Cascaded Estimation Architecture for Integration of Foot-Mounted Inertial Sensors

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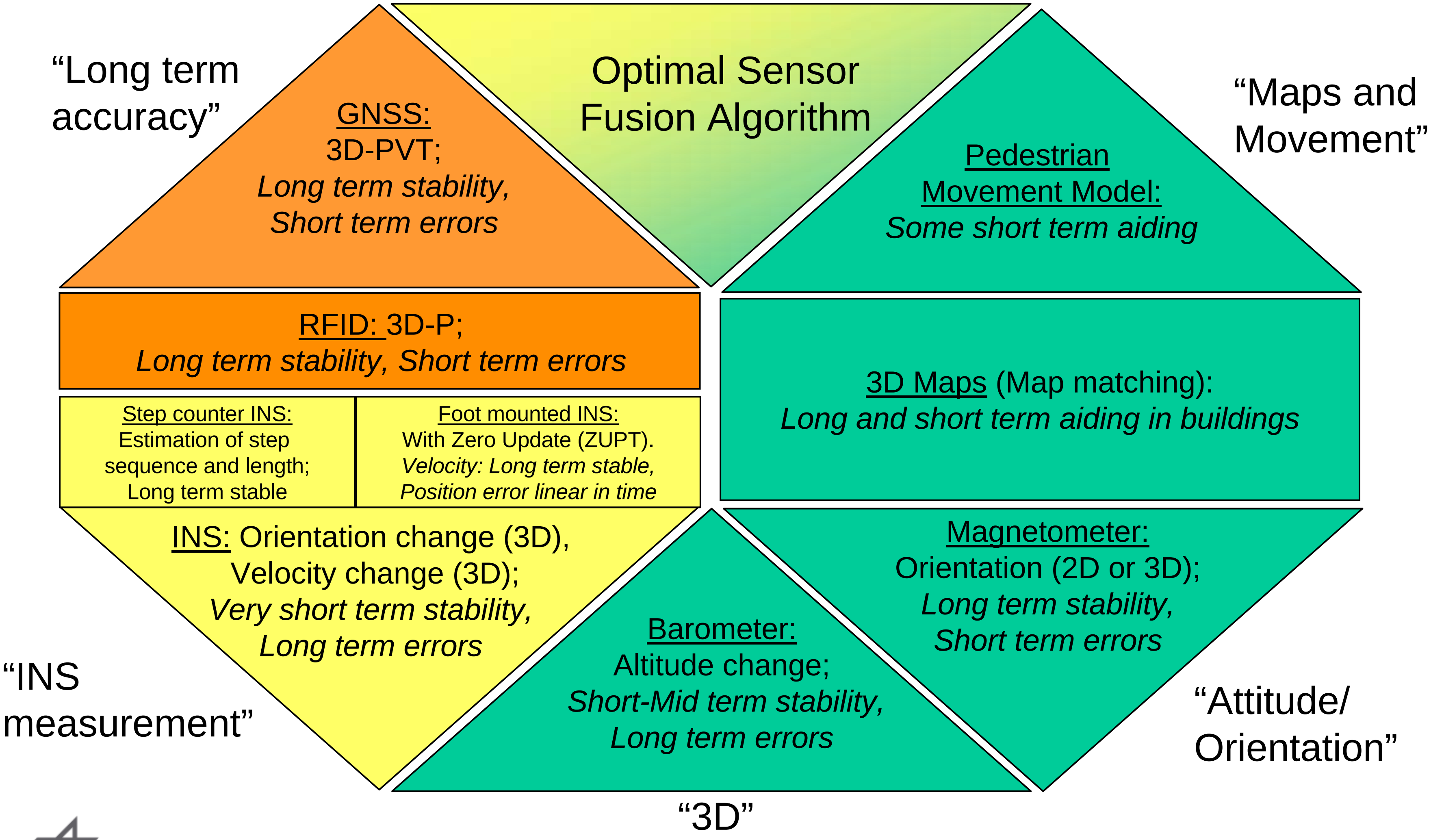
Sensor Fusion for Pedestrian Applications



Sensor Fusion for Pedestrian Applications

"Long term accuracy"

GNSS:
3D-PVT;
Long term stability,
Short term errors

Optimal Sensor Fusion Algorithm

"Maps and Movement"

Pedestrian Movement Model:
Some short term aiding

RFID: 3D-P;
Long term stability, Short term errors

3D Maps (Map matching):
Long and short term aiding in buildings

Step counter INS:
Estimation of step sequence and length;
Long term stable

Foot mounted INS:
With Zero Update (ZUPT).
Velocity: Long term stable,
Position error linear in time

INS: Orientation change (3D),
Velocity change (3D);
Very short term stability,
Long term errors

Magnetometer:
Orientation (2D or 3D);
Long term stability,
Short term errors

Barometer:
Altitude change;
Short-Mid term stability,
Long term errors

"INS measurement"

"Attitude/ Orientation"

"3D"

Motivation

Soft-Location: Sequential Bayesian estimation for localization

$$x_k = f_k(x_{k-1}, v_{k-1})$$

Current state depends on the previous state and some noise *v* only

Hidden Markov Model

Measurements depend on the current state and some noise *n* only

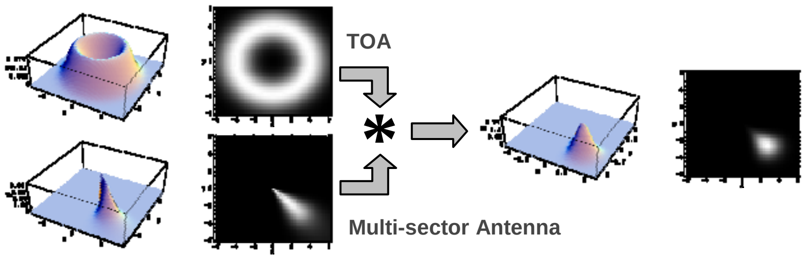
$$z_k = h_k(x_k, n_k)$$

Transition Model $p(\mathbf{x}_k|\mathbf{x}_{k-1})$ → **Prediction**

Prediction → Prior $p(\boldsymbol{x}_k|\boldsymbol{z}_{k-1}, \ldots, \boldsymbol{z}_0)$ → **Update**

Measurements ***Z*** → Likelihood $p(\boldsymbol{z}_k|\boldsymbol{x}_k)$ → **Update**

Update → Posterior $p(\boldsymbol{x}_k|\boldsymbol{z}_k, \ldots, \boldsymbol{z}_0)$ → k=k+1 → **Prediction**

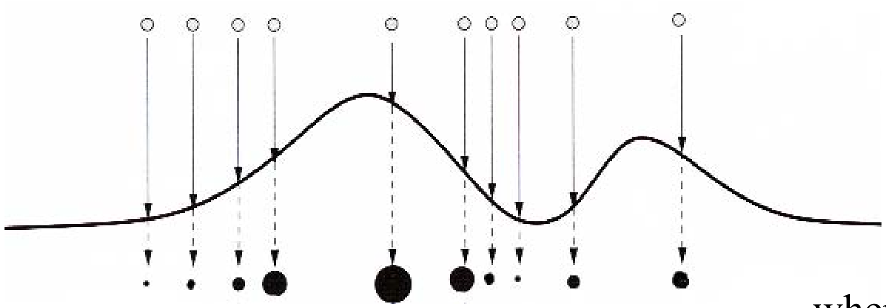


Independent errors: Factorization of Likelihood

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.



