Using the Magnetic Field for Indoor Localisation on a Mobile Phone

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Introduction

- localisation is precondition for LBS
- current indoor systems have several drawbacks
- smart phones provide useful sensors
  - accelerometer, magnetic field, light sensor

Figure: from building & automation [aut]

Motivation and Goals

- RF-based systems suffer from signal shielding
  - make positioning with fingerprint, RSSI etc. difficult
  - infrastructure is needed
- visual localisation is computationally intensive (not well feasible for mobile phones)
- little attention was paid to magnetic field based localisation
  - artificial fields are possible (but need infrastructure)
  - geo magnetic field is everywhere available
- light intensity is also possible
  - especially areas with static light

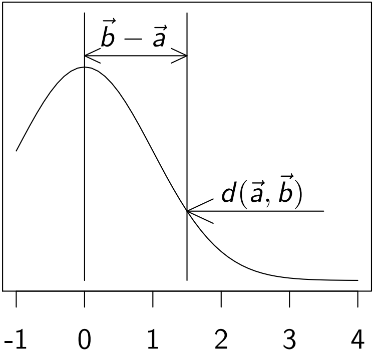
Fingerprint Approach

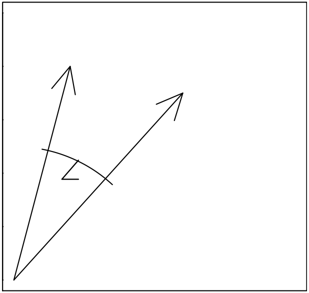
- geo magnetic field is distorted in buildings
- distortion can be recognised (fingerprinting)
- **off-line phase**
  - 3-axis magnetic field (+ light intensity) is saved
- **on-line phase**
  - actual sensor data is compared to saved one
  - different vector similarity functions are evaluated

Vector Similarity Functions

- Euclidean Distance

(a) Gaussian Sim. (b) Cosine Sim.



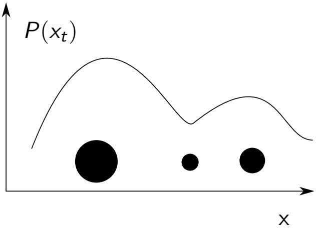


Problems Using Sensors

- sensors are affected by measurement errors (noise)
- position has always an error

Solution – Particle Filter

set of particles: consist of state and non negative weight:
$\mathfrak{X} = \{\langle x_i, w_i \rangle \mid i = 1, \ldots, N\}$



- multiple extensions available
- evaluation on accuracy benefit

Concept of Particle Filter – when data arrives

- each particle
  - move particle using movement model
  - evaluate position according to measured data
- apply resampling to avoid degeneracy
- determine position

Movement Model – $x_{i,t} \leftarrow P(x_t \mid x_{i,t-1})$ [Wid10]

Speed of a Particle

$$v_t = \mathcal{N}(v_{t-1}, \sigma_v) \quad \sigma_v = \min\left(Max_{\Delta t}, \sqrt{\Delta t}\right)$$

Direction of a Particle

$$\alpha_t = \mathcal{N}(\alpha_{t-1}, \sigma_\alpha) \quad \sigma_\alpha = 0{,}4\pi - \arctan\left(\frac{\sqrt{v_{t-1}}}{2}\right)$$

Updated Position

$$x_{i,t} = \begin{pmatrix} p^x_{i,t} \\ p^y_{i,t} \end{pmatrix} = \begin{pmatrix} p^x_{i,t-1} + v_{i,t}\cos\left(\alpha_{i,t}\right)\Delta t + \eta_t \\ p^y_{i,t-1} + v_{i,t}\sin\left(\alpha_{i,t}\right)\Delta t + \eta_t \end{pmatrix}$$

Measurement Model – $w_{i,t} \leftarrow P(z_t \mid x_{i,t})$

- particle is in state $x_{i,t}$
  - $w_{i,t}$: probability of a particle of being in state $x_{i,t}$
- when using fingerprints; state is equal to a fingerprint position
- comparison of measurement vector with data of fingerprint

