

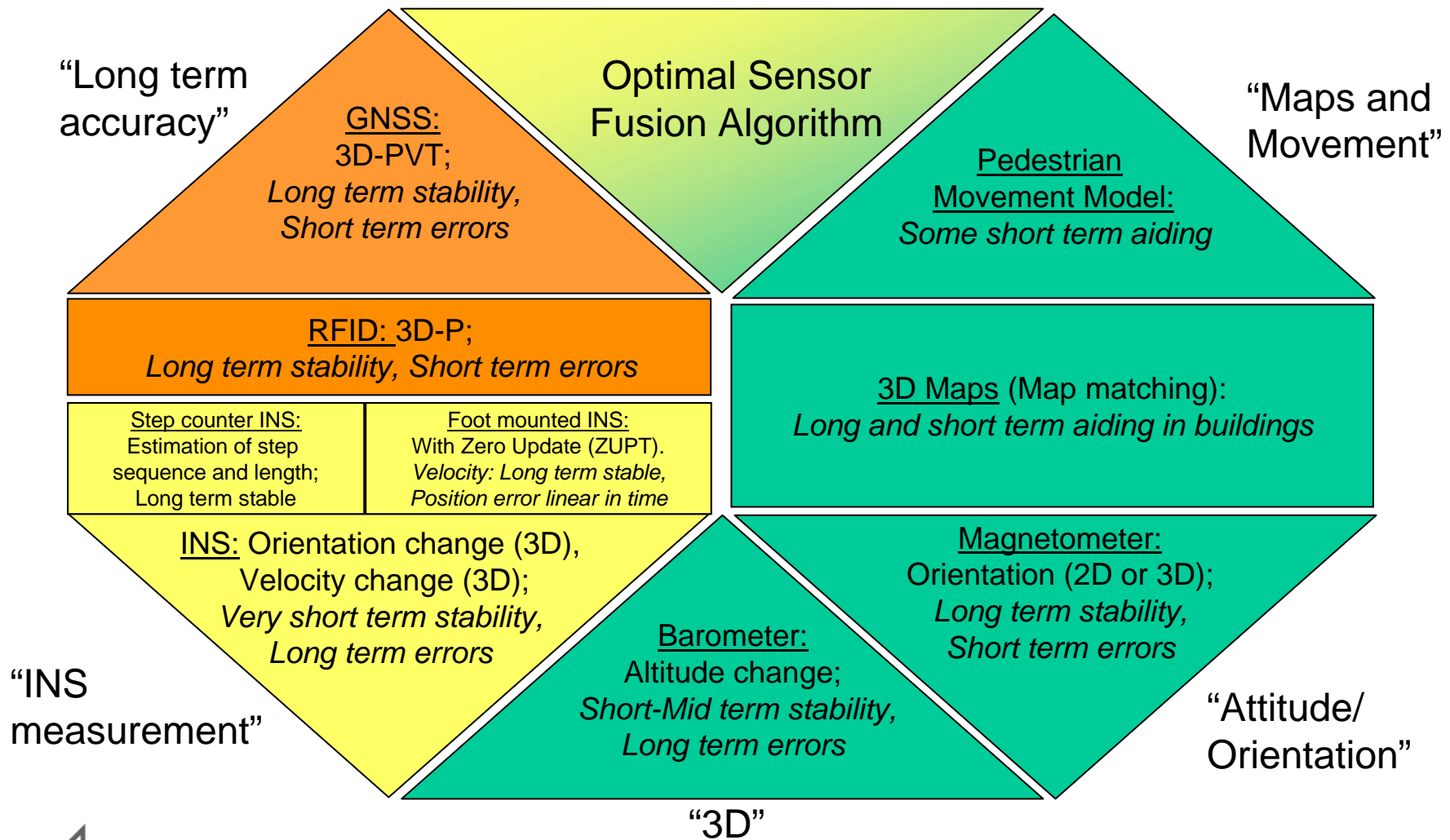
Cascaded Estimation Architecture for Integration of Foot-Mounted Inertial Sensors

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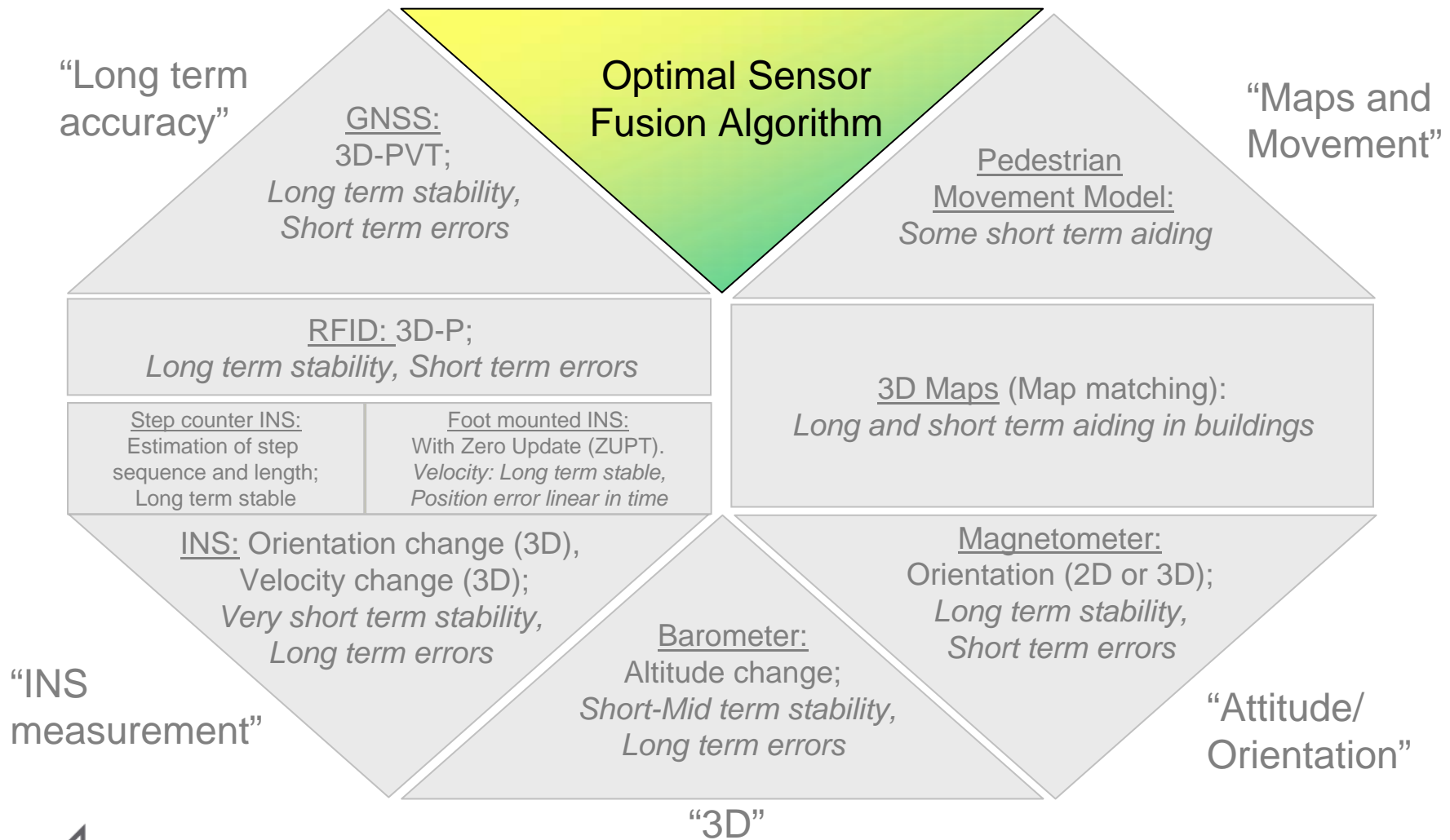


