GNSS orbit prediction and Parametric Fingerprint Positioning Methods Using Crowdsourced Data

Workshop II: Traffic Estimation
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Positioning algorithms group at TUT
Research Topics

Computing the 3D position coordinates using a variety of measurements:
satellite-based systems (such as GPS, GLONASS, BeiDou, Galileo),
terrestrial radio systems (such as cellular networks), and
on-board sensors.

- Bayesian inference,
- sequential Monte Carlo methods,
- (extended) Kalman filters, and
- numerical integration methods

http://www.tut.fi/posgroup

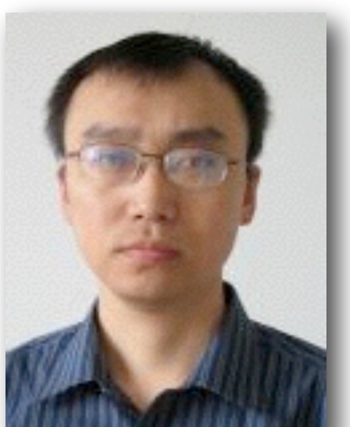
Positioning algorithms group at TUT


Robert


Simo


Matti


Pavel


Xiaolong


Henri

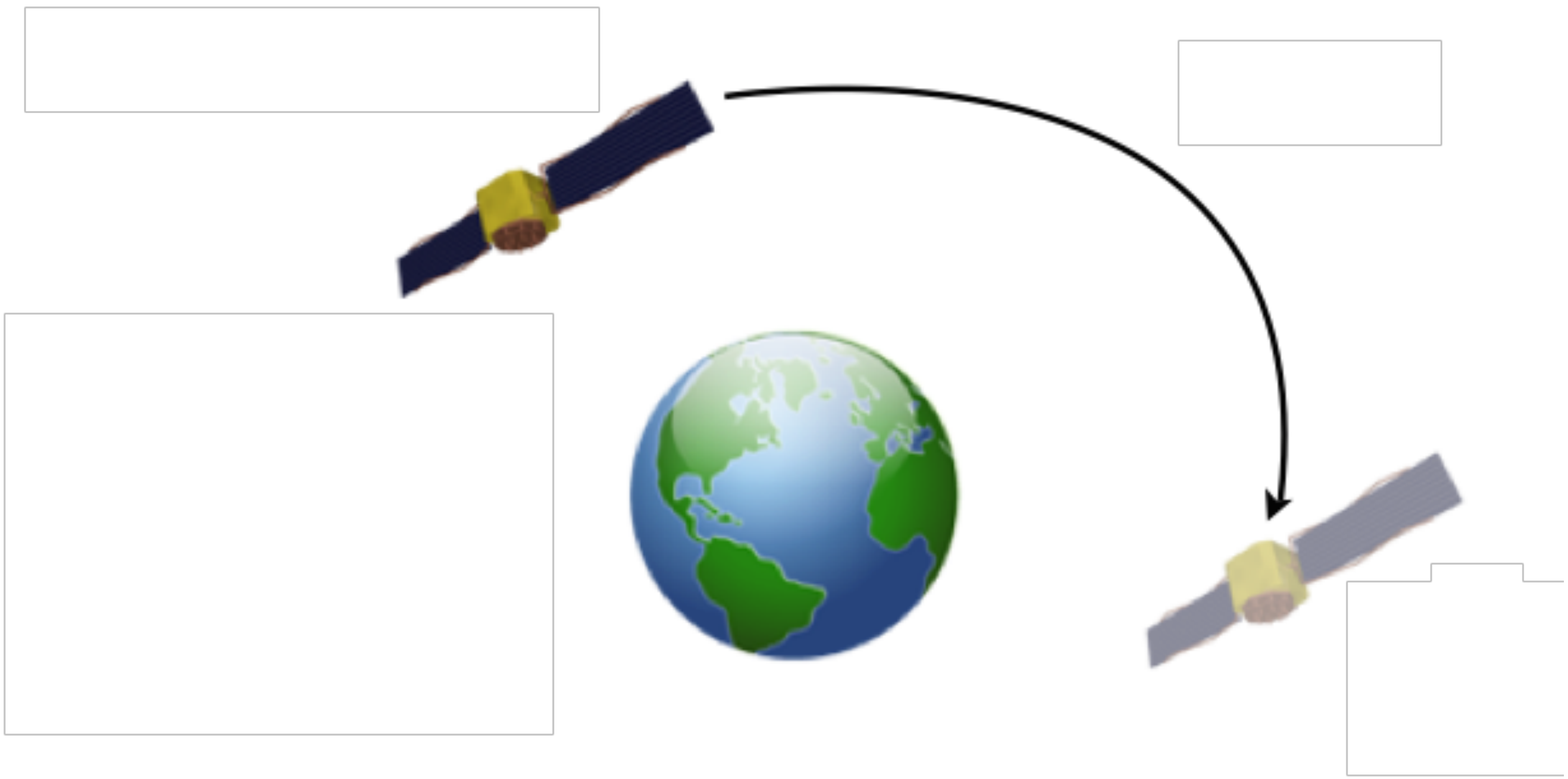

Alejandro


Philipp


Juha

Helena, Sakari, Miika, Mike, …

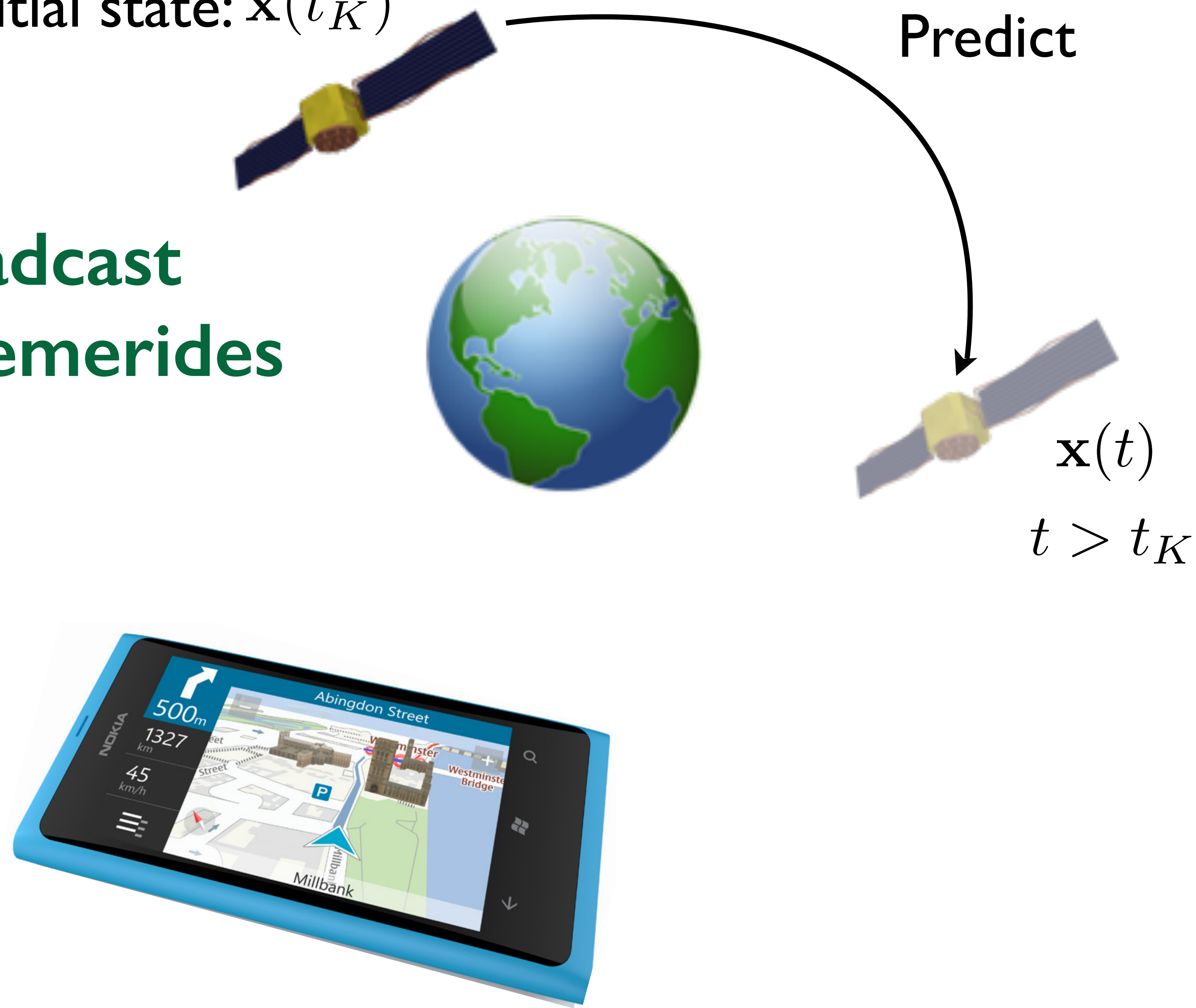
GNSS orbit prediction



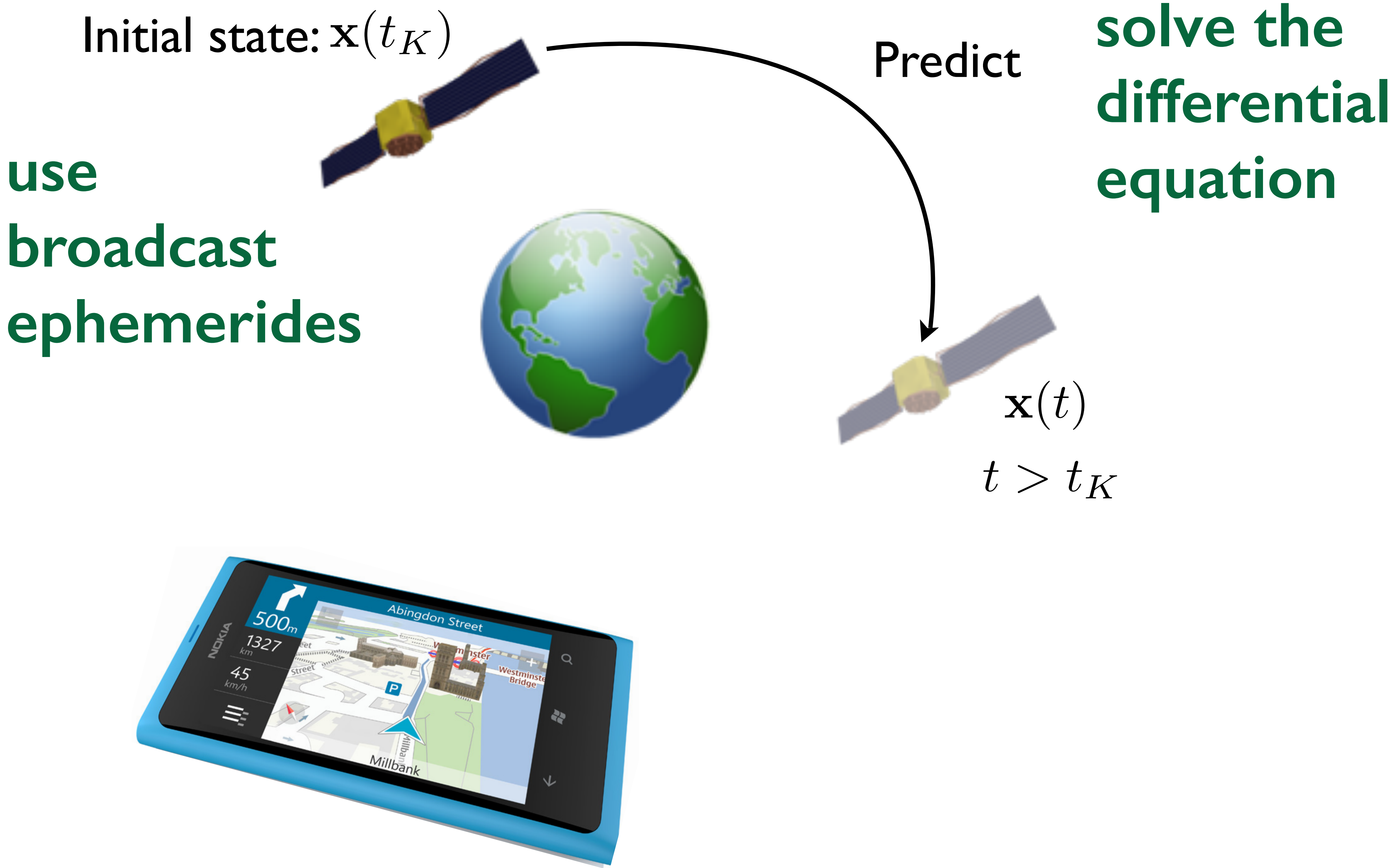
A smartphone can compute where a GNSS satellite will be in a few days

