Indoor Navigation System Using Foot-Mounted IMUs

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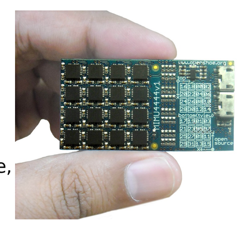
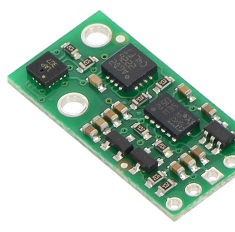
Introduction



Multi IMU



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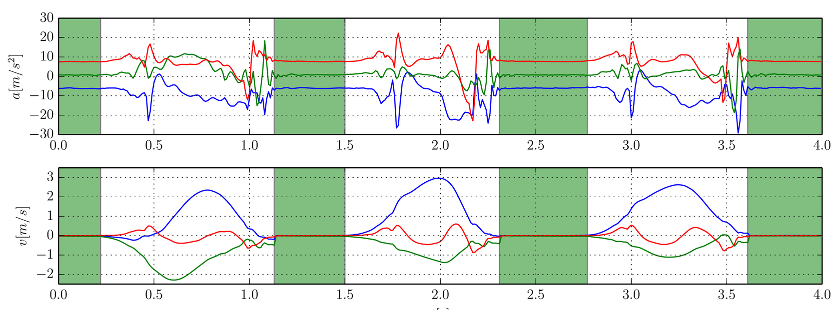
Indoor Navigation for Fire Fighters:

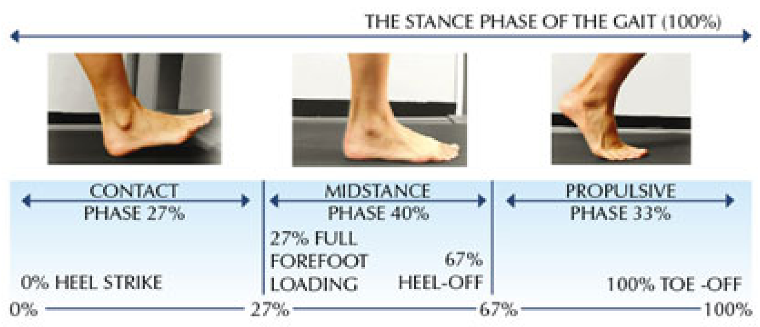
- Non-GPS
- Infrastructure-free

Dead Reckoning navigation using foot-mounted Micro-Electro Mechanical Systems that can yield accelerations, angular rates and magnetic field strength in three axis.

ZUPT-based INS

Direct integration of the sensor readings outputs unusable results due to the sensor noise and numerical instability. **Z**ero-velocity **Up**dat**e** is a technique for inertial-based INS in which simple model of the step (namely stance phase or zero-velocity phase) is used to correct the integration.





Kalman Filter for INS

Foxlin [2] proposed a ZUPT-based technique implemented by the means of the Kalman Filter in which zero-velocity states are treated as pseudo-observations. Error in sensor (or foot) orientation is computed by "alignment transfer" (using Caley's Formula) — a technique that correlates errors in velocity with orientation estimation errors.
Our approach (described below) uses model fusion: orientation is computed continuously by the state-of-the-art orientation filter and then utilized in simplified form of Foxlin technique.

PREDICTION

A priori state $\hat{\mathbf{x}}_k$ can be derived from time-controlled recursive equation

$$\hat{\mathbf{x}}_k := \begin{bmatrix} \mathbf{p}_k \\ \mathbf{v}_k \end{bmatrix} := \begin{bmatrix} \mathbf{p}_{k-1} + \mathbf{v}_{k-1}\Delta t \\ \mathbf{v}_{k-1} + \mathbf{a}_k^N \Delta t \end{bmatrix}, \quad (1)$$

where conversion from sensor frame to navigational frame is given by

$$\mathbf{a}_k^N := \mathbf{q}_{est,k} \otimes \mathbf{a}_k^S \otimes \mathbf{q}_{est,k}^{-1} - \mathbf{g}_0, \quad (2)$$

and error covariance

$$\hat{\mathbf{P}}_k := \mathbf{A}_k \mathbf{P}_{k-1} \mathbf{A}_k^T + \mathbf{Q}, \quad (3)$$

with state transition matrix

$$\mathbf{A} := \begin{bmatrix} \mathbf{I}_{3x3} & \mathbf{0} \\ \Delta t \mathbf{I}_{3x3} & \mathbf{I}_{3x3} \end{bmatrix}. \quad (4)$$

