Self-Improving Indoor Localization by Profiling Outdoor Movement on Smartphones

Conference Paper · June 2017

DOI: 10.1109/WoWMoM.2017.7974311

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***Abstract*—Smartphones are equipped with many low-cost sensors. As a result, opportunities open for smartphones to serve as a platform for many challenging ubiquitous applications, including indoor localization. By employing accelerometers on smartphones, dead reckoning is an intuitive and common approach to generate a user's indoor motion trace. Nevertheless, dead reckoning often deviates from the ground truth due to noise in the sensing data. We propose `iLoom`, an indoor localization approach that benefits by transferring learning from tracking outdoor motions to the indoor environment. Via sensing data on a smartphone, `iLoom` constructs two datasets: relatively accurate outdoor motions from GPS and less accurate indoor motions from accelerometers. Then, `iLoom` leverages an Acceleration Range Box to improve a user's acceleration value used for computing dead reckoning. After using a transfer learning algorithm to the two datasets, `iLoom` boosts the Acceleration Range Box to achieve better indoor localization results. In addition, `iLoom` exploits indoor GPS exception cases and pedometer to further improve dead reckoning. Through case studies on 15 volunteers for the indoor and outdoor scenarios, we show `iLoom` is a non-infrastructure and low-training complexity indoor positioning approach that achieved a localization accuracy of 0.28∼0.51m in multiple scenarios.**

I. Introduction

Indoor localization is a fundamental service for various location based applications. Despite the extensive research and development of indoor positioning systems [1]–[4], location-based services are not yet ubiquitous indoors. 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 [5]–[8].

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?*

In this paper, we propose `iLoom` (indoor Localization through transferring learning of outdoor motion), 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, `iLoom` provides a sensing service on a smartphone that detects whether the smartphone is indoors or outdoors. Then, `iLoom` uses dead reckoning [5]. An Acceleration Range Box is introduced to filter the accelerations that do not represent the user's movement. To determine the range of the Acceleration Range Box, `iLoom` collects the average speed and acceleration from the indoor and outdoor environments. Since the outdoor motion data using GPS is more accurate than movement determined by accelerometer data, `iLoom` not only uses indoor datasets but also uses the outdoor GPS datasets. In the outdoor dataset, we employ Transfer Learning [9] 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 Acceleration Range Box.

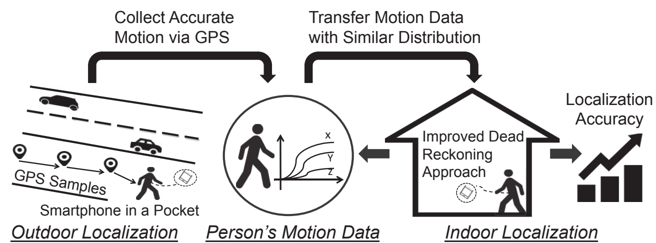

Fig. 1 iLoom in Action: employ outdoor data to improve indoor positioning

Two additional techniques for using outdoor/indoor information are proposed to enhance the original dead reckoning method: `iLoom` adopts a pedometer to construct other types of Acceleration Range Boxes that reduce the errors of indoor localization; indoor GPS exception cases are used to decrease deviations. We prototype `iLoom` and conduct a set of experiments in indoor and outdoor scenarios. Fifteen volunteers' cases

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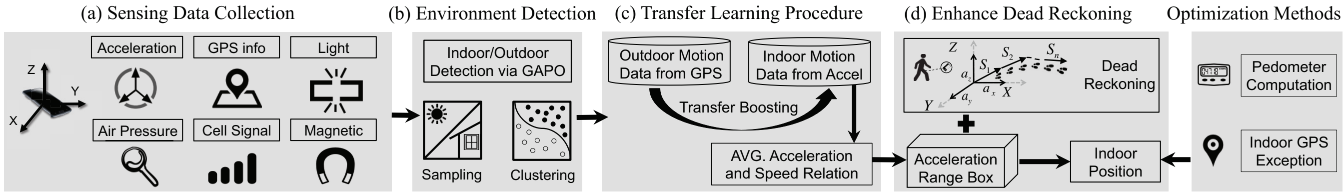


Fig. 2 System architecture of iLoom.

have been studied. The evaluation results demonstrate `iLoom` 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 $0.28m$ and $0.51m$. Also, `iLoom` does not request users to do special off-line training. By opening `iLoom` and the GPS option for daily walking, `iLoom` can estimate indoor position more accurately.