Sensor Fusion for Pedestrian Applications





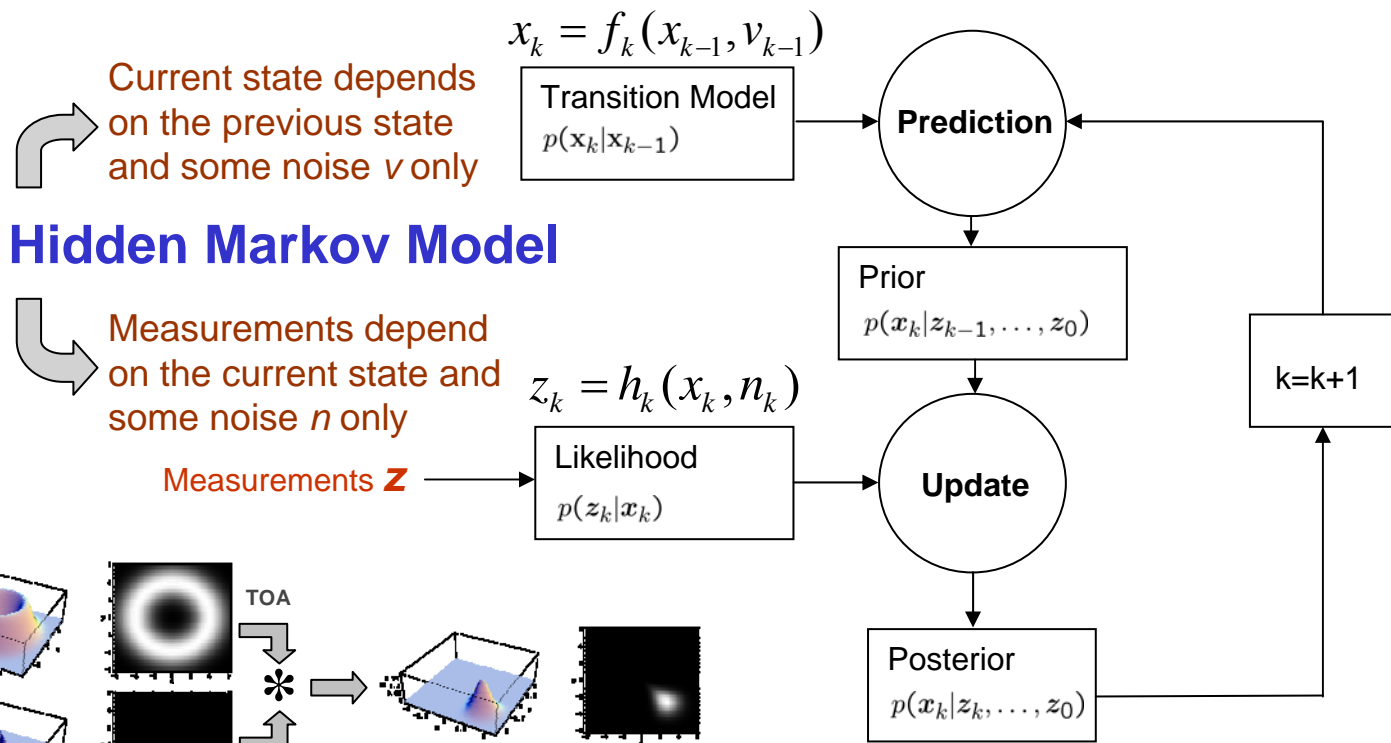
Sensor Fusion for Pedestrian Applications





Motivation

Soft-Location: Sequential Bayesian estimation for localization



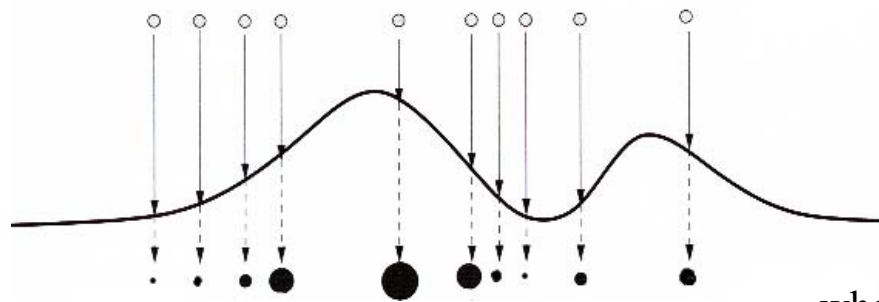
Independent errors: Factorization of Likelihood



Estimation of the **state x** : Posterior PDF contains inferable knowledge about the state



Implementation via Particle Filter

- Particle filter is a technique for implementing recursive Bayesian filter by Monte Carlo sampling
- **The idea:** represent the posterior density by a set of random samples (particles) with associated weights.



higher density  more particles
 more weight

$$p(x_k | z_{1:k}) \approx \sum_{i=1}^{N_s} w_k^i \delta(x_k - x_k^i)$$

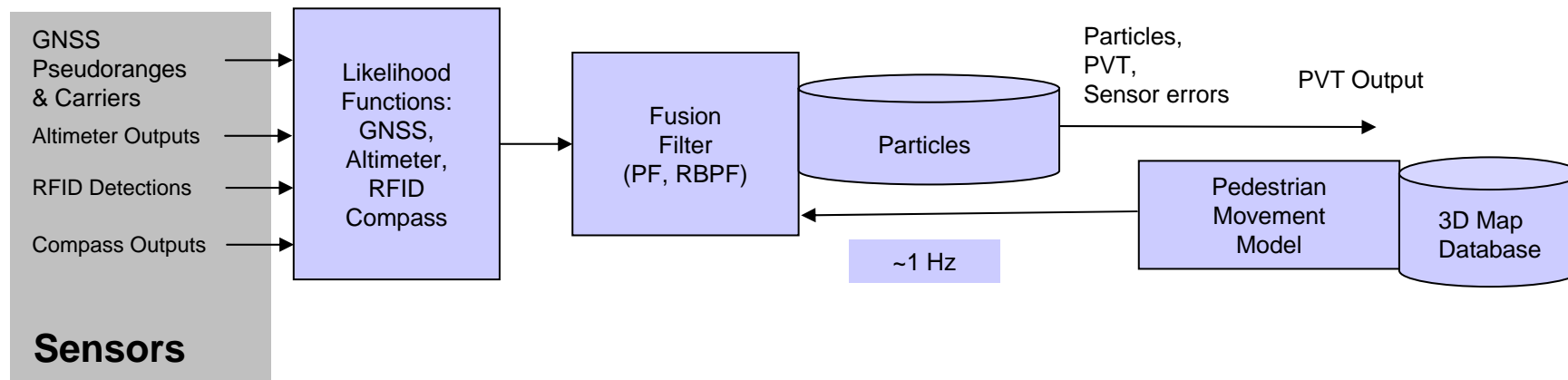
where, N_s : number of samples(particles)

$\{x_k^i, i = 0, \dots, N_s\}$: set of sampled states

$\{w_k^i, i = 0, \dots, N_s\}$: weights of sampled states

- For large numbers of samples the Random (Monte Carlo) Sampling approximation **converges** to the true PDF and is an optimal estimate.

