Real-time Indoor Localization using Magnetic, Time of Flight, and Signal Strength Inference Maps

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ABSTRACT

This paper presents a localization system that fuses inertial, magnetic field strength (MAG), RF time of flight (ToF), and received signal strength (RSS) measurements to track a pedestrian moving indoors in real time. Our method uses a pose graph to model a pedestrian's trajectory as a sequence of discrete positions. Rather than using range predictions directly in the pose graph, our approach draws values from a Gaussian Process ($\mathcal{GP}$) inference map built in advance from training data. To improve scalability, our implementation is divided into two separate threads. The first thread uses inertial measurements and Kalman filtering to produce a series of displacement vectors. These displacements are forwarded to a second thread where they are inserted into a pose graph along with ToF and RSS measurements. Finally, a gradient descent method is used to obtain the sensor trajectory that minimizes the sum squared difference between the predicted and measured ToF, RSS and MAG values.

Keywords

Indoor localization, Pedestrian localization, Data fusion

1. INTRODUCTION

Despite considerable research efforts over the past decades, indoor localization remains an unsolved problem. Although inertial dead reckoning can be used over short periods, its position error typically scales cubically with time. Alternate methods of localization use radio measurements between mobile and fixed points, either through fingerprinting or range-based methods. However, the accuracy of such approaches is inherently limited by the complex non-linear effect of clutter and noise on radio propagation.

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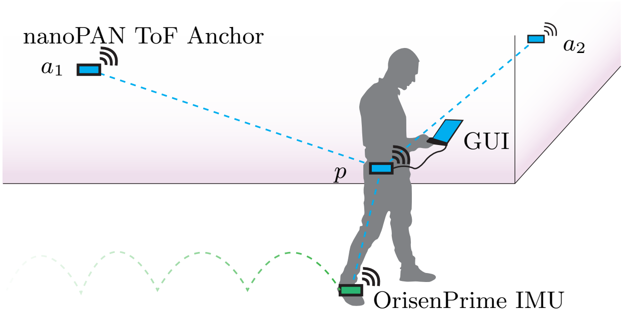

Figure 1: Proposed hardware setup and data flow

The value of the proposed localization system is that it benefits from the accuracy of inertial measurements over short periods while remaining globally accurate because of measurements to anchor points with known global positions. This is described in more detail in Section 2.

2. LOCALIZATION ALGORITHM

Consider a localization system that includes m static anchor nodes $a_i = [x_i, y_i]^T, i = 1, 2, \ldots, m$, and one (mobile) target node $p(t) = [x(t), y(t)]^T$. The target node makes two sets of observations: (1) ranging estimates to nearby anchor nodes at each time step made possible by RF modules with RSS and ToF measurement capabilities, and (2) relative rotation and translation estimates between subsequent pedestrian *poses* provided by body-mounted inertial and magnetic sensors. An illustration of this system is shown in Fig. 1.

Given this setup, the objective of the localization algorithm is to estimate the position of the *unknown* sensor position $p(t)$ at time t using the pose of the previous iteration as initial states, *known* anchor node positions $a_1, \ldots, a_m$, *processes* $f(\cdot)$ that relate two sequential sensor positions through kinematic filters, and *corrections* $g(\cdot)$ that relate a sensor position to a subset of anchor nodes through magnetic and radio measurements as well as predictions from trained $\mathcal{GP}$ models. A graphical representation of these var-

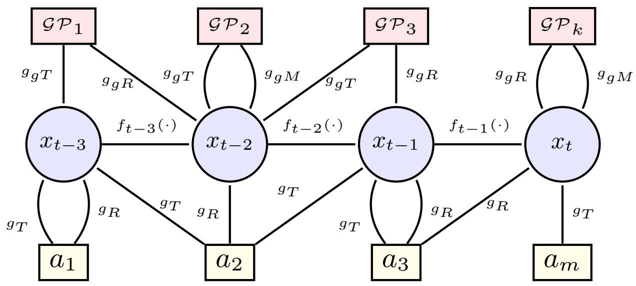

Figure 2: The localization problem expressed as a pose graph, having measurements as edges

ious interacting components and processes in the proposed localization scheme is shown in Fig. 2.

