Applied Indoor Localization: Map-based, Infrastructure-free, with Divergence Mitigation and Smoothing

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ABSTRACT
We describe an indoor pedestrian tracking system developed for homeland security nuclear radiation search and mapping. The user initializes approximate position and orientation on a prior map. A low-cost body-mounted IMU is used to detect steps and heading change, and this dead-reckoned estimate is registered onto the map using a particle filter. . Experimental evaluation in two buildings with two walkers shows position accuracy of 0.5m – 2m RMS, depending on the degree of local constraint in the floorplan. Extended traverses in open areas are well tolerated.

Categories and Subject Descriptors
C.2.8 Communication/Networking and Information Technology: Mobile Computing – Support Service.

General Terms
Algorithms, Measurement, Economics, Reliability, Experimentation, Human Factors.

Keywords
Particle filter, indoor localization, map-based localization, smoothing.

1. INTRODUCTION
Ongoing work in radiation data fusion required indoor pedestrian localization, and no suitable off-the-shelf solutions were available, so we adapted a previously developed particle filter (PF) localizer. A Personal Dead Reckoning (PDR) system enables infrastructure-free pedestrian navigation. In the taxonomy of ref. [2], we have implemented a map-aided Step-and-Heading System. An IMU worn by the operator is used to detect steps and changes in heading. The IMU (Phidgets Inc. "Spatial", $140) uses commodity MEMS sensors similar to those in smartphones, but the fixed IMU position avoids difficulties of dead-reckoning using a handheld device. In our indoor mapping and surveying task, we can require the operator to initialize the approximate position and orientation, so the PF need only keep the current estimate tracking correctly.

2. ALGORITHMS
2.1 Dead reckoning
While there are many possible variations [2], the approach taken here is shown in **Error! Reference source not found.**. Angular

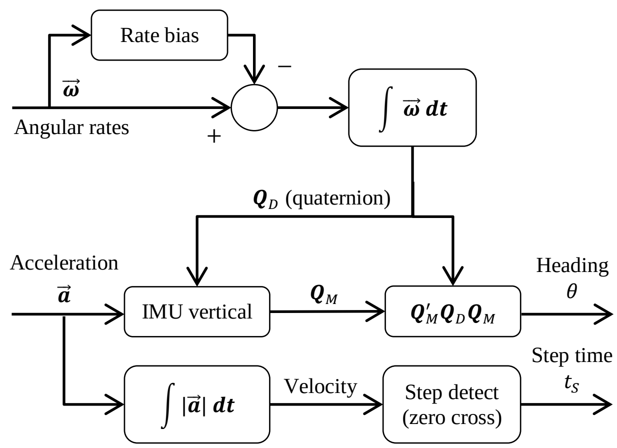


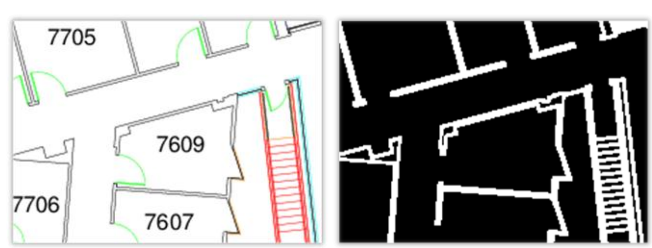
Figure 1. Inertial signal processing

rate bias is estimated by a Kalman filter. After bias compensation, a typical drift rate is $20°/\text{hour}$. The step duration Δt is then used to estimate the step length Δx by an empirical human biomechanical formula [3]:

$$\Delta x \approx 0.5\, \Delta t^{-0.59}$$

2.2 Map preparation
The map is a PNG binary image extracted from a PDF floor plan (Figure 1). We manually edit the result map to set the area outside the building to obstacle status (white). This binary obstacle map is then geo-registered by manually designating pairs of corresponding points on the map and on a Google earth view, establishing the origin, rotation and scale of the map in global Universal Transverse Mercator (UTM) coordinates.

