Transferring Localization Models Over Time

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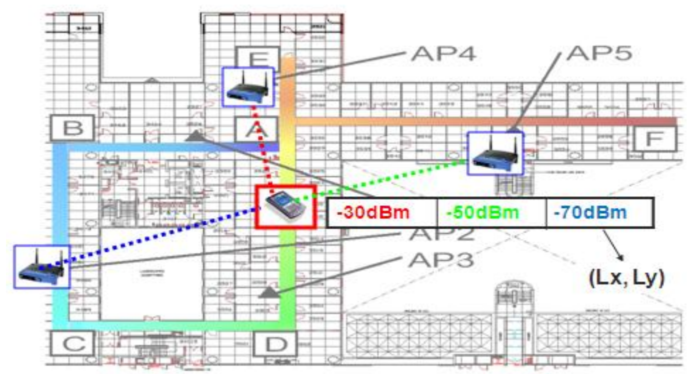
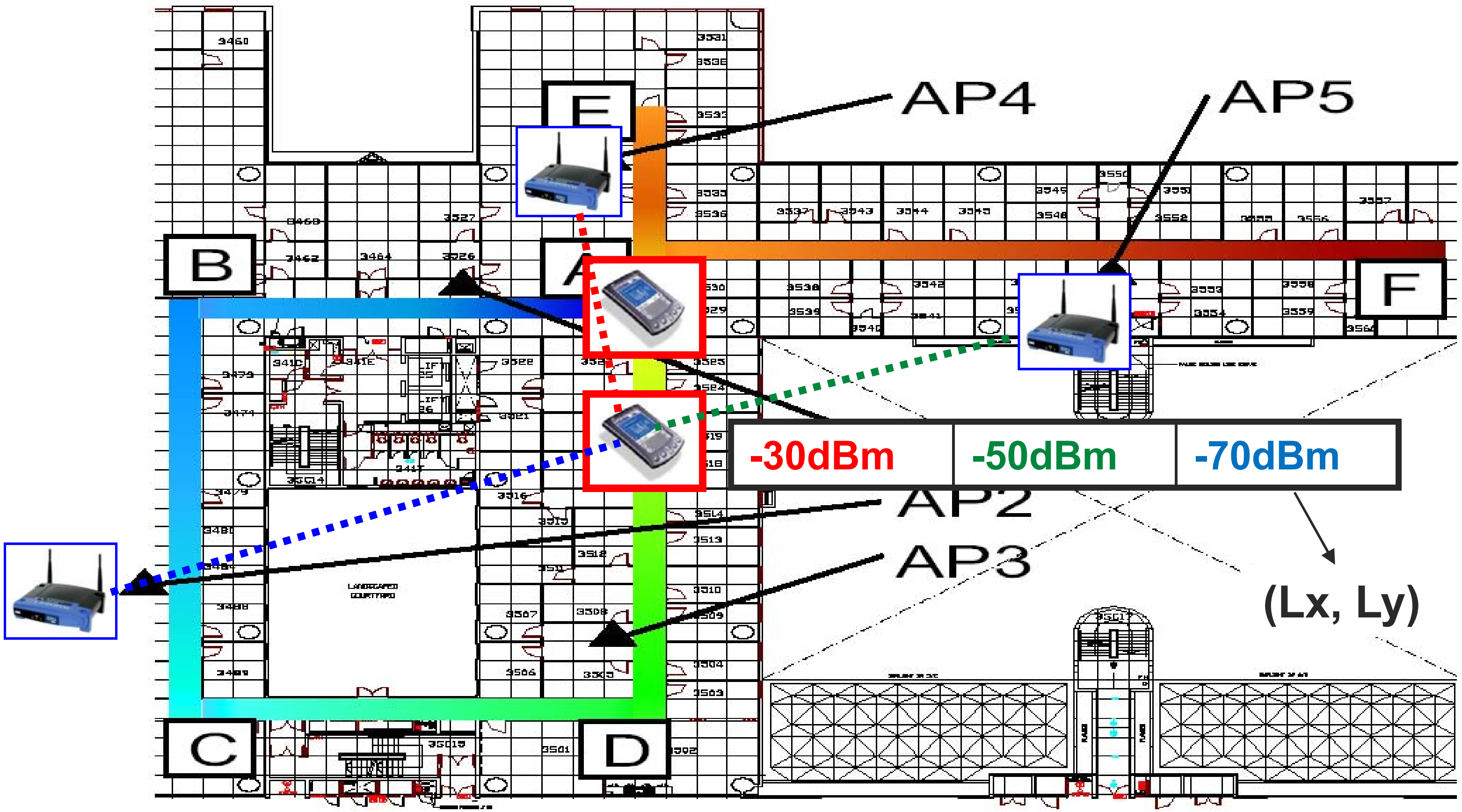