Bayesian Location Estimation Framework



- Real-time sensor fusion framework (JAVA)
- Fusion via Bayesian filtering: Particle filter
- Measurements are incorporated via likelihood functions
- Movement model takes dynamic constraints into account

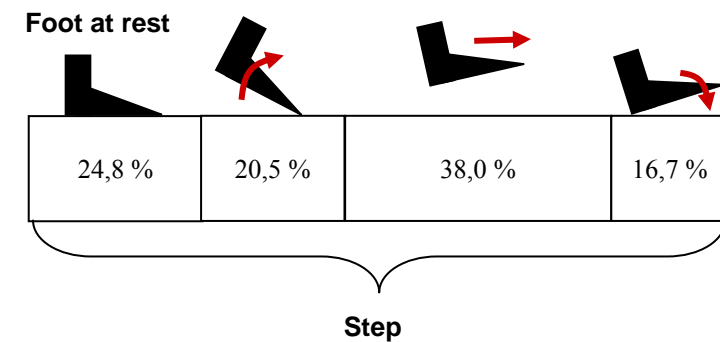
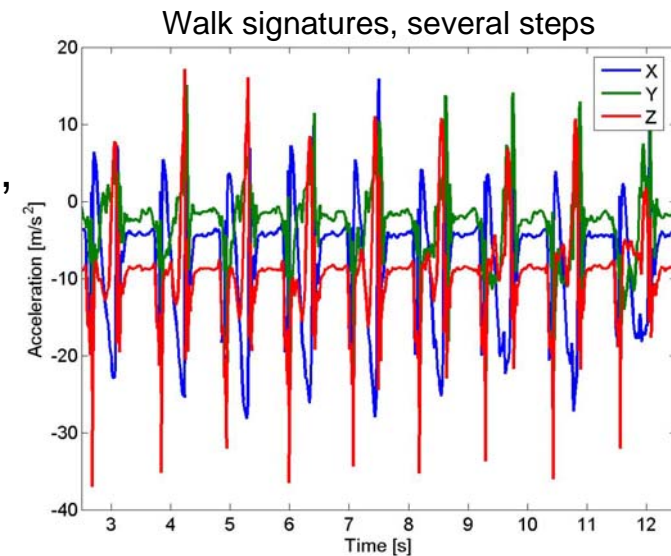
Idea: Extend framework towards inertial sensors





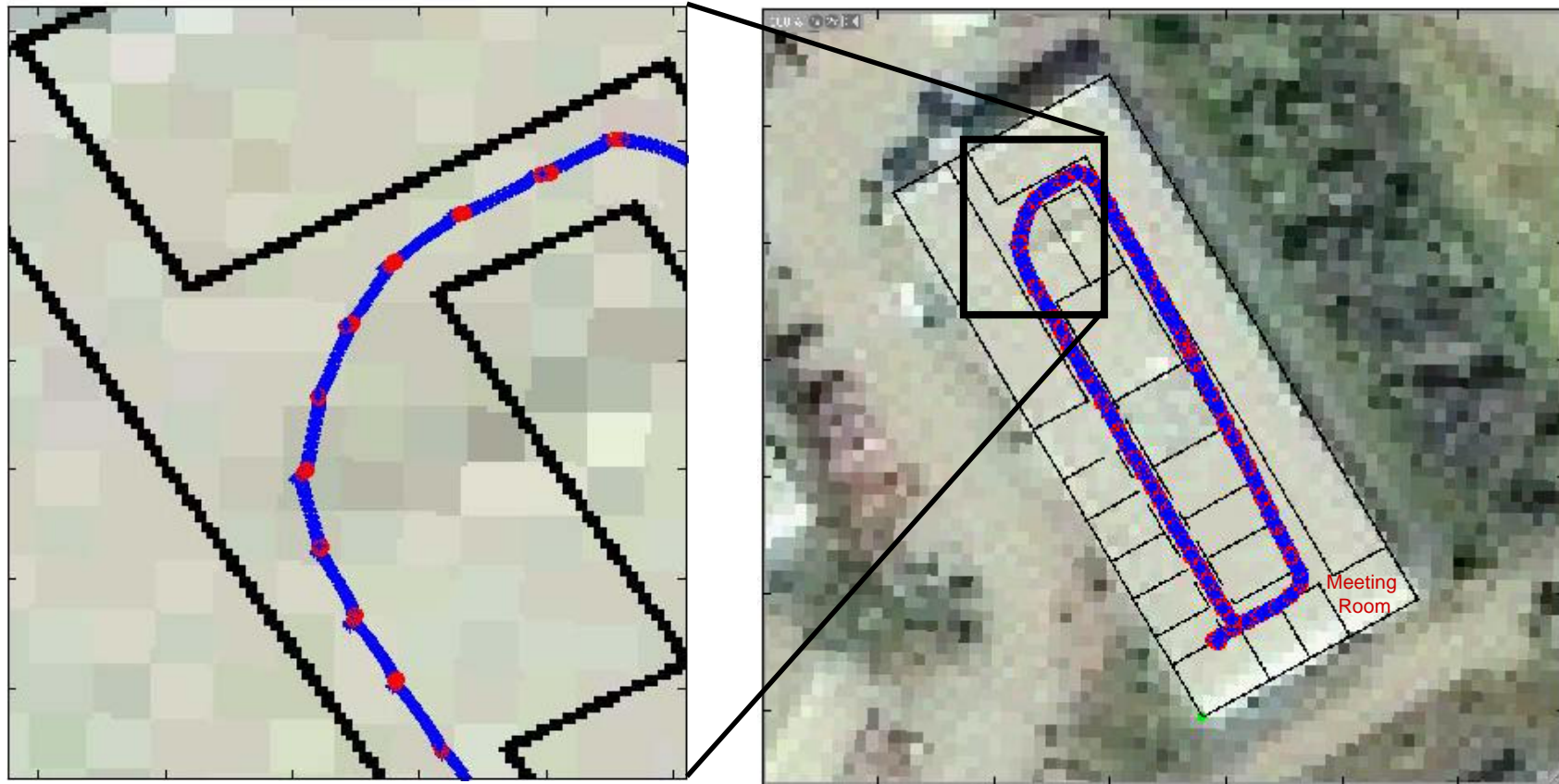
Foot Mounted Inertial Sensors

- Classical INS integration scheme:
Accelerometers, Gyros, INS computer,
Kalman filter
- Drift compensation via regular zero-velocity updates (ZUPT)
- Good performance even with low-cost MEMS