Initial state: $\mathbf{x}(t_K)$

use broadcast ephemerides



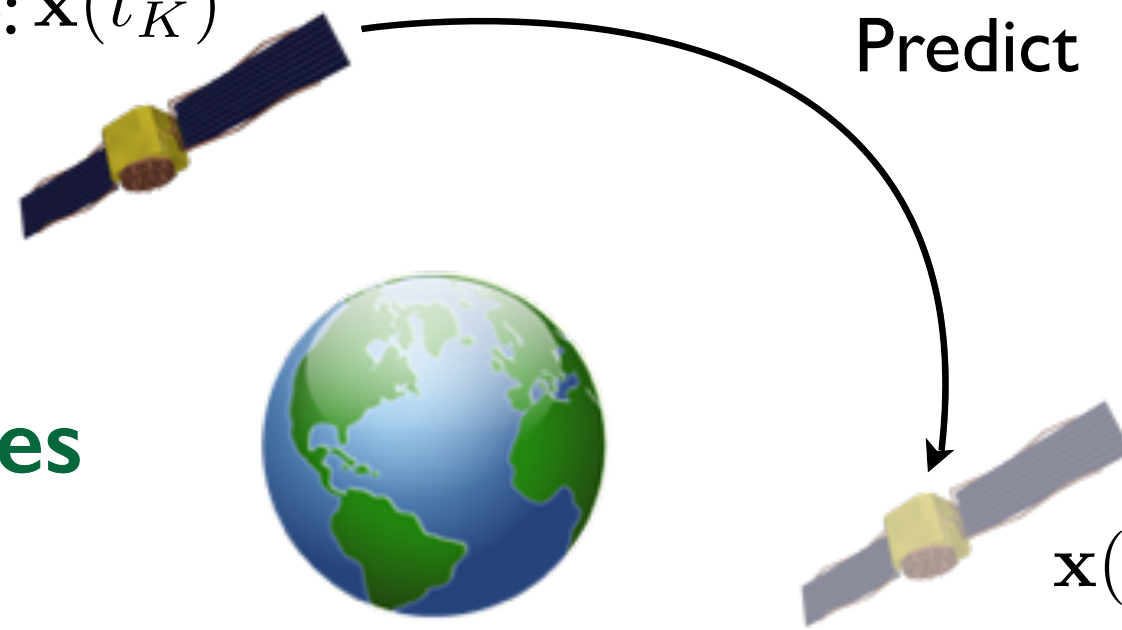
A smartphone can compute where a GNSS satellite will be in a few days



A smartphone can compute where a GNSS satellite will be in a few days

Initial state: $\mathbf{x}(t_K)$

Predict



use broadcast ephemerides

solve the differential equation

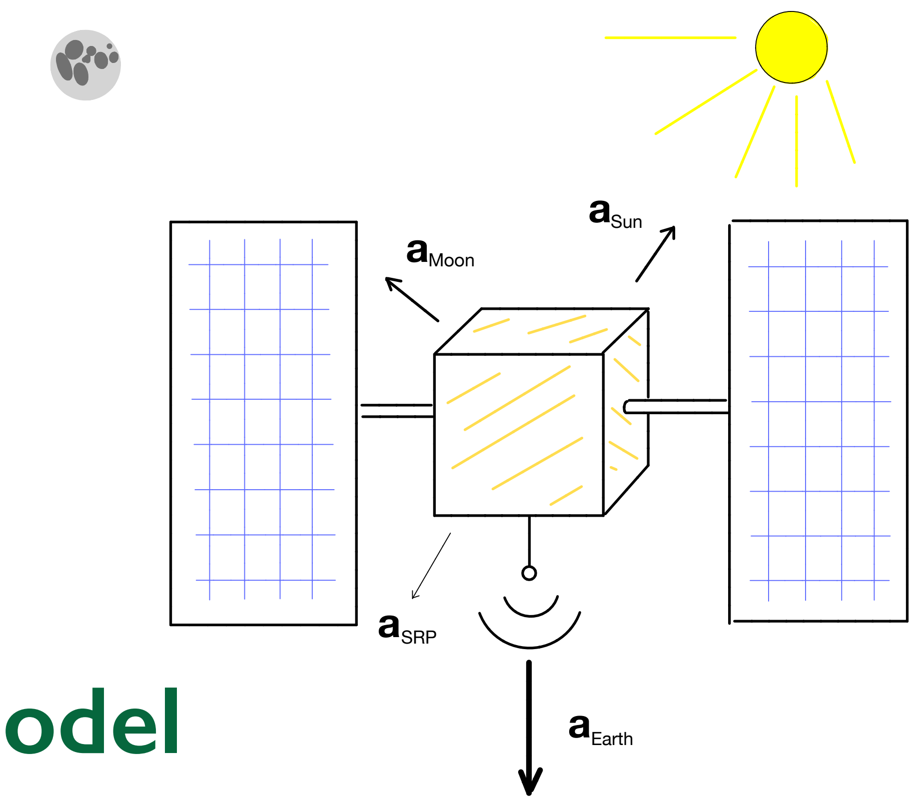
$\mathbf{x}(t)$

$t > t_K$

time to first fix
30s → 5s


Predicting satellite orbits

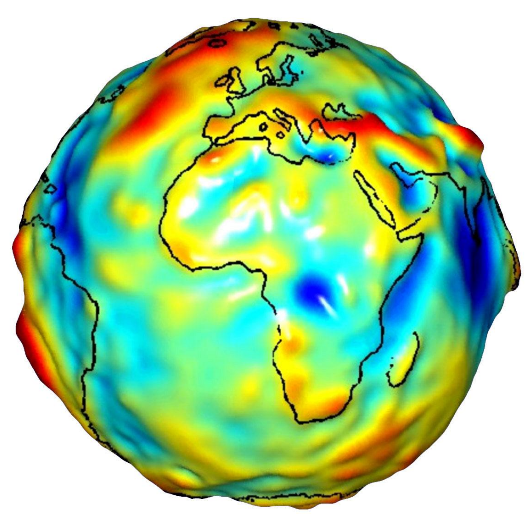
The basic dynamic model includes earth, sun & moon gravity, and solar radiation



empirical SRP model

$$\mathbf{a}_{\text{SRP}} = \lambda \left(-\alpha_1 \frac{1}{r_{\text{sun}}^2} \mathbf{e}_s + \alpha_2 \mathbf{e}_y \right)$$

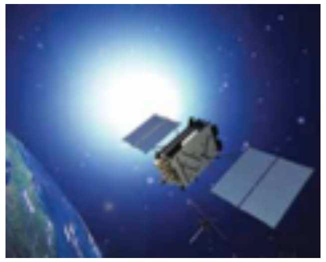
Ala-Luhtala et al.
IGNSS 2013

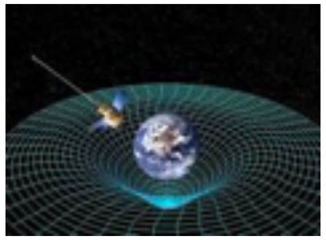


spherical harmonics up to degree & order 12

We looked at some additions and changes to the dynamic model

effect	km/s
earth gravity	6e-1
moon gravity	4e-5
sun gravity	2e-6
solar radiation	1e-7
solid tides	5e-9
earth albedo	5e-9
ocean tides	8e-10
earth gravity relativity correction	3e-10
venus gravity	3e-10
sun gravity relativity correction	4e-11
Jupiter gravity	3e-11
antenna radiation	2e-11





Solid tide is modelled by modifying terms in the gravity potential's harmonic series

$$\begin{Bmatrix} \Delta C_{2m} \\ \Delta S_{2m} \end{Bmatrix} = 4k_{2,m} \left(\frac{GM}{GM_{\oplus}} \right) \cdot N_{nm} \begin{Bmatrix} \cos(m\lambda) \\ \sin(m\lambda) \end{Bmatrix}$$

where

$$N_{2m} = \left(\frac{R_{\oplus}}{s} \right)^{n+1} \sqrt{\frac{(2+2)\,(2-m)!^3}{(2+m)!^3}} P_{2m}(\sin\phi)$$

Montebruck & Gill:
Satellite Orbits (2000)

We replace our simple Sun & Moon orbit formula with JPL ephemeris

http://www.cv.nrao.edu/~rfisher/Ephemerides/ephem_descr.html#ref8

Chebyshev coefficients, 150 kB/year

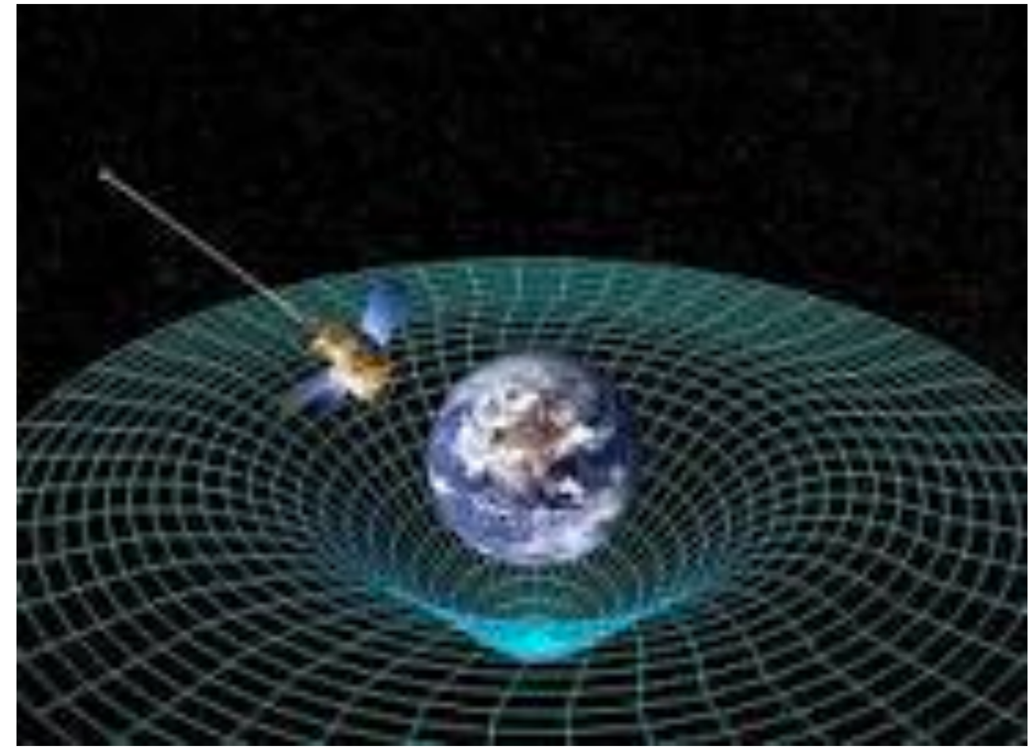
Accuracy in milliarcseconds
(simple formula's accuracy is arc minutes)