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

where, Ns : number of samples(particles)

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

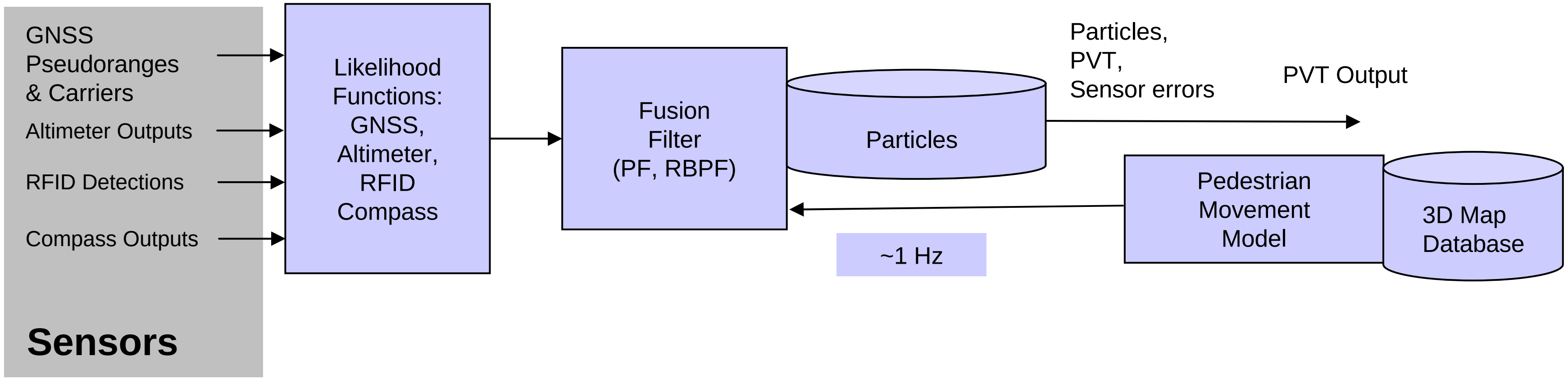
$\{w_k^i, i = 0,\ldots, Ns\}$: weights of sampled states

higher density → more particles

higher density → more weight

- 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

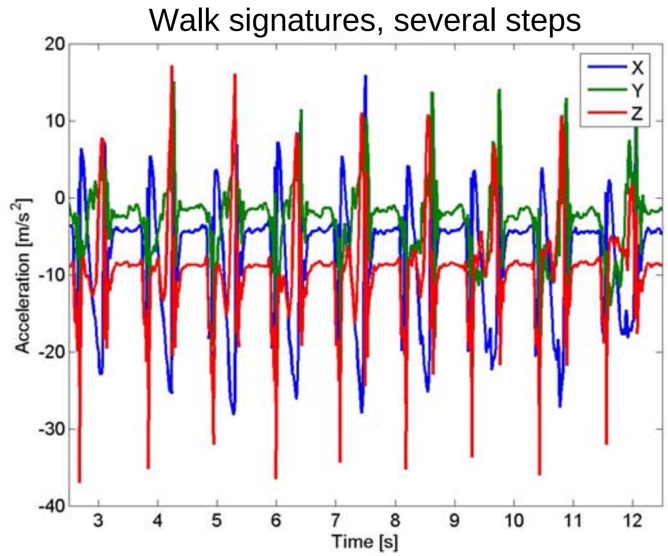


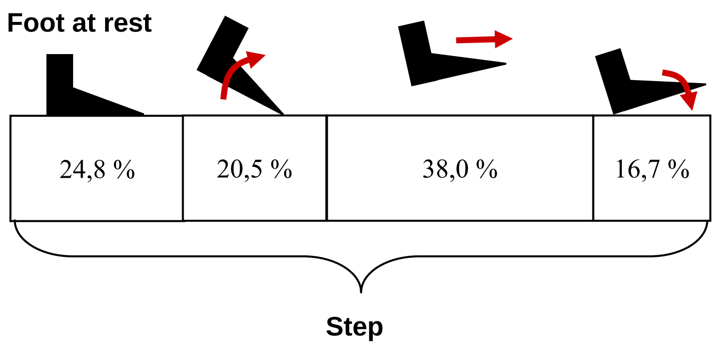
- Real-time sensor fusion framework (JAVA)
- Fusion via Bayesian filtering: Particle filter
- Measurements are incorporated via likelihood functions
- Movement model takes dynamic constraints into account