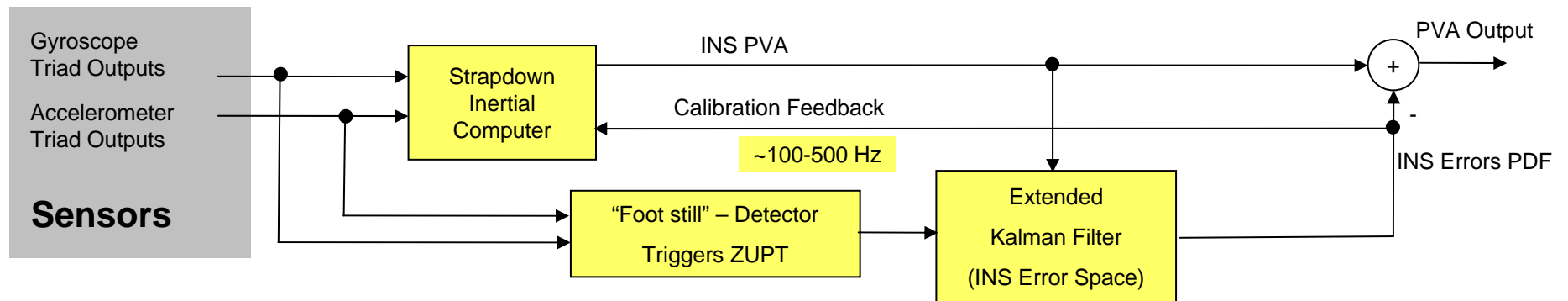
Experimental Results



● Stride ● Rest, ZUPT

IKN Building TE02

Conventional Integration of Inertial Sensors

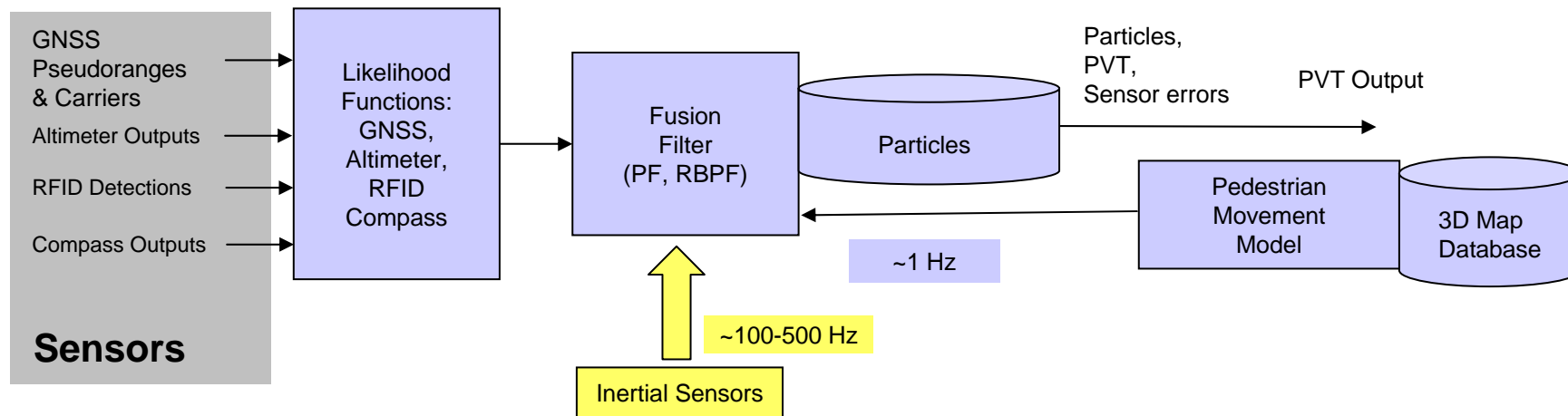


- Fusion via Bayesian filtering: Extended Kalman filter
- Measurements are **not** incorporated via likelihood functions
- Movement model **doesn't** take dynamic constraints into account

Problem: How to get things together ?

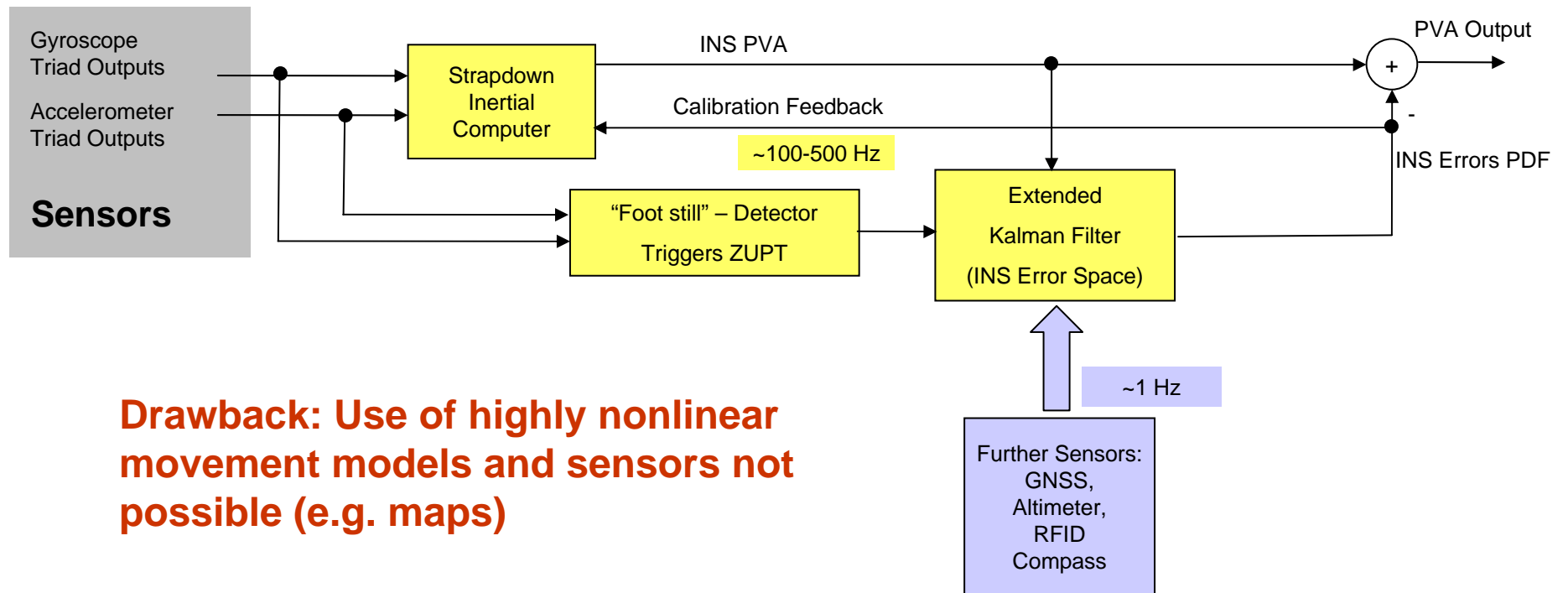


Solution 1



**Drawback: Increases filter rate,
requires extension of state space to
foot accelerations and turn rates,
movement models become complex**