We use DE202 (J2000) instead of DE400 (IERS)

Earth-gravity relativity, antenna radiation, and earth albedo effects are radial forces

satellite orbit speed $v = 10^{-5}c$

$$\Delta \mathbf{a}_{\text{Earth}} = -\frac{GM_{\oplus}}{r^2}\mathbf{e}_r \left(3\frac{v^2}{c^2}\right)$$



antenna radiation thrust

$$\mathbf{a}_{\text{ant}} = -\frac{P}{mc} \cdot \frac{\mathbf{r}_{sat}}{||\mathbf{r}_{sat}||}$$

empirical Albedo model

We added a term to GPS solar radiation model to model variation of satellite area exposed to sun

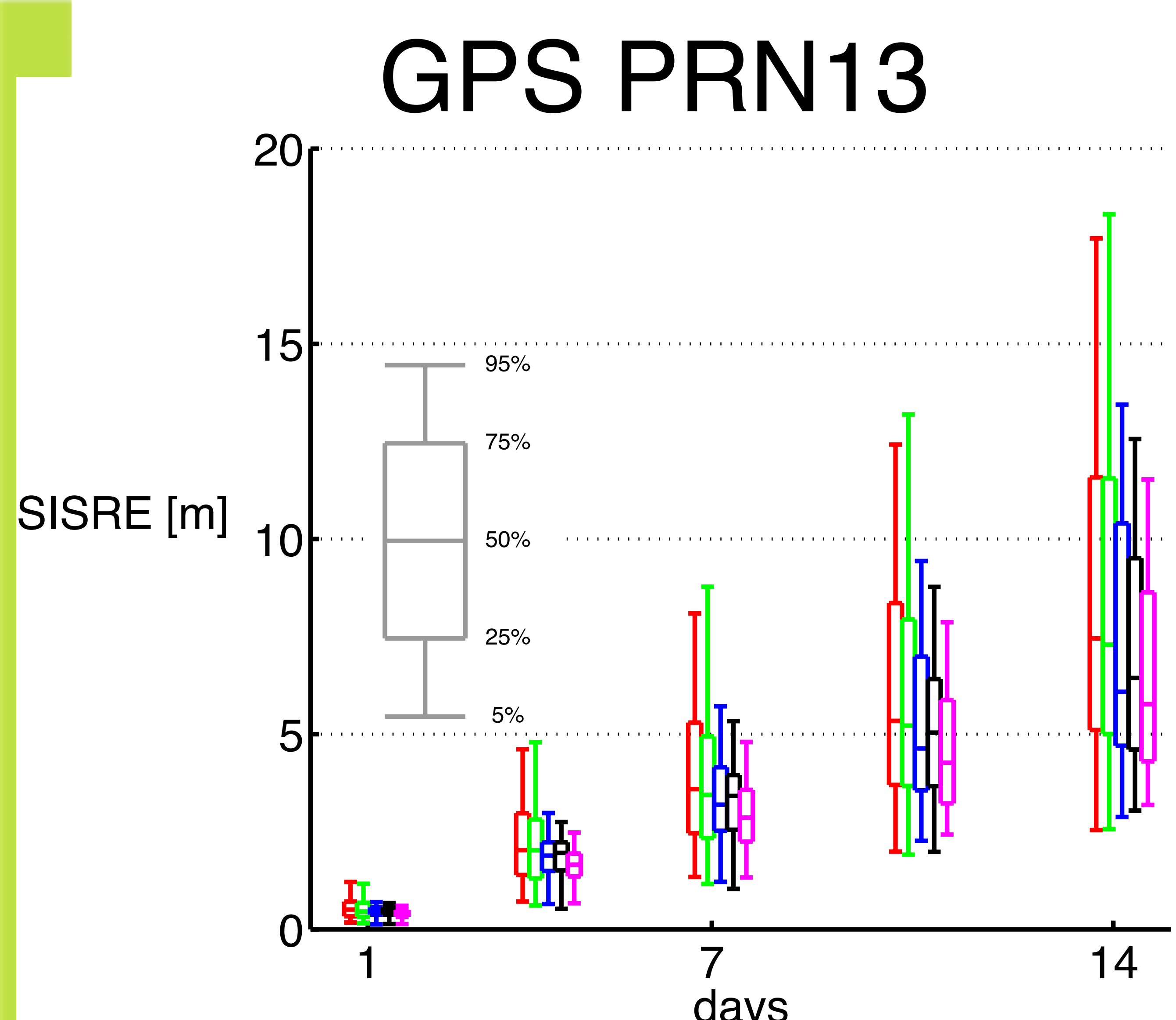
$$\mathbf{a}_{\mathrm{SRP}} = \lambda \left(-A \cdot \alpha_1 \frac{1}{r_{\mathrm{sun}}^2} \mathbf{e}_s + \alpha_2 \mathbf{e}_y \right)$$

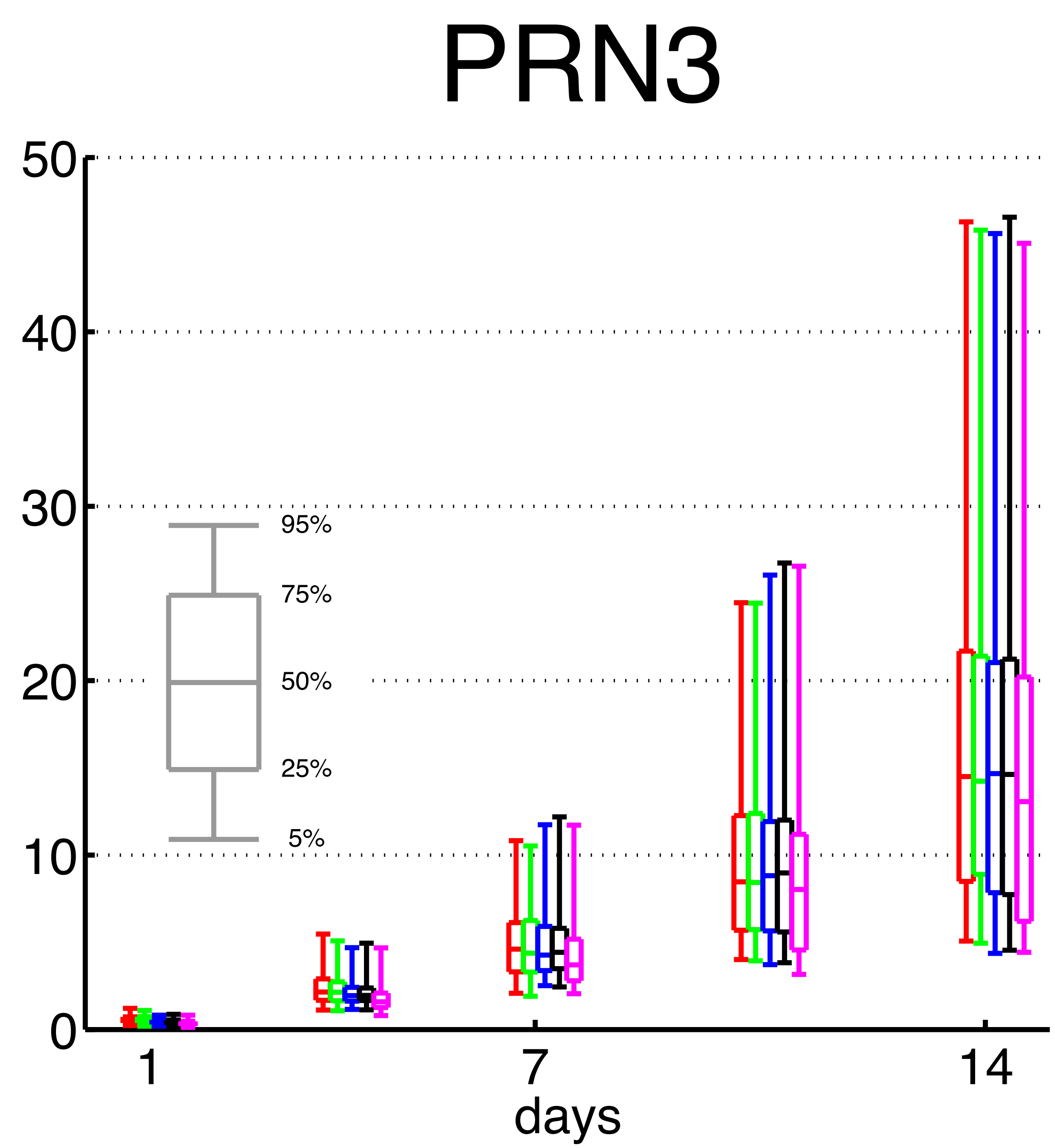
$$A = 1 + \alpha_3 \cdot (\sin(|\gamma|) - 0.5)$$

"simplified box-wing model"

