Indoor SLAM based on crowdsourced data with multiple smartphone sensors

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Background and problem statement

The topic of the project is related to the problem of indoor navigation. The context of the problem states that no GPS data are available at hand, which makes the use of usual navigation services impossible.

Most existing systems of indoor navigation require special mapping stage. Novel indoor navigation systems utilize the data recorded from users. This is what is called the crowdsource approach.

For realtime indoor navigation, in conditions where is no initial data is available, we have to pass stages of localization and mapping, which can be done simultaneously in SLAM approach. We aim to combine both SLAM and crowdsource approach for the best performance of positioning system.

The innovation of this research is in ability to provide same navigation services with less information and in more natural way, which means also the reduced cost of the system overall.

Objectives

We perform this research to create an indoor positioning system with special features. The objective of this research is to develop all algorithms needed to obtain these features.

We can write the criteria for the positioning system we develop.

Criteria for the proposed system:

- no prior map is available
    - the system can work as SLAM system (real-time navigation with no prior map)
- no special hardware for operation except smartphones
    - positioning accuracy enough for operation (1-2m is the usual accuracy in this conditions)
- the system aggregate data from many sources (crowd-source) and improves the localization accuracy

We formulate several hypotheses we evaluate during research:

Hypotheses:

1. The technology of magnetic field navigation can be implemented and fine-tuned for indoor croudsource SLAM

2. The data from magnetic field and inertial sensors is enough for running SLAM
3. The croudsource system satisfies the system optimality conditions and improve the accuracy

The hypothese #2 was not proved in existing systems. For most system, additional prior knowledge is needed. This is more the scientific interest to prove this hypotese.

Two other hypoteses are more the engineering questions. We have to compare performance and robustness of our algorithm and systems to other state of the art approaches. However for our problem statement, there is no much systems that have achieved any reasonable accuracy (1-2m). So we aim to achieve the accuracy that can be compared to other methods only.

Literature review

For the positioning technologies comparison, we may refer to the paper of [Lymberopoulos] which provides evaluation and comparison of different indoor location technologies and covers the almost full landscape of them.

While the information about technologies itself is more or less clear. What performance we can reach with given technology? What is the best approach to work with the given technology?

The answer to some questions is simple. The best accuracy is achieved with the biggest database and computational power. But for realistic implementation this is not good enough. The similar approach is to merge all information available in current location and time. The problem again is that how to localize when there is no information available at the current state. The answer is to use the correspondences between previous and future information, to reconstruct the current information. This formulation can be related to the classical SLAM formulation, even if some parts are different.

Different from existing work, we want to re-estimate or post-process all distance and orientations after measurements with information about previous steps are collected. This is called the loop closure process in SLAM literature [orb-slam], [orb-slam2]. In fingerprinting literature, there is low number of researches working with relocalization and loop closures. We have to recursively post-process existing data, which has to give us better localization during mapping, and thus better map for future localization.

If magnetic map is not given, the model training can be done by manually collection measurements and marking the locations by special trainers, then the localization model can be generated.

Why magnetic field localization is not a SLAM? SLAM techniques build a map of an unknown environment and localize the sensor in the map with a strong focus on real-time operation [orb-slam]. With magnetic field localization, in every new point we obtain only local information, which is not enough for real-time operation. The difference between camera-based and magnetic fingerprints based localization is significant. Because of this fact, magnetic field localization can't operate independently in unknown conditions and can't be considered as SLAM. Nevertheless, we may introduce special aspects of SLAM system to magnetic field localization for better robustness.

The usual camera-based SLAM has the ability to automatically close loops, which means the correction of the accumulated error in exploration after we detect the sensor has returned to a mapped area.

During mapping stage of magnetic field localization, we are constantly accumulating error. We have no tools for error correction because IMU and magnetic field provide both only relative information, and for error correction we need prior spatial information. The prior information can be collected from other sensors (e.g. beacons, such as WiFi and BLE beacons), information can be human input of location, the prior location can be obtained with camera based place recognition. The most interesting approach is to utilize the information we have in our conditions: previous measurements from magnetic mapping. That is the reason why we need loop closure features for robust magnetic field mapping.

The magnetic field in buildings is not stable and changing with time. Even after measurements collected, it is important to update map sequentially. The updates can be done by collecting and processing localization data from all system users. This approach is called crowdsoursing in related literature. This is why place recognition, map updates and loop closures are the main parts of magnetic field navigation.

In Maloc introduced magnetic field based localization system: particle filter which includes a dynamic step length estimation method. Human step length prediction can be introduced in the localization model, but this is only a part of information possible for given conditions.

Several researches states that the best performance is achieved in multi-sensor or hybrid localization steps. And for walking human localization we may consider a dynamic step length estimation method proposed in [maloc].

Methodology / theoretical framework

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 reckoning (PDR) is a relative navigation technique that uses these sensors.

We propose a PDR-based indoor positioning method, that integrates RSSI and magnetic field measurements with indoor environment map constraints by using particle filters.

For proper evaluation of algorithm performance, we have to obtain ground truth data. There are several methods of doing this process:

1. usage of verified tracking / positioning system with better accuracy
2. manual recording of position, using the constant measured track as ground truth (straight line, circle, rotation)
3. usage of public dataset with available ground truth

In our conditions, we choose to first use the dataset of IMU & MEMS and ground truth measurements provided by "RuDaCoP: The Dataset for Smartphone-based Intellectual Pedestrian Navigation".

Then we aim to develop a smartphone data-logging app for dataset collection to run the algorithm on smartphone data.

Techniques

The methods we are planning to use are Graph-SLAM, Gaussian process latent variable models (GP-LVM), magnetic fingerprinting (E. Grand and S. Thrun. 3-axis magnetic field mapping and fusion).

Timeline

Table 1. Project timeline

thesis proposal	10-12-2020
formal derivation of algorithm	25-12-2020
algorithm performance evaluation on existing dataset	12-01-2021
prototyping the mobile app for dataset collection	18-01-2021
dataset collection & data processing	25-01-2021
performance evaluation on collected data	01-02-2021
results formulation	

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