Server based Indoor Navigation Using RSSI and Inertial Sensor Information

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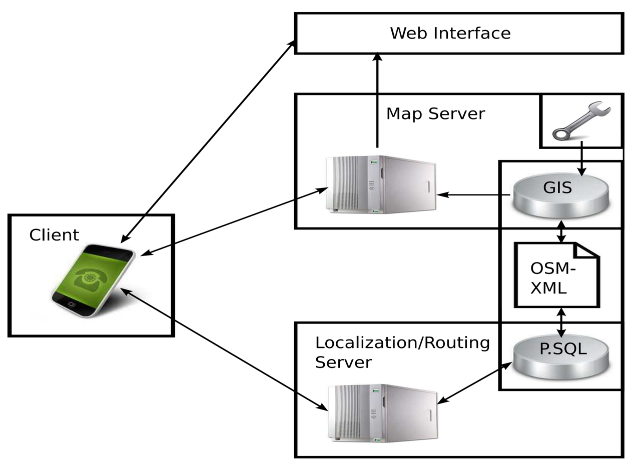
Introduction

- System for indoor navigation in a multi-level office building
- Server-Client architecture
  - Server: map tiles, localization & routing
  - Client: step detection, map visualization, RSSI measurements
- Hidden Markov Model
  - Fuses RSSI and step detection information
  - Enables position estimation even in areas without WiFi access points

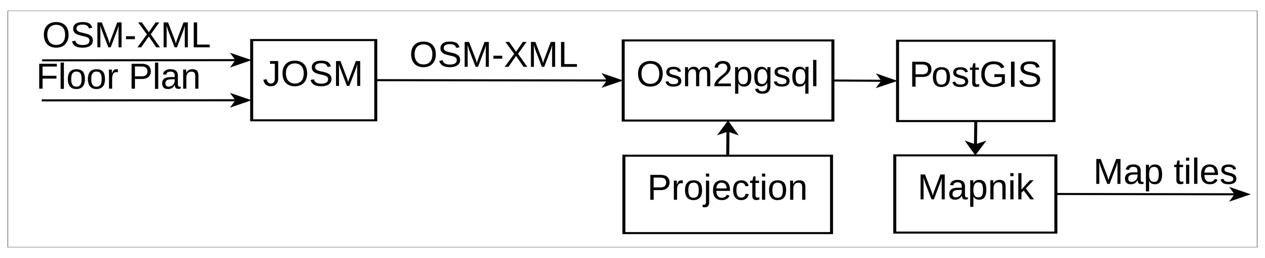
System overview

- Server infrastructure
  - Web interface for data exchange
  - Provides services for localization & routing
  - Reduced computational complexity on smartphone



- Smartphone application
  - Displays map & user's position
  - Displays calculated route
  - Gesture based map and route exploration