Signal-strength-based Localization



Learning-based Location Estimation

- Two phases: training and localization
- **Training phase** – collect a set of signal-location pairs and learn a mapping function

(AP1, AP2, AP3)	(Lx, Ly)
(-30, -50, -70) dBm	(2, 7) m
(-40, -45, -75) dBm	(3, 11) m
…….	…

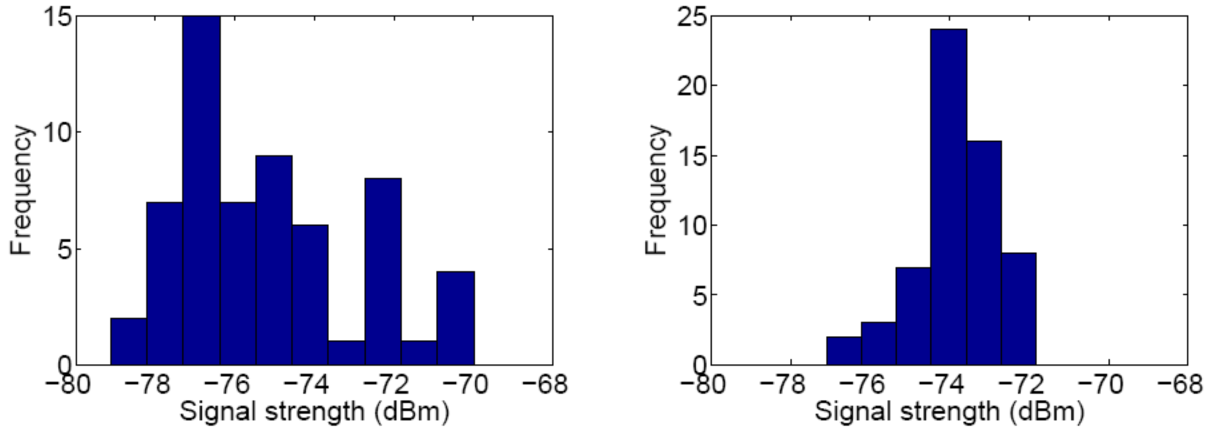
Mapping function
from signal to location

$$F : S \rightarrow L$$

- **Localization phase** – given a signal S, predict its most probable location L = F(S)

Our focus: signal variation over time

- Traditional localization methods assume:
  - Training and testing data have same distributions
  - Do not address whether localization model is out-of-date
- However, in practice,
  - Different time periods, different signal distributions