Idea: Extend framework towards inertial sensors

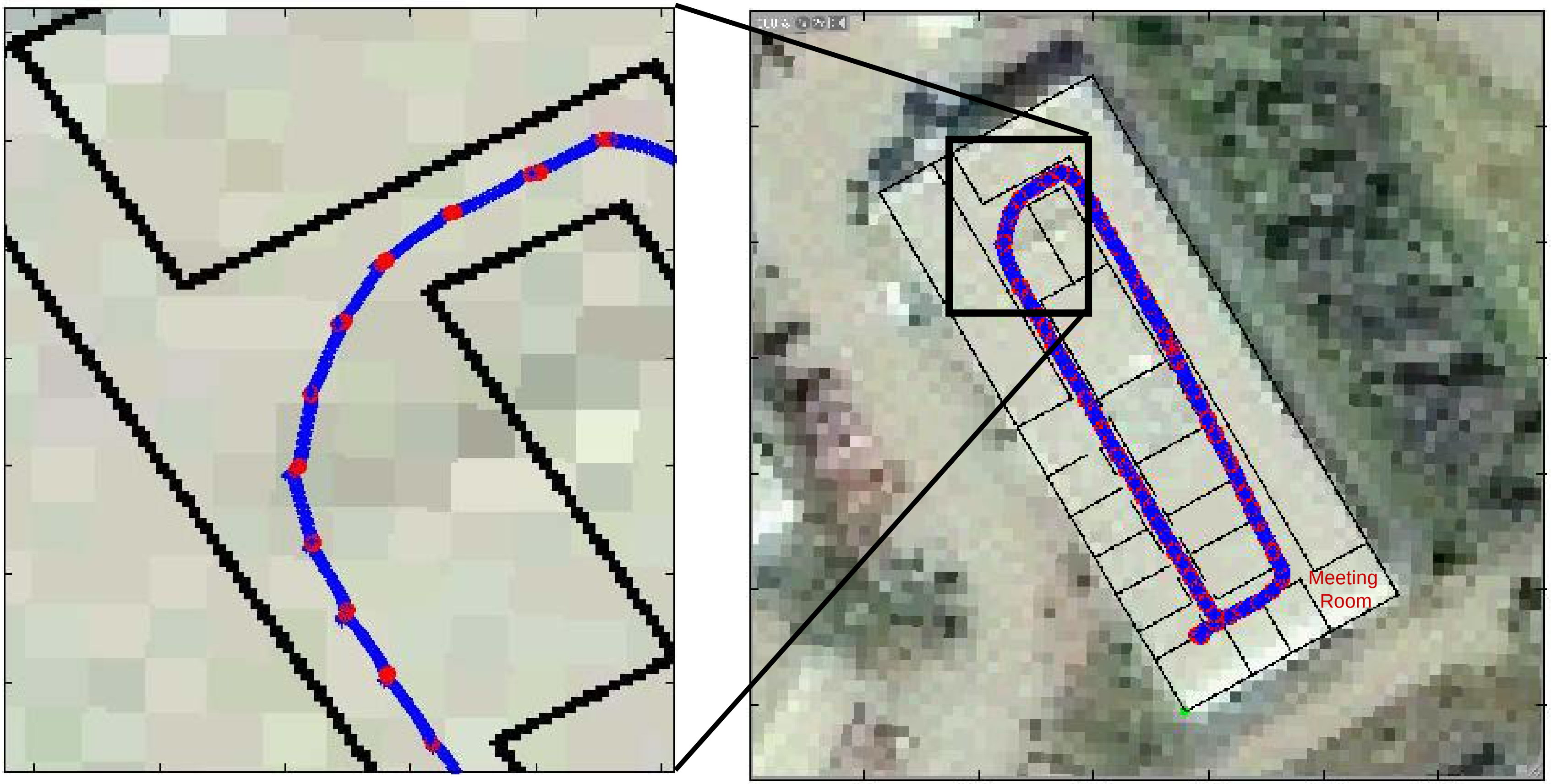
Foot Mounted Inertial Sensors

- 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





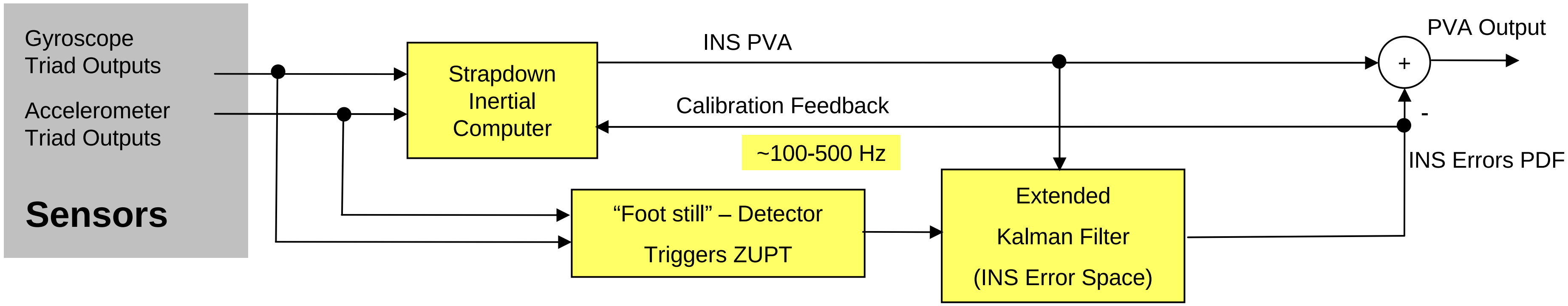
Experimental Results



● Stride ● Rest, ZUPT

IKN Building TE02

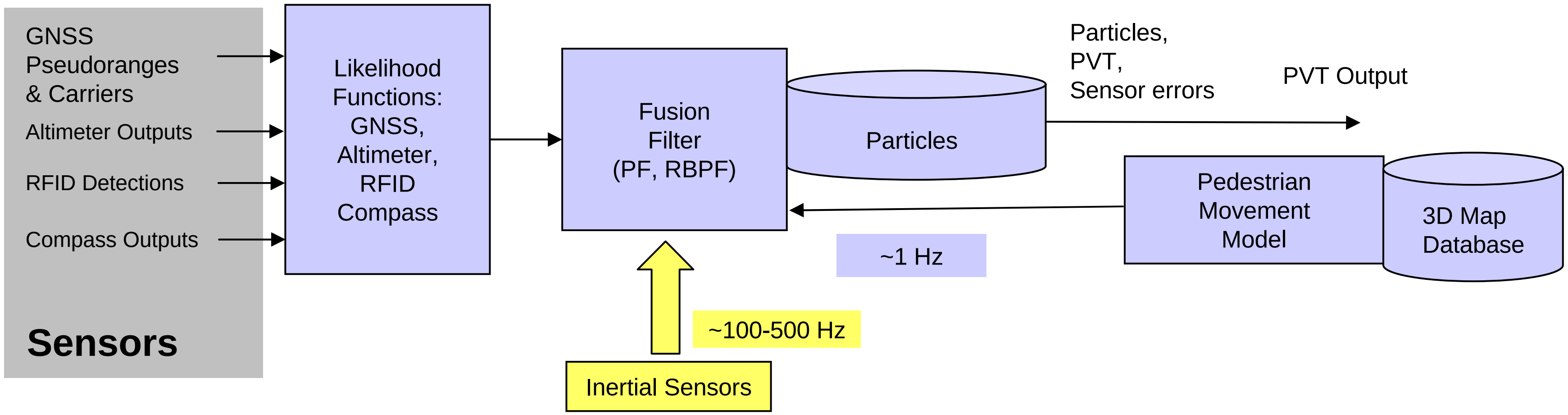
Conventional Integration of Inertial Sensors