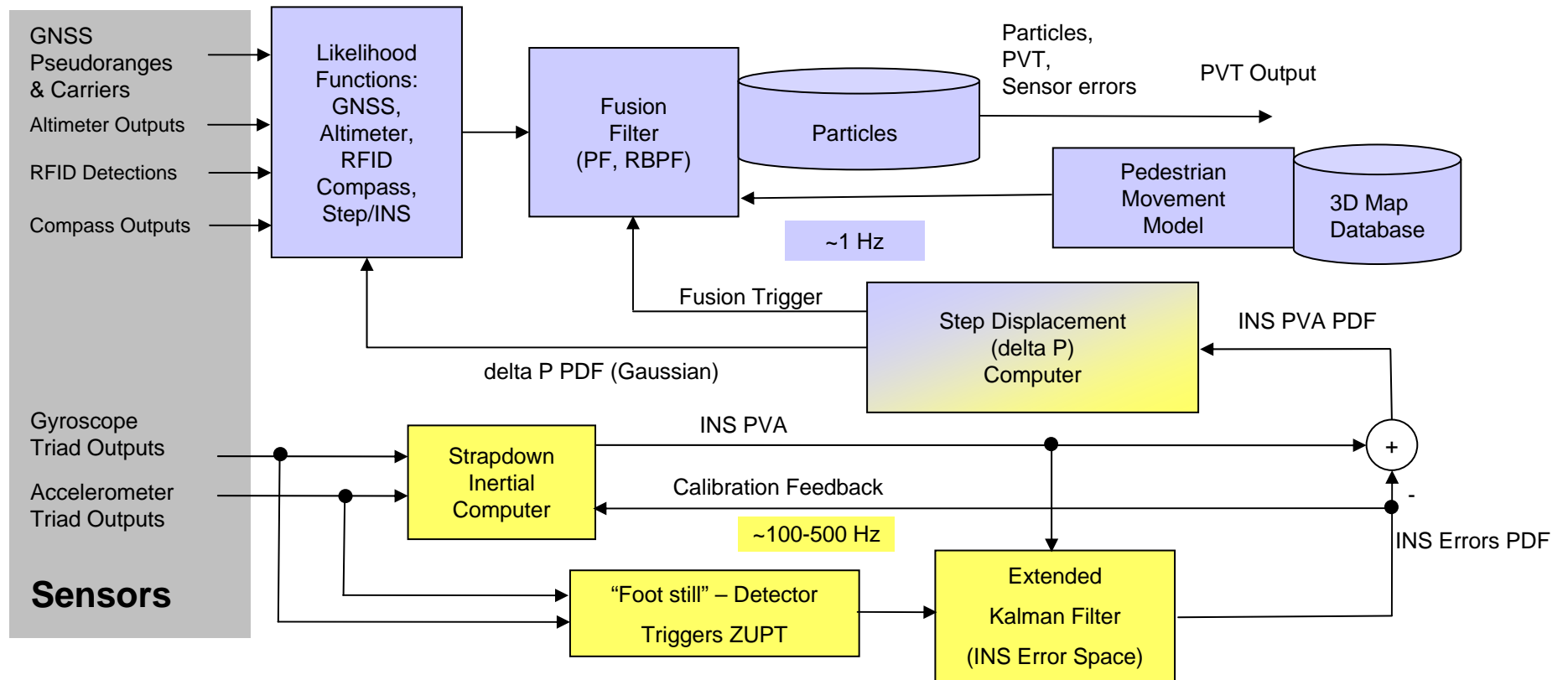
Solution 2



Drawback: Use of highly nonlinear movement models and sensors not possible (e.g. maps)