(a) WiFi signal at time period 1 (b) WiFi signal at time period 2

Related works

- Only some work address the signal variation over time

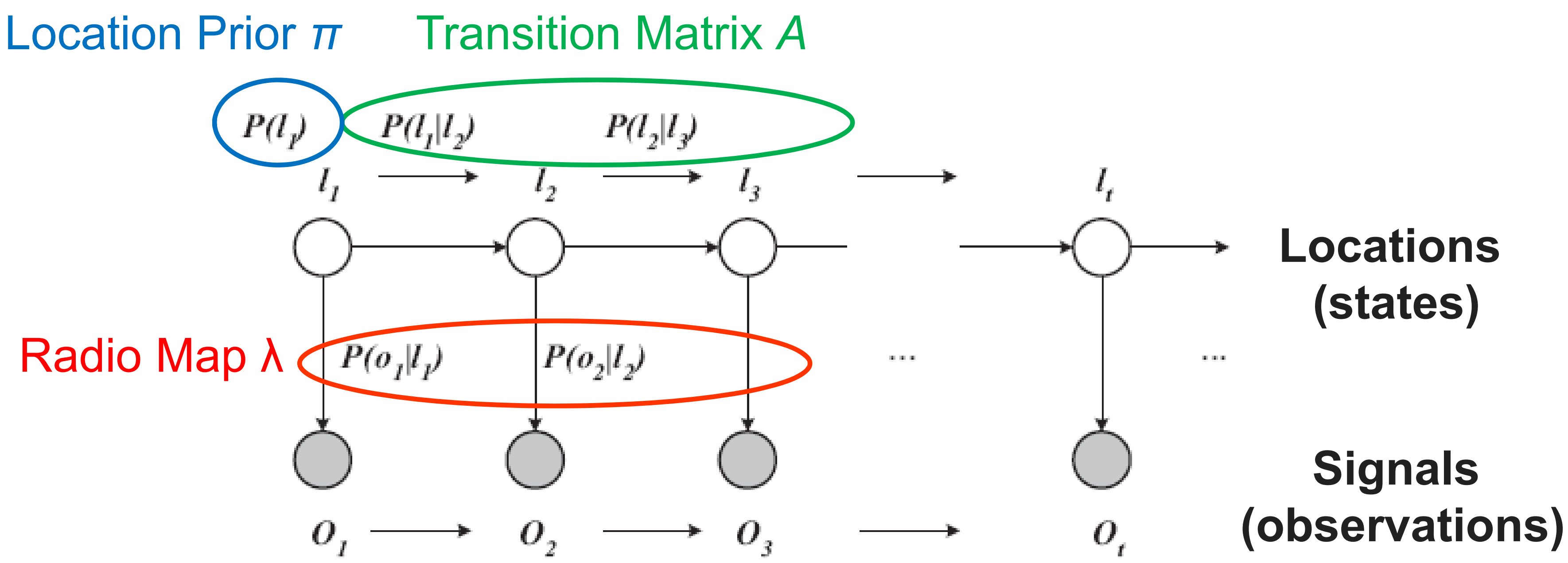
Algorithm	Basic idea	Con's
RADAR (Bahl *et al.* 2000)	KNN	Do not consider signal variation.
LANDMARC (Ni *et al.* 2003)	Weighted-KNN	Require a large amount of hardwares.
ModelTree (Yin *et al*. 2005)	Regression analysis and decision tree	Do not use the user trace information.
LeManCoR (Pan *et al*. 2007)	Manifold co-regularization	Do not use the user trace information.

Transferring Localization Models over Time

- The Question:
  - Given some labeled out-of-date data, how to use as few up-to-date labeled/unlabeled data as possible to calibrate the localization model?
- Our Solution: Transferred HMM (TrHMM)
  - Exploit the HMM for localization
  - What to transfer? – uncover which parts of the model knowledge can be reused, and which parts need to be adapted by up-to-date information
  - How to transfer? – A domain-specific solution for HMM model transfer

Our Solution: Transferred Hidden Markov Model

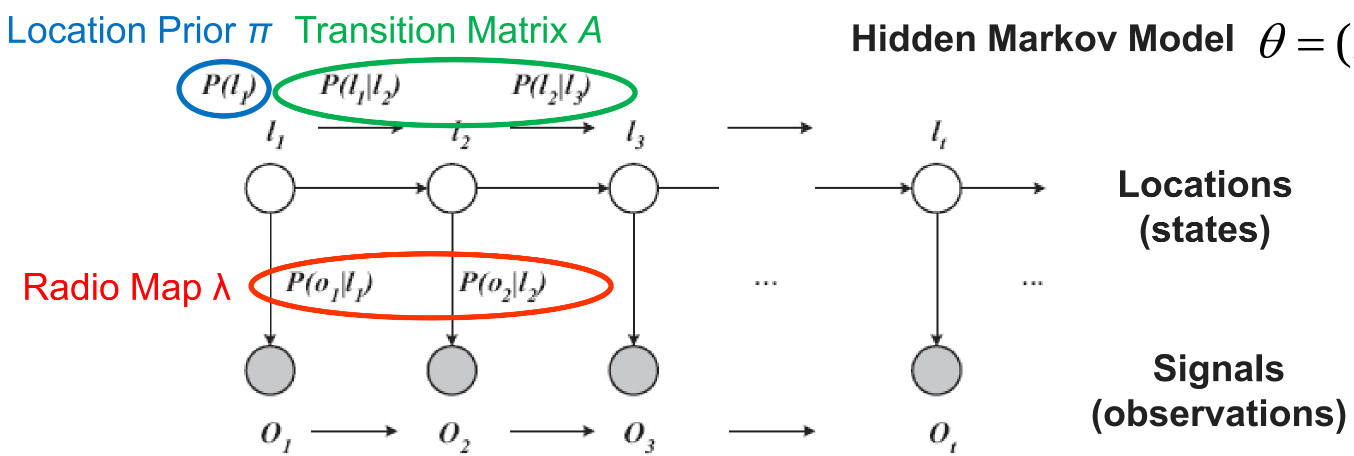
- Hidden Markov Model – $\theta = (\lambda, A, \pi)$



