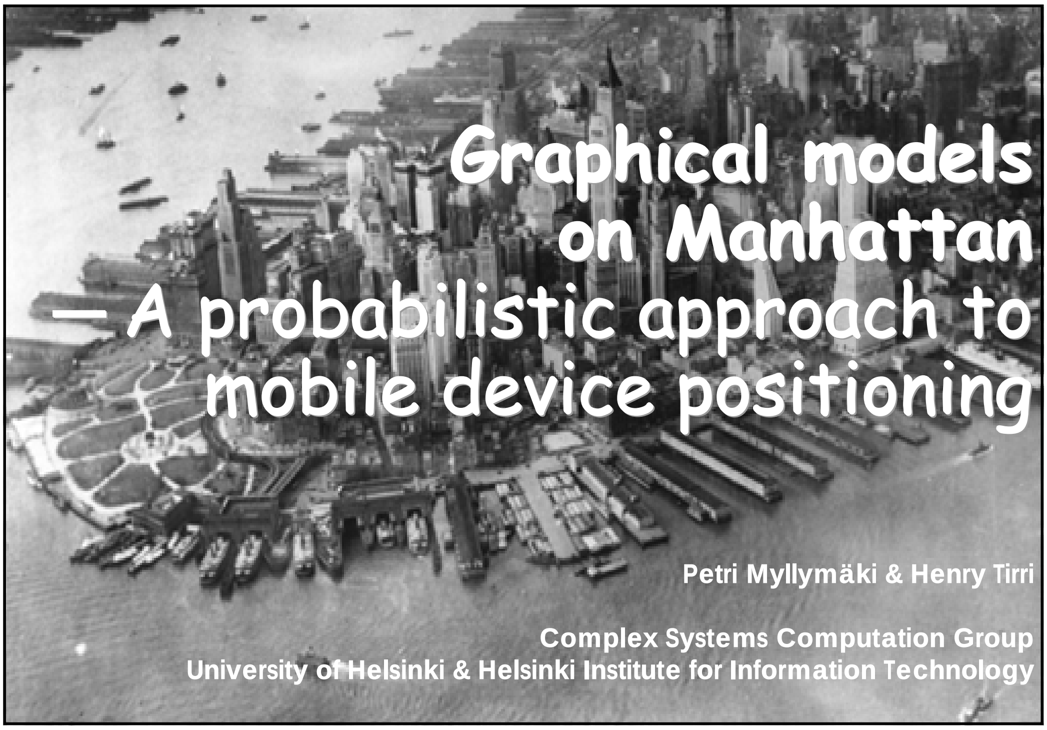
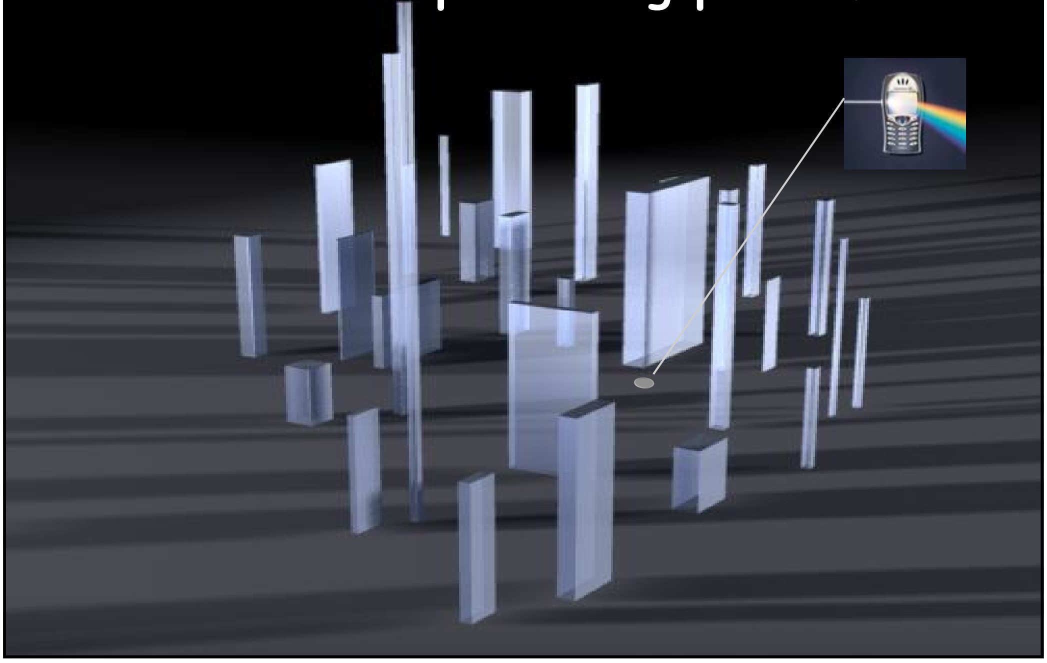