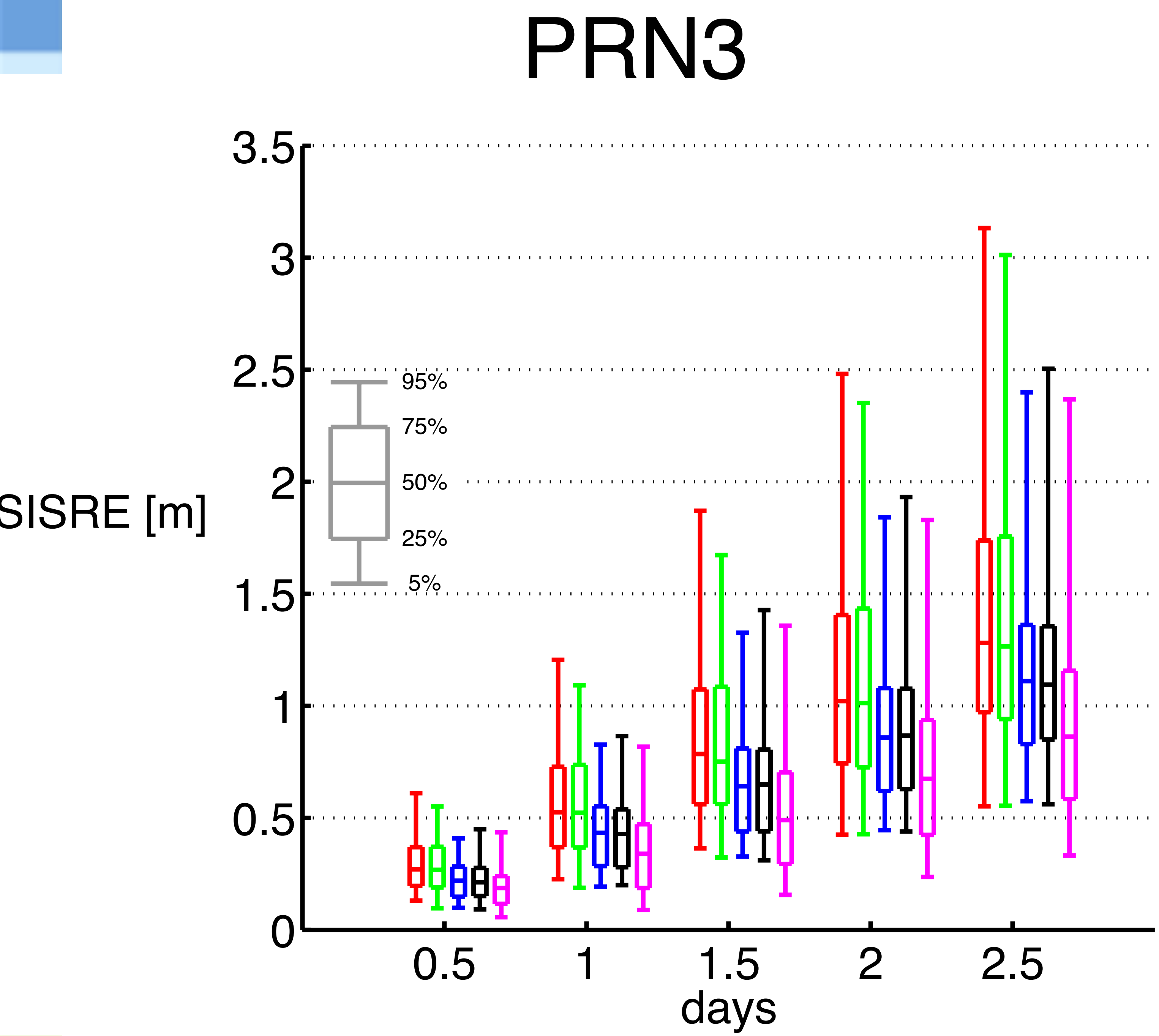
Prediction accuracy improvements are small, solid tide has most effect

old + solid tide + DE202 + relativity + SRP





The clearest improvements are in short-term predictions, but computation time increases too



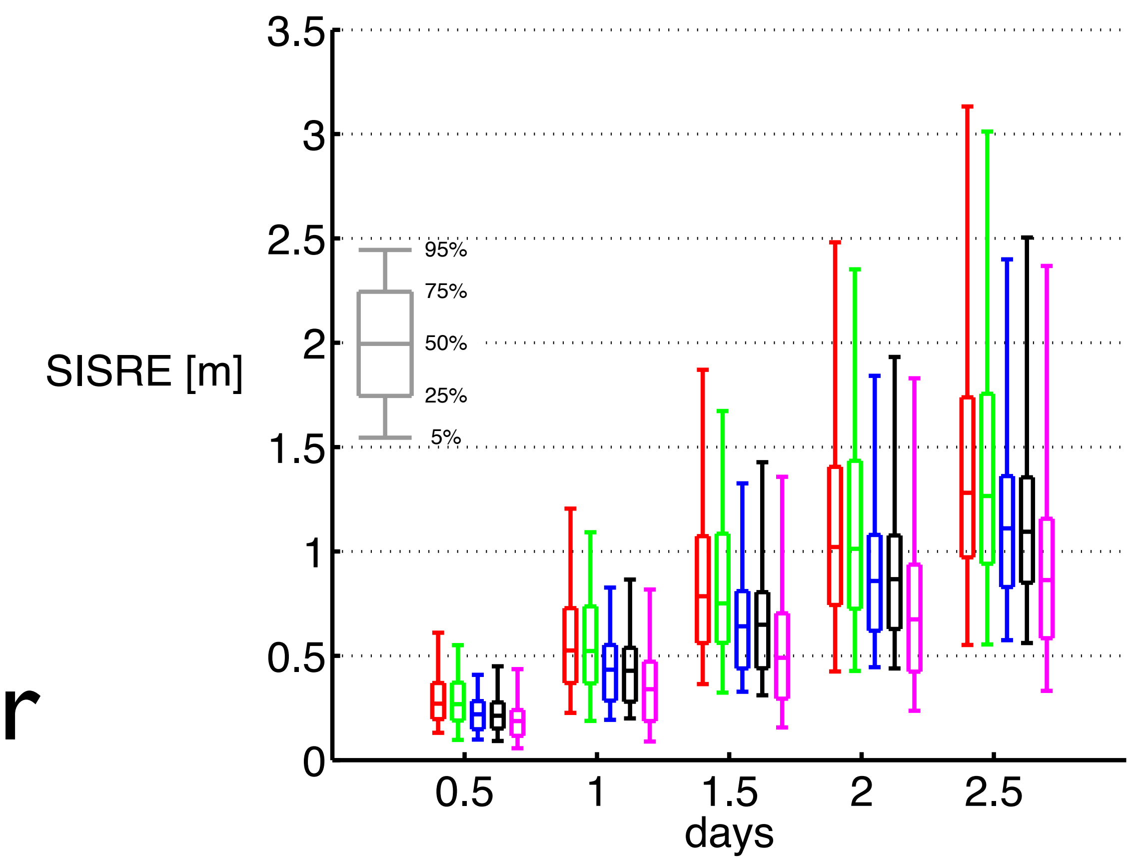
Force model addition	Increased computation time
DE202	5%
Solid Tide	5%
Relativity correction	3%
Antenna thrust	0%
Boxwing SRP	7%
TOTAL	20%

This study has found some small improvements to our dynamic model; what next?

speed up sun & moon ephemeris computation?

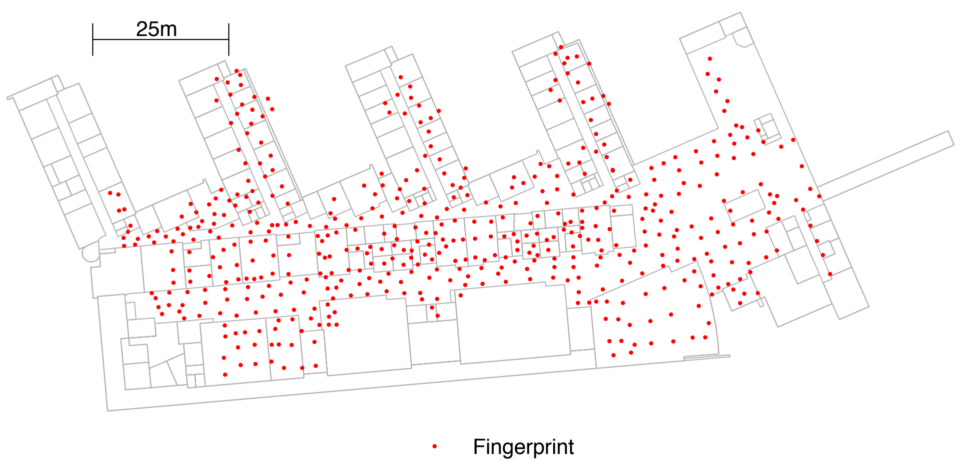
better models of solar radiation & earth albedo?

clock drift is a limiting factor



Andrei Pukkila, Juha Ala-Luhtala, Robert Piche, and Simo Ali-Löytty. GNSS orbit prediction with enhanced force model. In *2015 International Conference on Localization and GNSS (ICL-GNSS)*, pages 1-6, June 2015.

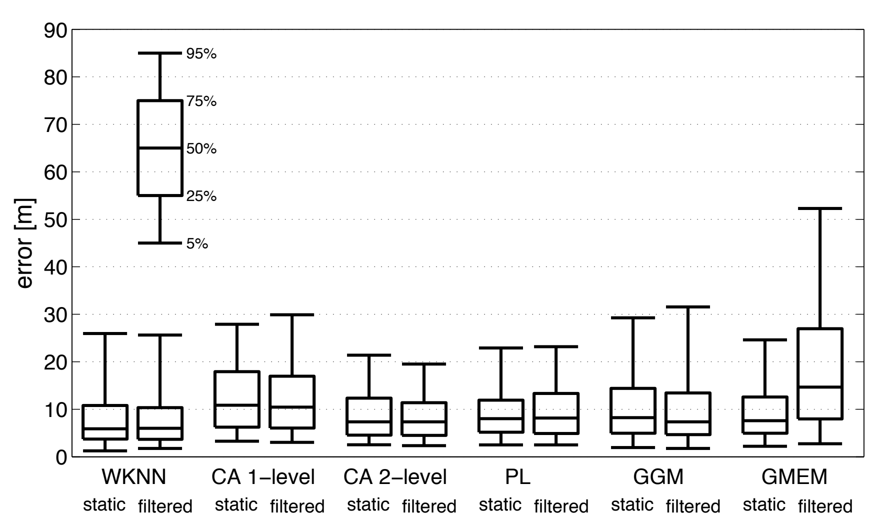
Parametric Fingerprint Positioning Methods Using Crowdsourced Data



1. Nonparametric methods

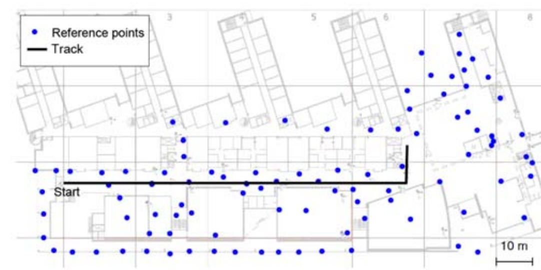
2. Parametric methods

3. Field test results

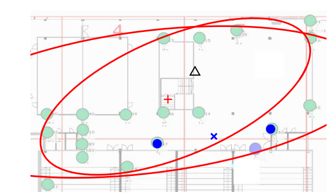


Location fingerprinting

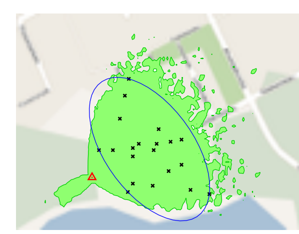
RSS-based methods

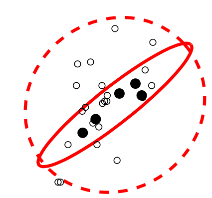


positioning using coverage area ellipses



fitting ellipses





Location fingerprinting is a popular technique for indoor positioning

Two stages

Survey: Collect radio reception reports ("fingerprints") of WiFi, Bluetooth, cell id etc at known locations into a database ("radio map")

Position: Compare mobile device reception with the radio map

Features

+ Uses available hardware and infrastructure
+ Works indoors and in dense urban areas
+ Low power (compared to GPS)
- Database needs to be built and kept up to date