Map database

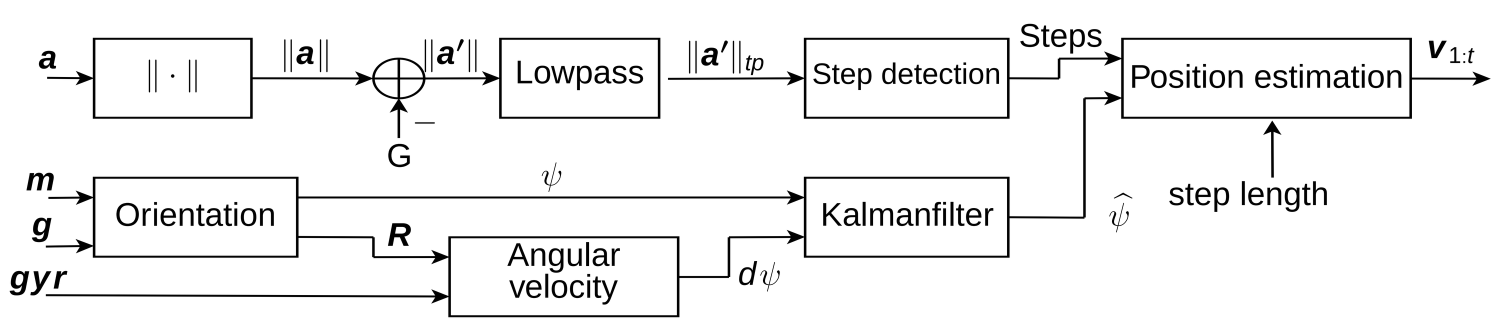


- OSM database delivers raw data for building bounds
- Hand-created indoor map data
- Regards aspects of multi-level buildings

Fingerprint database

- Stores the WiFi information together with the map data in a PostGIS database
- Stores RSSI measurements either offline or online
- Single extendible database for the campus

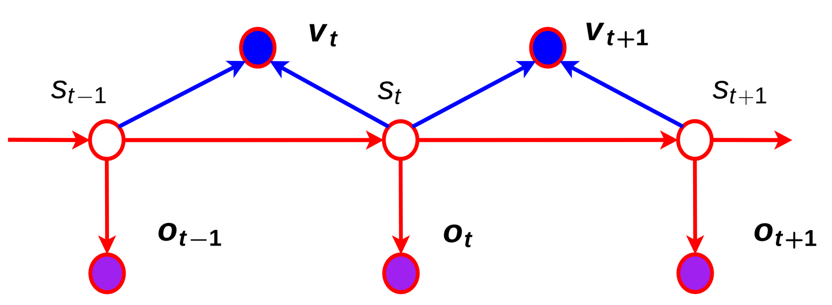
Inertial Navigation



- Step detection uses accelerometer data $\boldsymbol{a}$
- Movement heading estimation uses a Kalman filter to fuse the magnetometer $\boldsymbol{m}$, gravity $\boldsymbol{g}$ and gyroscope data $\boldsymbol{gyr}$
- Accumulates steps and movement heading estimations towards movement vector $\boldsymbol{v}$

Hidden Markov Model

- Hidden state variable at time instance t: s_t
- RSSI: $\boldsymbol{o}_{1:t} = [\boldsymbol{o}_1, \ldots \boldsymbol{o}_t]$
- Step: $\boldsymbol{v}_{1:t} = [\boldsymbol{v}_1, \ldots \boldsymbol{v}_t]$



- Probability of being in j-th state at time instance t:

$$P(s_t{=}j|\boldsymbol{v}_{1:t}, \boldsymbol{o}_{1:t}) \sim P(s_t{=}j, \boldsymbol{v}_{1:t}, \boldsymbol{o}_{1:t}) := \alpha_t(j)$$

where

$$\alpha_t(j) = \sum_i p(\boldsymbol{v}_t|s_t{=}j, s_{t-1}{=}i) \cdot p(\boldsymbol{o}_t|s_t{=}j) \cdot P(s_t{=}j|s_{t-1}{=}i) \cdot \underbrace{P(s_{t-1}{=}i, \boldsymbol{v}_{1:t-1}, \boldsymbol{o}_{1:t-1})}_{=\alpha_{t-1}(i)}$$

- Movement information:
  - $\boldsymbol{\mu}_{i,j} = \boldsymbol{\ell}_j - \boldsymbol{\ell}_i$
  - Σ_v: predefined diagonal covariance matrix