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

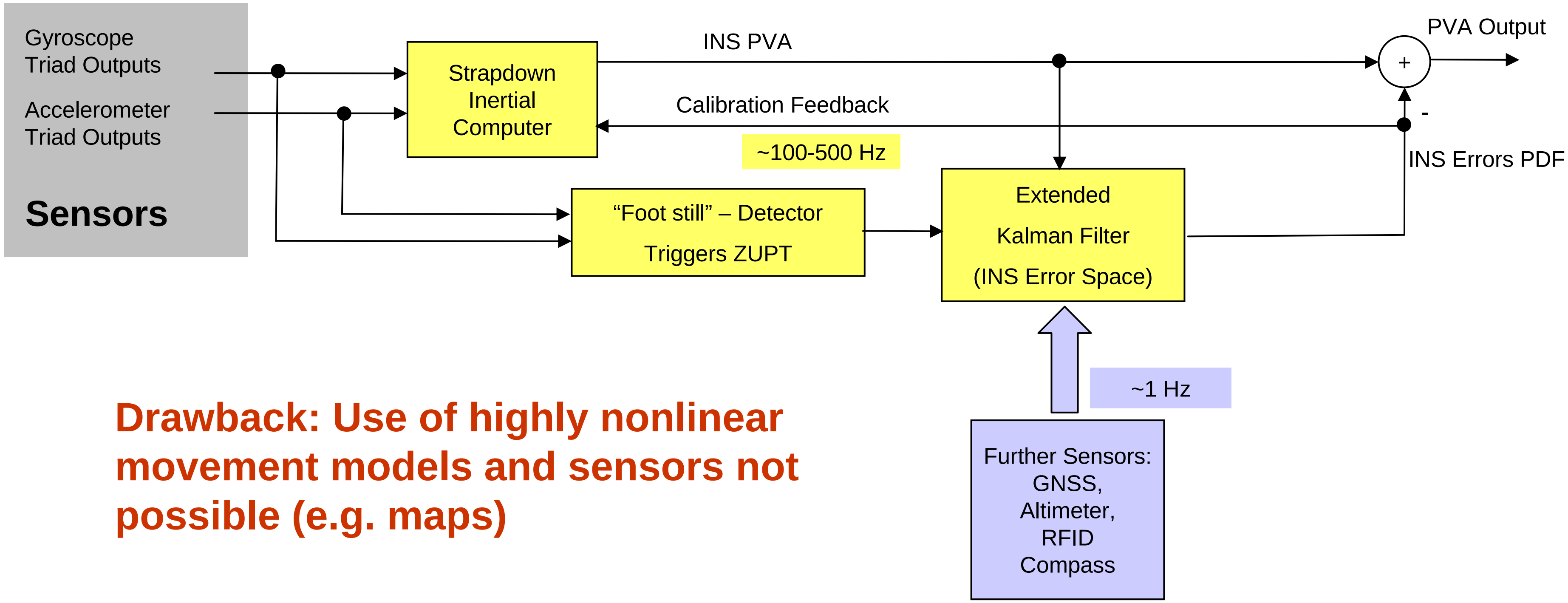
Problem: How to get things together ?

Solution 1



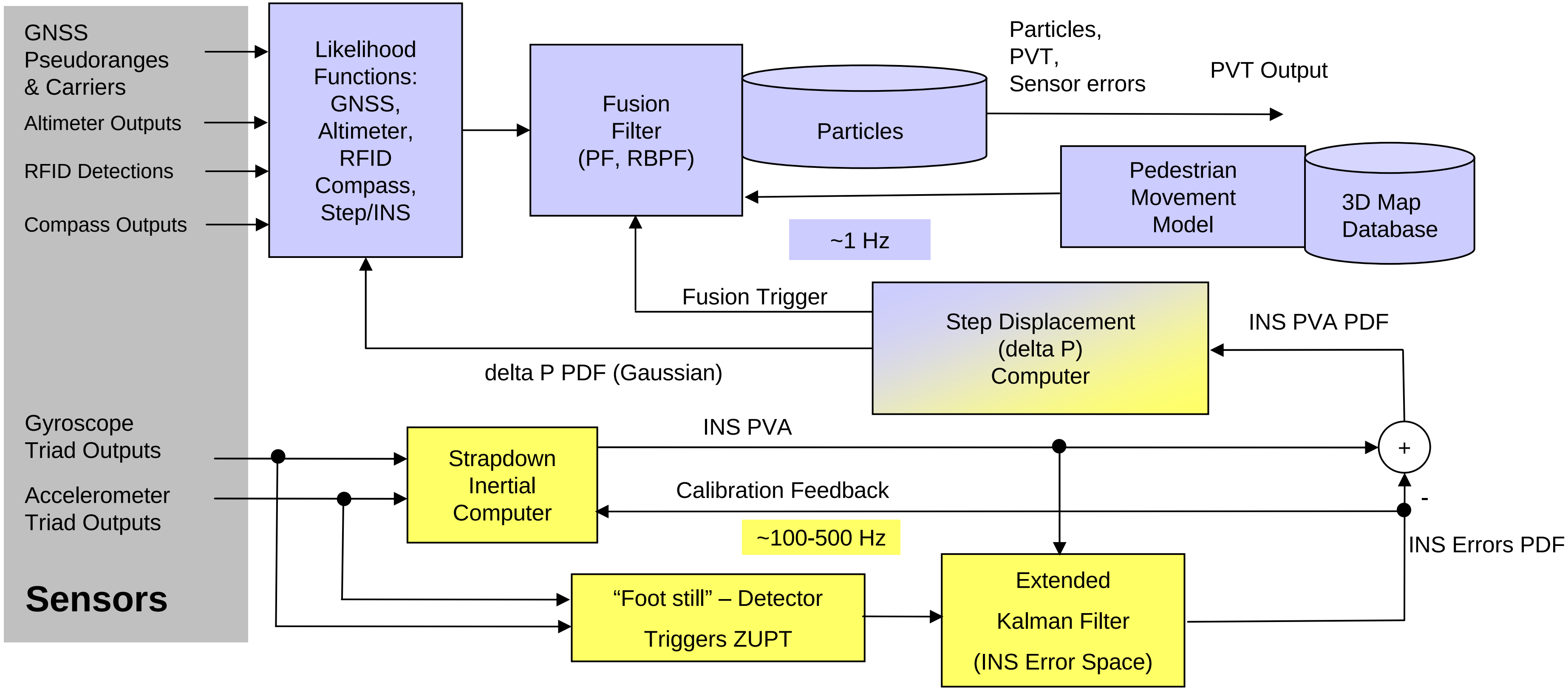
Drawback: Increases filter rate, requires extension of state space to foot accelerations and turn rates, movement models become complex