2.3 Particle filter
The state is a vector $\boldsymbol{x} = [x, y, \Theta, S_{xy}]$, representing the two dimensional position and orientation (or pose). S_{xy} is a scale factor which compensates for any consistent error in the step length. The basic particle filter is derived from Monte-Carlo



(a) **(b)**

Figure 2. Original map PDF (a), PNG result image (b).

Localization (MCL) [1, 6]. A notable modification is that particles are resampled only when their weight becomes small (reducing sample condensation during times that no new constraints are discovered). Another departure from common practice is that trajectories passing through map obstacles are possible (though frowned upon). See Figure 3. This increases robustness to false obstacles in the map.

Figure 3. Probability model

2.4 Divergence mitigation

PFs are vulnerable to converging to a false state (divergence). The simplest divergence is the unnormalized sum of particle weights. Others have used KL divergence and Bayesian techniques [5, 7]. Here, we measure the mismatch between the dead-reckoned path and the map by using the current fix to superimpose the recent dead-reckoned path onto the map. Then the sensor probability model (Figure 3) can be used to compute the probability of this back-projected path (amber, Figure 4). The PF output is shown in blue. Note how PF trajectory is forced to follow the map, but the back path reveals a persistent heading error.

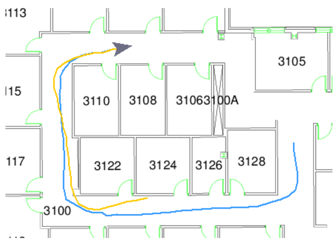


Figure 4. Back-projection of path for divergence detection.

2.5 Smoothing

Smoothing makes use of later measurements in a time series to refine earlier state estimates. The backtracking PF [4] is one example. We use the reverse pass of the Rauch-Tung-Streibel Kalman smoother, which propagates successfully across longer distances.

3. EVALUATION

We evaluated position error 4.3 km (100 minutes) of test data with two walkers in two buildings. Ground truth was via fiducial marks on the floor. Figure 5 shows a typical smoothed path with error vectors (red). Figure 6 shows the CDF of the position error for the bare particle filter (MCL), the RTS Kalman smoother and the backtracking PF.

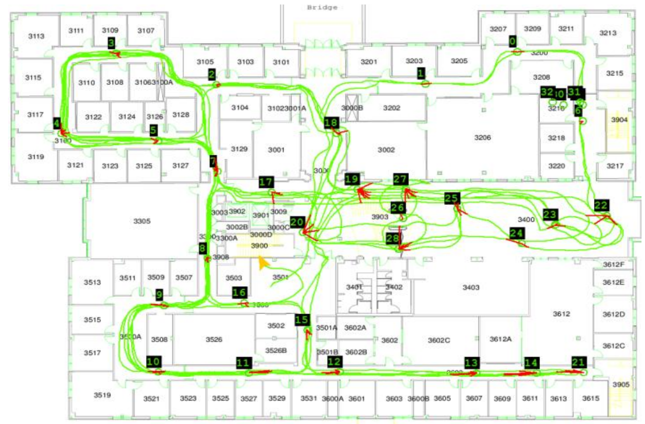


Figure 5. Smoothed trajectory and error vectors.

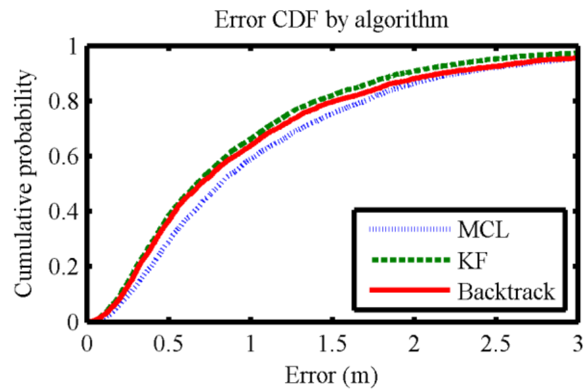


Figure 6. CDF of position error, by algorithm.

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