Our Solution: Transferred Hidden Markov Model (Cont')

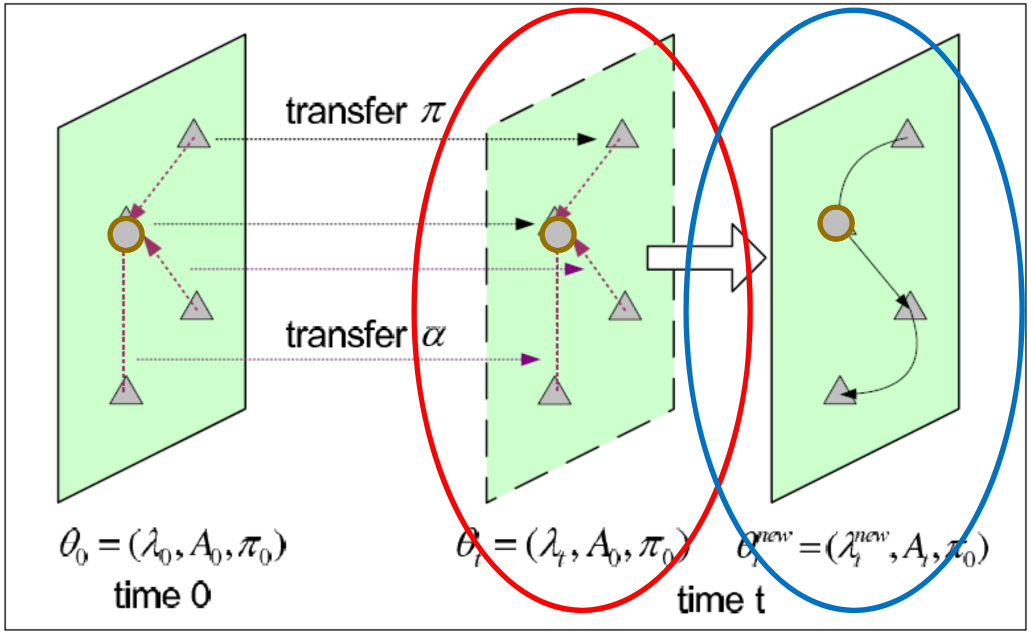
- What to transfer?
  - λ changes, due to signal variation over time
  - A changes, since behaviors are different at different time
  - π keep unchanged, since basic behaviors does not vary much

Hidden Markov Model $\theta = (\lambda, A, \pi)$



Our Solution: Transferred Hidden Markov Model (Cont')

- How to transfer?



Update radio map:

(1) Employ reference points* to collect up-to-date signals;
(2) Apply regression analysis to fit the signals on non-reference points.

Update transition matrix & radio map:

(1) Collect unlabeled traces;
(2) Expectation maximization (EM) to update the model.

* Reference points are the hardware installed in the environment to continuously collect signals.

Our Solution: Transferred Hidden Markov Model (Cont')

- Update the radio map
  - Step 1 – at time 0, for each AP *j*, fit the (signal) regression model α among reference points and non-reference point *k*

    $$s_j^k = \alpha_{0j}^k + \alpha_{1j}^k r_{1j} + \cdots + \alpha_{nj}^k r_{nj} + \varepsilon_j$$

    where, r_{ij} is the signal at reference point *i* (*i* =1,…,n).
  - Step 2 – at time t, collect up-to-date signals on reference points, and use α to predict signals on non-reference points;
  - Step 3 – update the radio map by trading off predicted value with the base radio map

$$\mu_t = \beta \cdot \mu_0 + (1-\beta) \cdot \mu_t^{reg}$$

$$\Sigma_t = \beta \cdot \left[\Sigma_0 + \left(\mu_t - \mu_0 \right) \left(\mu_t - \mu_0 \right)^T \right] + (1-\beta) \cdot \left[\Sigma_t^{reg} + \left(\mu_t - \mu_t^{reg} \right) \left(\mu_t - \mu_t^{reg} \right)^T \right]$$

