Construct probabilistic framework for smartphone localisation in zero infrastructure conditions

Documentation Abstract

Problem: no effecient algorithm for smartphone localisation in conditions with:

- no/low number hardware (beacons) available
- available measurements are noisy
- map/measurements are changing over time

Algorithm effeciency:

- accuracy
- computational difficulty (we may compare relative only by the factor of space size)

Sota accuracy: 1m for magnetic fingerprinting, 1-5 m for wifi RSSI, 0.1 m for tdoa and other special techniques - requirement is multiple beacons in field of view Limits: real needed limit approximately 0.3m to 1m. Higher accuracy requires special hardware and environment conditions, not important in research.

Cannot be achieved by ordinary Rssi

zero infrastructure localisation can be done with smartphone's imu, magnetometer and wifi RSSI. We want to utilize magnetic field fingerprinting data for improving accuracy in locations with no ability to use wi-fi RSSI data. current methods show accuracy 1m and 15 degrees. We want to reach same accuracy and define a scalable framework for indoor localisation and mapping.

Conditions:

map is known, no real slam.

Database is a:

- matrice containing measurements
- approximation of surface

We propose to construct a specific auxiliary map which is easy to sample from.

- magnetic field is continious
- rssi data (knn clustering, trilateration) may be considered as continious after transformation.

We may represent the building space as the mesh of poligins, the nodes are placed with only restriction to accurately represent rssi data. The usual rssi model - signal loss model, reflections, multipath, …. Possible to replace with either fingerprint databases + knn, or preprocess knn in some way.

Assume we have rssi auxiliary map created.

There are ways to represent magnetic field in location. We consider this as some approximation, easy to sample from.

We travel over the building and collect measurements. We process absolute value. To avoid recalibration on some scope we operate with **first derivative** of measured magnetic field. **(We have to store absolute values for specific device and timeframe only)**

Absolute measurements » gradients

Mapping, we have a time series of gradients. The process with noise (imu measurements) We may construct Markov chain from this measurements (Gaussian noise, known target distribution, each measurement step is a transition to new point with some probability)

1. Measurements are noisy, we don't process measurements itself. If we use filters, we obtain smoothed data. Using running window or other methods (correlation metrix, … distance) we can compare signal to prorosal trajectory.
2. We sample similar trajectories with known variance. From trajectories we have another predictive measurements. We want to get the best fit between measurements and trajectory. If the magnetic data is changed we have to detect it from wifi RSSI relocalization if possible. We store all localisation chain until we have not confirmed user location (wifi or ble close signal). To process this we have to work in Markov chain framework (reversibility requirement, we construct a transition kernel).
3. To sample accurately, we have to filter signal before. Running mean is ok because we deal with signal variance on higher level, possibly needed try other duscussed methods.

Progress by now

1. Some part of data generation
2. Random trajectories generation using Bezier curves + Gaussian noise

What to do . What is a particle filter . How to construct the pdf to sample from? - we find similar signal. We know orientation and don't know distance (speed). We may want to find similar points in multiple directions (2dim»1 dim case) . Support vector machine is connected with particle filter? . We construct a continuous approximation for k neighborhood clustering, what solutions are known? . How-to apply hmc and MCMC for reversible localisation. - HMC allows to explore high dimensional space. We may represent our task as continious/probability density function approximation and traverce over this space - We have to set exploration speed low. Possibly the usual hmc is not applicable for implementation. Check what are conditions for Markov chain in this model

lecture 9 data association

problem of data association, the distribution of correspondences of observations to states can't be calculated explicitly (?) we need some assumptions for data association, we do iterative updates of correspondences data.

calculating online

- only the last position matters history of correspondences only depend on the last estimate

previous correspondences were correct - assumption (conditional independence from previous correspondences)

c_t = {c_t^1, c_t^2, ...}

batch optimization - evaluation of previous correspondences back in time

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IF there is no landmarks, how to create landmarks from measurements??
clustering of data based on signal similarity, graph clustering, corridor == edge,
splitting into parts
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similarity of trajectories, similarity of measurements (cross-covariance)
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