UPDATE

When the zero-velocity test is triggered Kalman Gain matrix is computed:

$$\mathbf{K}_k := \mathbf{P}_k \mathbf{H}^T (\mathbf{H}\mathbf{P}_k \mathbf{H}^T + \mathbf{R})^{-1}, \quad (5)$$

and according to our initial hypothesis we can compute *a posteriori* state:

$$\mathbf{x}_k := \mathbf{K}_k (\mathbf{0}_{1x3} - \mathbf{H}\hat{\mathbf{x}}_k), \quad (6)$$

and *a posteriori* covariance error:

$$\mathbf{P}_k := (\mathbf{I3x3} - \mathbf{K}_k \mathbf{H})\hat{\mathbf{P}}_{k-1}, \quad (7)$$

since our initial assumption concer velocity, observation matrix is:

$$\mathbf{H} := \begin{bmatrix} \mathbf{0}_{3x3} & \mathbf{I}_{3x3} \end{bmatrix}. \quad (8)$$

MODEL FUSION

Following iterative schema is used to estimate orientation:

$$\mathbf{q}_{est,k} := \mathbf{q}_{est,k-1} + (\dot{\mathbf{q}}_{\omega,k} - \beta \dot{\mathbf{q}}_{\epsilon,k})\Delta t. \quad (9)$$

In the fusion step estimated sensor orientation $\mathbf{q}_{est,m}$ is computed using previous estimate and quaternion calculated from gyroscope angular rates $\dot{\mathbf{q}}_{\omega,m}$. Simultaneously, the direction of estimated error $\dot{\mathbf{q}}_{\epsilon,m} := \frac{\nabla \mathbf{f}}{\|\nabla \mathbf{f}\|}$ is discarded, where $\nabla \mathbf{f} := \nabla_q \mathbf{f}(\dot{\mathbf{q}}_{\omega,m}, \mathbf{a}^E, \mathbf{a}^S)$ is the objective function gradient with respect to $\mathbf{q}$ Objective function is defined as:

$$\mathbf{f}(\mathbf{q}, \mathbf{a}^E, \mathbf{a}^S) = \mathbf{q}^{-1} \otimes \mathbf{a}^E \otimes \mathbf{q} - \mathbf{a}^S. \quad (10)$$

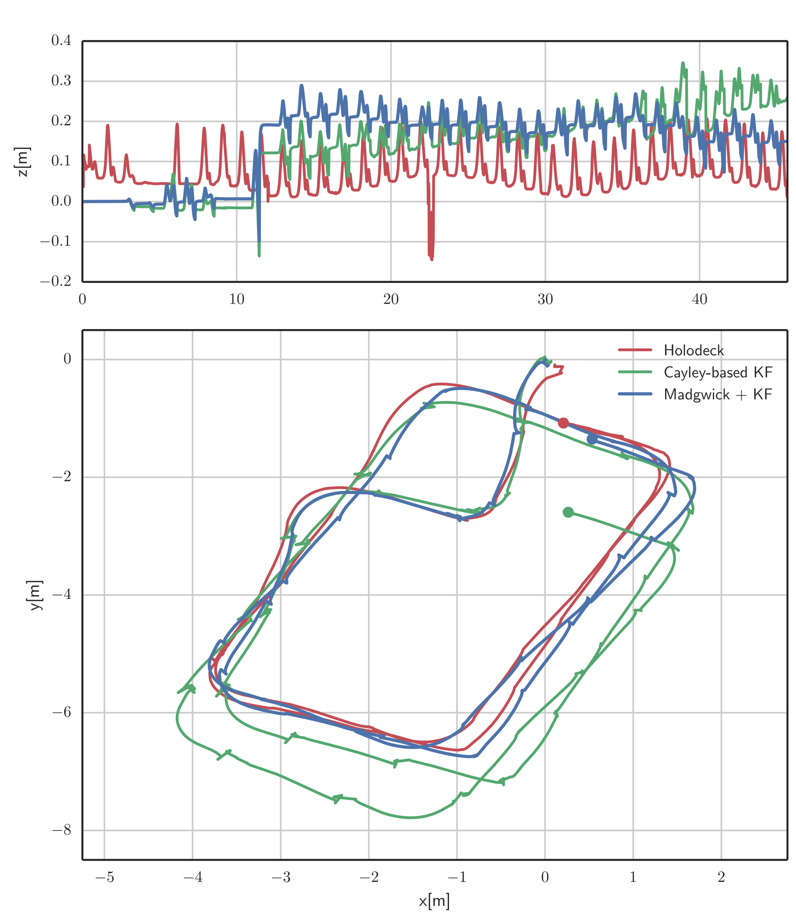
We refer to [3] for details of the Madgwick's algorithm.