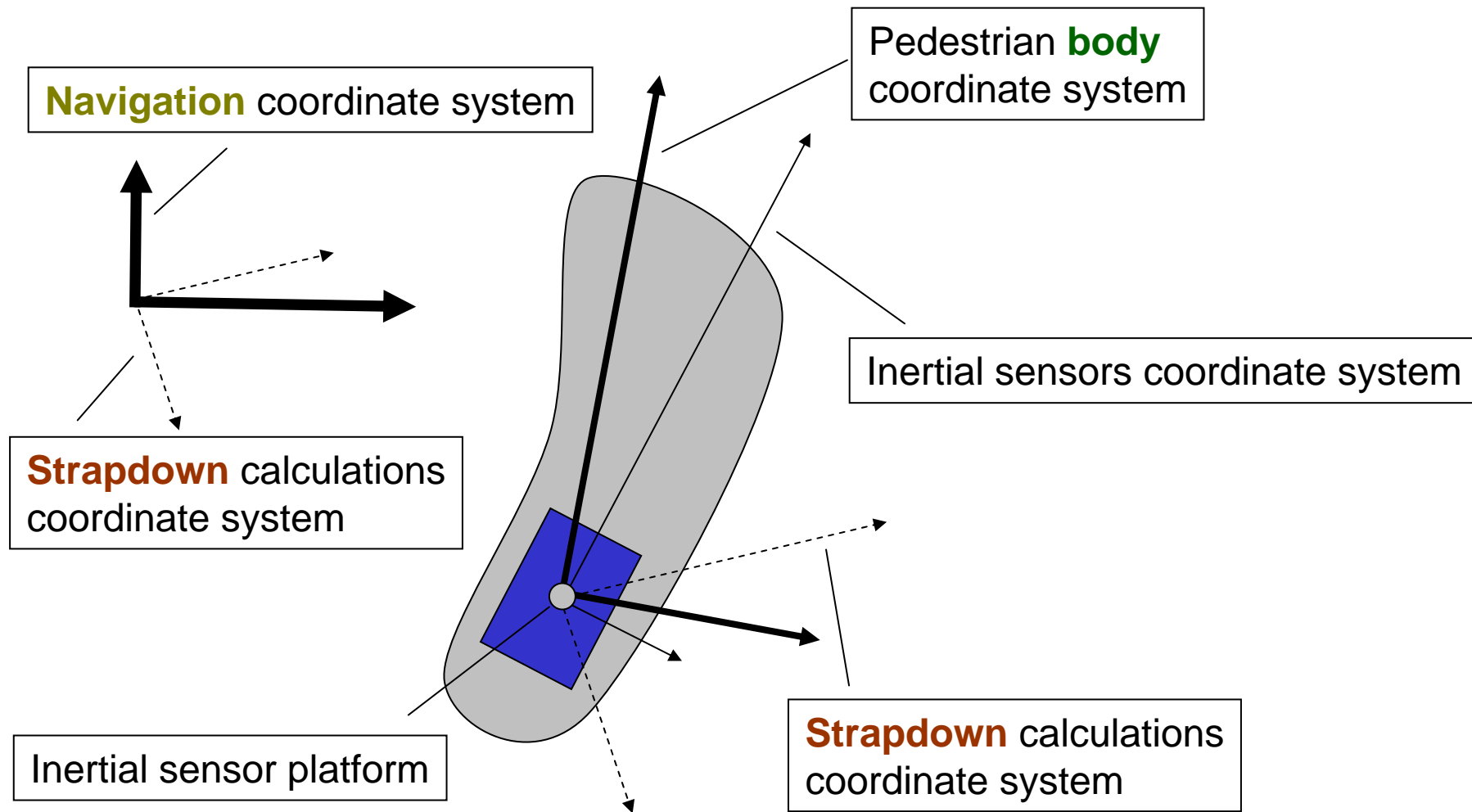
Solution 3: Our Approach



Use the lower filter to provide “step-measurements” to the upper filter



The Step-Measurement

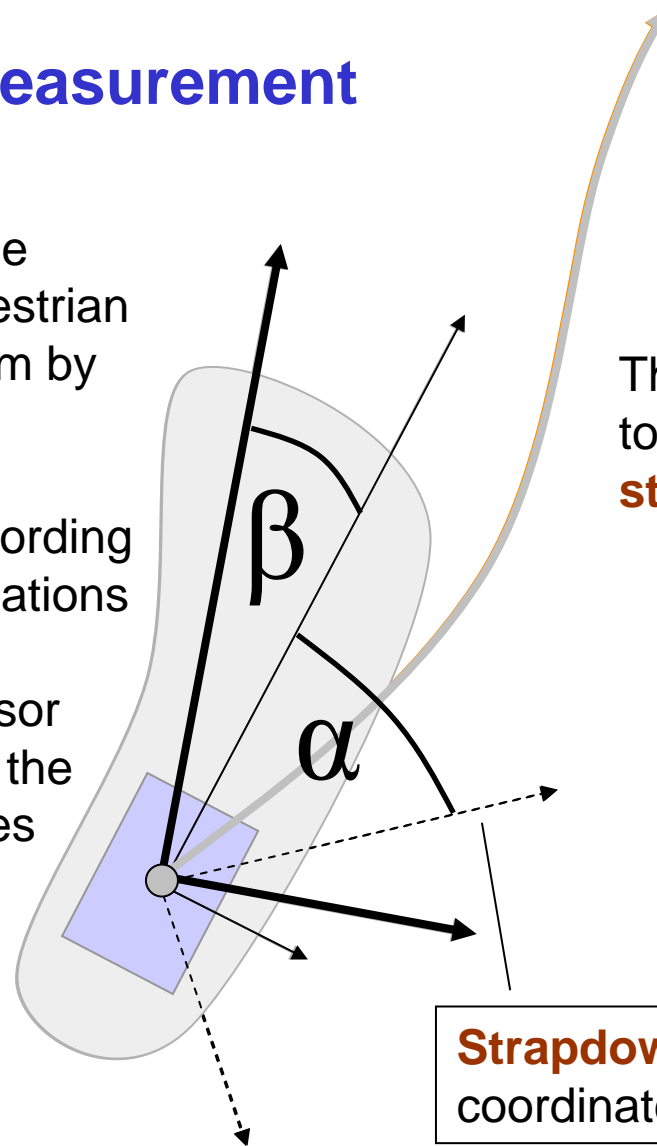


The Step-Measurement

Transformation from the **strapdown** to the pedestrian **body** coordinate system by a rotation via:

α : Current heading according to **strapdown** calculations

β : Misalignment of sensor axes with respect to the pedestrian **body** axes



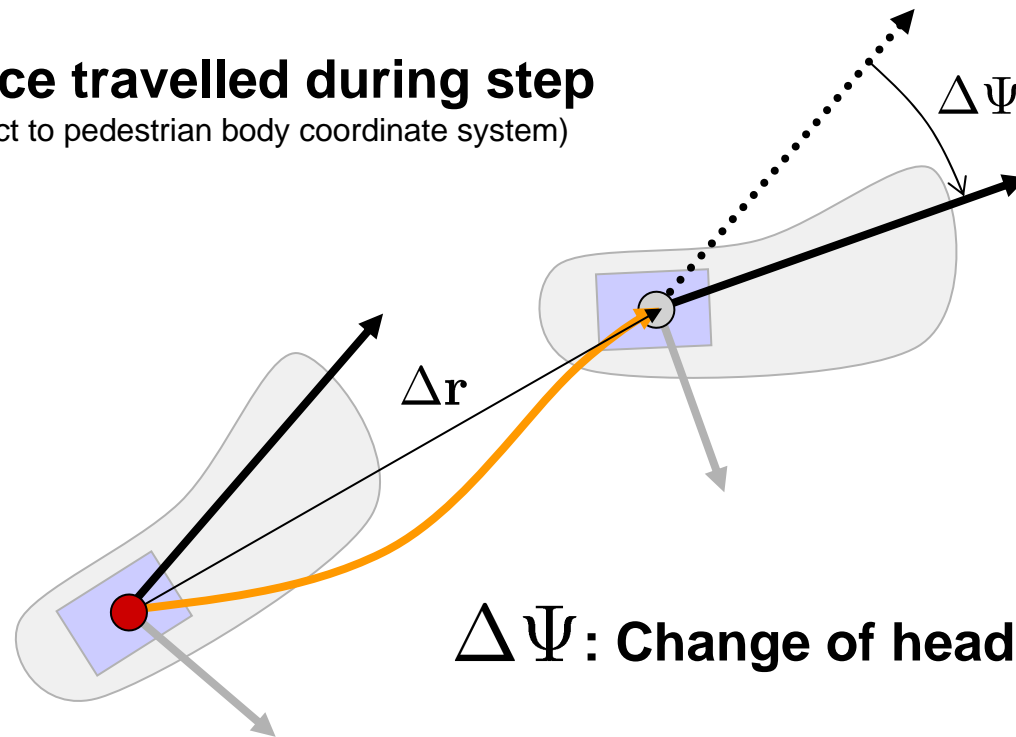
The **step** is sensed with respect to the coordinate system of the **strapdown** calculations

Strapdown calculations
coordinate system



The Step-Measurement

$\Delta \mathbf{r}$: Distance travelled during step
(with respect to pedestrian body coordinate system)



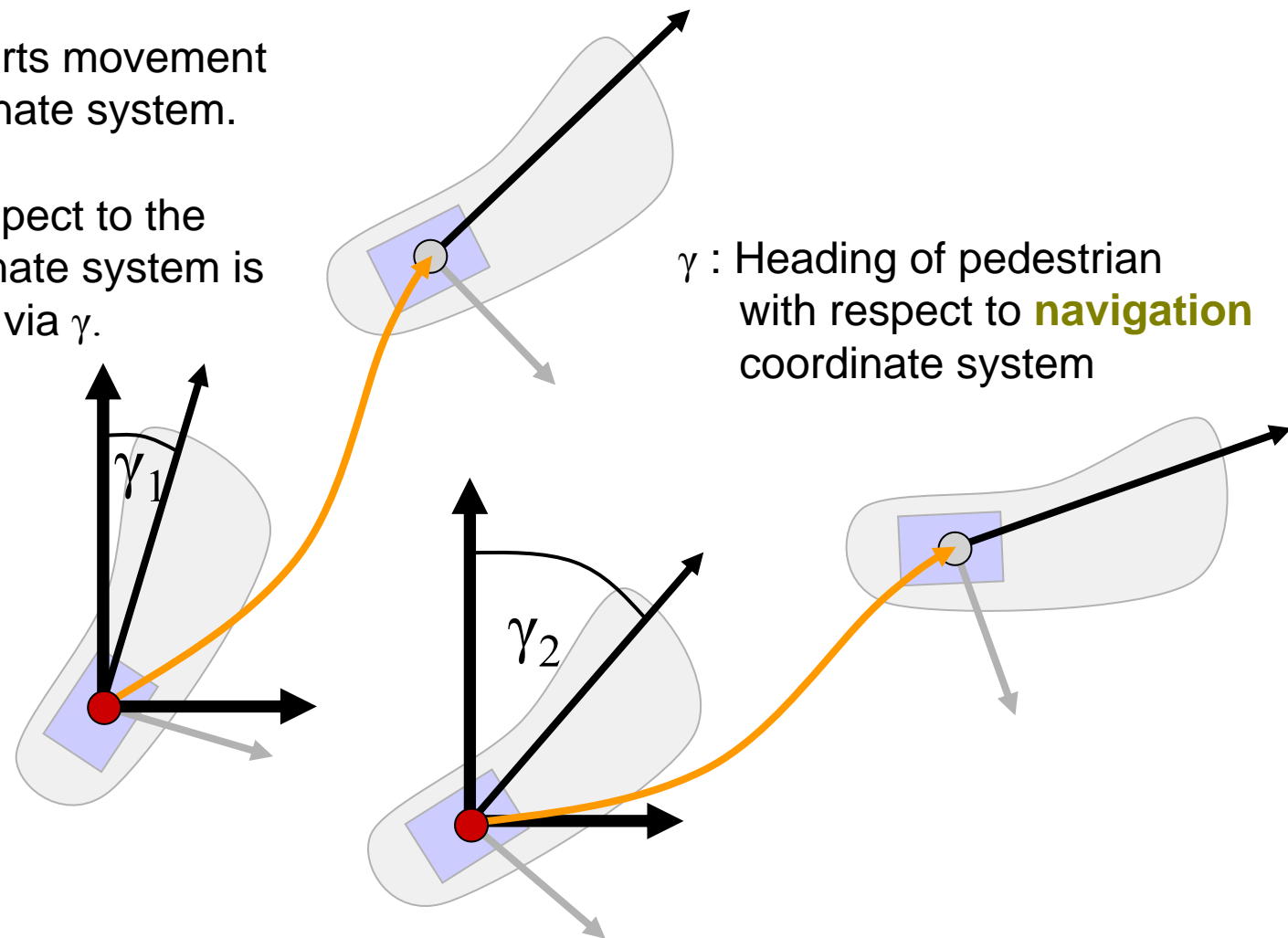
$\Delta \Psi$: Change of heading during step



