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Improving Positioning Accuracy using Particle Filter with Enhanced IMU Velocity Estimation

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Summary. The study introduces a methodology that integrates a novel velocity estimation approach with the Particle Filter for accurately estimating the position of an object navigating within a magnetic anomaly field. To accurately determine position in GPS-denied environments, the acceleration measurements obtained from the Inertial Measurement Unit are augmented with magnetic field measurements and a previously designed magnetic anomaly map. Then, Bayesian statistics are employed to fuse information from the Inertial Measurement Unit and magnetometer, enabling accurate estimation of the object's velocity. The estimated velocity serves as input for the propagation model within the Particle Filter, which accurately predicts the object's position. This study showcases the efficacy of Bayesian-based velocity estimation in enhancing the classical Particle Filter approach, resulting in an approximate 40-55% reduction in the mean trajectory error. This refined methodology holds promise for applications across diverse domains, including GPS-independent navigation for vehicles.

POSITIONING BASED ON PARTICLE FILTER SUPPLIED WITH MAGNETIC ANOMALY MAP AND IMU MEASUREMENT

The Particle Filter aims to sequentially estimate the distribution of the state X_t at time t given the observation z_t:

$$p(X_t|z_t) = \sum_i w_t^i \delta\left(X_t - x_t^i\right) \tag{1}$$

where x_t^i and w_t^i is the location and weight of ith particle, respectively.

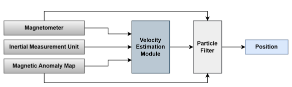
The computation of (1) relies on the three major steps:

A Calculation of the weights w_t^i which are proportional to the measurement density $p(z_t, X_t)$.

B Re-sampling, which discards the least significant particles and generates new particles according to $p(z_t, X_t)$.

C Updating the positions of samples by employing a propagation model.

In this study, we supply the Particle Filter with measurements of the magnetic field and velocity, the latter estimated by integrating the acceleration data obtained from IMU, see Fig. 1.



Due to the presence of significant drift in the velocity obtained from the IMU, **our aim** is to incorporate a magnetic-based correction into the velocity estimation process to improve the accuracy of the propagation model.

THE PROPAGATION MODEL

We utilize the propagation model, which updates the location of the ith particle x_t^i at each time step t using the Euler's scheme:

$$x_t^i = x_{t-1}^i + \Delta t \mu_{v_{t-1}} \tag{2}$$

Here, μ_{v_t} represents the velocity estimated through the fusion of data from the IMU and magnetometer.

To compute the velocity μ_{v_t}, we follow the steps:

1. Combine the velocity information from $\bar{V}_t = V_{t-1} + \Delta V_t^{IMU}$ and V_t^{IMU} into a unified random variable W_t. Under certain simplifying independence assumptions:

$$W_t \sim \mathcal{N}(\mu_{W_t}, \Sigma_{W_t}), \tag{3}$$

where

$$\mu_{W_t} = \Sigma_{W_t}\left(\Sigma_{\bar{V}_t}^{-1}\mu_{\bar{V}_t} + \Sigma_{V_t^{IMU}}^{-1}\mu_{V_t^{IMU}}\right)^{-1}, \Sigma_{W_t} = \left(\Sigma_{\bar{V}_t}^{-1} + \Sigma_{V_t^{IMU}}^{-1}\right)^{-1}. \tag{4, 5}$$

2. Utilizing Bayesian inference, integrate the data from W_t and the time derivative of the magnetic field, which is estimated during movement as $G_t = g_t$ (with the variation σ_G^2), into the final velocity V_t. Let the location estimated by the Particle Filter be x_t. Assuming the independence of W_t and G_t, the final velocity V_t follows a normal distribution:

$$V_t \sim \mathcal{N}(\mu_{V_t}, \Sigma_{V_t}), \tag{6}$$

$$\mu_{V_t} = \mu_{W_t} + \frac{g_t - \mu_{W_t}^T \nabla M(x_t)}{\sigma_G^2}\Sigma_{V_t}\nabla M(x_t), \quad \Sigma_{V_t} = \left(\Sigma_{W_t}^{-1} + \frac{\nabla M(x_t)\left(\nabla M(x_t)\right)^T}{\sigma_G^2}\right)^{-1}. \tag{7, 8}$$

In (7) and (8), $\nabla M(x_t)$ represents the gradient of the magnetic field at location x_t which is the expected value of the distribution generated by (1).

EXPERIMENTAL STAND

As depicted in Fig. 2, we have set up a stand equipped with ferromagnetic magnets capable of generating a magnetic field with smooth characteristics, see Fig. 3. Localization was performed using a robotic platform equipped with an Inertial Measurement Unit (IMU) and an embedded magnetometer.

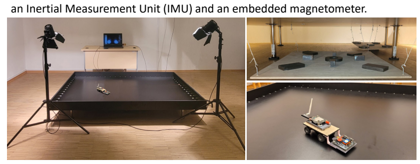


Fig. 2. Experimental stand: plate, ferromagnetic magnets applied for magnetic anomaly generation and mobile platform with IMU and magnetometer.

RESULTS

The performance evaluation of our method involves comparing three localization scenarios: one using uncorrected IMU data (where the position is estimated based on the integration of measured acceleration), another using Particle Filter (PF) with uncorrected IMU velocity (obtained through the integration of measured acceleration), and a third using PF incorporating the velocity corrected using the proposed magnetic-based correction. The cases were recorded for various initial localization errors. As demonstrated in Tab. 1 and Fig. 3, the proposed method led to a reduction in the mean position error ranging from 40% to 55% compared to the PF with uncorrected velocity.

Tab. 1. Mean error of uncorrected IMU and two variants of PF.

$\varepsilon(t=0)$ [mm]	$J = \frac{1}{T}\int_{t=0}^{T} \varepsilon(t)dt$ [mm]		
	Uncorrected IMU velocity	Particle Filter inc. uncorrected IMU velocity	Particle Filter inc. **corrected** IMU velocity
0	230.4	36.7	16.6
50	258.9	39.3	18.0
100	294.2	52.2	30.2
200	372.6	59.6	29.5

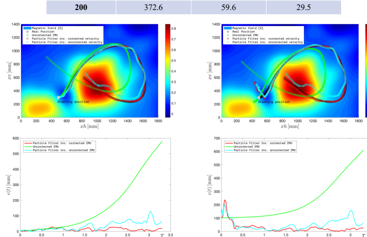


Fig. 3. Comparison of PF performance depending on the velocity estimation method for lack of initial error (l.h.s) and initial error of 100 mm (r.h.s.).

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