A Hidden Markov Model for Indoor User Tracking Based on WiFi Fingerprinting and Step Detection

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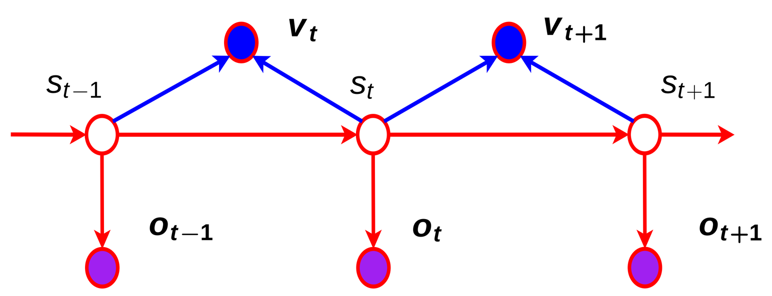
Introduction

- Hidden Markov models (HMM) for data fusion of
  - WiFi received signal strength index (RSSI)
  - Inertial sensor information
- Introduction of "pseudo" HMM states
  - To reduce quantization error due to finite number of HMM states and thus allowable user positions
  - Their emission probabilities are synthesized by those of "real" states
- Forward algorithm for position estimation

HMM based Sensor Fusion

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



- 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" likelihood (from step detection):

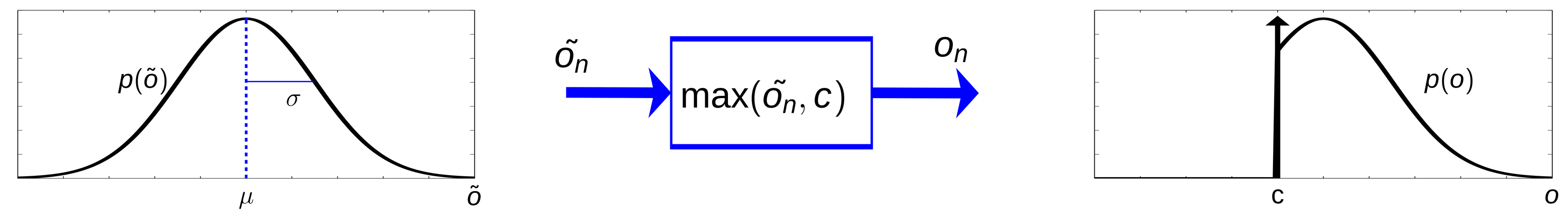
$$p(\boldsymbol{v}_t|s_t{=}j, s_{t-1}{=}i) = \mathcal{N}(\boldsymbol{v}_t; \boldsymbol{\mu}_{i,j}, \Sigma_v)$$

  where
    - $\mu_{i,j} = \ell_j - \ell_i$
    - Σ_v: predefined diagonal covariance matrix
  - RSSI likelihood: $p(\boldsymbol{o}_t|s_t{=}j)$
  - Transition probability: $P(s_t{=}j|s_{t-1}{=}i)$
- Position estimate: weighted average over the set of the most likely positions $\mathcal{P}$:

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

Treatment of Censored Data

- Censored observations due to the limited sensitivities of WiFi sensor



$\tilde{o}_n, n = 1, ..., N$: complete data — $o_n, n = 1, ..., N$: observed data