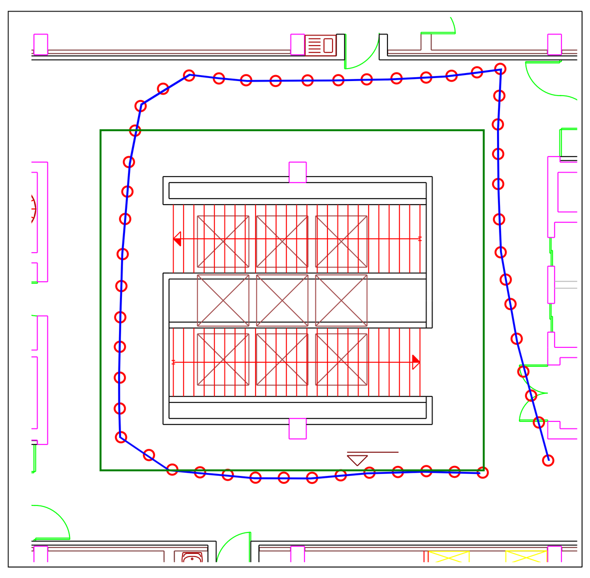
$$p(\boldsymbol{v}_t|s_t{=}j, s_{t-1}{=}i) = \frac{e^{\left(-\frac{1}{2}(\boldsymbol{v}_t-\boldsymbol{\mu}_{i,j})^T \Sigma_v^{-1}(\boldsymbol{v}_t-\boldsymbol{\mu}_{i,j})\right)}}{\sqrt{(2\pi)^2|\Sigma_v|}}$$

- RSSI likelihood: $p(\boldsymbol{o}_t|s_t{=}j) = \prod_{i=1}^{N_{AP}} p(o_i|\boldsymbol{\ell}_j)$
  - $\boldsymbol{\ell}_j$: the location when $s_t{=}j$
  - o_i: observation of the i-th AP in the RSSI measurement $\boldsymbol{o}_t$
- Transition probability: $P(s_t{=}j|s_{t-1}{=}i)$
- Position estimate: weighted average over the set of the most likely positions $\mathcal{P}$:

$$\hat{\ell} = \frac{1}{\sum_{k\in\mathcal{P}} p(s_t = k|\boldsymbol{v}_{1:t}, \boldsymbol{o}_{1:t})} \sum_{k\in\mathcal{P}} p(s_t = k|\boldsymbol{v}_{1:t}, \boldsymbol{o}_{1:t})\boldsymbol{\ell}_k.$$

Experiments

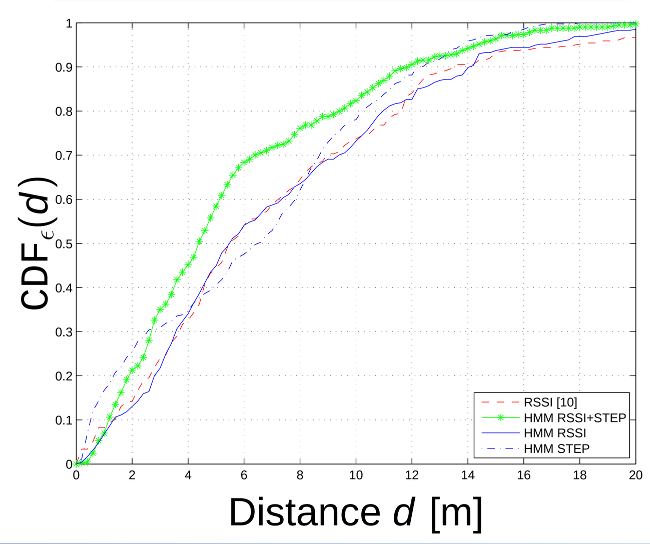
- Step detection example in a staircase
  - Movement heading estimate was highly affected by eletrical machines (right side)
  - Localization remains in sufficient accuracy



- Field data
  - CDF is defined as:

$$\mathrm{CDF}_\epsilon(d) = P(\epsilon \leq d) \quad d \geq 0$$

  - Proposed approach mostly outperforms the other approaches which only use RSSI or step detection information



Conclusions

- Flexible client-server architecture for indoor navigation
  $\Rightarrow$ Offers navigation services to low-cost smartphones
- Step detection system for dead reckoning
  $\Rightarrow$ Route guidance even if no internet access is available