Our Solution: Transferred Hidden Markov Model (Cont')

- Update the transition matrix & radio map
  - Step 1 – collect up-to-date unlabeled traces $T=\{tr_i\}$
  - Step 2 – expectation maximization to update model
    - E-step:

$$P(q \mid tr, \theta^k) = \frac{P(tr, q \mid \theta^k)}{P(tr \mid \theta^k)} = \frac{P(tr \mid q, \theta^k) P(q \mid \theta^k)}{\sum_q P(tr \mid q, \theta^k) P(q \mid \theta^k)}$$

where, $P(tr \mid q, \theta^k) = \prod_{n=1}^{|tr|} P(\mathbf{o}^n \mid l^n, \theta^k)$ … λ

$$P(q \mid \theta^k) = P(l^1 \mid \theta^k) \times \prod_{n=1}^{|tr|} P(l^n \mid l^{n-1}, \theta^k)$$ … π + A

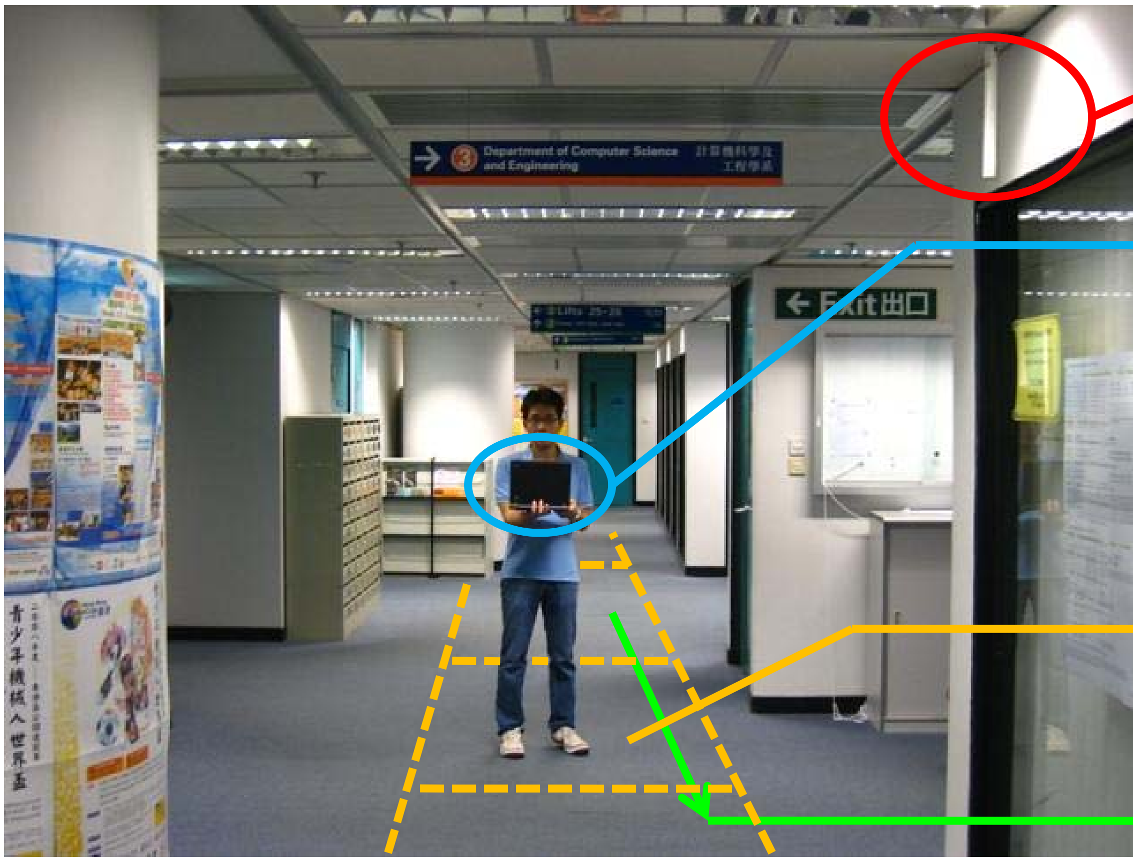
    - M-step:

$$\theta^{k+1} = \arg\max_\theta Q(\theta, \theta^k) = \arg\max_\theta \sum_{tr \in T} \sum_q P(q \mid tr, \theta^k) \log P(tr, q \mid \theta)$$

