Retrieval-Based Inertial Localization

Draft Proposal

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Abstract

Nowadays there are more accurate solutions you can use for outdoor localization with the help of technologies like global positioning systems and GPS. While they are well established in outdoor scenarios, they are still not available in indoor environments. The reason for this is there is no line-of-sight for the GPS systems inside an indoor environment and the unavailability of indoor environment maps. This has led to numerous studies to develop a well-established indoor localization system. Thus, several technologies have been implemented and proposed. Most of them are usually based on radio networks (e.g.: Wi-Fi, Bluetooth, etc.) and predictions and calculations are done based on the knowledge of fingerprints of signal strength in various locations. The main drawback of these systems is customized hardware infrastructures, privacy concerns, and energy consumption. Due to these reasons, there are two main approaches taken by the research community, 1) technologies like Bluetooth Low Energy Beacons have been introduced to reduce the cost and promising availability. 2) technologies that make use of mobile phone sensor data like IMU data. This paper proposes a retrieval-based indoor localization technique that utilizes only the IMU sensor data collected from mobile phones. We have used a dataset with 53 hours of inertial sensor data with the related ground truth locations.

Introduction

In the age of automation, positioning technologies like navigation and localization have seen tremendous growth over the years with the help of modern smartphones equipped with accurate positioning systems like GPS. These advancements have made locating a person or a GPS-equipped device in an outside environment easy. However, all these systems are only well established in an outdoor environment with a clear line of sight with the satellites.

In an indoor environment, where there is hardly any line of sight with the satellites, the problem becomes more complex to position a person or a device. This has become a major bottleneck preventing accurate positioning in all environments. Numerous applications for indoor location need a workable technical solution. A well-established indoor localization system has the potential to create many opportunities for industries. This has attracted the attention of researchers in the field of indoor localization. Apple's iBeacon technology [1] is a recent commercial development in this domain.

Looking at the current developments in this field, it is obvious that most of the state of art technologies implemented or proposed to need customized hardware infrastructure and many need a map of the indoor environment. Further, these systems have a high concern for privacy, energy, and cost for Maintenace of the systems. Due to these reasons, the state of art technologies that utilize the signal strength of radio networks have created a lack of interest and are less attractive in the industry.

Because of the issues mentioned in the paragraph above, in recent years there has been much research done to tackle the above issues mentioned. The research community has approached these issues and proposed solutions in different ways. We can categorize them into two main branches.

1. Develop new hardware infrastructures or algorithms for existing solutions that minimize or remove the mentioned risks [1].
2. Solutions that don't require customized hardware infrastructure.

Considering the above two branches, although the first one tries to identify the risks of privacy, power consumption, and maintenance cost, they still require customized external hardware infrastructure, and the resulting accuracy will also depend on this structure. This has opened a new area of exploration for researchers in the field of indoor localization. That is the second category of solutions that don't require customized hardware infrastructure.

The wide adoption of ubiquitous, robust, and context-aware modern smartphones helps to get higher accuracy sensor data. In this paper we propose and implement a solution that does not require a customized hardware infrastructure but uses the existing IMU sensor data only in mobile phones, hence falls into the second category of solutions. We have used a retrieval-based approach for the prediction of absolute location. For this purpose, we have used a dataset with 53 hours of inertial sensor data with the related ground truth locations.

Background

With the advancement of outdoor localization systems and AI in the last two decades, indoor localization has been always a research topic, there have been multiple research projects done on this domain featuring different approaches.

Localization using special devices

The early research on this domain focused on developing special devices for indoor localization, but they disappeared from the market because of their high cost and deployment and maintenance efforts. Active Badge[2], Cricket[3], Bat[4], and LANDMARC[5] are some of the research that falls into this type of special device.

