

Indoor Positioning using IMU and Radio Receiver

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- ▶ For areas where the signals are not available, several other positioning solutions has been proposed using WiFi, UWB, cameras etc.
- ▶ Our approach: use the cellular network and the hardware available in a phones for positioning.



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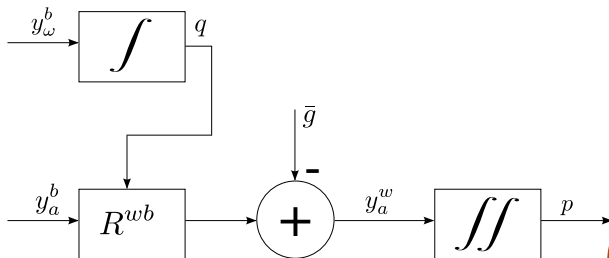
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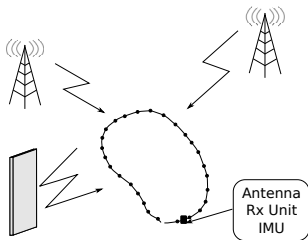
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Background - Synthetic Arrays

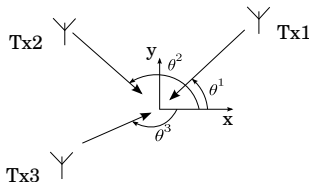
A synthetic antenna array is formed by moving a single receiver antenna and simultaneously tracking the local position with the IMU.



Modeling - Measurements

The phase of the received radio signal is dependent on the local position where the signal was sampled and angle of arrival of the radio signal. Measurements from radio receiver:

$$y_k = \sum_{n=1}^N \alpha_k^n e^{i[\cos(\theta_k^n)p_k^x + \sin(\theta_k^n)p_k^y + v_k]} + e_k \quad e \sim \mathcal{CN}(0, \sigma_r^2)$$



Modeling - Sensor Fusion

The unknown states that we want to estimate are

$$\{p_k, v_k, q_k, \alpha_k^{1,\dots,N}, \theta_k^{1,\dots,N}, v_k\}^T \in \mathbb{R}^{12+2N}$$

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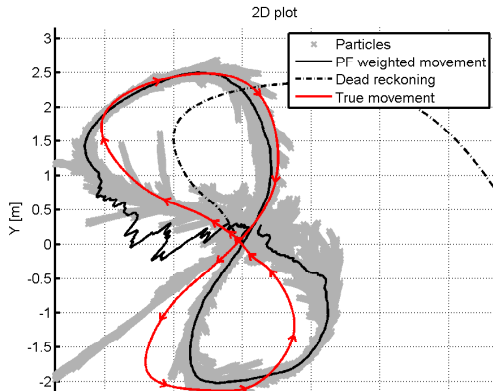
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- ▶ The extended Kalman filter
- ▶ The unscented Kalman filter
- ▶ The particle filter
- ▶ Marginalized particle filter



Results from simulations

A marginalized particle filter has been implemented in Matlab and IMU and RF signals are generated. The filter is initialized without any knowledge about the radio channel but the AOA are known to $\pm 20^\circ$.



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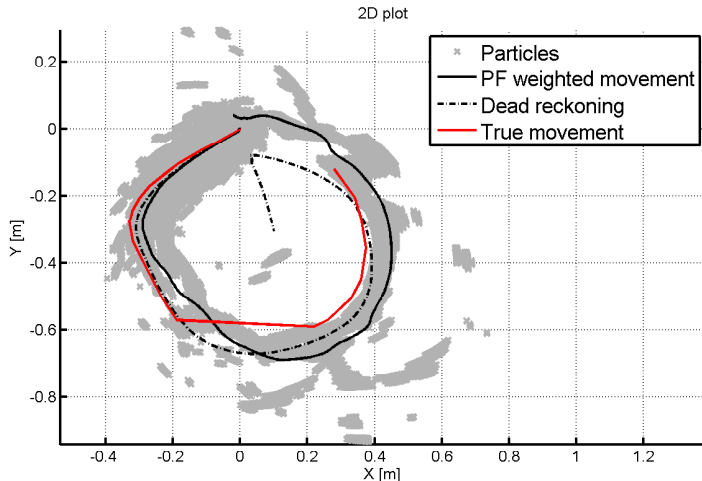
- ▶ A monopole antenna and a low cost IMU is mounted to a stick. A pen is attached and a big sheet to laid out to capture the ground true movement.
- ▶ Two transmitter antennas placed around the tripod acting as “controlled” scatterers. The antennas were fed from a single signal generator using two splitters.
- ▶ Synchronized signals from the receiver antenna and the IMU were recorded with a software defined radio from National Instruments.



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- ▶ Glue the filter together with initializing algorithms fro AOA estimation.
- ▶ Study the influence of phase drift in the reciever.
- ▶ Do experiments indoors and in other radio environments.