Incorporating all inertial measurements into a single pose graph yields a representation with a solution complexity that scales poorly with time. For this reason our implementation is divided into two threads. The first thread executes 6DoF kinematic tracking filter that estimates a relative displacement vectors from high frequency inertial and magnetic measurements. The second thread builds a coarse 3D-embeddable pose-graph, and runs slower than the first thread due to lower-frequency ToF and RSS measurements. An architectural overview of our algorithm is given in Fig. 3.

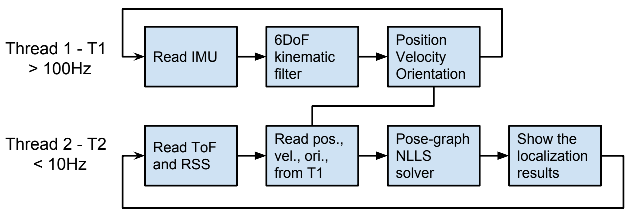

Figure 3: Localization algorithm overview

2.1 Thread 1 - Kinematic Filter

The mobile sensor implements a linearized version of the Extended Kalman Filter (EKF) to perform inertial pedestrian dead reckoning. Standard 6DoF rigid body kinematics [2] is used to propagate the navigation-frame position forward in time, given body-frame angular velocity and linear acceleration in a local frame. The filter also includes sensor bias states to model in-run sensor drift. A double integration of acceleration measurements inherently causes high positional error with respect to time, and so the localization system periodically corrects the state estimate.

2.2 Thread 2 - Pose-graph Solver

The main structure of the proposed pose-graph localization solver is an example of a robustified, non-linear least squares problem of the form: $\min_{\mathbf{x}} \frac{1}{2}\sum_i \| f_i\left(x_{i_1}, \ldots, x_{i_k}\right) \|^2$. The optimization problem that needs to be solved can be defined as the objective function shown in (1)

$$\bar{X} = \arg\min_{X} \sum_{i \in M} \left(z_i - h_i(X)\right) R_i^{-1} \left(z_i - h_i(X)\right) \quad (1)$$

where $X = \{\mathbf{x}_i, i = t - \Delta t, \ldots, t\}$ contains unknown sensor positions in a selected time window Δt, z_i are observations, $h_i(\cdot)$ is the measurement model, and R_i is the measurement noise covariance. The processes $f(\cdot)$ obtained from the kinematic filter and the corrections $g(\cdot)$ are bundled into a set of measurements M. The measurement model $h_i(\cdot)$ for the ith measurement extracts the relevant states from X to *predict* the measurement value. A residual is then calculated using the observation z_i and measurement noise covariance R_i [1].

3. HARDWARE

Our system consists of static anchor nodes, a body-mounted tag node, and a portable computer. The portable computer is used to carry out complex computation and display real-time localization results. The nodes are based around *Orisen Prime* development board, shown in Fig. 4, which features an IEEE 802.15.4 compatible Freescale MC13224 microcontroller, a low-cost single chip IMU, and a Nanotron nanoPAN 5375 RF Module to provide ToF measurements.

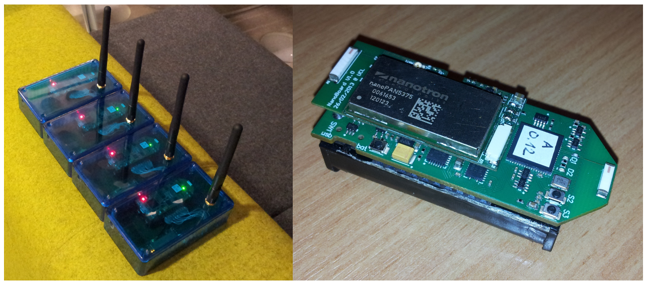

Figure 4: Four anchor nodes (left) and a sensor node (right), both based on the *Orisen Prime* development board with a nanoPAN transceiver

4. DEPLOYMENT REQUIREMENTS

Our localization algorithm requires ToF measurements, which means that we cannot exploit an existing WiFi infrastructure. We therefore need to deploy our own hardware – consisting of eight anchor nodes of size 5x10x3 cm each – in the corners of rooms using double-sided tape. Power is supplied to anchors either through USB, or by an internal battery. The ToF radio modules operate cooperatively on standard 2.4GHz channels. Both the wearable sensors and the portable computer use a rechargeable battery, and communicate over IEEE 802.15.4 2.4GHz. The tag node is plugged into a portable computer, on which the real-time localization results are shown.

5. ACKNOWLEDGMENTS

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6. REFERENCES

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