The Algorithm for TrHMM

- Input: Labeled data at time 0, labeled data from reference points and unlabeled traces at time *t*, test traces at time t
- Output: labels for test traces
- Training phase
  - Time 0 – build the base Hidden Markov Model θ_0
  - Time t – update the base model to θ_t
    - update the radio map λ – regression analysis by using reference points data
    - update the transition matrix *A* – EM by using unlabeled traces data
- Localization phase
  - Predict the labels for test traces by using updated model θ_t

Experimental Setup



WiFi Access Point (AP)

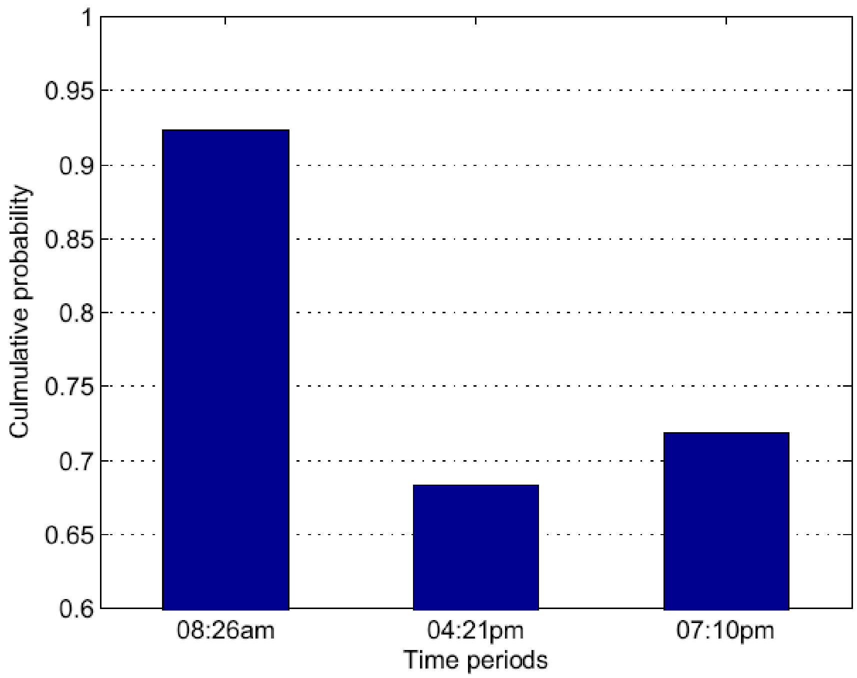
Collect WiFi signals

Academic building
64 x 50 m^2,
discretized into 118
1.5x1.5 m^2 grids.
Each grid = a reference point

User moves in the building

Experimental Results

- Necessity for considering time-variation problem



Time 0:
08:26am

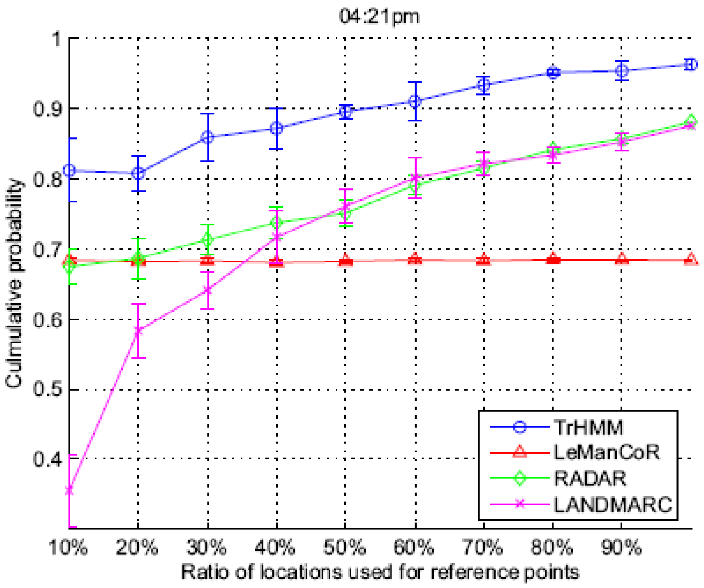
Time t:
04:21pm & 07:10pm

Measurement:
prediction accuracy*
(with 3-meter error distance)