Graphical models on Manhattan – A probabilistic approach to mobile device positioning

Petri Myllymäki & Henry Tirri

Complex Systems Computation Group
University of Helsinki & Helsinki Institute for Information Technology

Location positioning problem

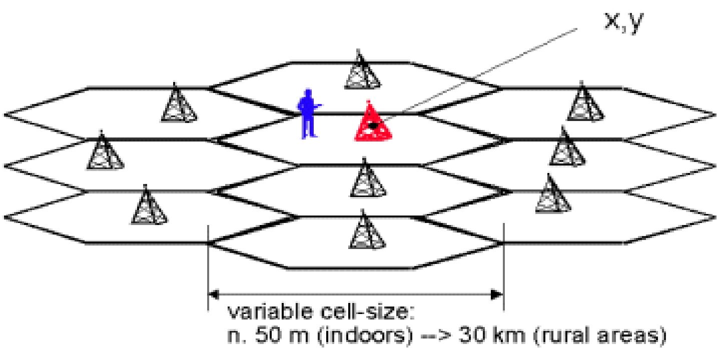


The positioning problem

- Given some location-dependent observations *O*, measured by a mobile device, determine the location *L* of the device
- Why is this a good research problem?
  - The goodness of different solutions is extremely easy to validate (just go to a known location and test)
  - The results have immediate practical applications
    - » Location-based services (LBS)
    - » FCC Enhanced 911:
      - Network-based solutions: error below 100 meters for 67 percent of calls, 300 meters for 95 percent of calls
      - Handset-based solutions: error below 50 meters for 67 percent of calls, 150 meters for 95 percent of calls