Approaches that utilize radio frequency signals

These approaches were utilizing the signal strength of the devices that were installed in the infrastructure. Although these technologies provide better accuracy, they need individual care for different buildings. The notable developments are using Wi-Fi infrastructures and low-energy Bluetooth infrastructures. Chen Chen, Yan Chen, et al. Propose a high-accuracy indoor localization using Wi-Fi infrastructure[6]. Ahmed H. Salamah, Mohamed Tamazin et al. Propose an enhanced Wi-Fi indoor localization system based on machine learning in [7]. While [8], [9] propose how Bluetooth low-energy beacons can be used to minimize the risks of WIFI infrastructures. The recent development of Apple’s iBeacon technology [1], is an example of a currently available solution on the market. These types of technologies also are less attractive because of the maintenance and cost.

Localization approaches used in Indoor Robotics

Due to the lack of GPS (Global Position System) information, indoor robot localization is a necessary component for robots to conduct autonomous services. The prominent technology used in robotics localization is Simultaneous Localization and Mapping (SLAM)[10].

Approaches that utilize mobile sensor data

With modern mobile phones, it is possible to get sensor data with higher accuracy. In [11] Philipp, Damian et al. Propose ALIMAC, an approach for indoor mapping based on activity landmarks and crowdsourcing. Using the crowd-sourcing information gathered by smartphones, ALIMC can automatically create indoor maps of unidentified structures. The main challenge for this type of approach is the repetitive structures commonly found in buildings.

[12] discusses an approach that utilizes IMU (Inertial Measurement Unit) data and floor plan for indoor localization. [13] proposes dubbed neural inertial localization (NILoc) which only utilizes the IMU sensor data to predict the absolute location.

Starting from specialized devices and now in the stage of utilizing mobile sensor data, indoor localization technologies have evolved significantly, but still, they lack interest in the market due to their complexity and privacy issues. In this paper, we have identified these issues and were inspired by the research [8], [11], [12], and [13]. we propose an IMU-only retrieval-based indoor localization approach.

Research Question

In our research, we are going to address the indoor localization problem, which is to predict the absolute location of a given smartphone user, by using a sequence of inertial measurements (IMU). The main aim of the research is to solve the indoor localization problem using a retrieval-based methodology. The output of the model will not be exact in one absolute location. The model will output a likelihood map that contains all possible absolute locations.

Objectives of the Research

Explore the problem Identified in NILOC [13] using a different approach which is a retrieval-based approach. Estimate the absolute location from a sequence of inertial sensor measurements (Only IMU). Find Energy efficient indoor localization mechanism, which preserves the privacy of users. Present Indoor localization mechanism which can be used anytime, anywhere without the need of external infrastructure such as Wi-Fi, BLE, Floorplan, GPS, etc.

Literature Review

Localization is a broader topic. Works done under localization can be divided into two main categories, indoor localization, and outdoor localization. Outdoor localization is a mature area, where several types of successful research are done. Outdoor localization based on Global Positioning System (GPS) and Radio Frequencies(RF) are most commonly used these days.

Our research focuses on the indoor localization problem, which can not be solved by popular outdoor localization techniques such as GPS due to no line-of-sight, reflection, etc. When it comes to indoor localization, a vast amount of research done in this area. These indoor localization methodologies rely on multiple data sources such as images, Bluetooth, WiFi, Ultra Wide Band, RFID tag, etc.

The research described in the paper [7] discusses a methodology to enhance the accuracy of the WiFi indoor localization systems based on a machine learning approach and to reduce the required computational cost and time. First, the radio map was built by saving the RSSI fingerprint at each grid point. Each grid point is defined by 2-dimensional coordinates. Then ML model was built using these RSSI fingerprints, which predict the 2D coordinates of the user's location. However, the main drawback of this methodology is the requirement for RSSI fingerprints and the need for external infrastructure. The paper [14] proposes a feasible fusion framework by utilizing a particle filter to integrate data-driven inertial navigation with localization based on Bluetooth Low Energy (BLE). The method described uses both IMU and Bluetooth sensors. The system uses BLE received signal strength to predict the position and uses IMU sensor data to find the displacement. In the end, both these positions and displacement will be handed over to a particle filter to estimate the user location. The main drawback of this methodology is the requirements of external infrastructures, such as Bluetooth beacons. The above two methodologies use wireless signals to solve the localization problem. The methodologies described under [15], [8], [16], and [17] try to solve the same inertial localization problem using wireless signals. As discussed previously the requirement of external infrastructure is the main drawback of these methodologies based on wireless signals.