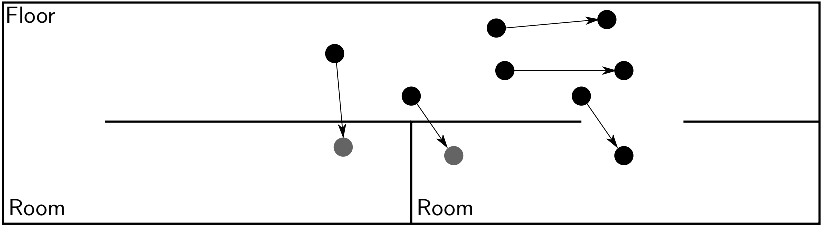
Total Probability

$$P(z_t \mid x_t) = P(m_{x,t} \mid x_t) \cdot P(m_{y,t} \mid x_t) \cdot P(m_{z,t} \mid x_t) \cdot P(l_t \mid x_t)$$

Particle Filter Extension: Wall Aspect [Wid10]

measurement model extension

$$w_{i,t} = \begin{cases} 0, & \text{if wall crossed} \\ P(z_t \mid x_{i,t}), & \text{else} \end{cases}$$



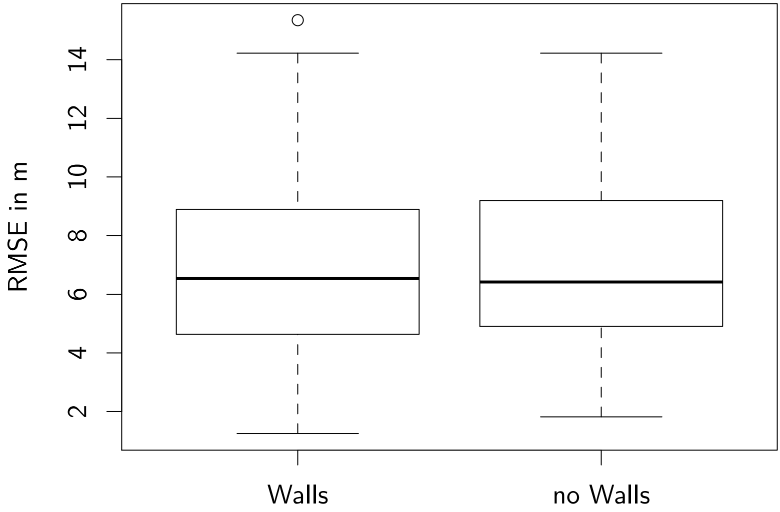
Testbed

- measurements take place in university office building
  - 52 fingerprints for complete floor
- five tests took place
- measurement data were saved for later evaluation

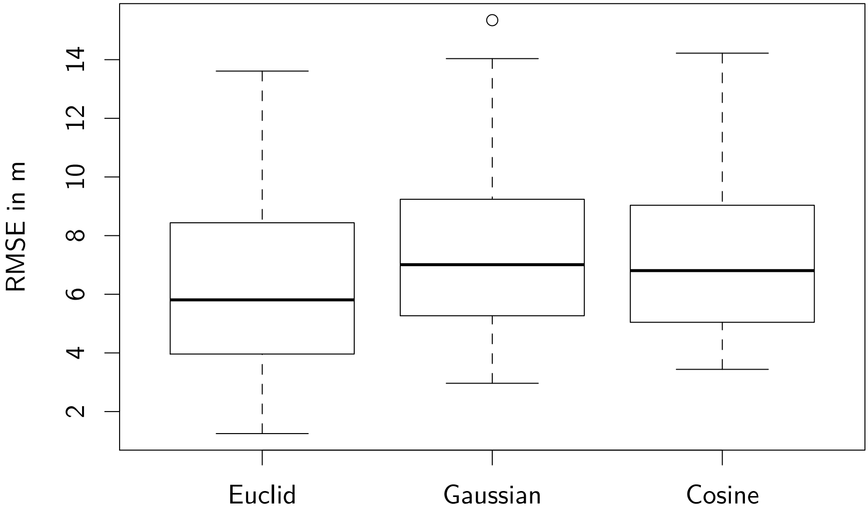
Evaluated Configurations

- influence of configurations on localisation accuracy
- data were used to simulate influence on different configurations
- configurations
  - wall aspect
  - direction
  - sensor combination
  - similarity functions
  - number of particles
- for each configuration: estimated position was compared with real
- RMSE as estimation error