The Step-Measurement

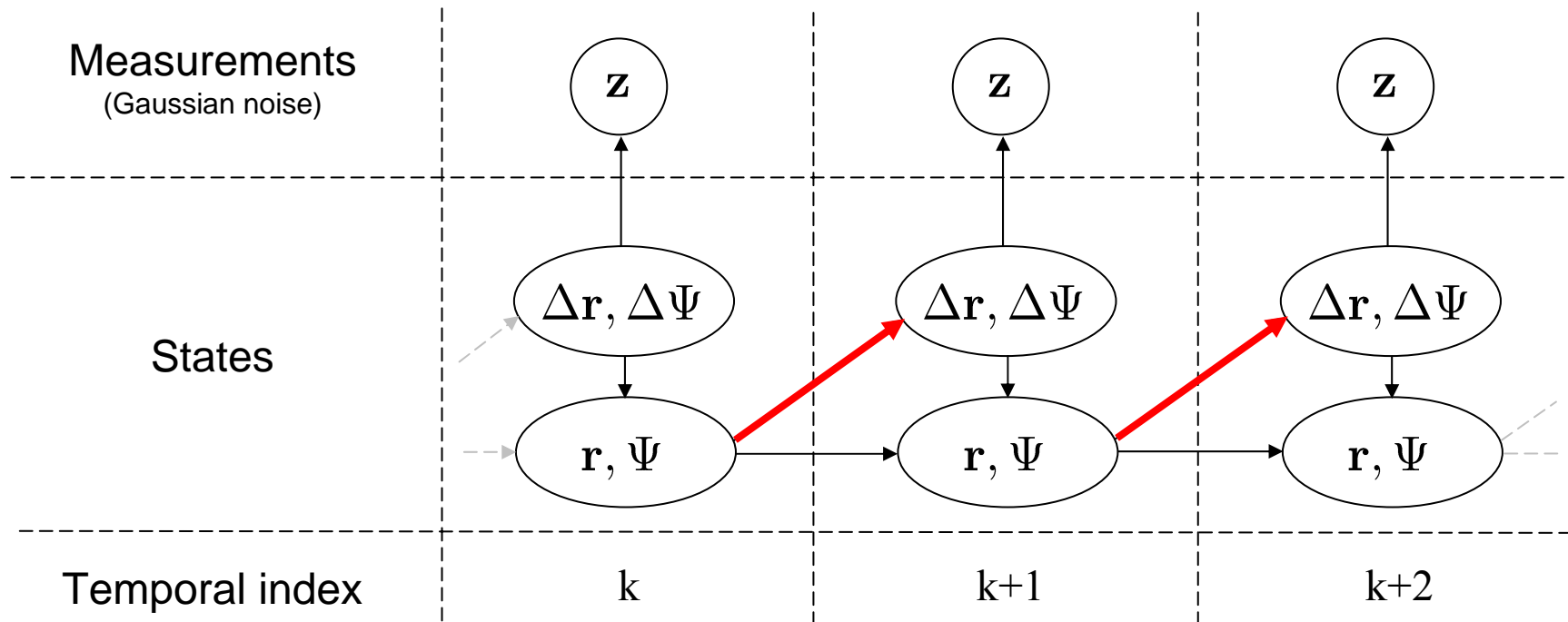
Measurement reports movement in the **body** coordinate system.

Movement with respect to the **navigation** coordinate system is given by a rotation via γ .





Dynamic Bayesian Network



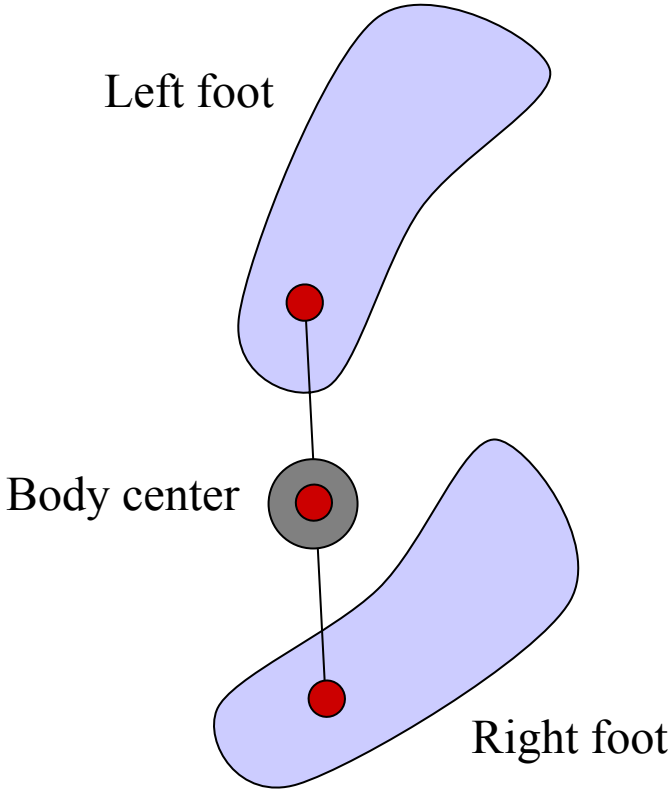
Movement:

- Position $\mathbf{r}_k = \mathbf{C}(\Psi_{k-1})\Delta\mathbf{r}_k + \mathbf{r}_{k-1}$
- Heading $\Psi_k = \Psi_{k-1} + \Delta\Psi_k$

Probabilistic movement model (including walls)