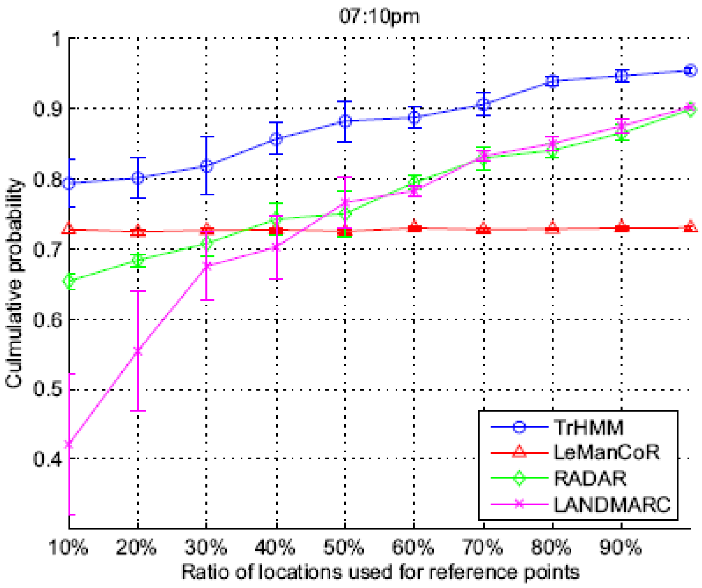
* The *higher*, the *better*.

Experimental Results (Cont')

- Impact of reference points (labeled data)



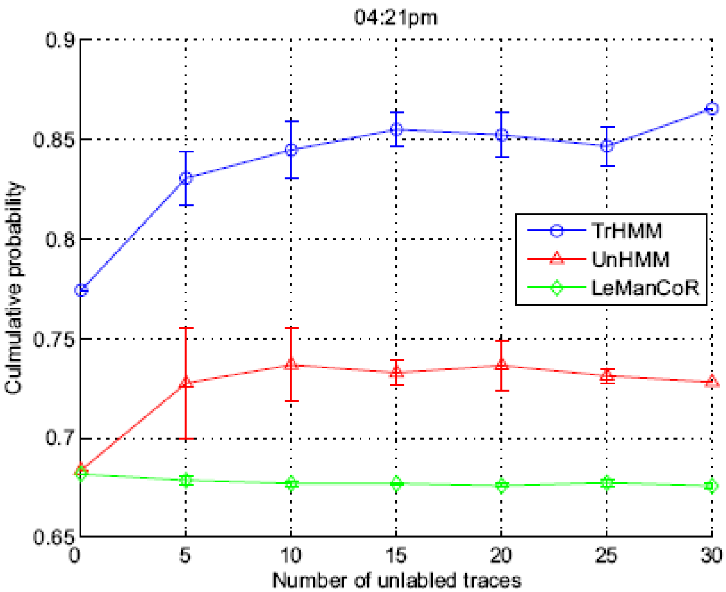
(a) Impact of reference points for 04:21pm



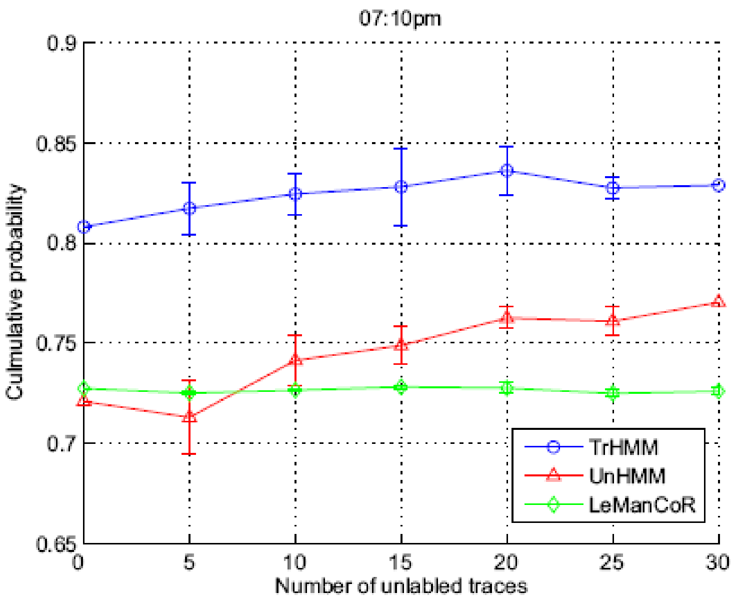
(b) Impact of reference points for 07:10pm