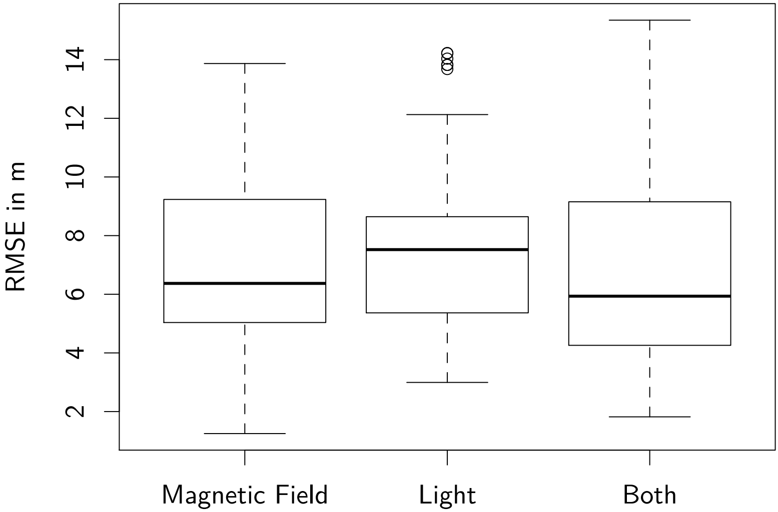
Using Wall Aspect



Different Similarity Functions



Different Sensors



Best Algorithm Configuration

- wall aspect: no influence on accuracy
  - but prevents algorithm from repositioning
- Euclidean distance as similarity function
- combination of light and magnetic field sensors
- at least 200 particles

Conclusion

- localisation using magnetic fields and ambient light is possible
- accuracy: $\approx$4.1 m in arithm. mean
- influence on different algorithm configurations was evaluated
- comparison to other systems:
  - infrastructure less
  - at least room level accuracy
  - extension possible with more sensors
- drawbacks:
  - high installation effort
  - other systems reach better accuracy

Further Work

- test more environments
- accuracy lowered if area increases
  - reduction of sensor noise—better recognition of fingerprints
  - magnetic field/light only as synchronisation point, else MEMS sensor

Questions?

Thank you for your attention.

Literatur I

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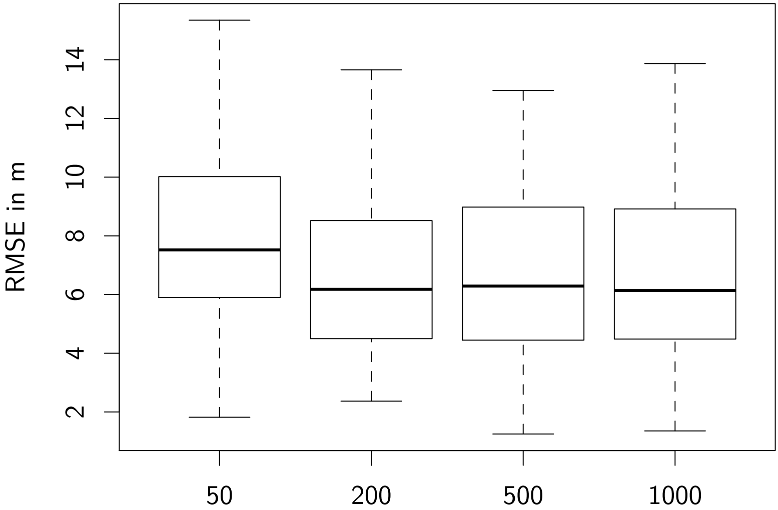
Different Number of Particles



Cummulative Probability Function