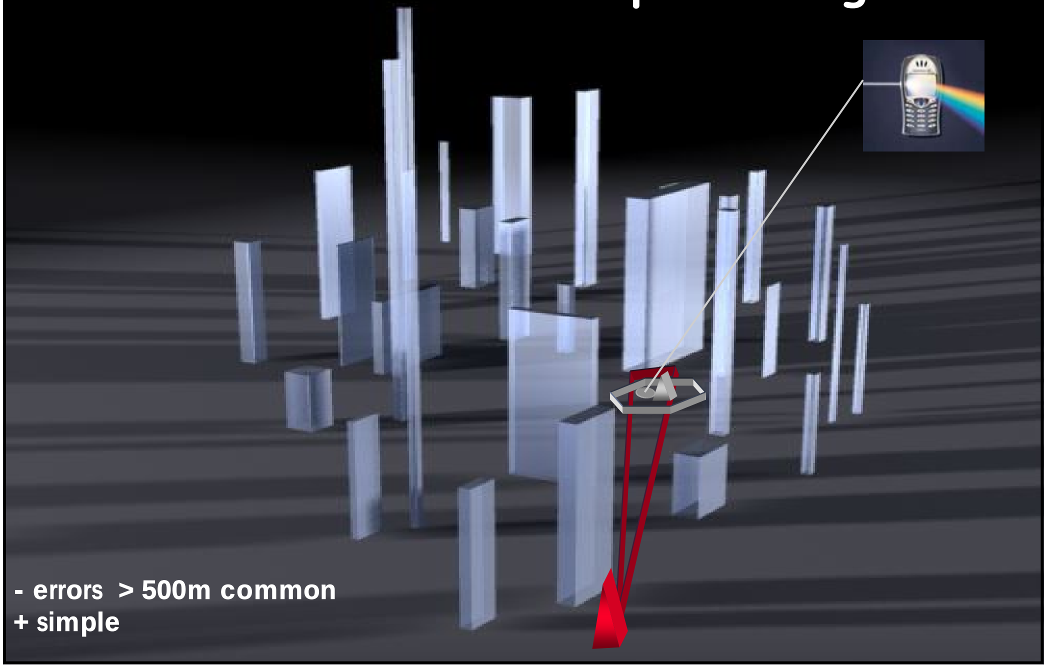
 3

Cell ID

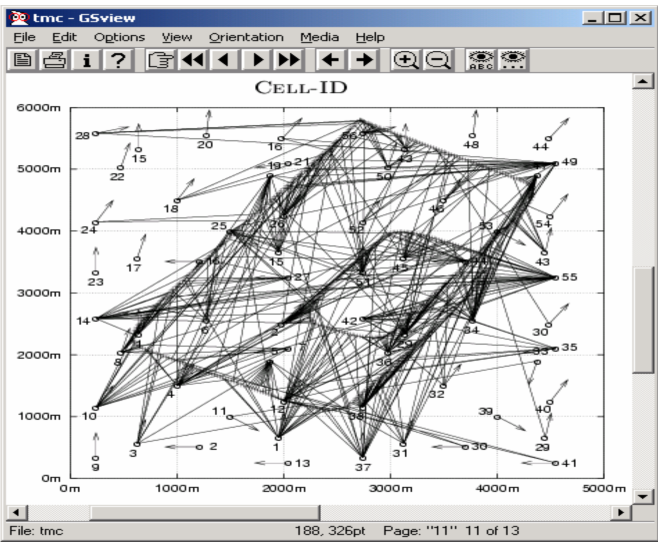


 4

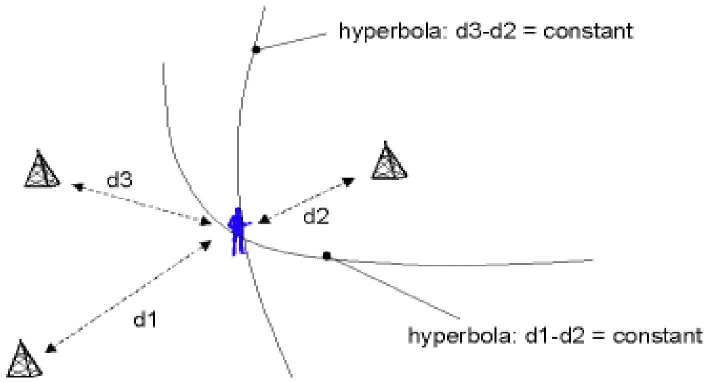
Cell-id in urban positioning



Cell ID errors

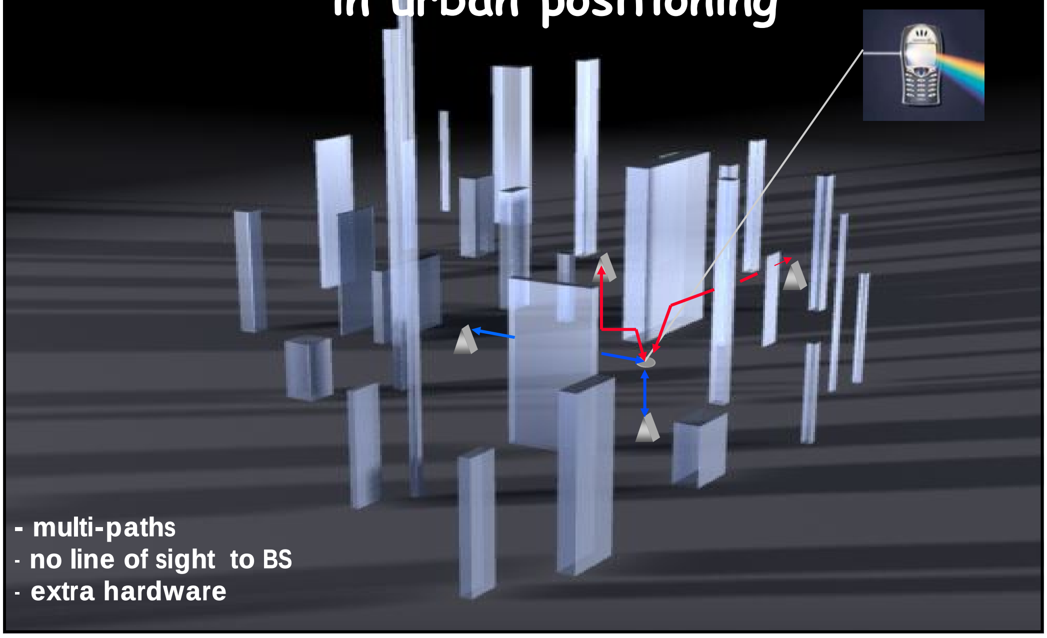


Enhanced Observed Time Difference (E-OTD)