Solution 2



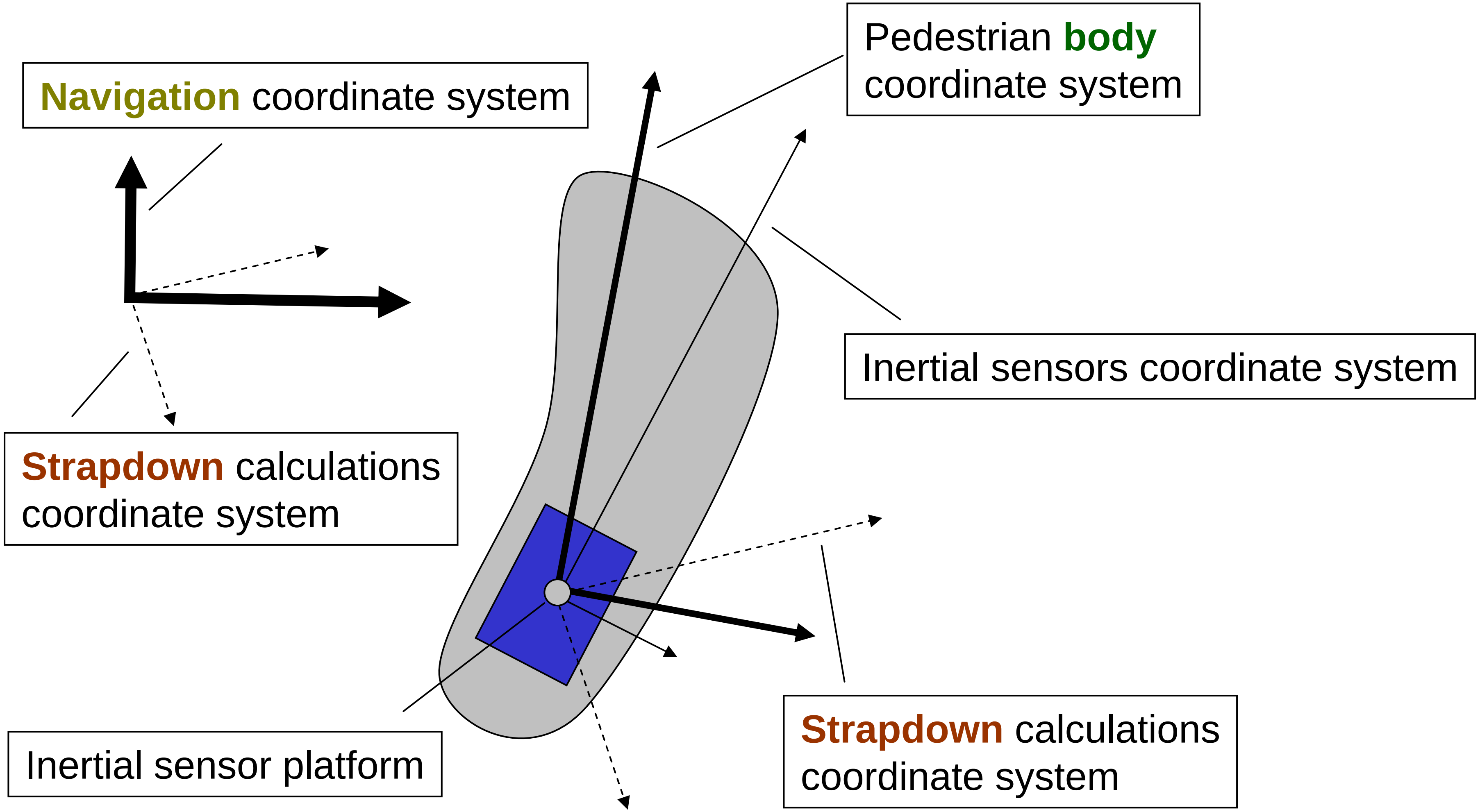
Drawback: Use of highly nonlinear movement models and sensors not possible (e.g. maps)