In summary, we make the following contributions:

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

In the rest of the paper, we first detail the system design in section II. The implementation and evaluation of `iLoom` are shown in section III. We review related work in section IV. Section V provides the conclusions and future work.

II. System Design

A. System Overview

Fig. 2 presents the system architecture of `iLoom`. `iLoom` has four steps: 1) leverage the inertial sensors on a smartphone to obtain the acceleration, GPS, air pressure, cell signal, light and magnetic information; 2) use the acquired sensing data from `iLoom` to distinguish between the indoor and outdoor environments with high accuracy by applying a *k-means* clustering algorithm; 3) create an Acceleration Range Box, which is a range of accelerations in different directions to filter the incorrect accelerations that lead to dead reckoning errors. In order to characterize the Acceleration Range Box, we construct a relation from the user's average speed to the average acceleration in each time period. Taking the average speed as the bridge, `iLoom` chooses the transfer learning approach to transfer the worthwhile outdoor GPS information to the dataset that stores acceleration samples that were received indoors. 4) via the Average Acceleration Range Box constructed by transfer learning and other optimization technologies, `iLoom` calibrates the errors of dead reckoning to achieve accurate indoor localization results.

We propose two other approaches to assist the indoor localization: 1) `iLoom` adopts a third-party pedometer to modify and boost the Acceleration Range Box; 2) although a user walks indoors, he/she may receive a GPS signal occasionally. Such GPS samples cannot be used for indoor positioning and may cause a false positive when a localization system detects the user is indoors or outdoors. We design an approach that not only avoids such mistakes but also improves indoor localization accuracy.

B. Indoor and Outdoor Detection

Before transferring the useful motion data from outdoors to indoors, we need to identify the samples obtained from the smartphones that belong to either the indoor or outdoor environments. An intuitive detection scheme estimates the positions via GPS. When the smartphone receives a GPS sample, the user can assume he/she is in an outdoor environment. In reality, while a user is walking in a building, e.g., when he/she is close to a window, he/she might receive GPS samples on his/her smartphone occasionally. However, these samples do not represent the user when outdoors.

To tackle this problem, researchers at Nanyang Technological University developed IODetector [10], which uses three types of information on smartphones: light intensity, cell signal strength, and magnetic sensor values. Even if each of them cannot determine the environment, IODetector aggregates them and provides the solution. Based upon IODetector, researchers at the University of Edinburgh developed a semi-supervised learning model to analyze the indoor/outdoor location of smartphones [11]. They used more than three types of sensors on smartphones to collect physical signals. By applying the semi-supervised learning model, the accuracy of IODetector increases to 92.5%.

In this section, we introduce a novel approach, GAPO. By leveraging the GPS, Air Pressure, and Other cyber-physical information on the smartphones (light intensity, cell signal strength, magnetic sensing values), we distinguish the indoor/outdoor context for the smartphones.

Apart from the two above approaches, the proposed purpose of `iLoom` is to transfer outdoor GPS information to improve indoor positioning. Hence, GPS samples can be borrowed to detect environments. Considering both the current and historical information, a parameter tsi (*t*ime *s*equence *i*ndex of GPS) is defined as formula (1):

$$tsi = (\sum_{i=1}^{t} \lambda \times 2^i)/(\sum_{i=1}^{t} 2^i) \tag{1}$$

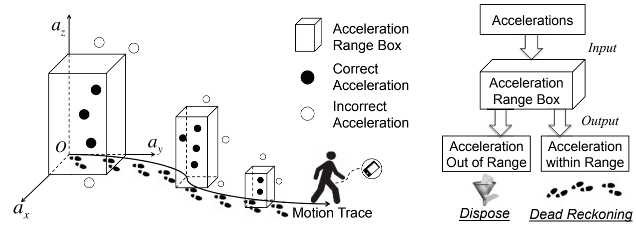
where t is the number of time periods, i refers to the time period. λ can be set as 0 or 1 (if the smartphone gets the sample in time period i, λ equals to 1, otherwise, it is set as

TABLE I CONFUSION MATRIX FOR THE SAMPLES REPRESENTING THE INDOOR/OUTDOOR DETECTION RESULTS.