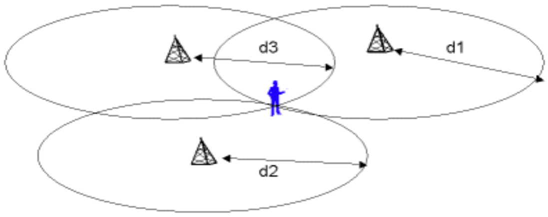
 7

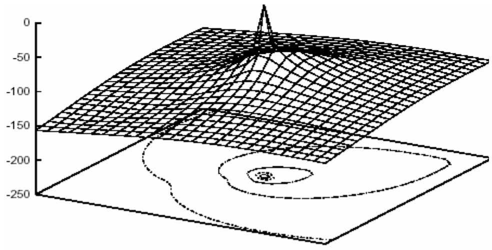
Problems with E-OTD in urban positioning

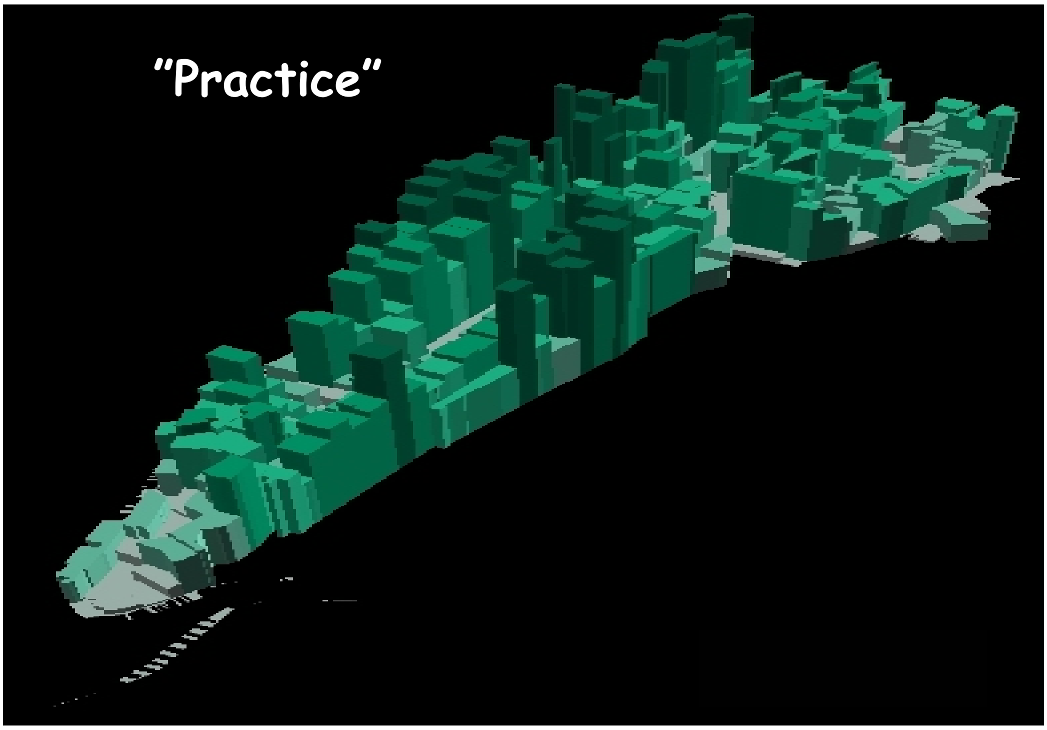


- multi-paths
- no line of sight to BS
- extra hardware

"Theory"