Another popular type of indoor localization methodology used in robotics is retrieval-based visual localization, which identifies the image most similar to a query photo in a database of geo-tagged images and then approximates the location of input images based on the most similar image. The paper [18] describes retrieval-based visual localization, which extends support to nighttime images, of retrieval-based visual localization which uses daytime images for training. This research focuses on building the ToDayGAN model and building a mechanism for localization using nighttime images with the help of ToDayGAN. The paper [19] describes the visual-inertial localization problem, which uses both inertial sensor data and visual inputs to solve the localization problem. The paper proposes a dual Kalman filter (DKF) to decrease IMU accumulative posture error and combining with stereo vision (SV) location to optimize the IMU location. However several drawbacks come with these visual-based approaches are the camera needs a clear line of sight, uses a lot of battery power, and records details of passersby. Being independent of external infrastructure is one of the main advantages of these methods.

Magnetic field-based indoor localization is another type of unique approach researchers tried to use to solve the indoor localization problem. Buildings contain several types of magnetized materials such as steel, frames, etc. Due to these magnetized materials, the indoors of a given building may contain unique magnetic fluctuations. The paper [20] proposed a method, which uses these unique fluctuations inside a building to solve the indoor localization problem. The paper [21] proposes a novel approach, which uses a multi-scale attention-guided indoor localization network to predict indoor location by extracting features of a given geomagnetic sequence. Even though these magnetic field-based indoor localization approaches showed successful results, interference from magnetic fluctuations generated by other devices remains a challenge.

Remarkably, the combination of both IMU and floorplan gives high accuracy for indoor localization problems. The paper [12] proposes a mathematical model based on a particle filter to address this localization problem. First, the model takes input from the accelerometer, gyroscope, and compass. Then it detects a step using peaks and valleys in accelerometer readings. Once a step is detected step length model will calculate the step length. The heading direction of the user will be calculated using the compass and the gyroscope. Map data, step length, and heading direction will be passed to the particle filter, which predicts the current location of the user. Moreover, researchers identified the step length of each person may be different. As a solution to this, they created a step model as an initially trained mathematical model, which will get automatically trained with user-specific data. They have conducted several experiments and showed that their methods work better than others. However, according to the authors, heading direction inference and magnetic inference are some of the open problems. Using the advantage of machine learning approaches the researchers of the paper [22] introduced a novel approach, which uses conditional random fields, with the Viterbi algorithm to address the indoor localization problem. However, all of these IMU/Floorplan based approaches require a processed floorplan of a building. However, practically it is hard to maintain the same floorplan for the long term. Because there will be a change of positions of objects in the building. Due to this floorplan may change frequently. This has become the main disadvantage of these IMU/Floorplan based methodologies. Moreover, these methods are required to provide starting position and orientation of the user.

A few years back it was impossible to tackle the indoor localization problem only using IMU data. However, with the availability of a high amount of IMU data and advanced deep learning technologies, indoor localization using only IMU data became feasible. The NILOC paper [13] proposes a method to solve this indoor localization problem using a data-driven transformer-based neural architecture, which uses a sequence of IMU data to predict the indoor location of a user. With the help of data-driven approaches and large datasets, it can be identified places based on IMU data patterns. For example, the pattern of inertial measurement sequences near a notice board in the building will be almost equal. NILOC uses this methodology to address the localization problem.

