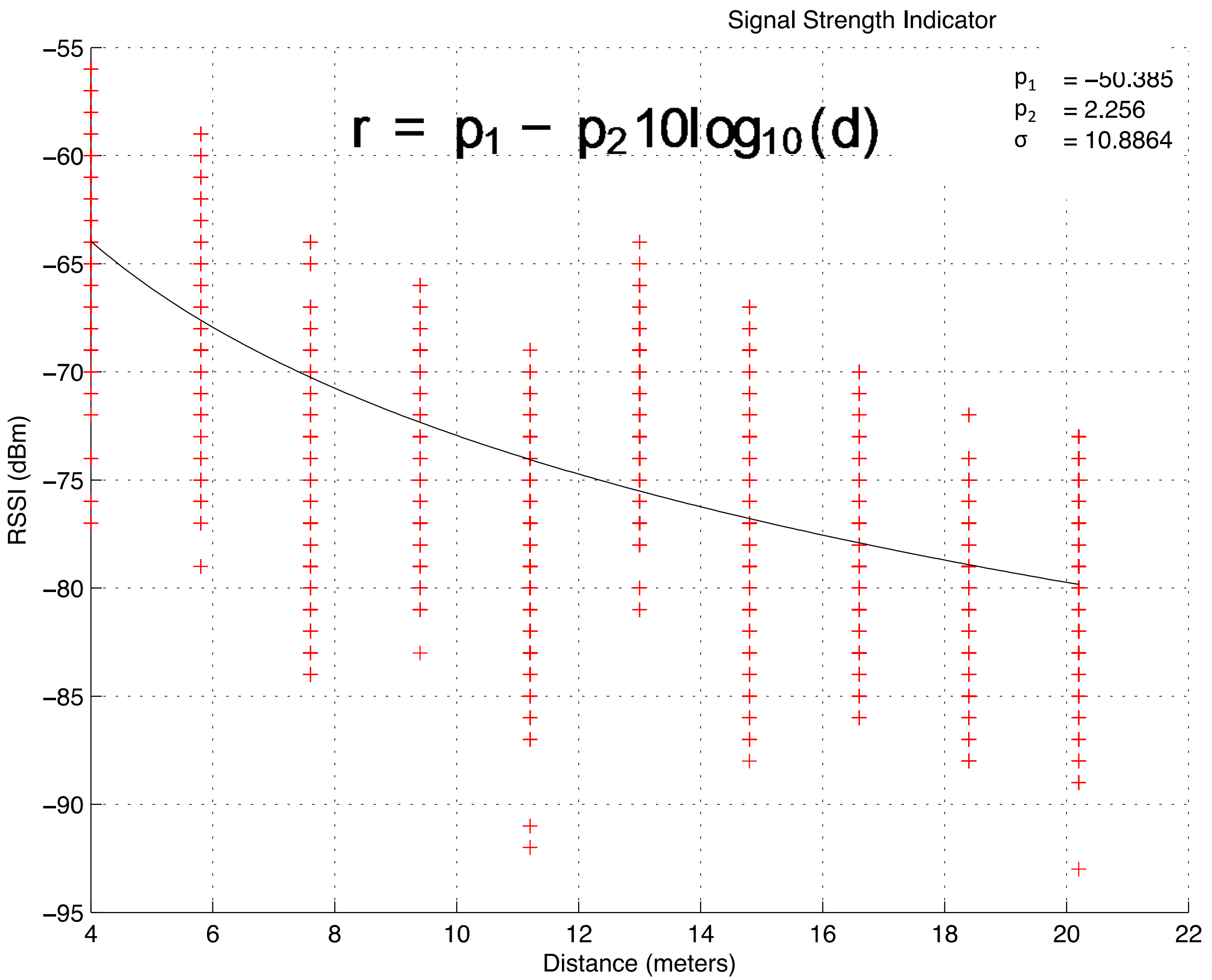
Conservative



- Connect to preserve rigidity
- Rigidity → single embedding

Experimental setup

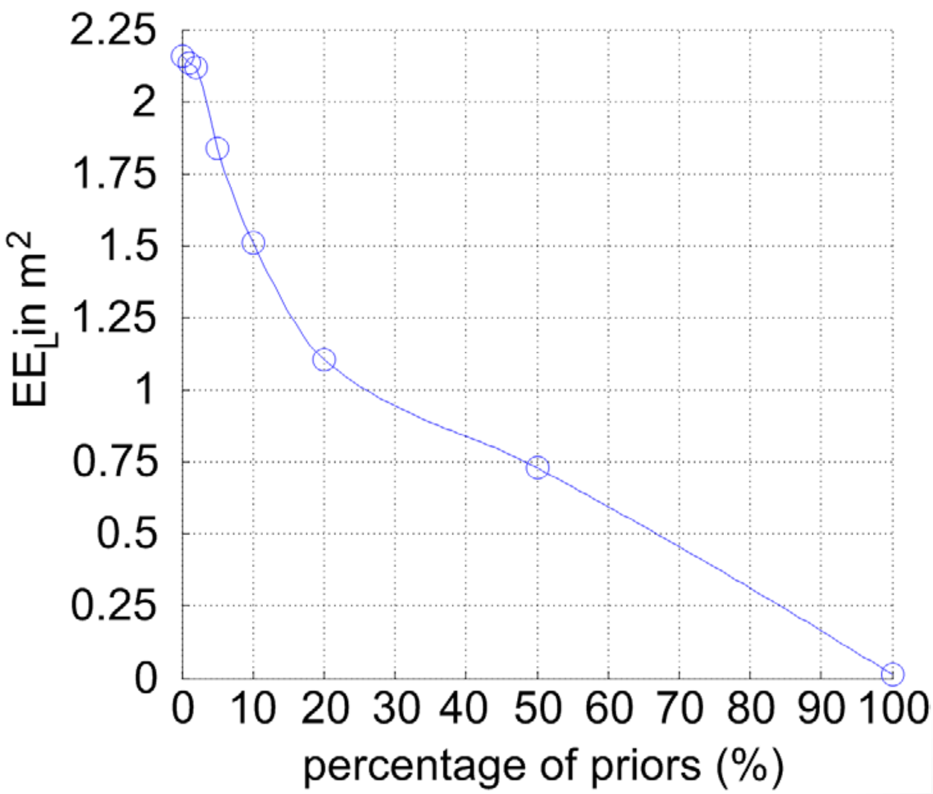