	Indoor (ground truth)	Outdoor (ground truth)
Indoor (estimate)	N_{ii}	N_{io}
Outdoor (estimate)	N_{oi}	N_{oo}

TABLE II SUCCESSFUL RATES OF DISTINGUISHING INDOOR/OURDOOR ENVIRONMENTS IN DIFFERENT SCENARIOS.

	GPS Only	IODetector	GAPO
Sports Center	83.50%	80.50%	94.50%
Laboratory Building	79.50%	77.50%	90.00%



(a) Motion trace generation. (b) Workflow.

Fig. 3 Acceleration Range Box. The value on each axis represents the average maximal acceleration in each direction.

0). For tsi, the obtained GPS samples that are closer to the current time period will be assigned more weight.

Additionally, modern smartphones include barometers. Highly accurate air pressure can be easily accessed. The accuracy of the barometer, such as the barometers on the Samsung Galaxy smartphones, can achieve within 0.1hPa. Although air pressure is determined by many factors, the differences of temperatures in indoor and outdoor scenarios often cause the variations of air pressure. Therefore, we add air pressure as a feature for distinguishing indoor and outdoor environments. After leveraging *k-means* algorithms, GAPO categorizes these samples into indoor and outdoor datasets.

We conducted a preliminary observation to explore GAPO: one user of a smartphone walks freely, receives 1000 samples from outdoor/indoor environments, and conducts GAPO to detect the environments. We compare the estimated indoor/outdoor results with the ground truth. Table I is a confusion matrix for representing the detection results. N in Table I denotes the number of samples. The metric P_e in formula (2) refers to the successful rate of estimating the indoor/outdoor environment.

$$P_e = (N_{ii} + N_{oo})/(N_{ii} + N_{io} + N_{oi} + N_{oo}) \qquad (2)$$

As shown in Table II, by running the GPS and IODetector APP from Google Play, we compare the P_e values with other approaches in two different buildings. GAPO archives better performance.

C. Dead Reckoning is Not Enough

Pedestrian dead reckoning methods have been widely used in indoor localization, especially for the smartphone based approaches [5]. Based on the accurate initial position, the application executing on the mobile device computes movement distance in each segment continuously. Then, it will form the whole trace of the user's motion. For dead reckoning, we use sensors on the smartphone (accelerometer, magnetometer, and gyroscope) to estimate the user's step length and obtain heading direction [12].

Although dead reckoning is easy to implement, a major difficulty in dead reckoning is that a smartphone only records its own accelerations rather than the accelerations of the human body's motion. In practice, when users of smartphones collect their motion data via smartphones, some cases often occur, such as giving a phone call to a friend, sending messages via typing on the screen, and swinging the hands holding the smartphones. These behaviors incur serious deviations from a person's walking pattern. Moreover, such errors grow with time because the next motion segment is calculated from the current one with inaccuracy. Due to these reasons, the dead reckoning trajectories are accurate in the beginning, but diverge from the ground truth over time.

D. Initial Noise Filtering

When we employ dead reckoning as a means to locate people, it is necessary to filter obtained accelerations that cause serious errors. In `iLoom`, even though we do not detect the place of a smartphone (e.g., in a pocket, on a user's hand, near an ear of user) and recognize human's activities in detail, we set basic constraints for collected accelerations. Because the reasonable range of human bodies' motions is within 0-5m/s^2 on x, y and z axes [13], we preliminarily eliminate the acceleration beyond the range while collecting the data from accelerometers.

E. Acceleration Range Box

Every user has his/her own motion features. For example, when people walk regularly (not considering jumping, running, and other special movements), the values of acceleration and average speed on the x, y, and z directions should be within certain ranges. Inspired by this point, we propose a technique to enhance dead reckoning: if we can estimate the maximum accelerations on x, y, and z directions, they can be abstracted as the three sides of a cuboid. The cuboid is called Acceleration Range Box (a_{rb}). As Fig. 3 shows, when we adopt dead reckoning to generate a user's motion trace, if the acceleration value is out of a_{rb}, we assume the value is invalid. We use the acceleration in the previous period to replace the invalid acceleration.