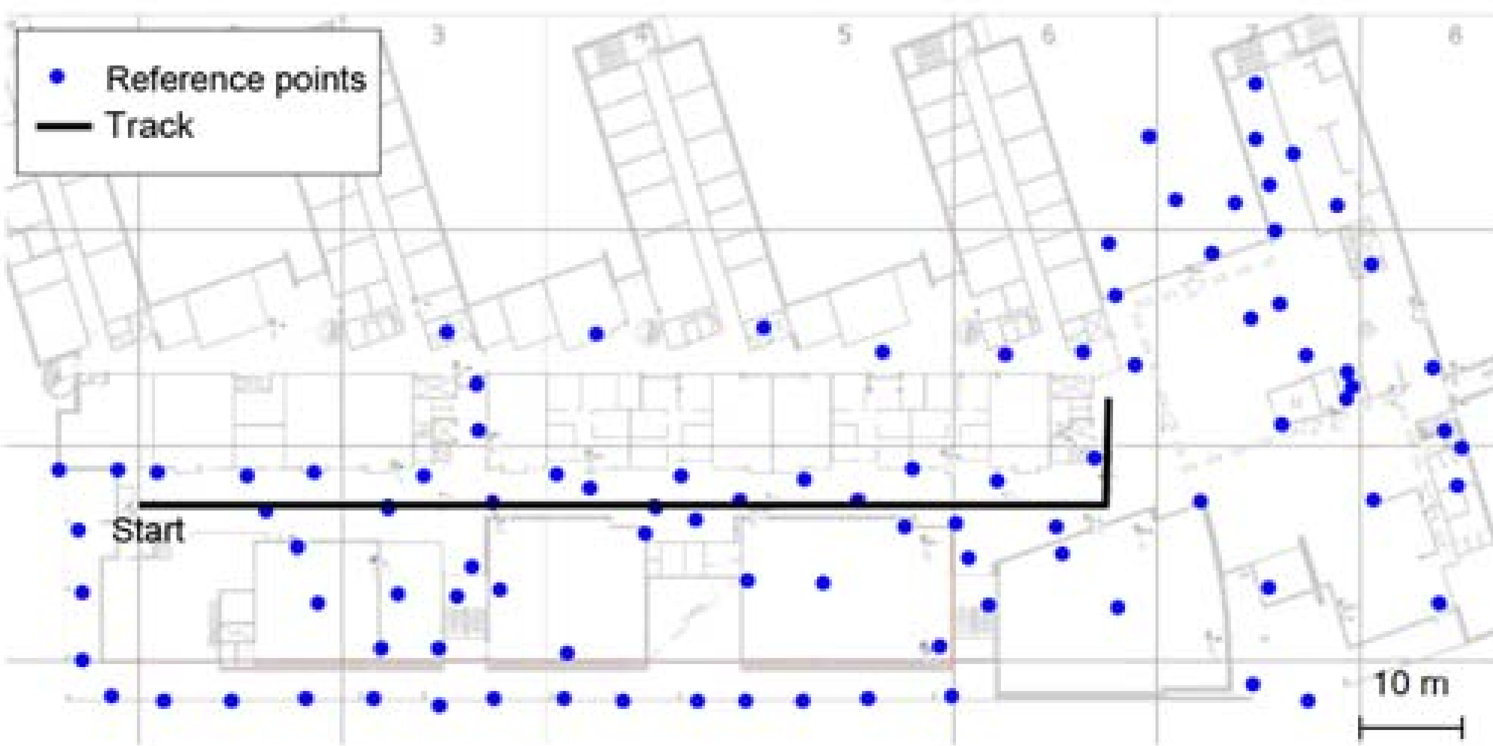
Existing solutions

- Cell-ID is standardized (3GPP)
- Indoor, WiFi: RADAR (2000), Ekahau, Horus, …
- Outdoor, WiFi: Navizon, Skyhook, Place Lab, Seeker Wireless, OpenBmap, …

Weighted K nearest neighbours (WKNN) algorithm is often used for indoor positioning

Estimate position as weighted average of K "nearest" reception report locations

"Nearness" is some measure of similarity of received signal strengths (RSS)

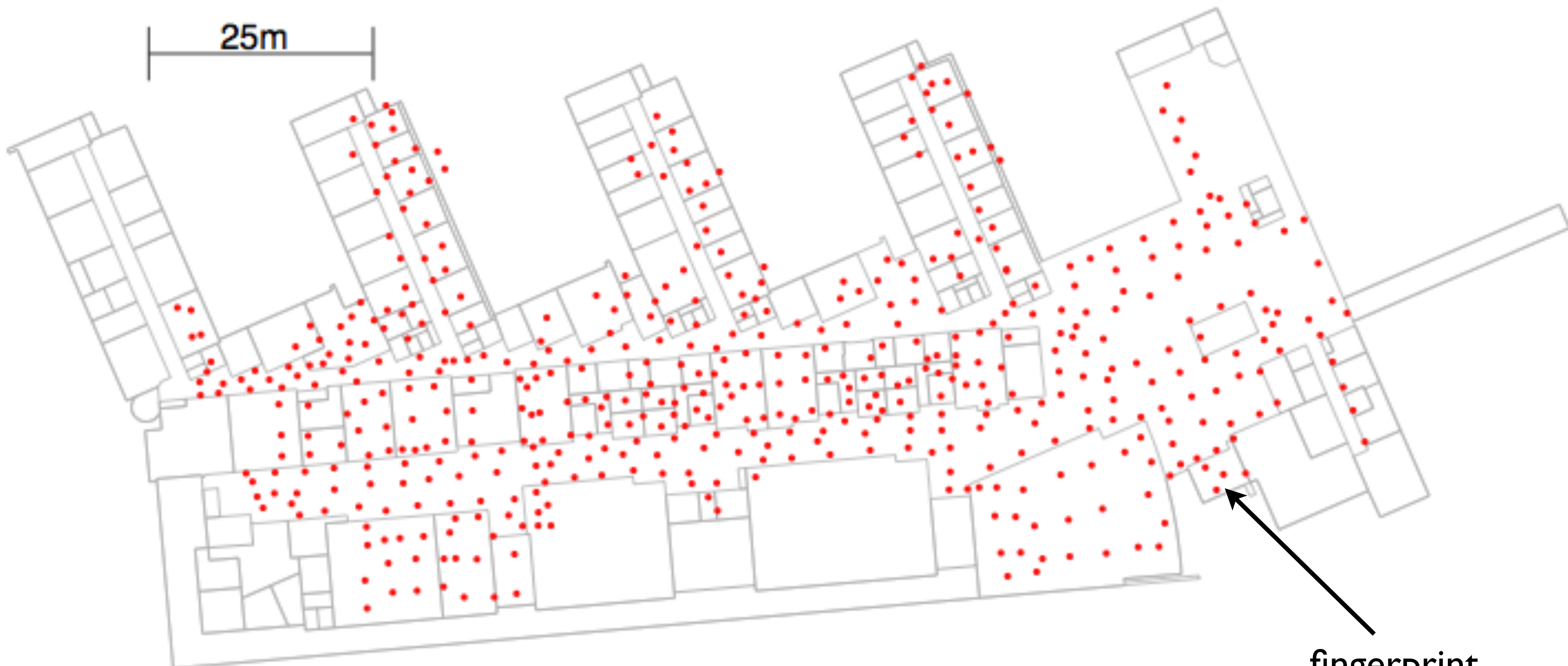


using WKNN, the mean positioning error along this track was 12m

Honkavirta, Perälä, Ali-Löytty, Piché, WPNC 2009

Ville Honkavirta

Nonparametric fingerprint methods require large radio maps that grow as more training data is collected