Integration of a Pair of Platforms

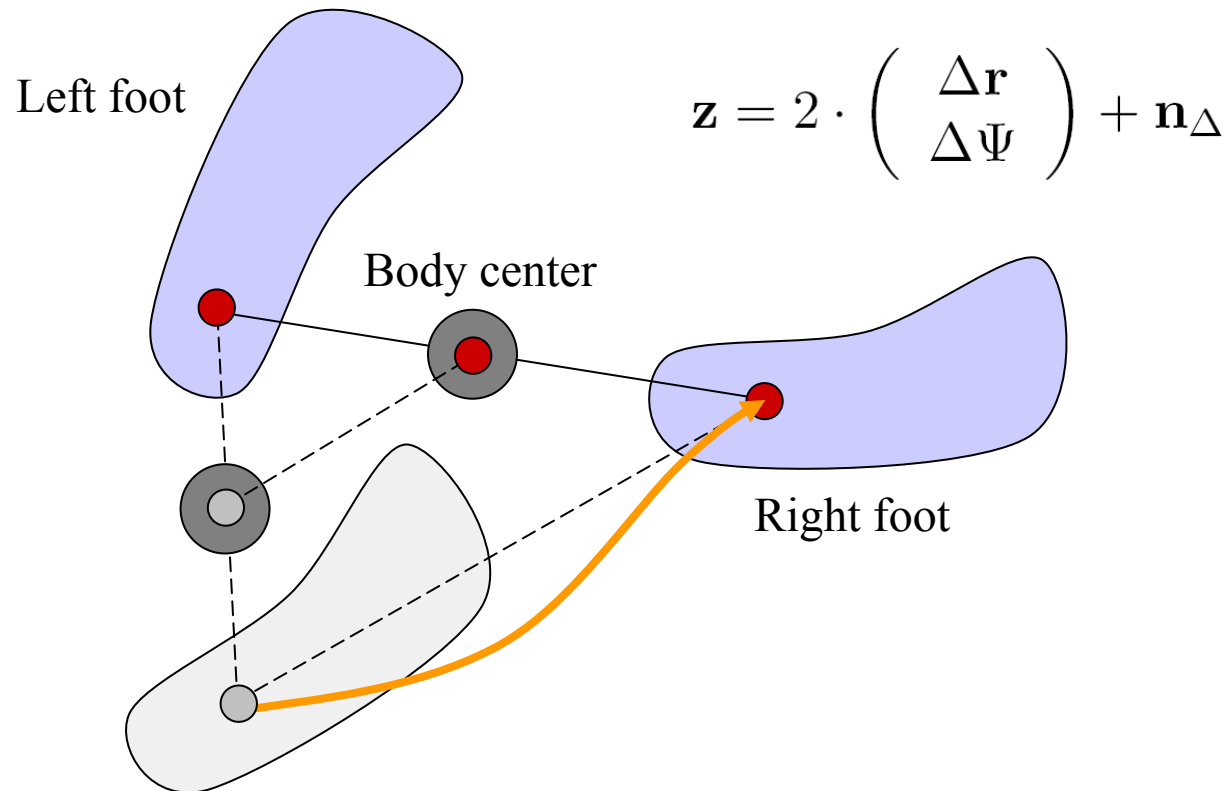


Pedestrian body model:
Body centered on connecting
line of foot centers



Integration of a Pair of Platforms

Foot movement is 2x body movement:

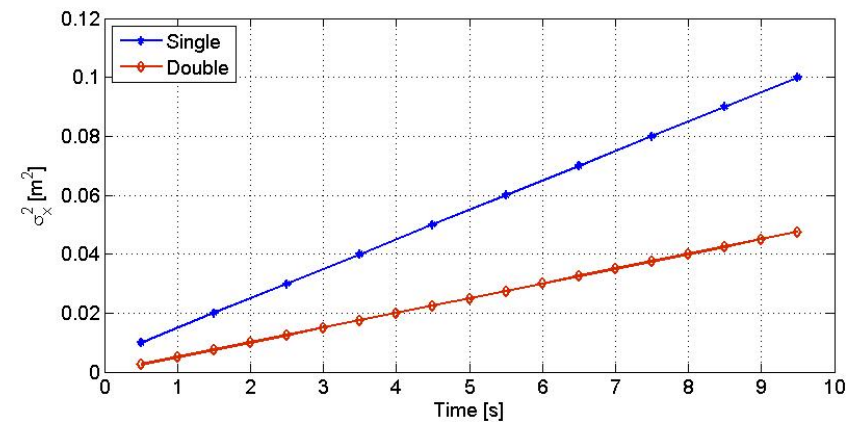
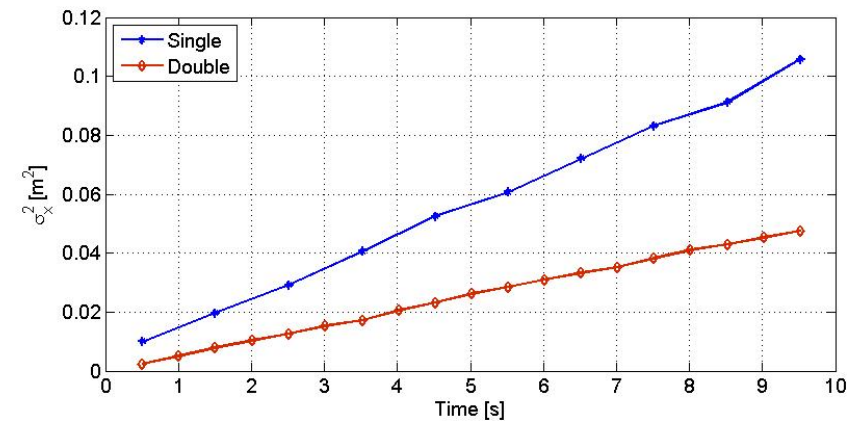




Performance Analysis

➤ **Simulation:** Particle filter, 2000 particles, linear Gaussian movement model

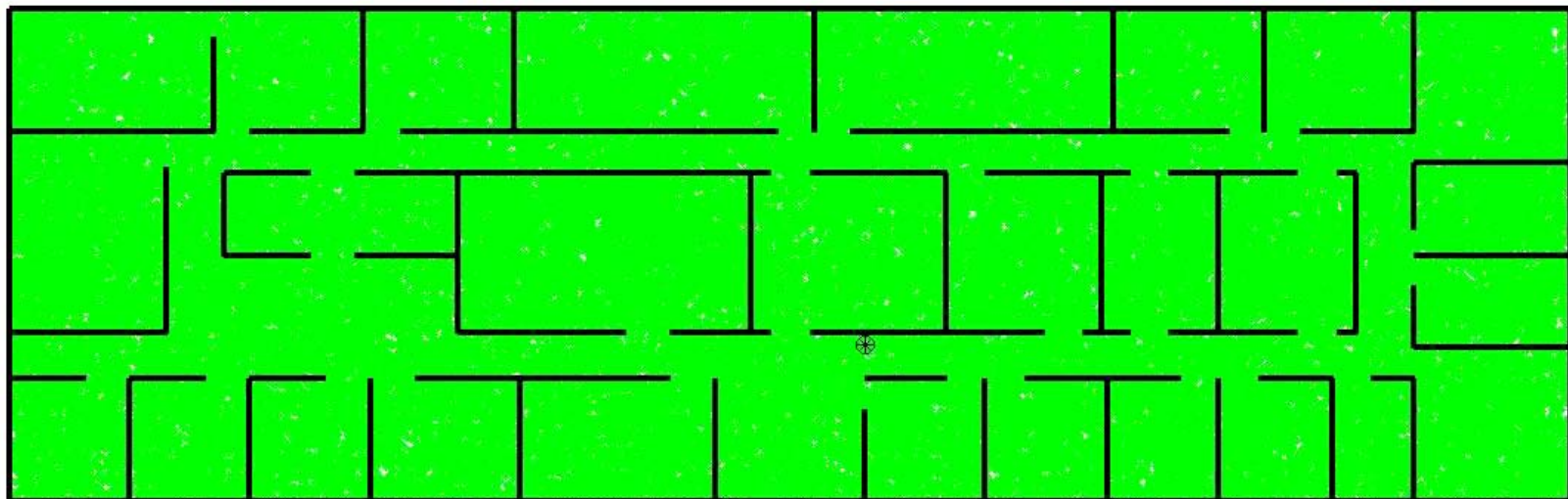
➤ **Error Analysis:** Covariance analysis based on Kalman filter framework





Experimental Results

- **Scenario:** Office building layout, initial position and heading unknown



Location hypotheses

Location hypotheses
having crossed a wall
during the recent step
(forbidden by movement model)

○ — True track



Conclusions

- **Kalman filter for foot-mounted inertial sensors**
 - Low-cost MEMS inertial sensors become highly valuable
 - Computational efficient for high rate INS (~ 100 Hz)

- **Main fusion algorithm based on Particle filtering**
 - Makes use of the provided step-measurements
 - Low rate fusion (~ 1 Hz) takes nonlinearities into account
 - Integration of a pair of platforms (right & left foot equipped) based on pedestrian model doubles PDR performance



Thank you & questions