Since we introduced the Acceleration Range Box (a_{rb}), an important challenge is how to build an efficient a_{rb} for each user. A brute-force approach is 1) recording all the accelerations on x, y, and z axes of a smartphone; 2) finding the maximum value in each direction as the side of a box. However, such a_{rb} cannot reflect people's motion feature and some invalid acceleration values will be accepted.

In `iLoom`, although we do not categorize people's movements in detail, a practical metric to classify people's motions is introduced. The metric is Average Speed ($\overline{v}$) of people's movement in a certain time period. For a certain Range of Speed, we assume there is a specific a_{rb} for a user. For example, a user's Average Speed in 1 minute is 1.4m/s, the related a_{rb}

is 2.4m/s^2 on x axis, 1.4m/s^2 on y axis, and 1.4m/s^2 on z axis.

We then construct an a_{rb} for each certain $\overline{v}$. In an indoor environment, as in formulas (3) and (4), we can capture the $\overline{v}$ in each segment through dividing the moving distance by time t. For the outdoor localization, the $\overline{v}$ in each time period can be obtained via GPS. For each time length of t, we record the maximum values of the acceleration on the three directions and form the a_{rb}. If there are more than one a_{rb} in a speed range, we will compute the average value of maximal acceleration on each direction and make use of it as the side of a cuboid. The newly generated box is named Average Acceleration Range Box ($\overline{a_{rb}}$).

For a certain Range of Speed ($R_{\overline{v}}$), it also has its corresponding $\overline{a_{rb}}$. Therefore, we can create the relation between Range of Speed and Average Acceleration Range Box. This relation in outdoor environments is named $\mathbb{R}_o(R_{\overline{v}}, \overline{a_{rb}})$ ($\mathbb{R}_o$ for short), and it is named $\mathbb{R}_i(R_{\overline{v}}, \overline{a_{rb}})$ in indoor environments ($\mathbb{R}_i$ for short).

F. *Can Outdoor Localization Help Indoor Localization?*

For dead reckoning based indoor localization, because the accelerations obtained from the accelerometer may not be consistent with the human body's motion, the indoor $\overline{v}$ might be computed incorrectly. However, since GPS has a relatively accurate performance in outdoor environments, the outdoor $\overline{v}$ does not have such a problem. The corresponding $\mathbb{R}_o$ is often more accurate than $\mathbb{R}_i$.

Therefore, we propose an audacious conjecture: *could we transfer the useful data from $\mathbb{R}_o$ to $\mathbb{R}_i$, and build a better relation to improve the dead reckoning approach?*

The intuition for `iLoom` is simple. For a certain person, his/her walking style does not change greatly whenever he/she is indoor or outdoor. For every speed range of each person, there is a particular distribution, e.g, a male adult whose age is 30, his speed range is mainly distributed from 1.2m/s to 1.7m/s [14].

To further verify this pre-condition, we did the preliminary observation: we recorded two users' walking data by leveraging the smartphones that are in left jean pockets. Two users walked regularly in three scenarios: outdoor playground (30 minutes), indoor fitness center (30 minutes), indoor shopping center (30 minutes). We build the 6 corresponding datasets based upon two types of features: Average Speed ($\overline{v}$) and Average Acceleration Range Box ($\overline{a_{rb}}$). The sampling frequency is 5HZ. We focus on the similarity of the six datasets. Two common metrics of similarities are leveraged:

1) Dist(C_i, C_j) - The Euclidean distance between the centers of datasets i and j;

2) Dist(s_i, s_j) - The average Euclidean distance between each sample in dataset i and dataset j.

By computing the similarities among different datasets, our case study provides the following relation: even if in different scenarios, for a certain user, walking datasets are highly similar. However, for a certain scenario, different users' walking datasets are different.

If we select the useful and highly accurate samples from $\mathbb{R}_o$ and combine them to $\mathbb{R}_i$, it is probable to build a larger and more accurate relation. For each speed range, we will recompute the corresponding $\overline{a_{rb}}$. If the new $\overline{a_{rb}}$ is more suitable for dead reckoning, it can boost the localization results.