Solution 3: Our Approach



Use the lower filter to provide "step-measurements" to the upper filter

The Step-Measurement

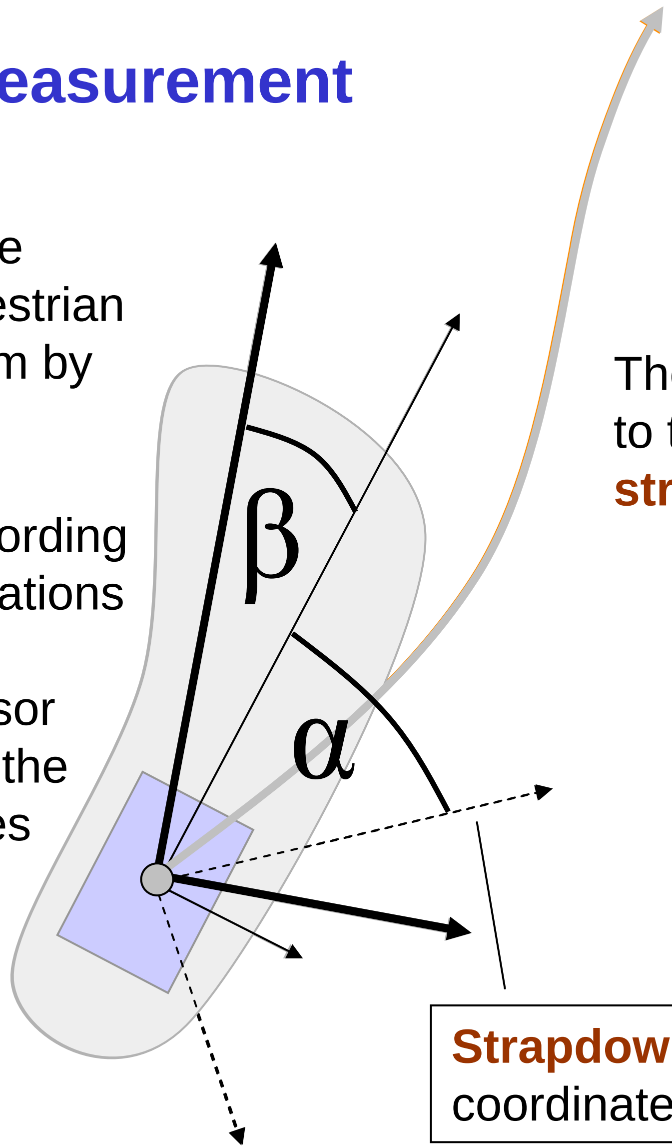


The Step-Measurement

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

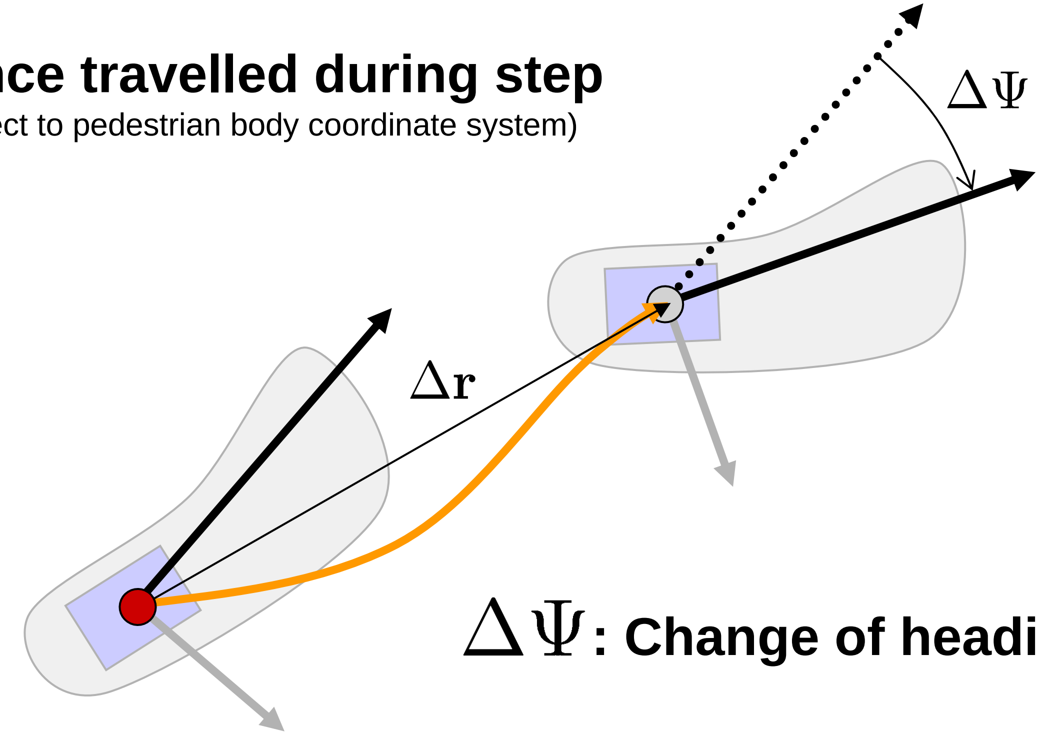


The **step** is sensed with respect to the coordinate system of the **strapdown** calculations