Radio model



Priors improve accuracy

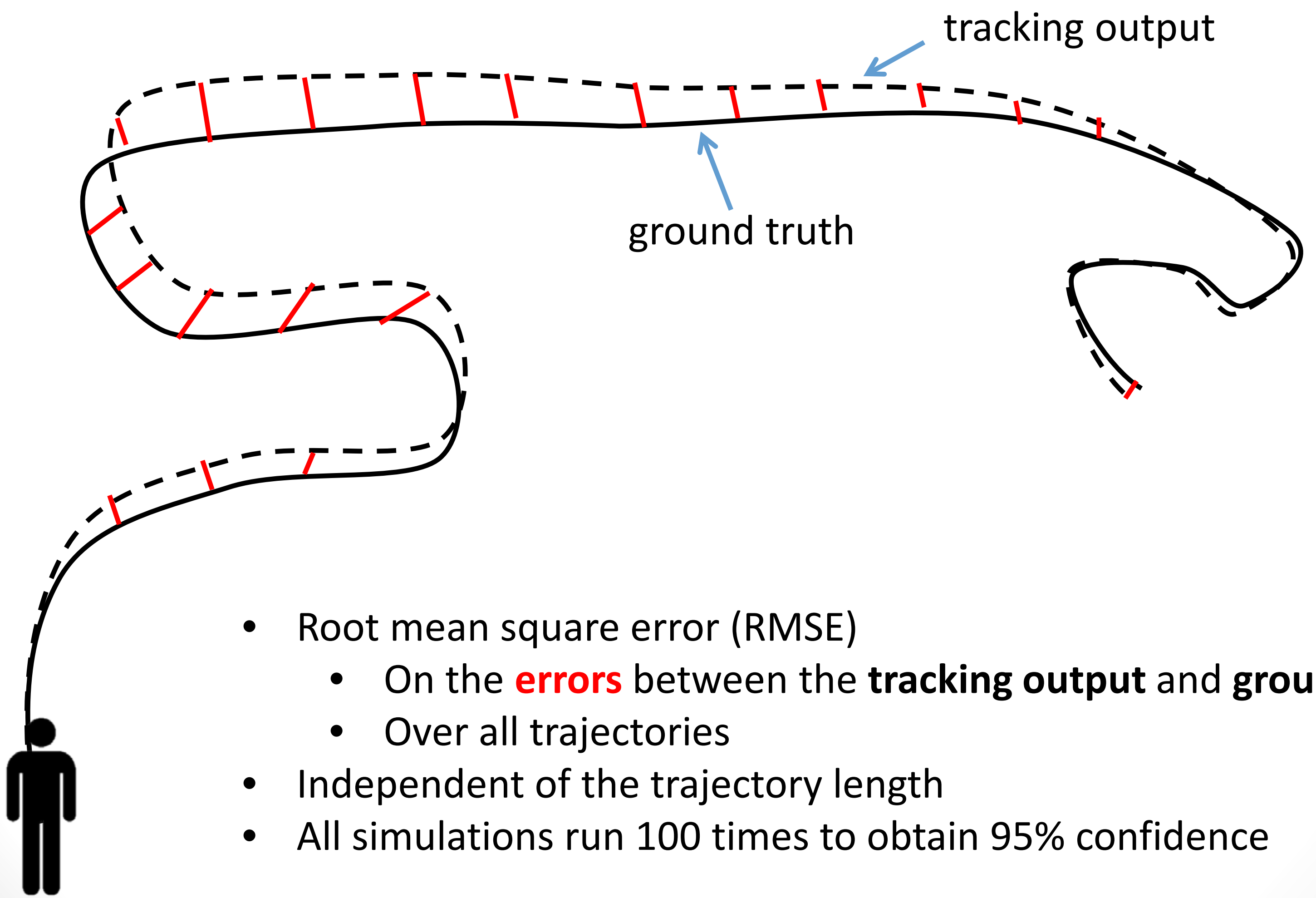
- Priors help the accuracy estimation
  - 20% of priors can reduce the estimation error by 50%