Experimental Results (Cont')

- Impact of unlabeled traces (unlabeled data)



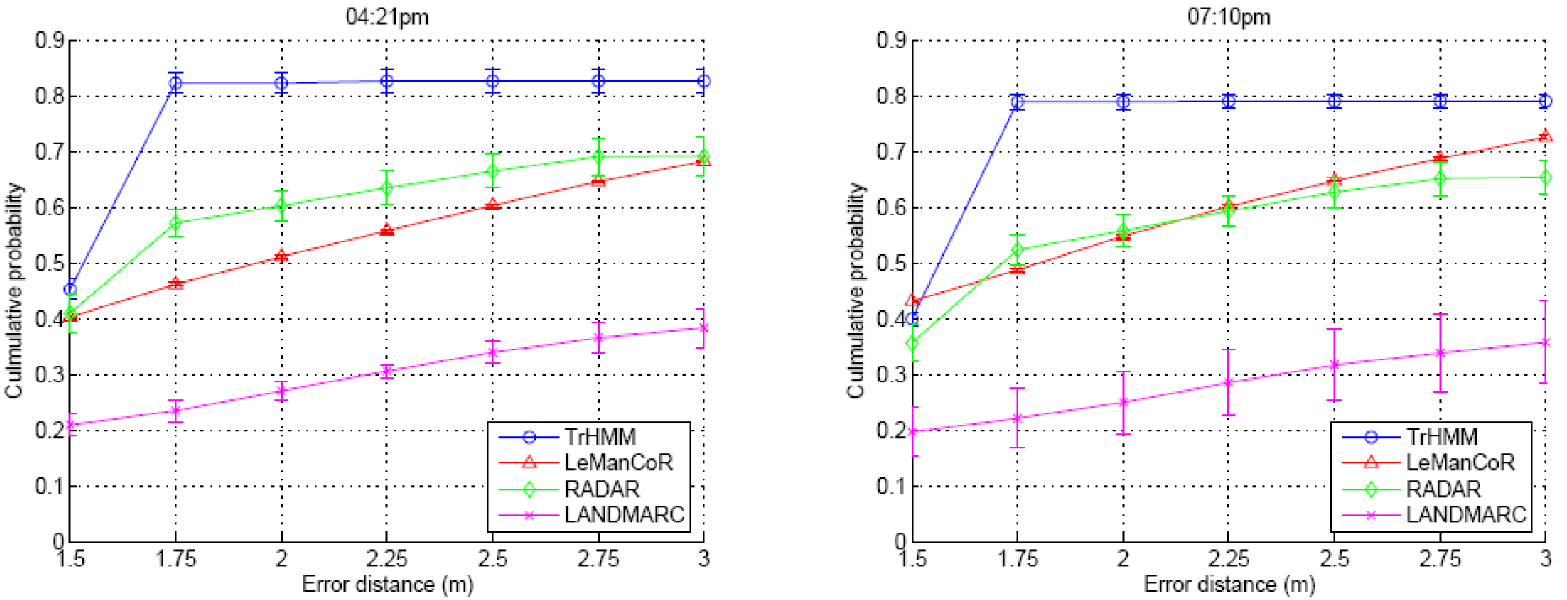
(c) Impact of unlabeled data for 04:21pm



(d) Impact of unlabeled data for 07:10pm

Experimental Results (Cont')

- Sensitivity to error distance



(e) Sensitivity to error distance for 04:21pm (f) Sensitivity to error distance for 07:10pm

Conclusion and Future Work

- The Algorithm **Conclusion**
  - Signal variation over time
  - Transferred Hidden Markov Model
  - Utilize the out-of-date data to help update model
  - Regression analysis and EM optimization

- Algorithm level **Future Work**
  - Extend to online setting
  - Exploit how to optimally select subset of labeled data
- Application level
  - Incorporate transfer learning with Gaussian Process (*Ferris, Fox, & Lawrence 2007*) for localization

The End

Thank You !

Welcome to our poster presentation!

Questions?