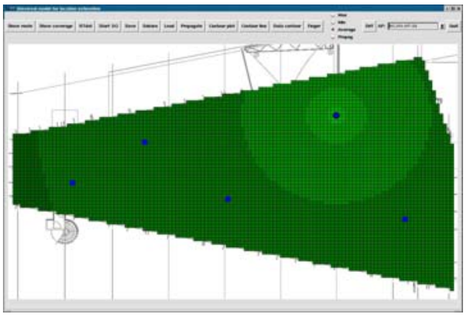


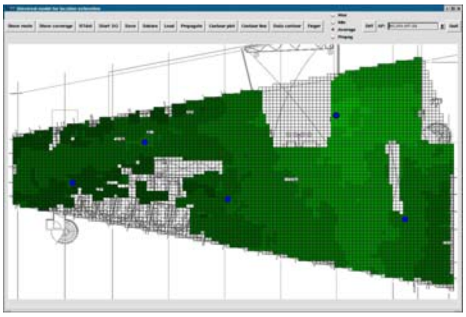




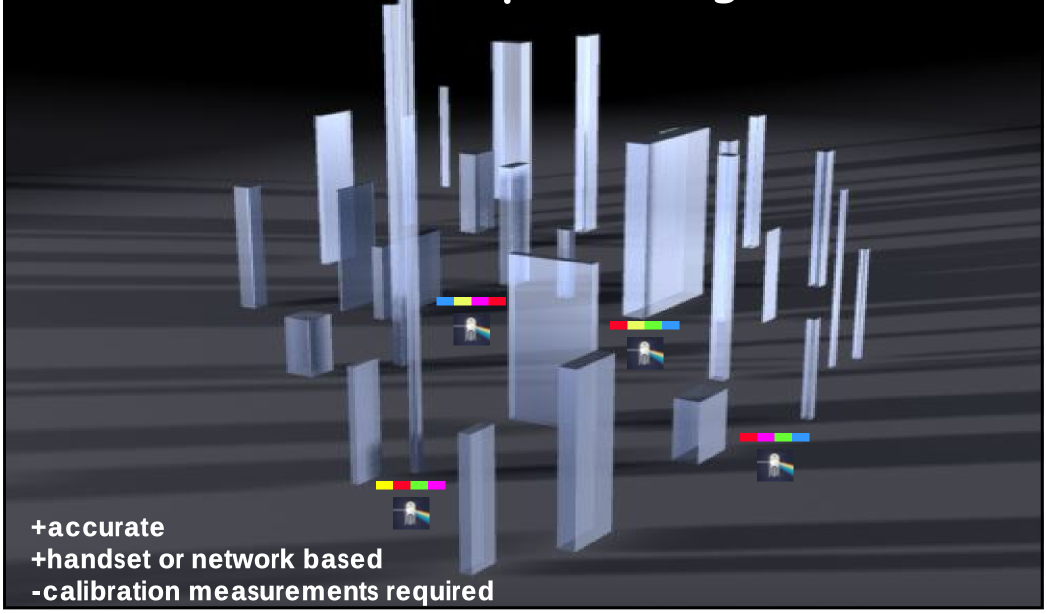
The signal propagation approach

Theory | **Reality**





Empirical modeling in urban positioning



+accurate
+handset or network based
-calibration measurements required

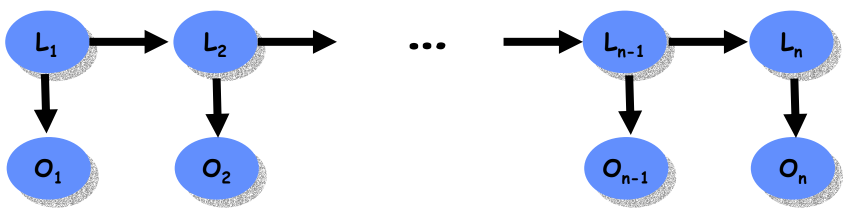
A probabilistic approach to positioning

$$P(L \mid O) = \frac{P(O \mid L)\, P(L)}{P(O)}$$

- A probabilistic model assigns a probability for each possible location L given the observations O.
  - P(O | L) is the conditional probability of obtaining observations O at location L.
  - P(L) is the prior probability of location O. (Could be used to exploit user profiles, rails etc.)
  - P(O) is just a normalizing constant.
- How to obtain P(O | L)? ⇨ Empirical observations + machine learning