As discussed above, it can be concluded that even though most of the proposed methodologies give us accurate results, some of those methodologies have significant drawbacks, which make those methods impossible to use in real-world scenarios. The wireless signal-based methodologies described in papers [7], [14], [15], [8], [16], and [17] require external infrastructure to proceed. Moreover, vision-based approaches described in [18] and [19] have drawbacks such as the camera needing a clear line of sight, using a lot of battery power, and recording details of passersby. And magnetic field-based approaches mentioned in [20] and [21] fail when there are magnetic interferences from surrounding devices. Although IMU/Floorplan based approaches proposed in [12] and [22] show perfect results, the requirement of floorplan makes these methodologies hard to use. A novel approach Neural Inertial Localization (NILOC), which does not rely on external infrastructure, was introduced in the paper [13]. But the approach described in the paper encodes IMU data into a machine learning model.

Our research focuses on the same approach introduced in NILOC [13], but with a retrieval-based approach. As of our knowledge, this methodology is not followed in any previous research. We hope that solving this indoor localization problem will bring a vast amount of advantages to society. By using this indoor localization methodology, people will explore real-time traffic/movements inside the buildings. Our reason for doing this project is to fill the gap in indoor localization literature and present an effective solution, which will bring benefits to society.

Proposed Research Methodology

Our research focuses on estimating the absolute location from a sequence of inertial sensor measurements. However, we should use a retrieval-based approach and only IMU data (no external infrastructure such as Wi-Fi, BLE, Floorplan). This is achieved by researching and developing a similarity metric for motion sequence data and performing a lookup method for the trajectories. It is basically to match the IMU data to motion trajectory using an ML approach. We will train the ML model to analyze IMU inputs and output the estimated motion path. After training the model we hope to evaluate and analyze the performance of our model against the state-of-the-art solution model proposed by S. Herath, D. Caruso, C. Liu, Y. Chen, and Y. Furukawa in [13] to address the indoor localization problem using a model-based approach. After validations, we will document the research findings and prepare the final report.

Scope

The project addresses the domain, of "Retrieval-based inertial localization" based on IMU inputs. So it will address the indoor localization problem using inertial sensor IMU inputs only. We will not use external infrastructure such as Wi-Fi, BLE, and Floorplan[23] or will not address Fingerprint Based and Ranged Based localization, only inertial-based [16]. Estimate the absolute indoor location,

1. Through retrieval-base approach
2. Given only a sequence of IMU data.
3. Without using external infrastructure such as Wi-Fi, BLE, Floorplan, etc.

Significance of the Research

The task of estimating the absolute indoor location only from a sequence of inertial sensor measurements is already introduced by NILOC[13] paper but uses an approach, which encodes data into a model to solve this problem. As stated in the literature review all the other papers we read have used a combined approach (visual, Wi-Fi, BLE, Floorplan) with IMU data. So it is safe to say that, as of our knowledge, no research has been done under IMU Only Indoor Localization using Retrieval Based Methodology. Our method will be an energy-efficient indoor localization mechanism, which preserves the privacy of users and can be used anytime, anywhere without the need for external infrastructure. This research gap will be filled because of our contribution. Also, we hope that our approach will be used and modified not only in academia but also in the industry (like target tracking, police patrolling, homeland security, inventory management, machinery fault detection, large shopping malls, business buildings, etc).

Research Timeline

The following table depicts the estimated timeline, goals, and deliverables which would be developed and researched during the project's duration.

Task	Start Date	End Date	Time Length	Deliverables
Domain analysis	TBD	TBD	1 Month	Presentation
Data retrieval, formatting, and preparation	TBD	TBD	1 Month	N/A
The training proposed ML Model	TBD	TBD	3 Month	Trained ML Model
Validation of the proposed model against the state-of-the-art models	TBD	TBD	3 Month	Validated Model
Documentation of Results Preparation of research report	TBD	TBD	1 Month	Research report
Summary			9 Months	

Table 1: Proposed Timeline

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