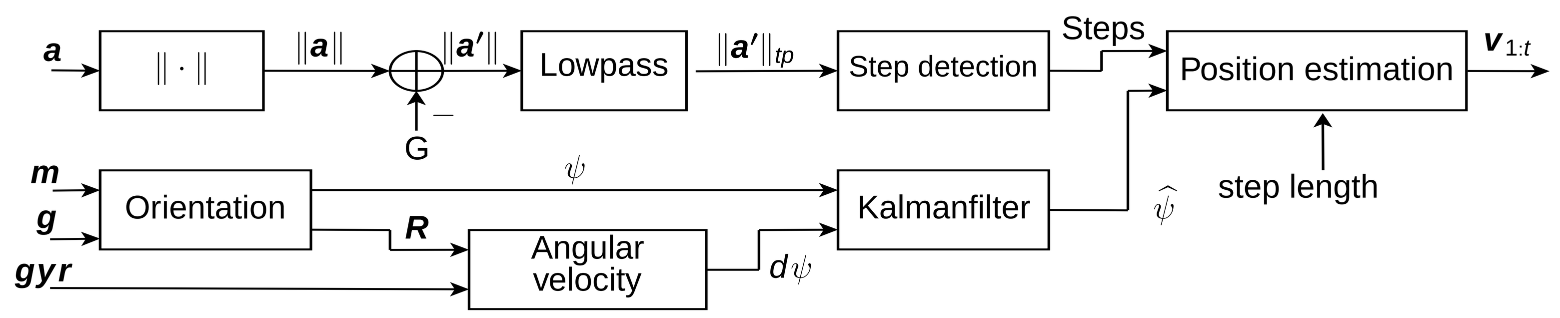
- Likelihood calculation

$$p(\boldsymbol{o}|\ell_k) = \prod_{i=1}^{N_{AP}} p(o_i|\ell_k) \quad \text{where} \quad p(o_i|\ell_k) = \begin{cases} \mathcal{N}(o_i; \hat{\mu}_{\ell_k,i}, \hat{\sigma}^2_{\ell_k,i}), & \text{if } o_i > c \\ I_0(\hat{\mu}_{\ell_k,i}, \hat{\sigma}^2_{\ell_k,i}), & \text{if } o_i = c \end{cases}$$

$$I_0(\hat{\mu}_{\ell_k,i}, \hat{\sigma}^2_{\ell_k,i}) = \int_{-\infty}^{c} \mathcal{N}\left(y; \hat{\mu}_{\ell_k,i}, \hat{\sigma}^2_{\ell_k,i}\right) dy$$

- For parameter estimation $(\hat{\mu}_{\ell_k,i}, \hat{\sigma}^2_{\ell_k,i})$, see [1]

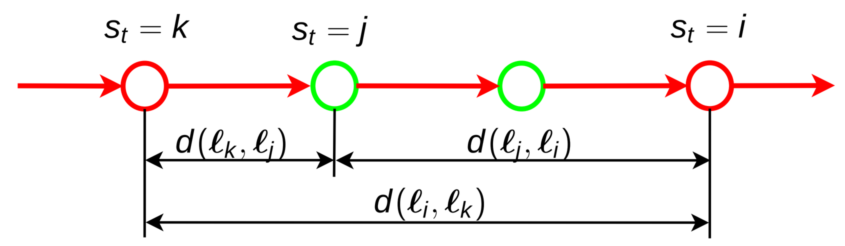
Inertial Navigation



- 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 $\boldsymbol{gyr}$
- Join step detection and movement heading estimation to obtain $2{-}D$ movement vector $\boldsymbol{v}$

Introduction of Pseudo States

- Reduce quantization error without increasing the training effort

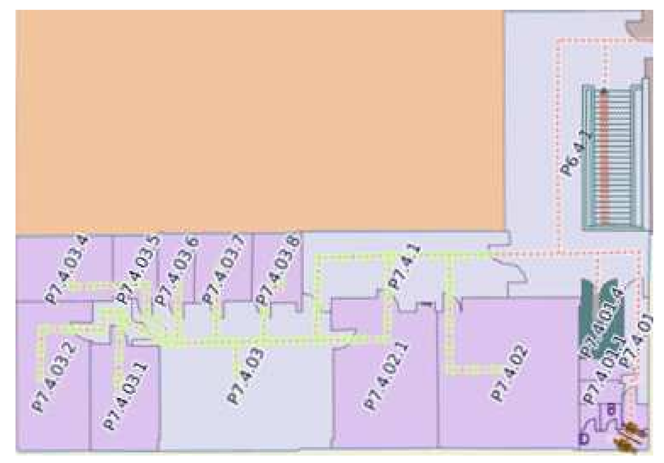


- Synthezise the emission probability density function of pseudo state j from those of regular states i and k