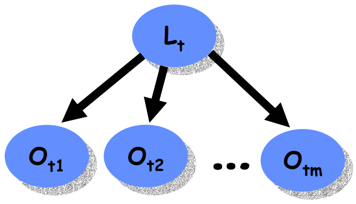
Tracking with Markov models

- Typically we have a sequence (history) of observations $O_1,\ldots,O_n$, and wish to determine $P(L_n \mid O^n)$
- Assumption: $P(O_t \mid L_t)$ are known, and given location L_t, the observation O_t is independent of the rest of the history
- The model: a hidden Markov model (HMM) where the locations L_t are the hidden unobserved states
- The transition probabilities $P(L_t \mid L_{t-1})$ can be easily determined from the physical properties of the moving object



One more assumption

- The observation at time *t* typically consists of several measurements (e.g., strengths of signals from all the transmitters that can be heard)
- If the wireless network is designed in a reasonable manner (the transmitters are far from each other), it makes sense to assume that the individual observations are independent, given the location
- The "Naïve Bayes" model



Tracking as probabilistic inference

- As our hidden Markov model is a tree, we can compute the marginal of any L_t, given the history O^n, in linear time by using the simple forward-backward algorithm discussed in Lecture 3
- Alternatively, we can compute the maximum probability path $L_1,\ldots,L_n$ given the history (this is known as the **Viterbi** algorithm)
- **Kalman filter**: all the conditional distributions of the HMM model are normal distributions (linear dependencies with Gaussian noise)

Recursive tracking

- Assume that $\mathbf{P(L_{n-1} \mid O^{n-1})}$ has been computed.
- Our model defies the transition probabilities $\mathbf{P(L_t \mid L_{t-1})}$ and the local observation probabilities $\mathbf{P(O_t \mid L_t)}$
- Now $\mathbf{P(L_n \mid O^n)\ \alpha\ P(L_n, O^n)}$

$$= \mathbf{P(O_n \mid L_n, O^{n-1})\ P(L_n, O^{n-1})}$$

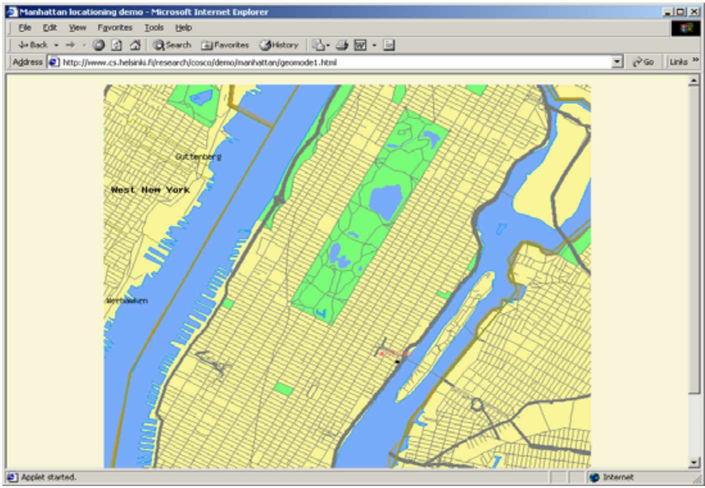
$$= \mathbf{P(O_n \mid L_n) \sum_{L_{n-1}} P(L_n, L_{n-1}, O^{n-1})}$$

$$\alpha\ \mathbf{P(O_n \mid L_n) \sum_{L_{n-1}} P(L_n \mid L_{n-1}) P(L_{n-1} \mid O^{n-1})}$$

- With a Kalman filter, the recursive process operates all the time with Gaussians

