Retrieval-Based Inertial Localization

Research Proposal

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Abstract

With the assistance of modern technology such as global positioning systems (GPS) and the availability of precise map information from commercial suppliers or communities such as that of the OpenStreetMap (OSM) projects have helped in the emergence of accurate outdoor localisation solutions. Although they are well-established for outdoor scenarios, they are still unavailable 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. Therefore, several technologies have been implemented or proposed. Most of these 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 at various locations. The main drawbacks of these systems are customized hardware infrastructure, 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 use cell phone sensor data like IMU data. This paper proposes a retrieval-based indoor localization technique that uses only the IMU sensor data collected from mobile phones. We have used a rich dataset of inertial sensor data with the related ground truth locations collected for 53 hours.

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 in the position of a person or a device. This has become a major bottleneck that prevents accurate positioning in all environments. The numerous applications for indoor locations require a workable technical solution.

A well-established indoor localization system can 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 the art technologies implemented require customized hardware infrastructure and many of them need a map of the indoor environment.Further, these systems have a high concern for privacy, energy, and cost for maintenance of the systems. Due to these reasons, the state of the art technologies that use 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, recently 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 identifying 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 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 to predict 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 always been 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 id 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 crowd-sourcing. 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 indoor location of a given user, by using sensor values of the user's device. Our research specifically focuses on retrieval-based inertial indoor localization, where we predict the absolute indoor location of a given user only using a sequence of inertial measurements (IMU) captured using the device sensors. The research uses retrieval-based techniques to find the best motion-to-motion matching between IMU sequences.

Objectives of the Research

1. Explore the problem Identified in NILOC[13] using a different approach which is a retrieval-based approach. Should be able to change the database without re-training the model.
2. Implement a machine learning model/ algorithm that predicts the location of an object. Present Indoor localization mechanism which can be used anytime, anywhere without the need of external infrastructure such as Wi-Fi, BLE, Floorplan, GPS, etc.
3. Estimate the absolute location from a sequence of inertial sensor measurements (Given only a sequence of IMU data).
4. Implementing a general motion to motion matching algorithm to find the best matching location from an external knowledge base, which is not model specific, will lead to loosely coupled model and data.
5. Find Energy efficient indoor localization mechanism, which uses IMU as the only sensor that preserves the privacy of users.

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 is 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 Wi-Fi 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 the ML model was built using these RSSI fingerprints, which predict the 2D coordinates of the user's location. The paper [14] addresses the same problem using retrieval based approach. However, the main drawback of these methodologies are the requirement for RSSI fingerprints and the need for external infrastructure. The paper [15] 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 [16],[8],[17], and [18] 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 [19] 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 [20] 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: 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 [21] proposed a method, which uses these unique fluctuations inside a building to solve the indoor localization problem. The paper [22] 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, the 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 [23] 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], [15], [16], [8], [17], and [18] require external infrastructure to proceed. Moreover, vision-based approaches described in [19] and [20] 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 [21] and [22] fail when there are magnetic interferences from surrounding devices. Although IMU/Floorplan based approaches proposed in [12] and [23] 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. Due to this the model is tightly coupled with the data. As a result of this the model should be retrained, when there is a change in the data. This can be mentioned as a drawback of this approach. However the NILOC [13] method, which uses only an IMU sequence to predict location likelihood, shows very successful results comparative to other approaches.

Our research focuses on the same approach introduced in NILOC [13], but with a retrieval-based technique. By using the retrieval-based technique, we hope to reduce the coupling between data and the model. As a result of this we will be able to change the data without retraining the model. 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 privacy preserved 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 the 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 history of IMU data to a motion trajectory using an ML approach. We will train the ML model to analyze IMU inputs and output the estimated motion path.

1. Observations - IMU sensor data (Accelerator, Compass and Gyroscope)
2. Knowledge Base Retrieval Model - Data collected on specific buildings. We will use the NILOC [13] dataset.
3. Personalization module - Floor plan , Personalization algorithms

There are three phases in the proposed methodology.

1. Phase01 - Using a contrastive learning algorithm, get k number of possible likelihood locations.
2. Phase02 - Using the Neural Network developed in phase01 to refine the location history to be consistent with the floorplan to get the absolute position.
3. Phase03 - Develop advanced personalization algorithms to get the absolute position of the object without the help of a floor plan.

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. In summary we will use the NILOC, CRF and Learned Prior models for quantitative evaluations on the localization task for the three buildings separately. This is done by measuring the success rate (SR) at a given error distance threshold and angle (A) threshold for each of the implementations and compare the results for

1. Fixed short sequence (100 m)
2. Full test sequence

For one trajectory from a building, show results by the three methods (columns) for one localization. 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[24] or will not address Fingerprint Based and Ranged Based localization, only inertial-based [17].

Estimate the absolute indoor location,

1. Through a retrieval-based 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 addressed by NILOC[13] paper but uses an approach, which encodes data into a model to solve this problem. This method has few limitations as well as the NILOC model (implicit map-based model) needs to be trained from one building to another. But in our research, the model will be a matching algorithm to find similar patterns according to input data in the database. Ideally, this algorithm is general (not model specific). 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. Though there are many approaches and technologies to address the inertial localization problem, they have drawbacks and some are not accurate.

Hence, it is safe to say that, as of our knowledge, no prior 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 any-time, anywhere without the need for external infrastructure. This research gap will be filled because of our contribution. Imaging a mobile app that can record the locations 24/7 anywhere using IMU data and inertial localization that can happen on device, giving users a higher degree of privacy control. Inertial localization will be a critical component in GPS indoor navigation. 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	Deliverables
Domain analysis	15/08/22	21/11/22	Literature Survey, Project proposal, Presentation
Data retrieval, formatting, and preparation	21/11/22	16/12/22	N/A
Training the proposed ML Model	19/12/22	20/03/23	1. Location likelihood (IMU only) (phase01 results) 2. Absolute position with floor plan(phase02 results) 3. Absolute position without floor plan/advance personalization algorithms (phase03 result)
Validation of the proposed model against the state-of-the-art models	21/03/23	04/04/23	Validated Model
Documentation of Results Preparation of research report	31/03/23	17/04/23	Research report
Design Mobile Application	01/03/23	28/04/23	Mobile app
Preparation of the research report	10/04/23	24/04/23	Research report
Preparation of the poster presentation	17/04/23	28/04/23	Poster presentation
Summary	15/08/22	28/04/23	Completed FYP

Table 1: Proposed Timeline

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