thesis draft navigation.
Design of smartphone based SLAM algorithm for indoor crowdsource mapping.

timur.chikichev

November 2020

Goal: The goal of our research is to build ***** GP signal strength maps without relying on location data.

1 Introduction

Goal: The goal of our research is to build ***** GP signal strength maps without relying on location data.

Research problem statement: Design of smartphone based SLAM algorithm for indoor crowdsource mapping.

2 measurements model

acceleration data from imu
magnetic field orientation vector
RSSI

3 Transition model definition

Copied all from [1]:

With the development of microelectromechanical systems(MEMS), a few MEMS-based sensors have been built and incorporated into smartphones: accelerometers, gyroscopes,magnetometers, etc. These sensors can be used to provide information on the user's actions. Pedestrian dead reckon-ing (PDR) [10] is a relative navigation technique that uses these sensors.

we propose a PDR-based indoor positioningmethod that integrates RSSI with indoor environment mapconstraints by using particle filters.

PDR-based indoor positioning can be expressed by the following equations

$$X_k = \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} = \begin{bmatrix} x_{t-1} & +l_k \sin(\theta_t) \\ y_{t-1} & +l_k \cos(\theta_t) \end{bmatrix} + \begin{bmatrix} \delta_x \\ \delta_y \end{bmatrix} \tag{1}$$

The orientation updates is independent from X_k updates, depends on accelerometer and gyro, same model.

Step Detection:Android mobile phones have two kinds of sensors to monitor steps: step counters and step detectors [25].

Peak detection is used in this paper for step detection

nonlinear step length estimation model based on statistics proposed by Weinberg [27]

$$s = k\sqrt[4]{a_{zmax} - a_{zmin}} \tag{2}$$

The Android system computes orientation angles by using the device's geomagnetic sensors in combination with its accelerometers [25]. Using these two hardware sensors,the system provides data for the following three orientation angles

The device is NOT assumed to be pointing in the heading direction. Need to apply additional space transformation.

3.1 RSSI methode

Usual path-loss model:

$$PL(d) = PL(d0) + 10\alpha \log d/d_0 + \omega = PL(d0) + 10\alpha \log d/d_0 + N(0, \sigma_\omega^2) \tag{3}$$

where d represents the Euclidean distance between the anchor node and the receiver,d0represents a specified distance,PL(d)and PL(d0)represent the RSSI at d and d_0, respectively(in dBm), and α represents the path loss exponent, which is closely related to the ambient environment; ω is a zero-mean Gaussian distribution variable with variance σ_ω^2.

The inverse function:

$$d_i = d_0 \cdot 10 \frac{PL(d_i) - PL(d_0)}{10\alpha} \tag{4}$$

Landmark model:

$$f_i(x, y) = d_i - \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{5}$$

$$min(x, y) = min \sum_{i=1}^{m} [f_i(x, y)]^2, m \geq 3. \tag{6}$$

In paper author transform this to linear system,

$$AZ = b \tag{7}$$

$$A = \begin{bmatrix} 1 - 2x_1 - 2y_1 \\ ... \\ 1 - 2x_m - 2y_m \end{bmatrix} \tag{8}$$

$$Z = \begin{bmatrix} x^2 + y^2 \\ x \\ y \end{bmatrix} \tag{9}$$

$$b = \begin{bmatrix} d_1^2 - x_1^2 - y_2^2 \\ ... \\ ... \end{bmatrix} \tag{10}$$

We have to check it

Good alternative was proposed in [] to bound region by min and max RSSI according to its variance - linear system.

3.2 Processing

Update step, prediction, correction State Estimation

Resample:In this step, importance resampling [20] isused to obtain a new particle set

some papers prove importance resampling can't be applied for this task because pf noise.

4 Update draft

4.1 RSSI Graph SLAM

Definition taken from [2].

Trajectory Modeling with GraphSLAM [3] is a classical framework for SLAM optimization.

