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

M.K. Hoang, J. Schmalenstroeer, C. Drueke, D.H. Tran Vu, R. Haeb-Umbach, University of Paderborn, Germany
{hoang, schmalen, tran, haeb}@nt.uni-paderborn.de, http://www-nt.uni-paderborn.de

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: $o_t = [o_1, \ldots, o_l]$ (where $o_l$ represents an RSSI level)
- Step: $v_{1:t} = [v_{1,1}, \ldots, v_{t,1}]$

Probability of being in $j$-th state at time instance $t$:
$$P(S_t = j | v_{1:t}, o_{1:l}) = P\left(S_t = j | v_{1:t}, o_{1:l} = o_t(j)\right)$$

- "Movement" likelihood (from step detection):
$$p(v_t | S_{t-1}) = N\left(v_t | \mu_{ij}, \Sigma_v\right)$$

Inertial Navigation

- Step detection uses accelerometer data $a$
- Movement heading estimation uses a Kalman filter to fuse the magnetometer $m$, gravity $g$ and gyroscope data $gyr$
- Join step detection and movement heading estimation to obtain $2D$ movement vector $v$
- For parameter estimation ($\hat{\mu}_{ik}, \hat{\sigma}^2_{ik}$), see [1]

Treatment of Censored Data

- Censored observations due to the limited sensitivities of WiFi sensor
- Likelihood calculation
$$p(o_k | \hat{\mu}_{k}, \hat{\sigma}^2_{k}) = \int_0^\infty N\left(y | \hat{\mu}_{k}, \hat{\sigma}^2_{k}\right) \, dy$$

Experimental Results

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

Mean Error [m]

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean Error [m]</th>
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<tbody>
<tr>
<td>RSSI only</td>
<td>1.74</td>
</tr>
<tr>
<td>RSSI + Step Det.</td>
<td>1.37</td>
</tr>
<tr>
<td>RSSI + Step Det. + Pseudo States</td>
<td>1.02</td>
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