Strapdown calculations coordinate system

The Step-Measurement

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

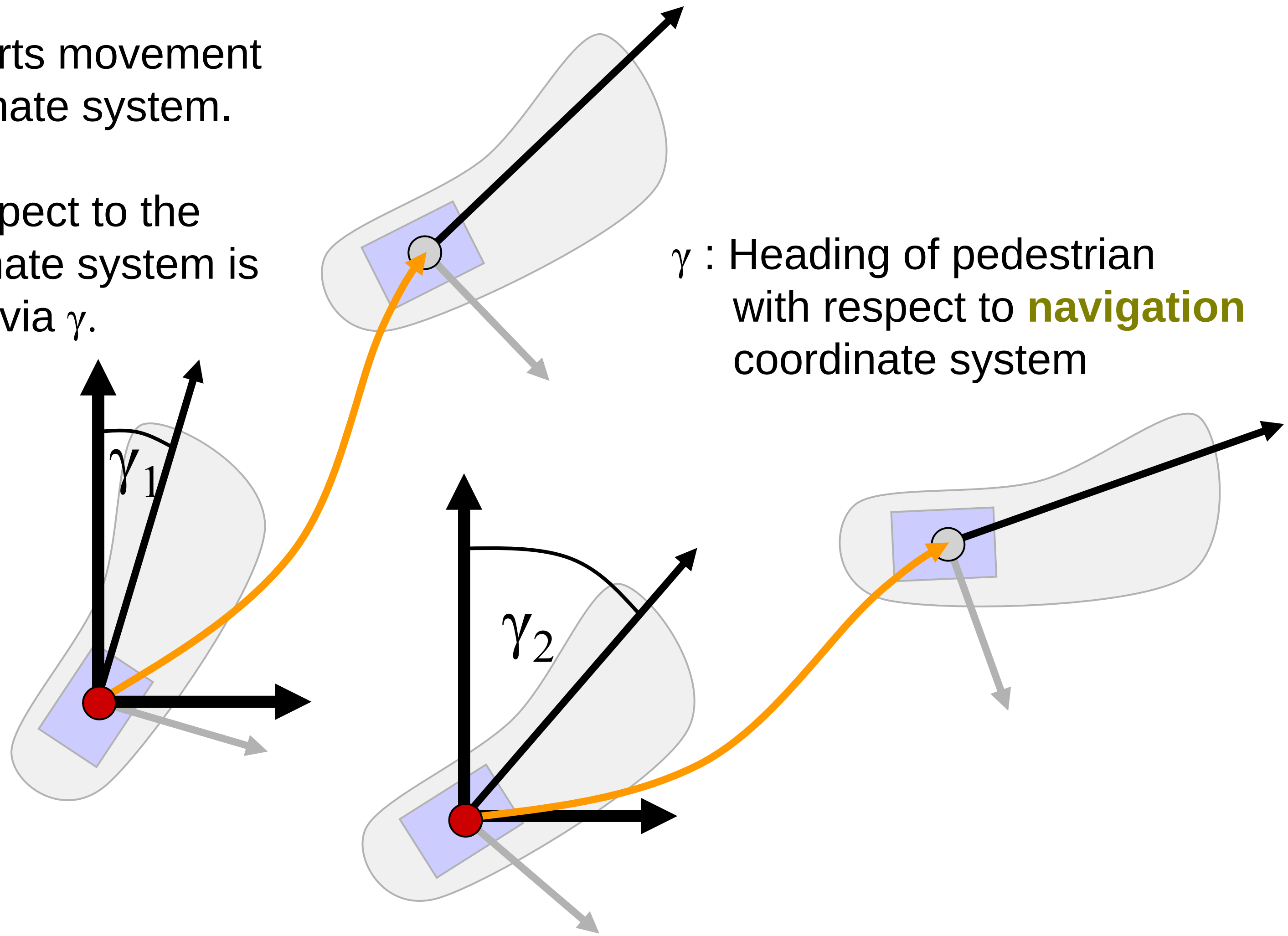


$\Delta\Psi$ **: Change of heading during step**

The Step-Measurement

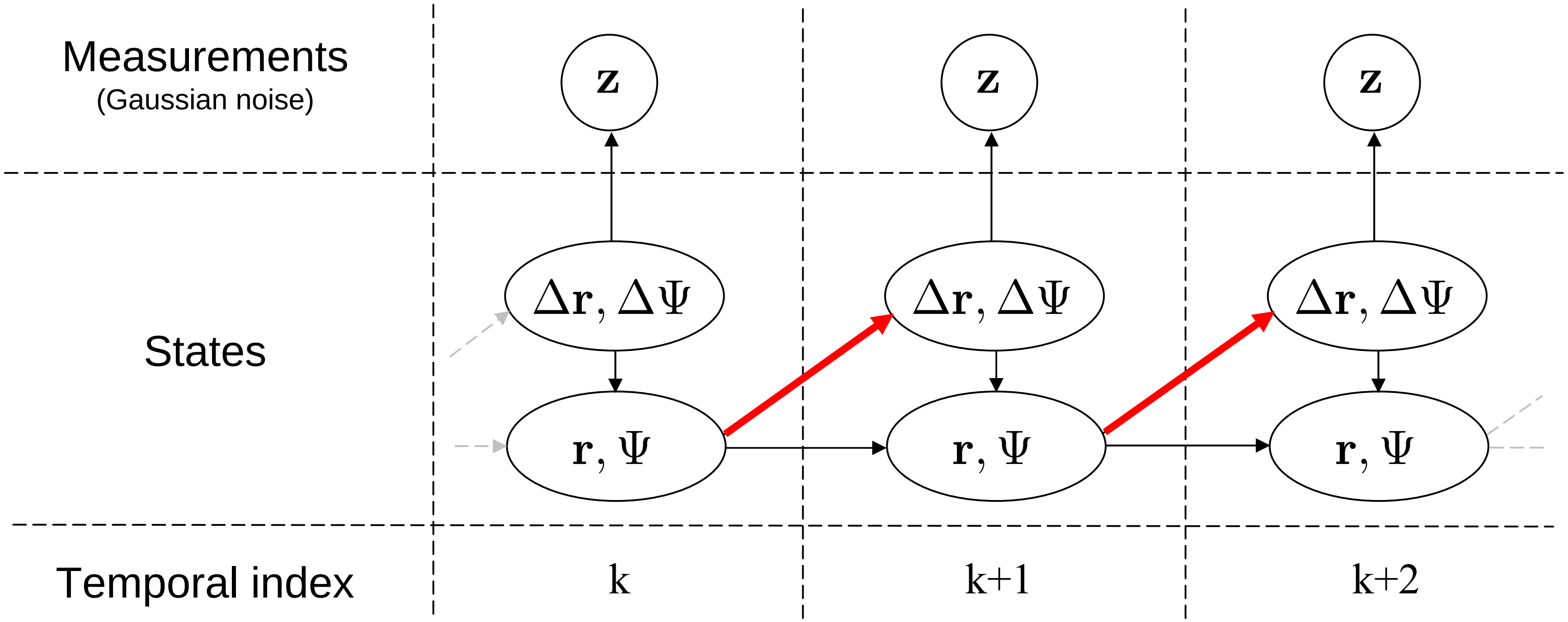
Measurement reports movement in the **body** coordinate system.