Main challenges

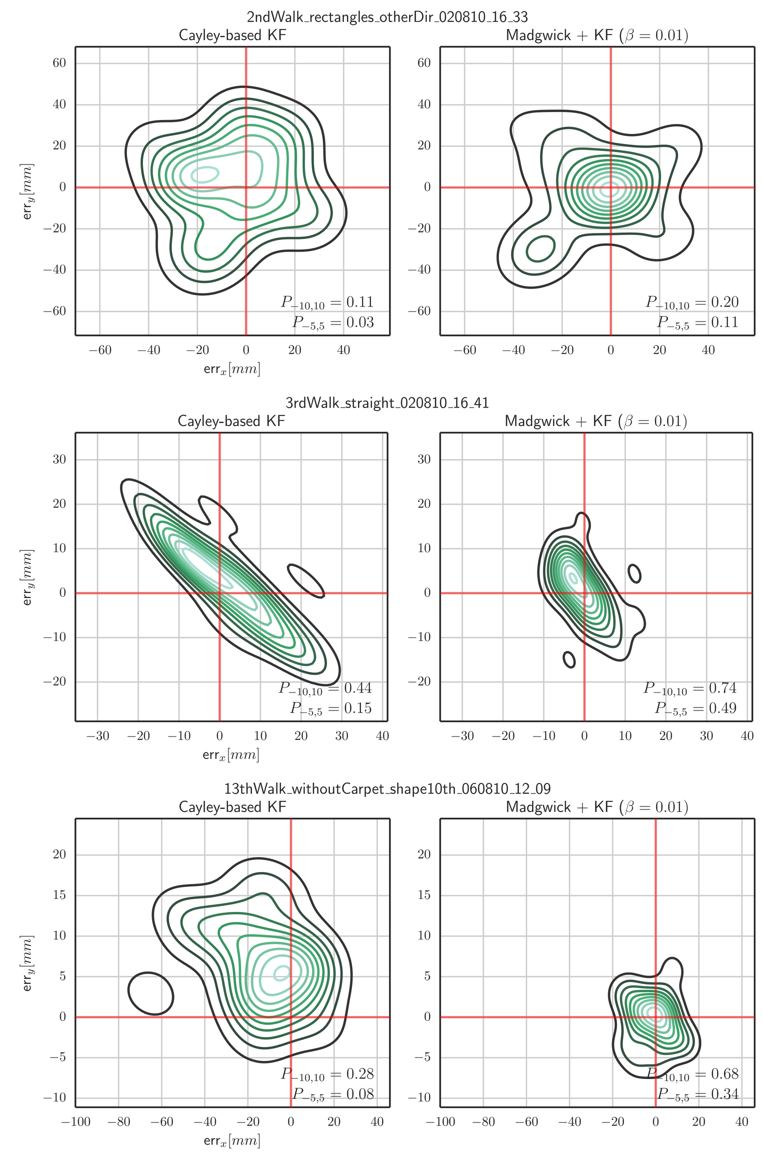
- Filter is not optimal (model mismatch),
- Sensor calibration and biases,
- Gyroscope drift,
- Fast movements are not recorded by off-the-shelf circuits

Experimental Results

Experiments were conducted by our prototype implementation and also using reference dataset [1] with ground-truth data obtained by optical system and visual markers.