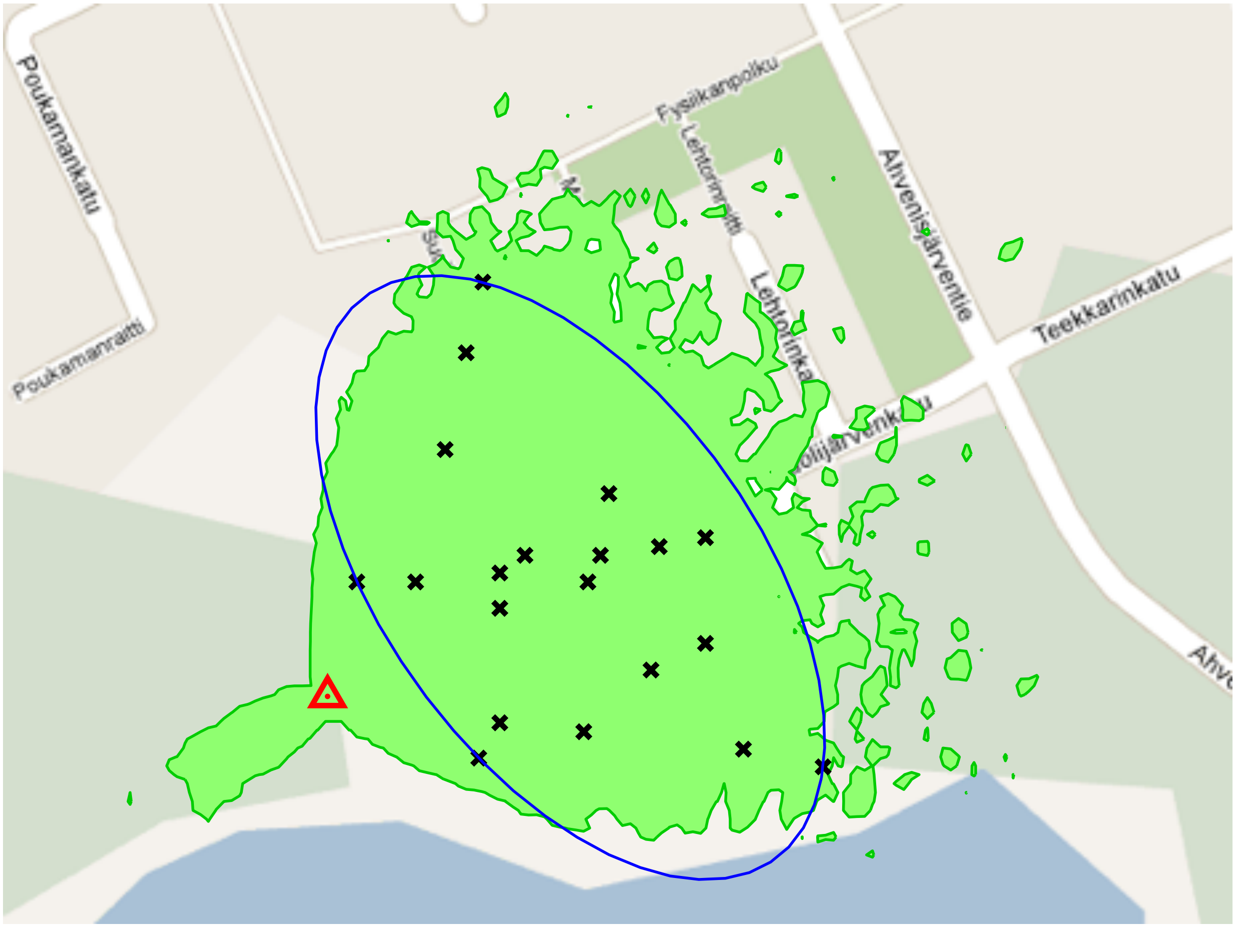


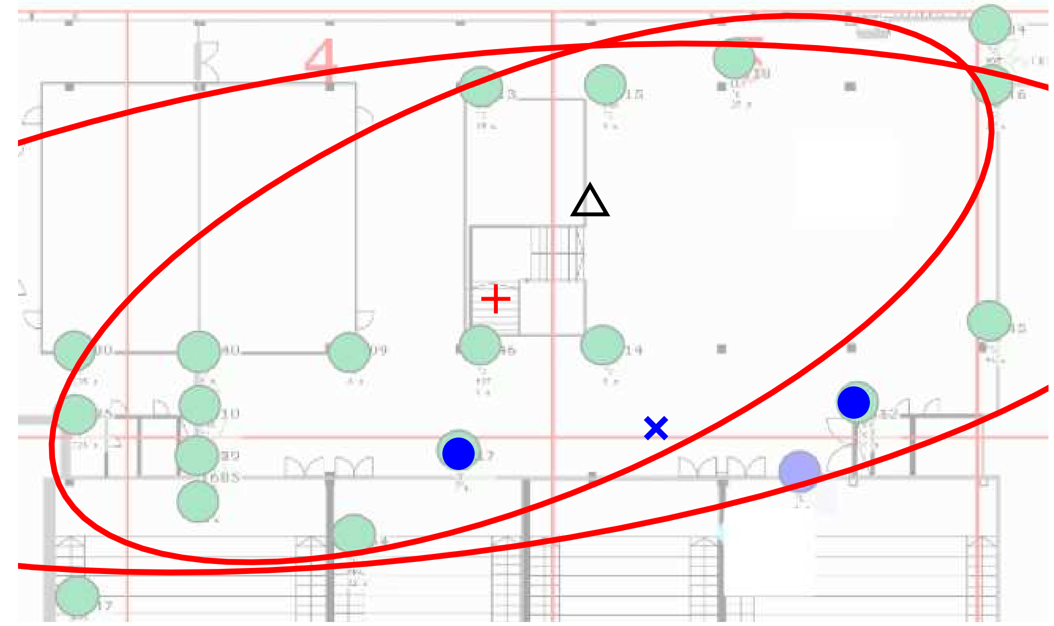
Radio map size depends on no. of fingerprints

Its transmission to a user device can be too slow for real time positioning

Also, the radio map itself requires large storage

Coverage area estimated by an elliptical probability distribution requires 5 parameters





Koski et al. 2010

Wirola et al. 2010

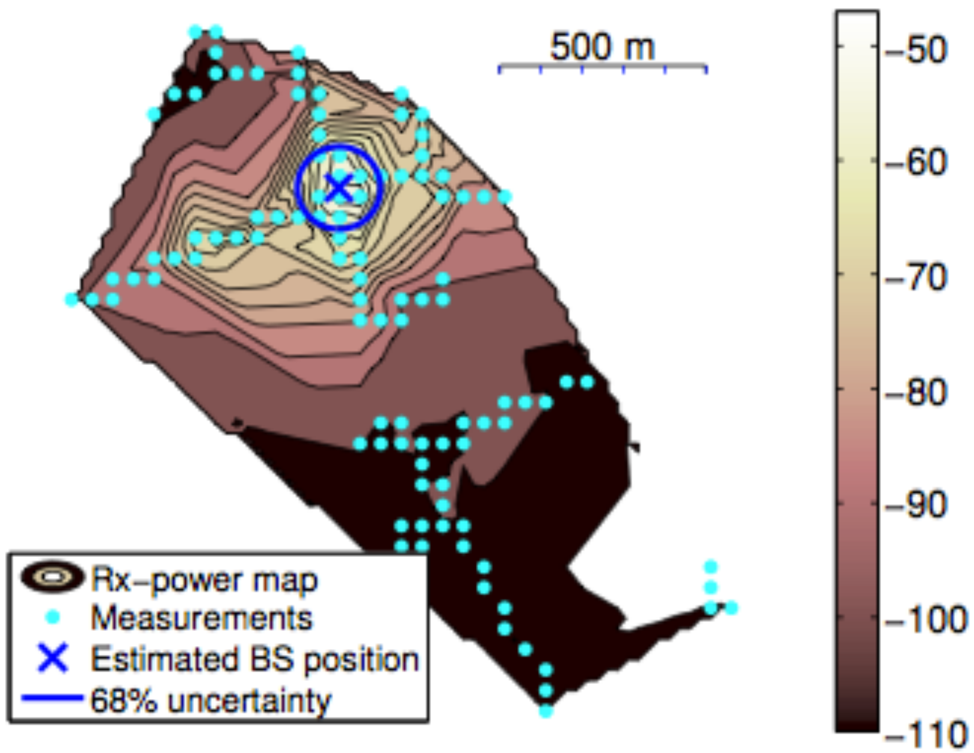
Raitoharju et al. 2013

Method models fingerprints of AP as a Gaussian distribution

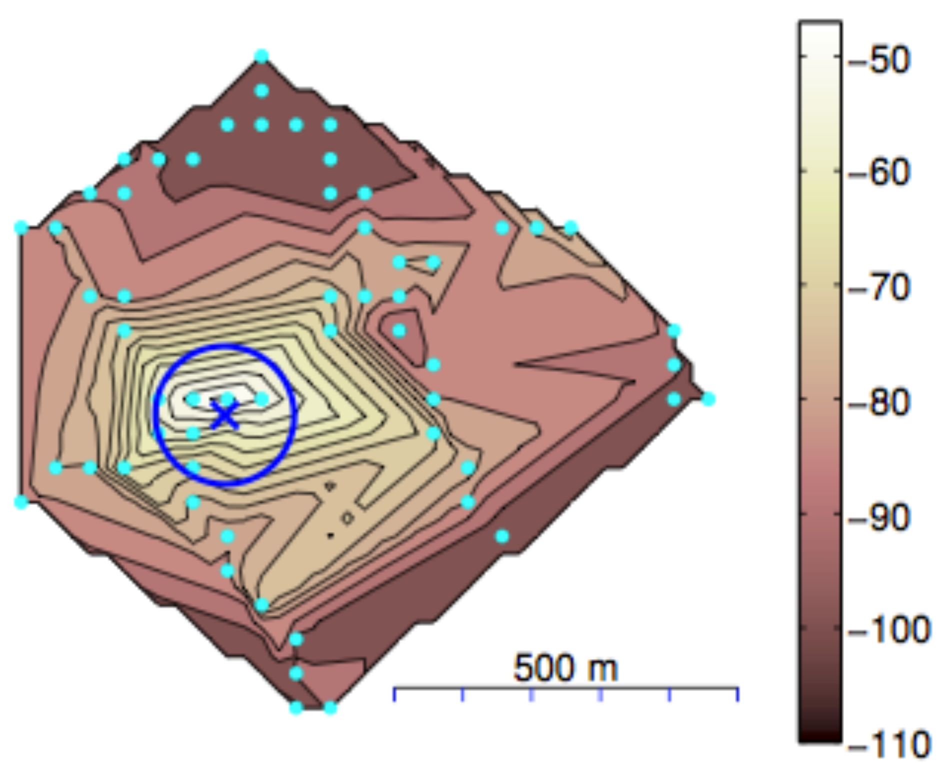
It uses Bayes' rule $p(x|y) \propto p(x)p(y|x)$ to compute position

Crowdsourcing coverage areas

Distance from access point to user device can be estimated using a path loss model



models of signal power loss or received signal strength



$$P_{\mathrm{RSS}}(d) = A - 10n\log_{10}(d) + w$$

Nurminen et al. 2012 (IPIN)

Nurminen et al. 2012 (UPINLBS)

Image adapted from Nurminen et al., "Statistical path loss parameter estimation and positioning using RSS measurements" in *Ubiquitous Positioning Indoor Navigation and Location Based Service (UPINLBS2012)*, pages 1-8, October 2012

Received signal strength distribution can be approximated by a Gaussian mixture

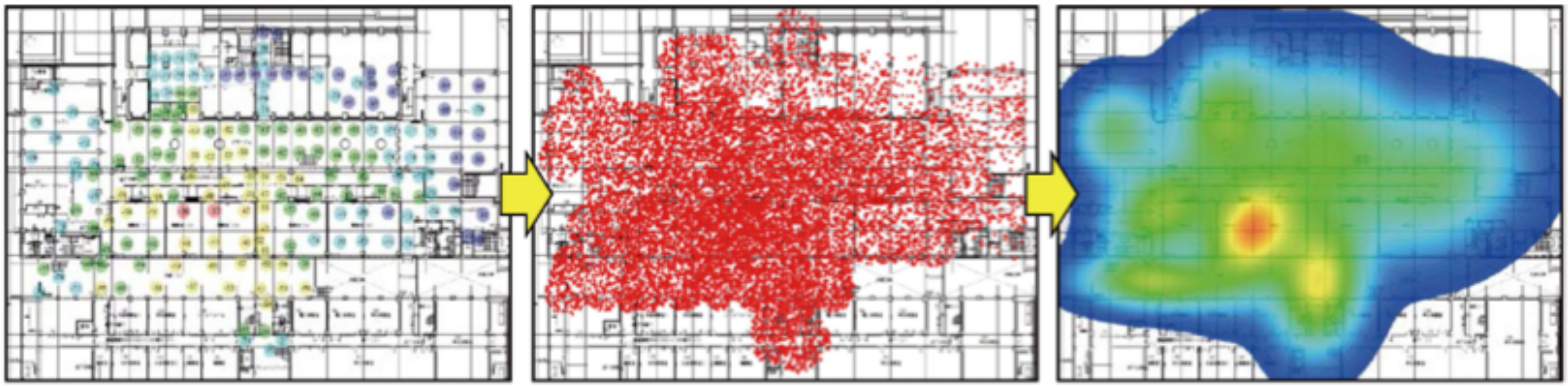


Image adapted from K. Kaji and N. Kawaguchi, "Design and implementation of WiFi indoor localization based on Gaussian mixture model and particle filter," in *2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, November 2012

