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Walk and learn: Enabling accurate indoor positioning by profiling outdoor movement on smartphones

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ABSTRACT

One of the key objectives in developing pervasive and mobile applications is to localize users within indoor environments. By employing accelerometers on smartphones, dead reckoning is an intuitive and common approach to generate a user's indoor motion trace via mobile devices. Nevertheless, dead reckoning often deviates from the ground truth due to noise in the sensing data. We propose `IOLoc`, an indoor localization approach that benefits by transferring learning from tracking outdoor motions to the indoor environment. Via sensing data on a smartphone, `IOLoc` constructs two datasets: relatively accurate outdoor motions from GPS and less accurate indoor motions from accelerometers. Then, `IOLoc` leverages a Motion Range Space to improve a user's acceleration and orientation values used for computing dead reckoning. After using a transfer learning algorithm to the two datasets, `IOLoc` boosts the Motion Range Box to achieve better indoor localization results. Additionally, `IOLoc` exploits indoor GPS exception cases, pedometer, and average speed estimation to further improve dead reckoning. Through case studies on 15 volunteers for the indoor and outdoor scenarios, we show `IOLoc` is a non-infrastructure, low-training complexity, and energy saving indoor positioning approach that achieved a localization accuracy of 0.26∼0.49 m in multiple scenarios.

1. Introduction

Indoor localization enables a huge space of location-based services, including indoor navigation, targeted advertisement, augmented reality, etc. Despite the extensive research and development of indoor positioning systems [1–6], localization service is not yet ubiquitous indoors. Since the capabilities of smartphones have become more powerful, many researchers use smartphones to locate people. Apart from the traditional device-based and device-free indoor localization approaches, smartphone-based approaches capture people's motions and traces by analyzing the acceleration, light, sound and other signals [7–13].

Although inertial sensing on smartphones can capture people's movement via the sensing data, there are some shortcomings: the sensing information, such as the 3-D acceleration from a smartphone does not always reflect features of a person's movements; the data training task is difficult: the size of data is small for statistical location accuracy and the learning algorithm is significantly complex for a smartphone. Based on this point of view, we ask the question: *Can we enhance smartphone users' capabilities to locate themselves accurately without complex indoor training and without an extra, perhaps expensive infrastructure?*

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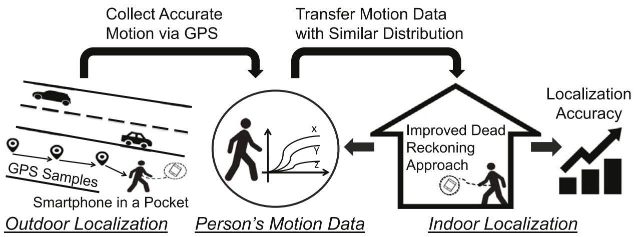

Fig. 1. IOLoc in Action: employ outdoor data to improve indoor positioning.

To this end, we propose IOLoc (transferring learning of Indoor and Outdoor motions to Localize users within an indoor scenario) [14], an accurate and low-cost indoor localization system that integrates an off-the-shelf dead reckoning approach, GPS information, and a transfer learning mechanism. Our idea is inspired by the observation that, when a certain user walks indoors or outdoors, some features of his/her walking patterns, such as the average speed and acceleration are not greatly affected by the different environments. Recognizing this opportunity, we use outdoor walking behaviors to assist users' indoor localization.

Initially, IOLoc provides a sensing service on a smartphone that detects whether the smartphone is indoors or outdoors. Then, IOLoc uses a dead reckoning approach [7]. Motion Range Space is introduced to filter the accelerations and directions that do not represent the user's movement. To determine the range of the Motion Range Space, IOLoc collects the average speed, acceleration, and orientation from the indoor and outdoor environments. Since the outdoor motion data using GPS is more accurate than movement determined by accelerometer data, IOLoc not only uses indoor datasets but also uses the outdoor GPS datasets. In the outdoor dataset, we employ Transfer Learning [15] to select the parts of accelerations for which people's outdoor movement behaviors are similar to indoor motions and add the chosen outdoor data to the indoor datasets for boosting the effectiveness of the Motion Range Space.

Three additional techniques for using outdoor/indoor information are proposed to enhance the original dead reckoning method: IOLoc adopts a pedometer to construct other adaptations to acceleration measurements that reduce the errors of indoor localization; indoor GPS exception cases are used to decrease deviations; since people's average speeds and directions of movement typically do not change sharply, we eliminate some incorrect accelerations and orientations by average speed prediction. In addition, an energy saving method is proposed without any hardware modification. We prototype IOLoc and conduct a set of experiments in indoor and outdoor scenarios. Fifteen volunteers' cases have been studied. The evaluation results demonstrate IOLoc is able to profile data and locate users seamlessly and effectively by enhancing the original dead reckoning approach. The errors of indoor localization are between 0.26 m and 0.49 m. Also, IOLoc does not request users to do special off-line training. By opening IOLoc and the GPS option for daily walking, IOLoc can estimate indoor position more accurately (see Fig. 1).

In summary, we make the following contributions:

- While many researchers have used dead reckoning as a means to specify a user's position in recent years, to the best of our knowledge, IOLoc is the first of its kind to apply transfer learning and retrieve the outdoor motion information to the indoor dataset for boosting indoor localization automatically.
- Indoor GPS Exception, Pedometer Measurements, and Average Speed Filter are implemented to assist the dead reckoning method.
- We employ outdoor GPS information and other sensing data obtained from smartphones to detect whether the smartphone is indoors or outdoors.

In the rest of the paper, we overview IOLoc in Section 2. Then, we detail the system design and optimization in Section 3 and Section 4. The implementation and evaluation of IOLoc are shown in Section 5. We review related works in Section 6. Section 7 provides the conclusions and future work.

2. System overview

Fig. 2 presents the system architecture of IOLoc. IOLoc has four steps: (a) leverage the inertial sensors on a smartphone to obtain the acceleration, GPS, air pressure, cell signal, light and magnetic information; (b) use the acquired sensing data, IOLoc detects the indoor/outdoor environments with high accuracy by applying a *k-means* clustering algorithm; (c) IOLoc proposes the Acceleration Range Box, a range of accelerations in different directions to filter the incorrect accelerations that lead to dead reckoning errors. Also, we add the orientation information to Acceleration Range Box and form the Motion Range Space. In order to characterize the Motion Range Space, we construct a relation from the user's average speed, average acceleration, and directions in each time period. Taking the relation as the bridge, IOLoc chooses the transfer learning approach to transfer the worthwhile outdoor GPS information to the dataset that stores acceleration samples that were received indoors. (d) by the Motion Range Space constructed by transfer learning and other optimization technologies, IOLoc calibrates the errors of dead reckoning to achieve accurate indoor localization results.