GSM-positioning trials

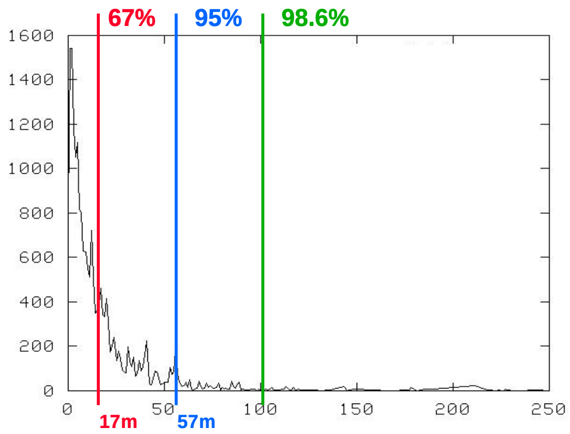
NYC Trial 2001



Details

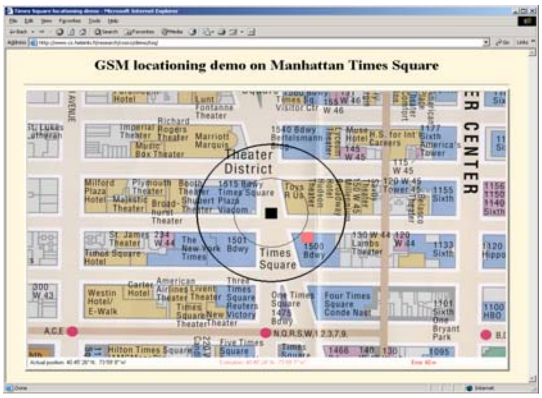
- Covering downtown Manhattan (10th - 114th St)
- Data gathering by car
- Modeling: 10 person days
- Target accuracy: less than 911 handset requirements
- Tests using cars

Accuracy of NYC Trial 2001



- 20166 points
- tracking; testing done in a car;

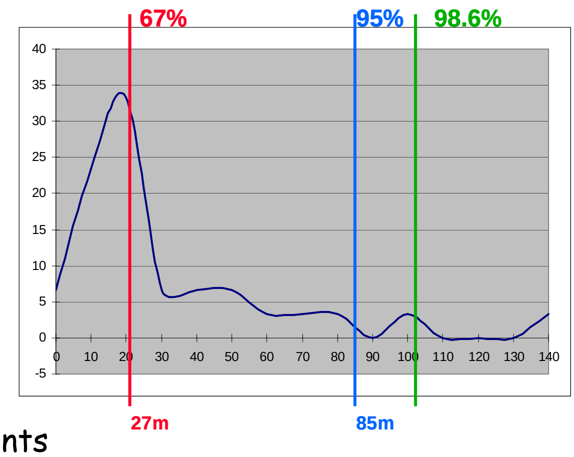
Trials: Manhattan 2002



Challenges

- "real 911" simulation
  - No tracking information
  - Only up to 60 seconds of signal measurements
- Target accuracy: "theater level"
- Indoor testing (without indoor modeling)

Accuracy NYC Trial 2002



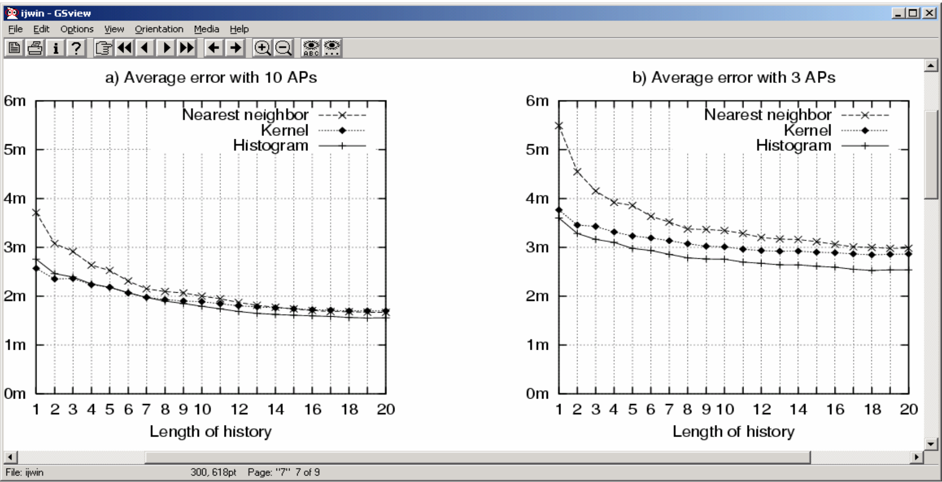
- 30 points
- static; testing done by walking;