A Gaussian mixture is defined as

$$p(\mathbf{x}) = \sum_{n=1}^{N} \omega_n \mathcal{N}(\mathbf{x}; \mu_n, \boldsymbol{\Sigma}_n)$$

where weights $\omega_n > 0$ and $\sum_{n=1}^{N} \omega_n = 1$

Measurement likelihood can be approximated by a generalized Gaussian mixture

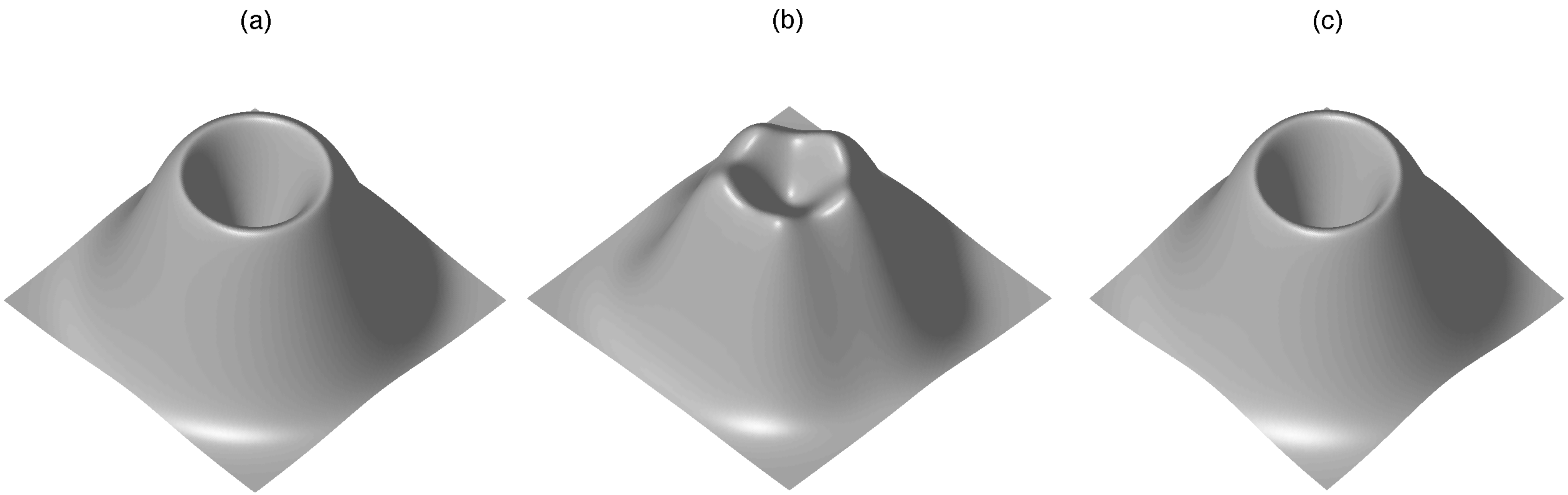


Image adapted from Müller et al., "UWB positioning with generalized Gaussian mixture filters," in *IEEE Transactions on Mobile Computing*, 2014 (in press)

Müller et al. 2012

Müller et al. 2014

$$p(y_{k,j}|\mathbf{x}_k) \approx \mathcal{N}(\mathbf{m}_1(y_{k,j}); \mu_{k,j}^{(1)}, \mathbf{\Sigma}_{k,j}^{(1)}) \cdot \left(1 - \bar{c} \cdot \mathcal{N}(\mathbf{m}_2(y_{k,j});\ \mu_{k,j}^{(2)}, \mathbf{\Sigma}_{k,j}^{(2)})\right)$$

one component can have negative weight

Field test was done at Tampere University of Technology, Finland

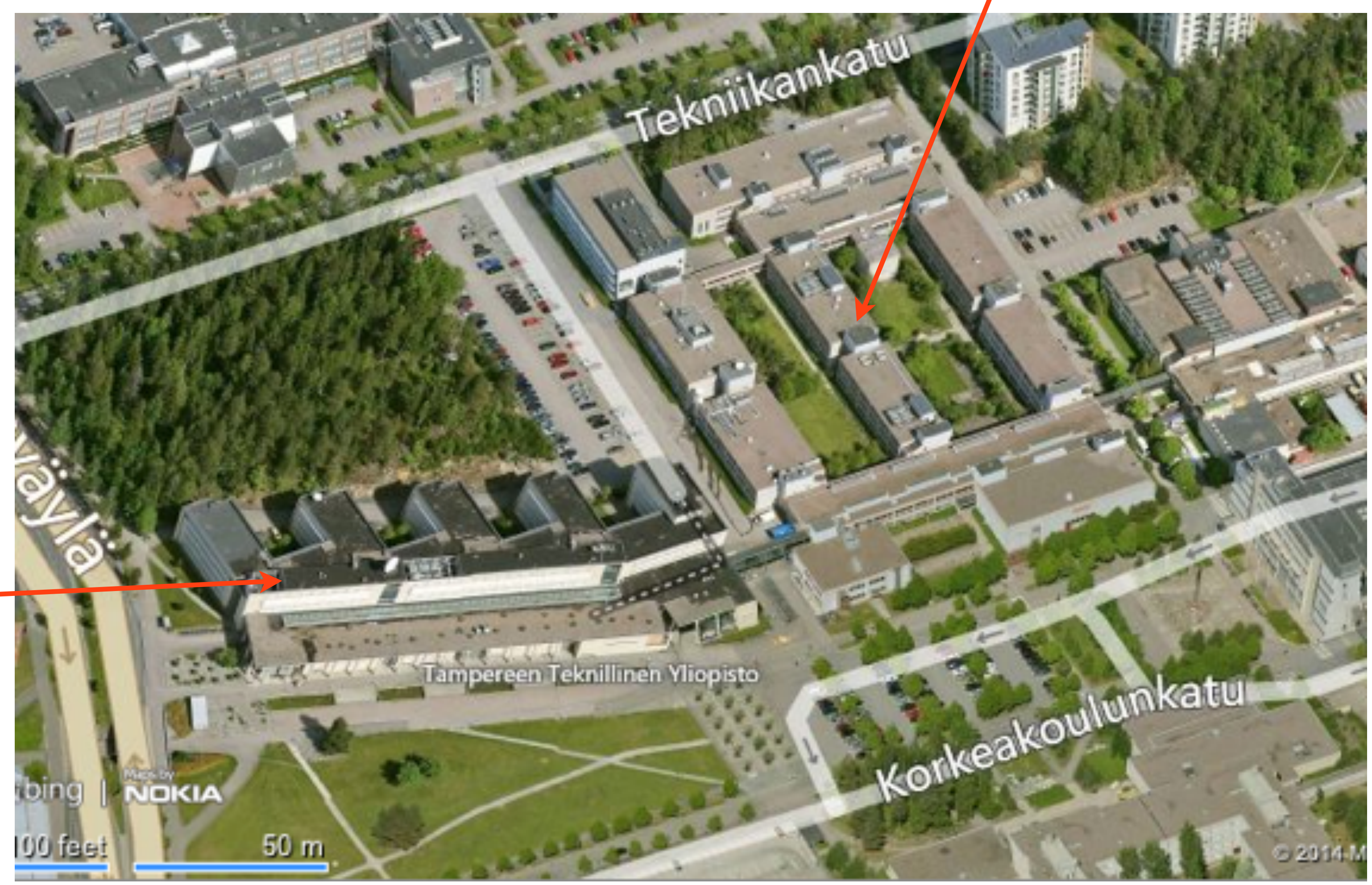
2 buildings, each with 3 floors, 48 000 m^2