GraphSLAM extends the traditional SLAM framework by considering the poses in a trajectory as nodes and raw measurements between poses and landmarks as edges in a graph.Note that each edge is attached with a probability distribution over the relative positions of its two vertexes since inherent noise in sensors need to be considered. In 2-D case, a pose x_t consists of a 2-D coordinates (x_1, t, x_2, t) and an yaw angle θ_t.

$$e_{ij}(x_i, x_j) = z_{ij} - \hat{z}_{ij}(x_i, x_j) \tag{11}$$

The item ω_{ij} in the equation is the information matrix representing Gaussian noise in sensor measurement.The GraphSLAM problem is now reduced to a constrained least square problem and it can be solved by some standard optimization techniques, like Gaussian-Newton or Levenberg-Marquardt algorithms, as proposed in [16]. Either of the two methods is based on local iterative linearization:

Then, the goal of GraphSLAM is to find an configuration of poses x^* that minimizes the squared error F(x) of all observations given a set of constraint edges C:

$$F(X) = \sum_{(i,j)\in C} e_{ij}^T W_{ij} e_{ij} \tag{12}$$

$$x^* = argmin_x F(x) \tag{13}$$

4.2 Latent Variable Models

part taken from [3].

So far we have assumed that the locations X of the training data are observed. The goal of our research is to build GP signal strength maps without relying on location data.

To build such maps, we treat the locationsXas hidden, or latent,variables. The resulting, much more challenging problem can be addressed by Gaussian process latent variable mod-els (GP-LVM),

4.3 Related work

We review the filed of human indoor localization. We focus on crowdsource mapping, e.g. mapping with limited sensor model (limited to existing infrastructure in building space and to sensors in human smartphones). In this field there are many approaches so solve the sub-problems or parts of given problem.

We know paper GraphSLAM-based Crowd sourcing framework for indoor Wi-Fi fingerprinting [2]. The approach of GraphSLAM is promising. We want to utilise more available spatial information.

The most promising results in terms of cheap sensor spatial information are magnetic maps. For magnetic fingerprinting there are well developed approaches.

One of well-known papers in magnetic fingerprinting is [4]. The authors present an approach for magnetic field mapping, in terms of not fingerprints, but a full grid mapping procedure. As a result of this mapping procedure we obtain a full filed image that is easy to work with. The problem with this approach that we have to collect full grid measurements, which is a time consuming procedure. We want to get magnetic field map without additional mapping procedure, this approach is called crowdsource mapping. We collect the data from a set of human travel trajectories. Then we merge them in single noised image (only analogy representation for better understanding), and apply optimisation procedure. We require the resulting image be smooth, so the optimisation constraints must be set to satisfy the image denoising procedure. This is just our idea and assumption that is have to be proved in further research. We see some similarities here with [5].

However they are highly dependent(?? prove statement) on the data collection procedure. This algorithms also are not intended for standalone usage in terms of sensors fusion. E.g. requires either special mapping procedures or additional hardware devices - beacons.

There are few papers on magnetic and inertial based navigation. However they were not implemented in SLAM frameworks such as [2]. Some of frameworks are a part of commercial interest and are not open source.

The interesting map construction algorithm were proposed in [5].

The full system consists of three subsystems, i.e. Dead Reckoning Subsystem (DRS), Map Construction Subsystem (MCS), and Localization and Navigation Subsystem (LNS).

Our intuition gives that Dead Reckoning Subsystem performs sensor fusion and smoothing. The localization and navigation subsystem utilises the existing map and the output of smmothed sensors measurements.

The map construction process is an optimisation problem with some constraints.

In [5], authors propose universal framework with no prior information of building map structure. But for real situation, the map of the building is known. We can define an indicator function similar to SLAM occupied cells mapping (????) With indicator function defined, we may fit the graph of trajectories to the building inner structure graph - topological map.

The similar approach with map constraints correction and resampling was shown in [1]. The paper utilizes a particle filter that combines PDR and RSSI data.

References

[1] Hao Xia, Jinbo Zuo, Shuo Liu, and Yanyou Qiao. Indoor localization on smartphones using built-in sensors and map constraints. *IEEE Transactions on Instrumentation and Measurement*, PP:1–10, 08 2018.

[2] Min Zhang, Ling Pei, and Xiaotie Deng. Graphslam-based crowdsourcing framework for indoor wi-fi fingerprinting. In *2016 Fourth International Conference on Ubiquitous Positioning, Indoor Navigation and Location Based Services (UPINLBS)*, pages 61–67, 2016.

[3] Brian Ferris, Dieter Fox, and Neil Lawrence. Wifi-slam using gaussian process latent variable models. volume 7, pages 2480–2485, 01 2007.

[4] E. Grand and S. Thrun. 3-axis magnetic field mapping and fusion for indoor localization. *2012 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, pages 358–364, 2012.

[5] X. Zhang, Y. Jin, H. Tan, and W. Soh. Cimloc: A crowdsourcing indoor digital map construction system for localization. In *2014 IEEE Ninth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)*, pages 1–6, 2014.