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



γ : Heading of pedestrian with respect to **navigation** coordinate system

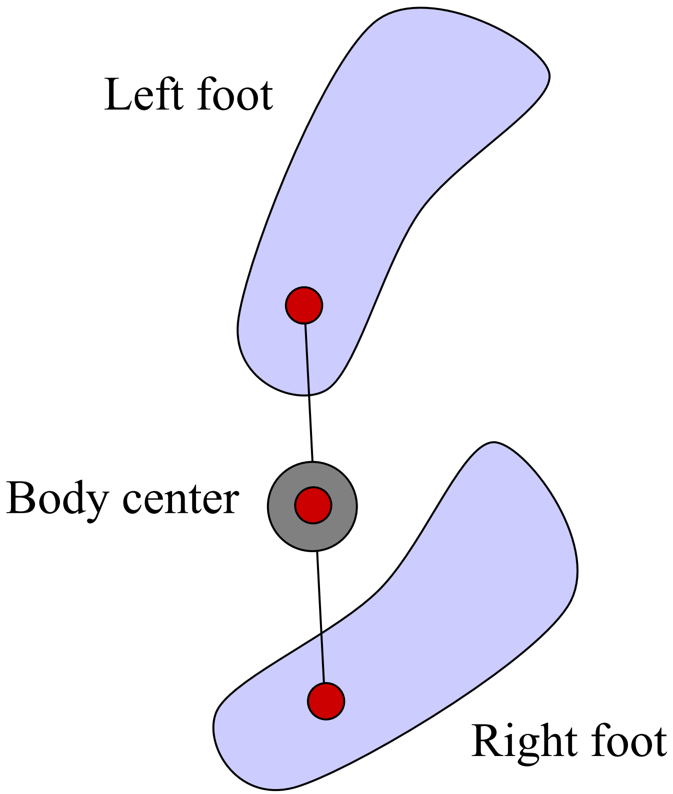
Dynamic Bayesian Network



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

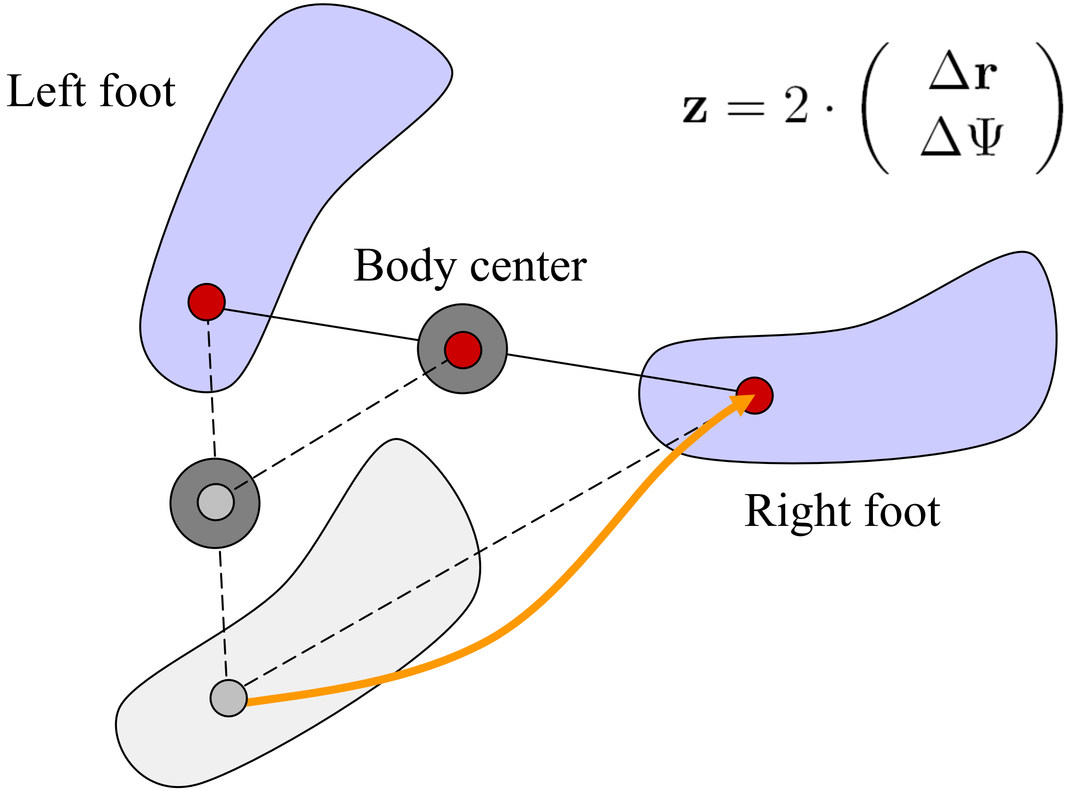


Pedestrian body model:
Body centered on connecting line of foot centers

Integration of a Pair of Platforms

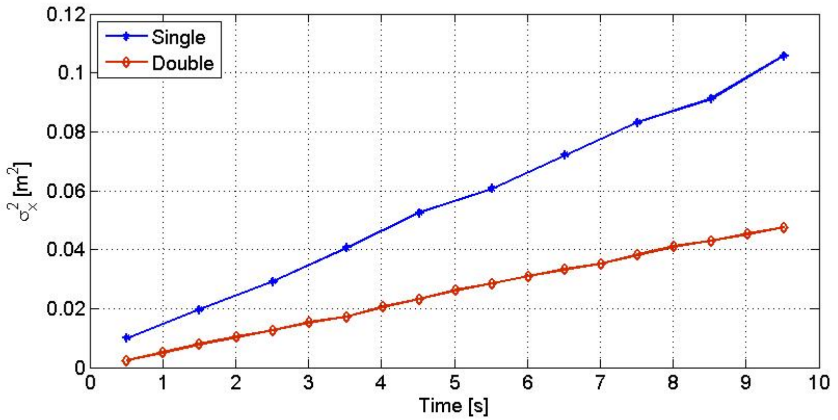
Foot movement is 2x body movement:

$$\mathbf{z} = 2 \cdot \begin{pmatrix} \Delta \mathbf{r} \\ \Delta \Psi \end{pmatrix} + \mathbf{n}_\Delta$$

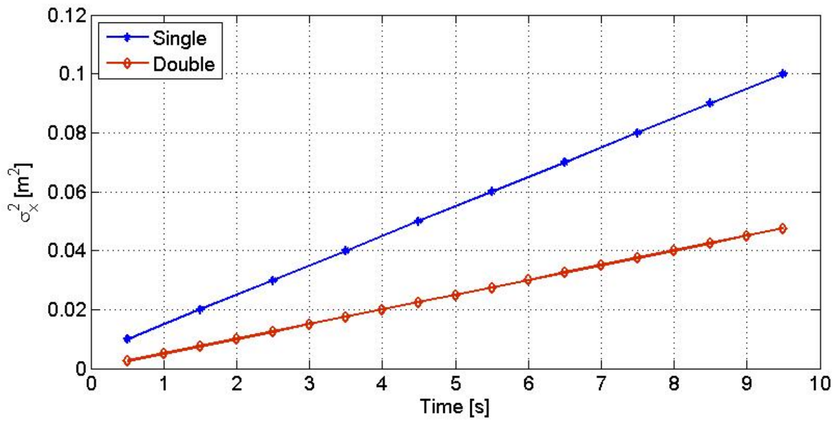


Performance Analysis

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

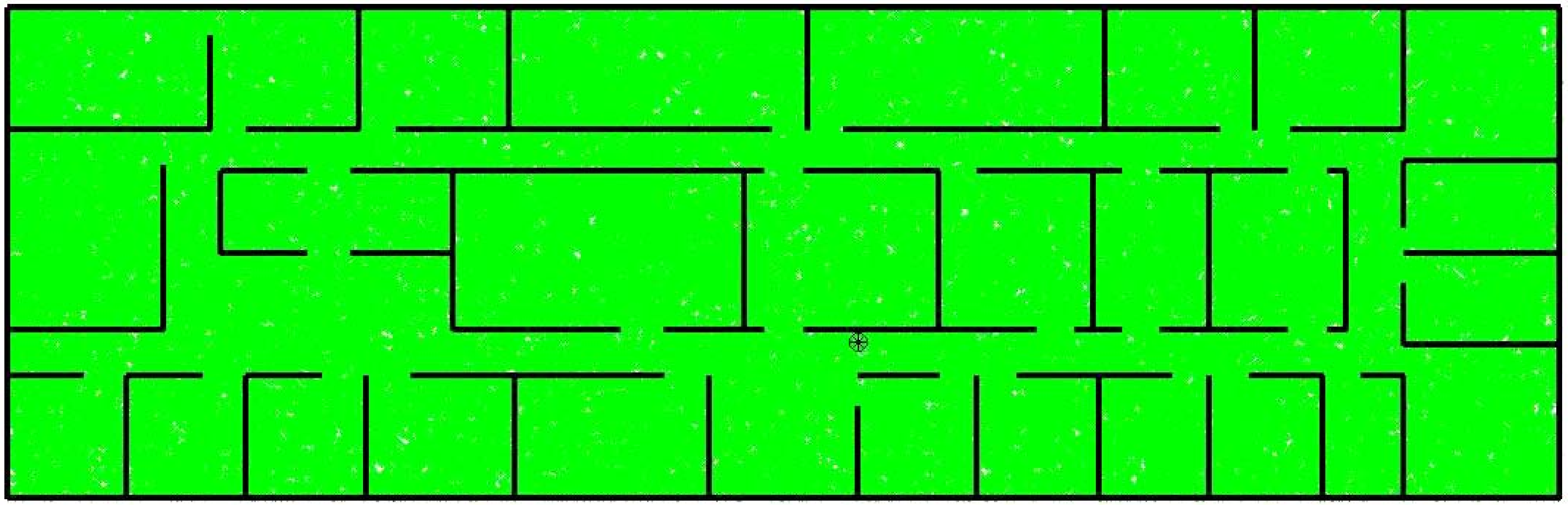


- **Error Analysis:** Covariance analysis based on Kalman filter framework



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