506 access points

4 737 fingerprints

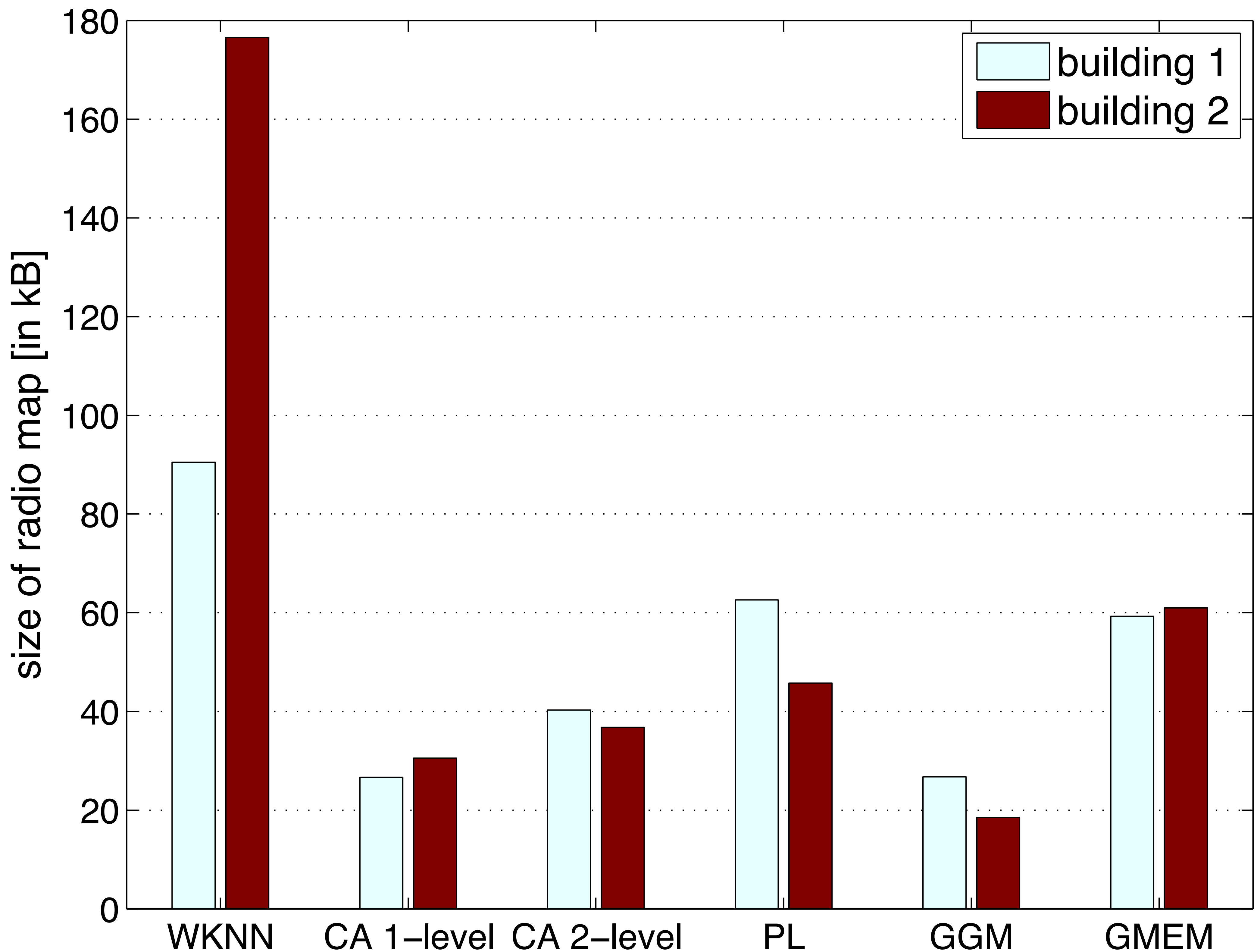
4 tracks with 308 position estimates

building 1

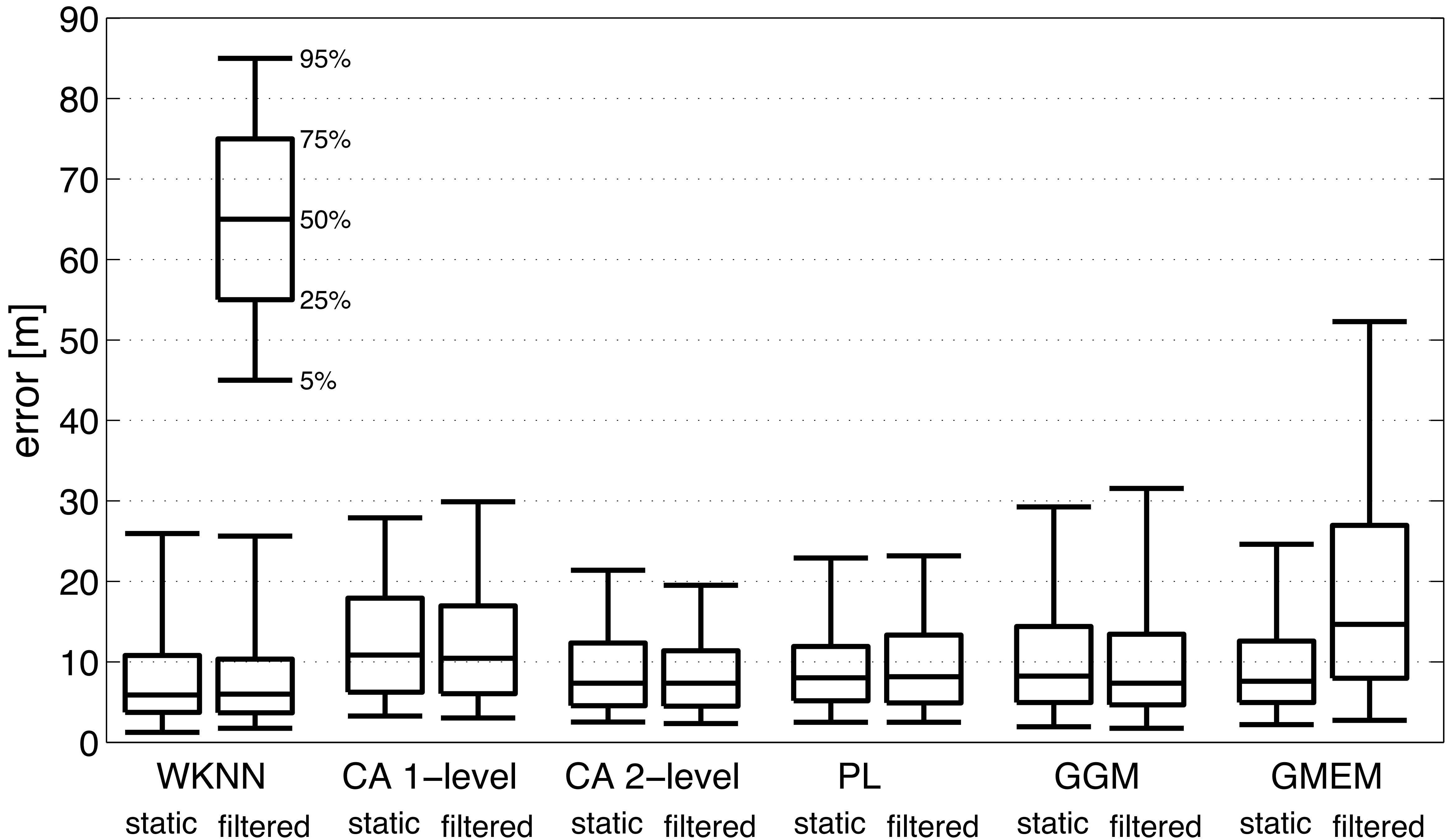


building 2

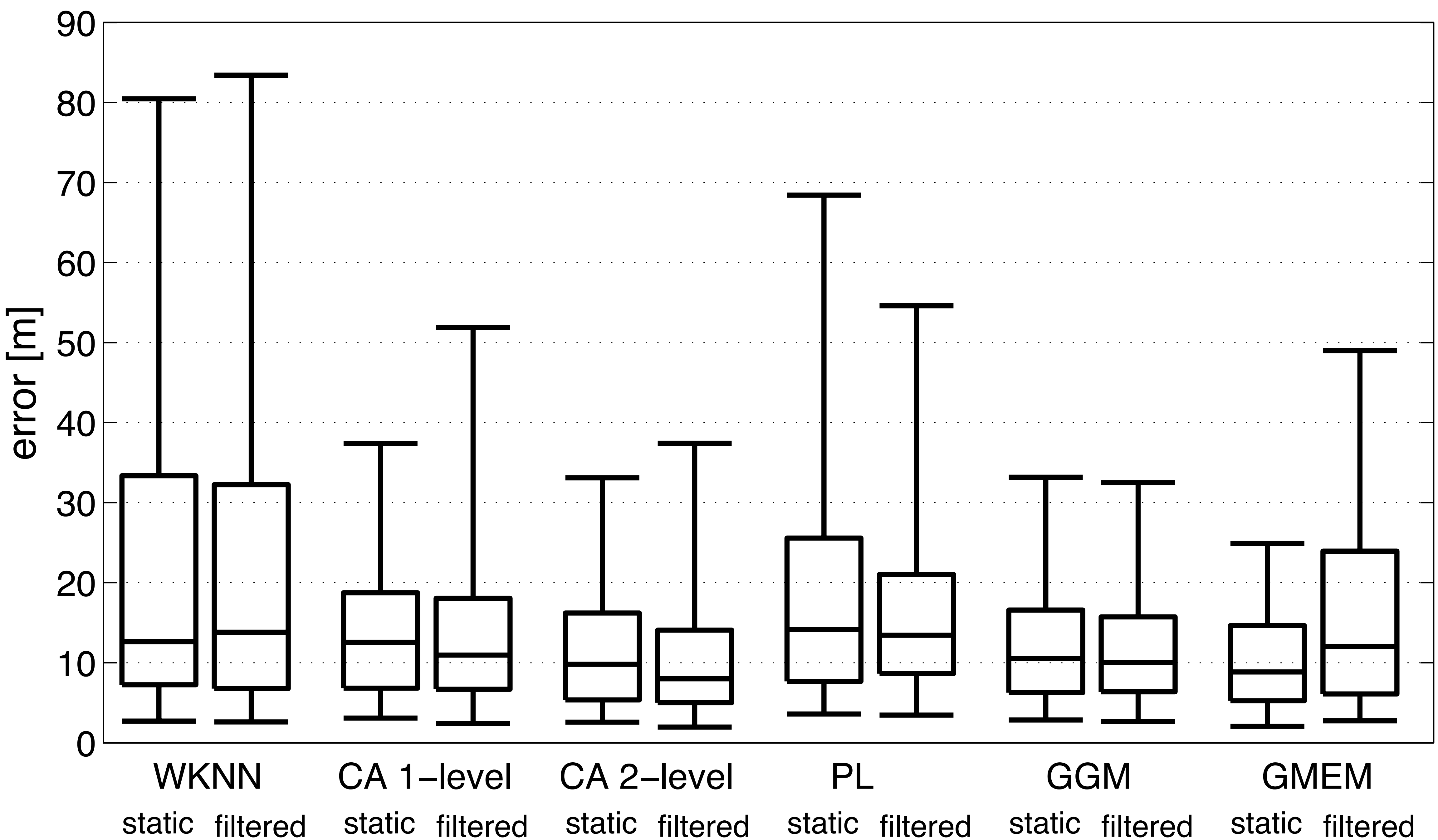
Parametric methods reduced radio map sizes between 30% and 90% in our tests



Nonparametric method is slightly more accurate than parametric methods when using all available data (506 access-points)



Parametric methods are more accurate than nonparametric method for low access-point density (51 access points)

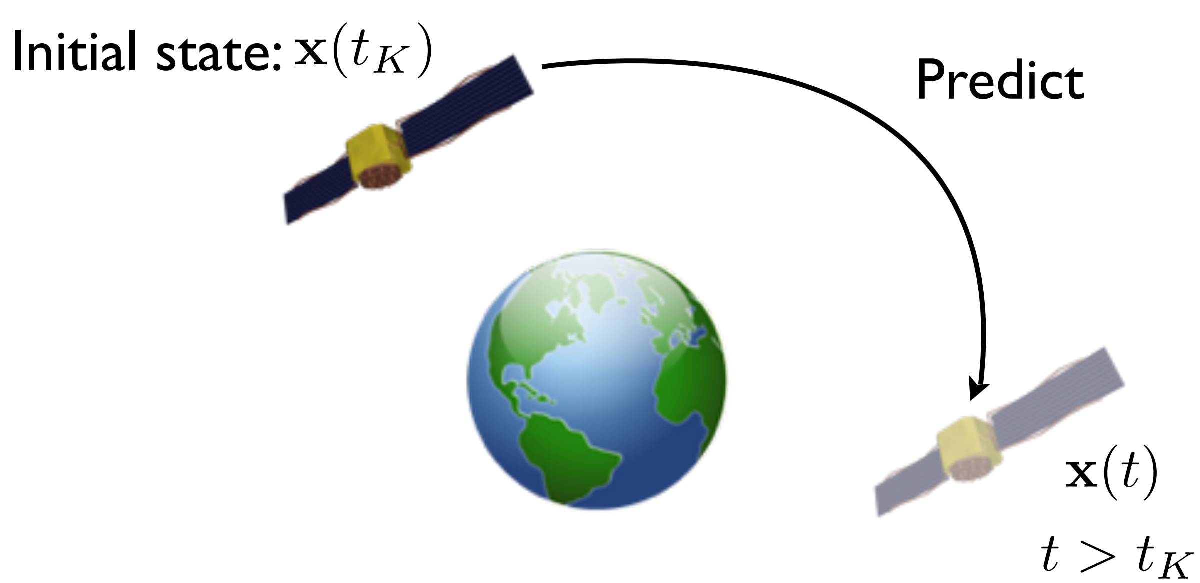


Parametric methods reduce radio map size and provide similar or better positioning accuracy than nonparametric method

Radio map size is reduced by 30% to 90% in our tests

Nonparametric and parametric methods show similar accuracies for high access-point density

Accuracies of parametric methods worsen only slightly for low access-point densities



Statistical path loss models [1]

The real-data tests with existing cell and WLAN infrastructure indicate that especially estimation consistency is improved. Consistency is crucial when different measurements are combined.

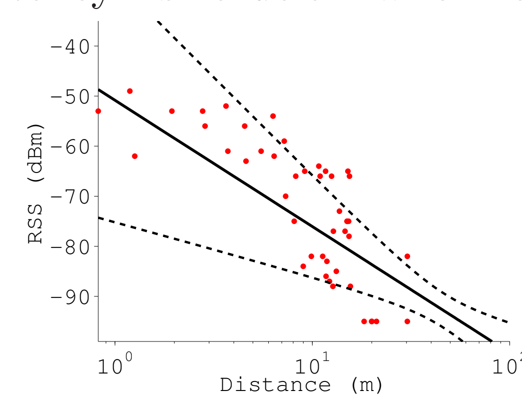


Figure 2: Fitted model with variance induced by unknown PL parameters (dashed curves).

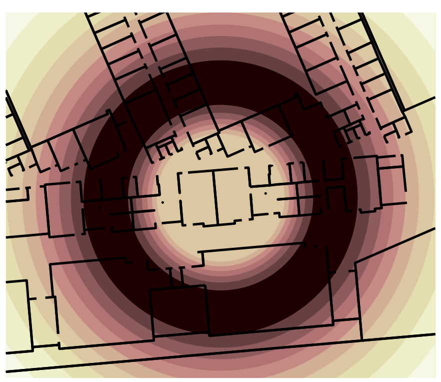


Figure 3: PL model likelihood is omnidirectional.

time to first fix

30s → 5s

Thank you!
Questions?