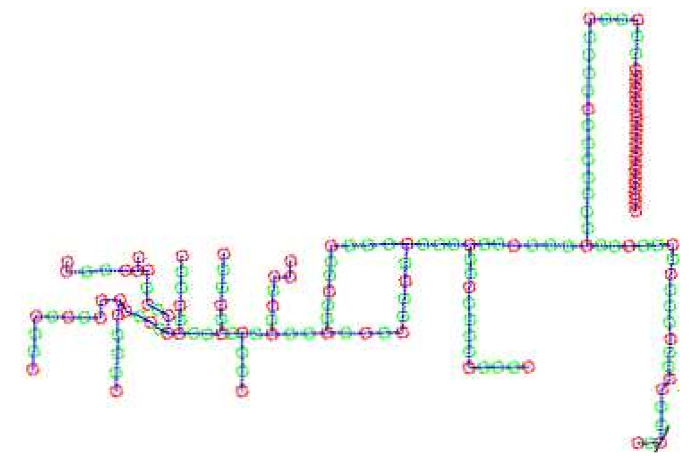
$$p(o|s_t = j) = p(o|s_t = k)^{\frac{d(\ell_i,\ell_j)}{d(\ell_i,\ell_k)}} p(o|s_t = i)^{\frac{d(\ell_k,\ell_j)}{d(\ell_i,\ell_k)}} = \mathcal{N}(o|\mu_{\ell_j}, \sigma^2_{\ell_j})$$

Experimental Results

- Testing area



Floor plan (23 m x 34 m)

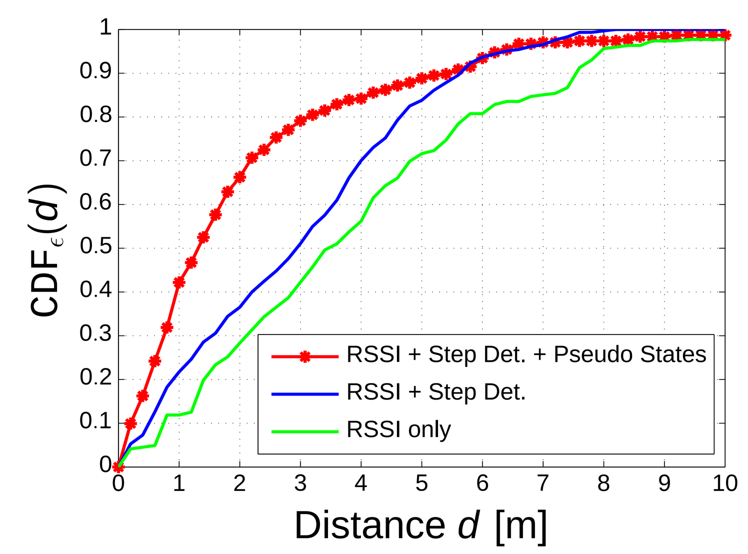


HMM with regular and pseudo states

- Classification on artificial data: $N_{AP} = 15$ access points, $N = 300$ training measurements at each regular state

Method	Mean Error [m]
RSSI only	1.74
RSSI + Step Det.	1.37
RSSI + Step Det. + Pseudo States	1.02

- Classification on field data:
  - Proposed method outperforms the others w.r.t. accuracy, especially up to 90% error quantile



Conclusions

- HMM to fuse the RSSI and step detection information
- Forward algorithm for position estimation
- Introduction of pseudo states significantly reduces positioning error
- The effectiveness of the proposed algorithm for indoor positioning was demonstrated both on artificial data and on field data

K. Hoang and R. Haeb-Umbach,
"Parameter Estimation and Classification of Censored Gaussian Data with Application to WiFi Indoor Positioning,"
in *Proc. ICASSP*, Vancouver, May 2013, IEEE.