mean squared error between estimated accuracy and ground truth accuracy



Experimental setup

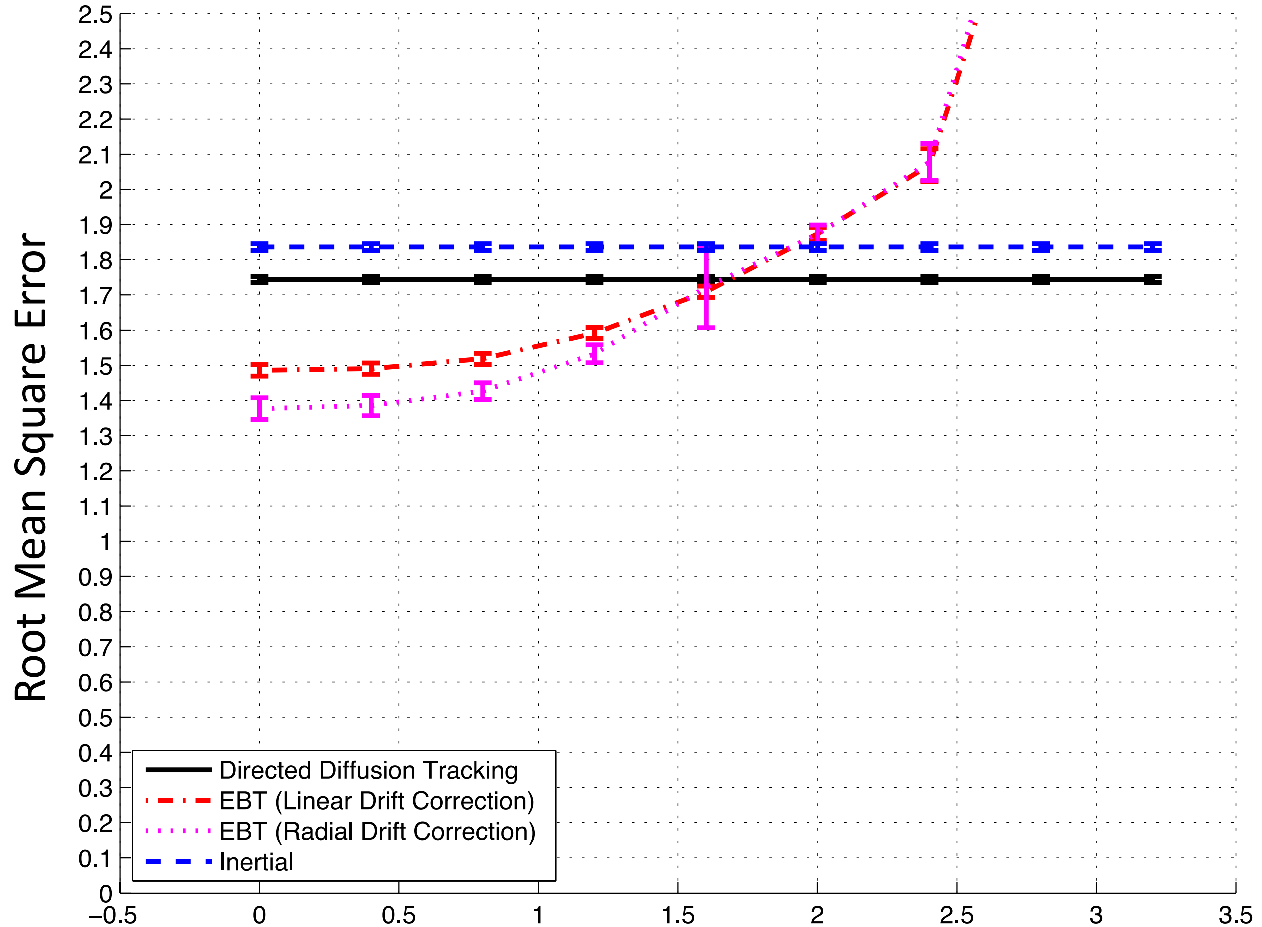
Performance metric



- Root mean square error (RMSE)
  - On the **errors** between the **tracking output** and **ground truth**
  - Over all trajectories
- Independent of the trajectory length
- All simulations run 100 times to obtain 95% confidence

Results: Radio noise

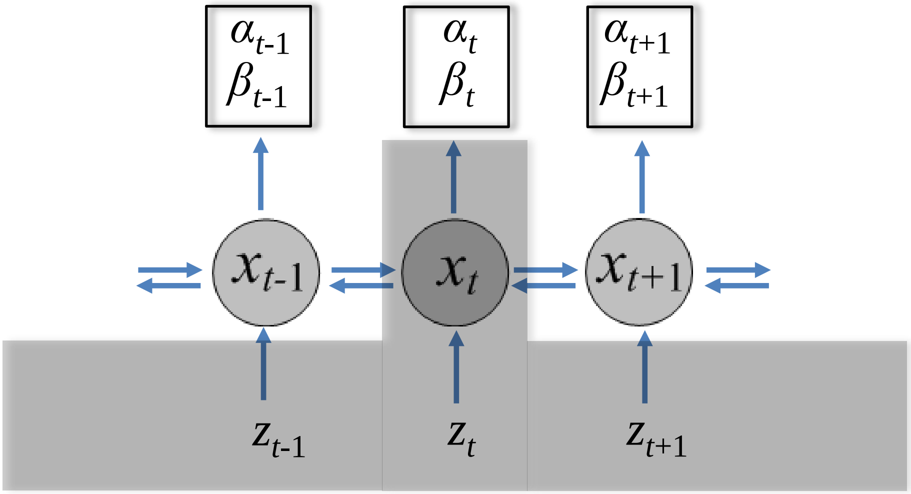
Effect of radio noise on tracking error (less is favourable)



Radio noise multiplier (scale factor for base RSSI variance)

Baum-Welch algorithm

- Forward and backward variables
  - $\alpha_t(j) = P(z_{1:t}, x_t = l_j \mid \lambda)$: joint probability of having all previous observations and landing at state l_j at time t, given the model parameter λ.
  - $\beta_t(i) = P(z_{t+1:T} \mid x_t = l_i, \lambda)$: probability of having all future observations given the state l_i at time t and the model λ
- Compute the new parameters $\lambda' = f(\alpha, \beta)$



Extension of Baum-Welch

- We use different definitions of forward and backward variables to take into account priors and probabilistic observations

- We provide a different function that combines forward and backward variables to infer the new parameters

Results: Number of anchors

Effect of number of anchors on tracking error (less is favourable)