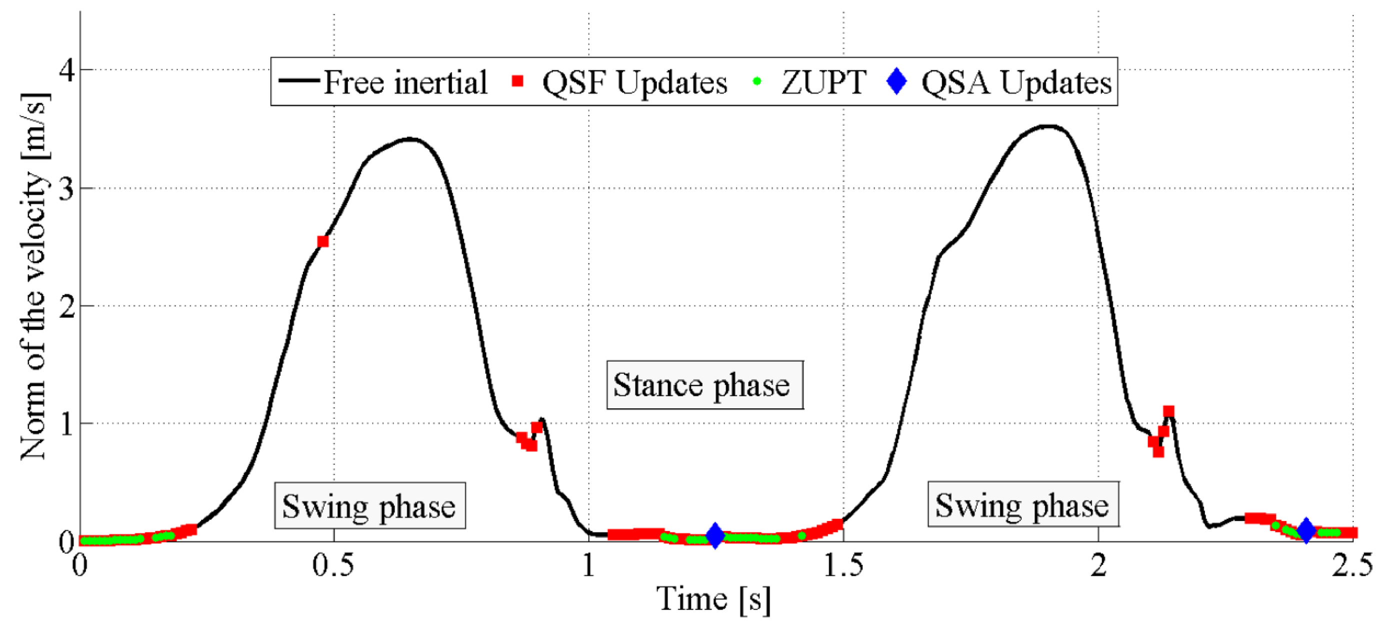
Path estimated by state-of-the-art algorithm (green), our model fusion technique (blue) and ground-truth data(red).



Probability of error on single step.

Most of the errors are introduced on certain steps (on turns and during sudden movements), in which sensors are not able to properly record the stride due to the sensor bandwith and range. Our simple approach outperforms existing state-of-the art implementation using the fact that acceleration vector should be aligned with respect to the orientation estimates — this works the best for estimating orientation in motion.

QSA, QSF and ZUPT



Illustation of different correction possible during single stride [4].

Quasi-**S**tatic **A**cceleration Update: if $\mathbf{v} = \mathbf{0}$ or $\mathbf{v}$ attains local extremum we can assume that $\mathbf{a}^N \approx \mathbf{g}_0$ therefore analytical correction of roll and pitch angles can be derived.

Quasi-**S**tatic **F**ield Update: yaw angle can be corrected using magnetometer — additional detection should be applied due to much interference in magnetic field indoors. See [4] for details.

Future Work

- Two shoe system (with synthetic magnetic field update),
- Inertial INS with inter-agent ranging via UWB TOF,
- Path-level correction using buildings maps.

Acknowledgement

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