WiFi-positioning trials

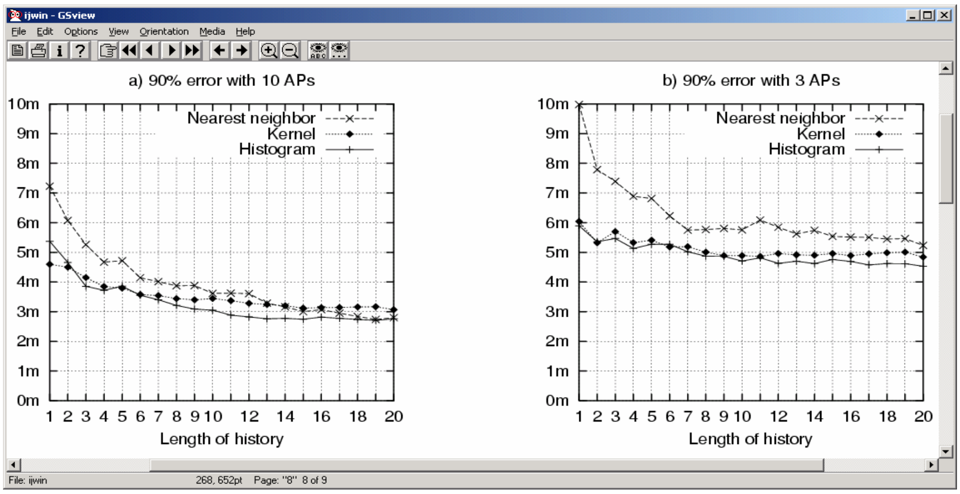
From: P.Myllymäki, T. Roos, H.Tirri, P.Misikangas and J.Sievänen. *A Probabilistic Approach to WLAN User Location Estimation*. International Journal of Wireless Information Networks, Vol. 9, No. 3, July 2002.

More information: www.ekahau.com

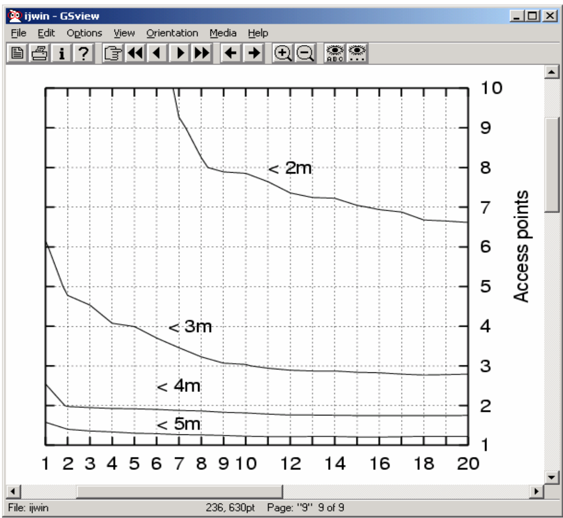
WLAN: average errors



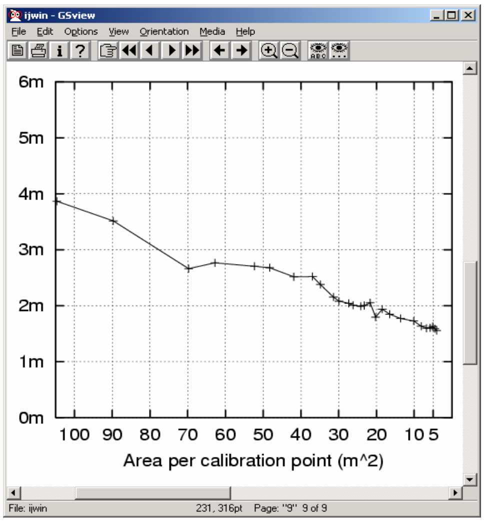
WLAN: 90% errors



WLAN: sensitivity



WLAN: calibration trade-off



…more:

- P.Myllymäki, T. Roos, H.Tirri, P.Misikangas and J.Sievänen: *A Probabilistic Approach to WLAN User Location Estimation*. International Journal of Wireless Information Networks, Vol. 9, No. 3, July 2002.
- T. Roos, P.Myllymäki, H.Tirri: *A Statistical Modeling Approach to Location Estimation*. IEEE Trans. on Mobile Computing, Vol. 1, No. 1, January-March 2002, 59-69.
- Fox, Hightower, Liao, Schulz, Borriello: *Bayesian Filtering for Location Estimation*. IEEE Pervasive Computing, Vol. 2, No. 3, July-September 2003, 24-33.
- Demo: http://cosco.hiit.fi/demos.html
- Software: www.ekahau.com