G. *Transfer Learning from Outdoor to Indoor*

In this subsection, we start to transfer the worthwhile information from the outdoor motion dataset to the indoor motion dataset. In this paper, we employ *Transfer Learning* [9]. It stores knowledge obtained from solving one problem and uses it for a similar problem.

In `iLoom`, we study the useful instances from $\mathbb{R}_o$ and apply them on $\mathbb{R}_i$, which are different but similar to $\mathbb{R}_o$. In each instance, it consists of two features: Average Speed ($\overline{v}$) and Average Acceleration Range Box ($\overline{a_{rb}}$).

When we apply transfer learning, the main challenge of transition is: for a certain user, even if his/her walking behavior is similar whenever he/she is indoors or outdoors, there is a small amount of differences in the speed distribution between $\mathbb{R}_i$ and $\mathbb{R}_o$. On the perspective of $\mathbb{R}_i$, we need to 1) choose the instances that keep the same-distributions as $\mathbb{R}_i$ from $\mathbb{R}_o$, and 2) transfer these instances to $\mathbb{R}_i$.

First, we define S and T to represent the test dataset (indoor information) and the training dataset (outdoor information). SVM [15] is the default classifier. We select part of the labeled training data having the similar distribution as the test data (indoor information) to build a better classifier. These data are named same-distribution training data (T_s), the size of T_s is *m*; The training data, whose distribution is different from the test data, are named diff-distribution training data (T_d); the size of T_d is *n*.

X and Y are two instance spaces. X_s and X_d represent same-distribution instance space and different-distribution instance space. $Y = \{0, 1\}$ is the set of category labels. Concept mf is a boolean mapping function from X to Y, and let $X = X_s \cup X_d$. The return value of the label for the data instance/sample x is $mf(x)$.

From $\mathbb{R}_o$, we can obtain 1) inadequate labeled same-distribution training data T_s, 2) diff-distribution training data T_d, and 3) some unlabeled test data S.

Our task is to train a classifier $mf' : X \to Y$ that minimizes the prediction error on the unlabeled dataset S. In the proposed approach, the *prediction* operation is defined as: if we use the $\overline{a_{rb}}$ and dead reckoning approach to localize people, and if the deviation distance is within $1m$, the prediction is successful; otherwise, the prediction is a failure.

To achieve this goal, we adopt the TrAdaBoost approach [16]: for diff-distribution training instances, when they are wrongly predicted due to the distribution modified by the learned model, these instances could be recognized as the most dissimilar instances to the same-distribution instances. TrAdaBoost provides a mechanism to decrease the weights of these instances in order to weaken their impacts. Algorithm 1 illustrates the procedure of TrAdaBoost. In each iteration round, once a diff-distribution training instance in $\mathbb{R}_o$ is not predicted successfully, the instance may conflict with the same-

TALBE III MAIN NOTATIONS IN THE DESIGN OF iLOOM

Symbols	Definition
$\overline{v}$, $R_{\overline{v}}$	Average Speed, Range of Average Speed
a_{rb}, $\overline{a_{rb}}$	Acceleration Range Box, Average Acceleration Range Box
$\mathbb{R}_i(R_{\overline{v}}, \overline{a_{rb}})$	Relation between $R_{\overline{v}}$ and $\overline{a_{rb}}$ in <u>i</u>ndoor environment
$\mathbb{R}_o(R_{\overline{v}}, \overline{a_{rb}})$	Relation between $R_{\overline{v}}$ and $\overline{a_{rb}}$ in <u>o</u>utdoor environment
$\mathbb{R}_c(R_{\overline{v}}, \overline{a_{rb}})$	Relation between $R_{\overline{v}}$ and $\overline{a_{rb}}$ in <u>*combined*</u> dataset
X_s,X_d	same-distribution / different-distribution instance space
S_d,S_s	diff-distribution / same-distribution as sample space
L	set of category labels, L= $(0, 1)$
mf	boolean mapping function from X to Y
S,T	test dataset and training dataset
k	size of the test set S that is unlabeled
T_s, T_d	same-distribution / diff-distribution training dataset
n, m	size of T_s and T_d
w	weight vector for dataset
h_t	hypothesis from $X \rightarrow Y$
ϵ_t	error of h_t on same-distribution training dataset
p	probability of instances transferred from T to $\mathbb{R}_i(R_{\overline{v}}, \overline{a_{rb}})$

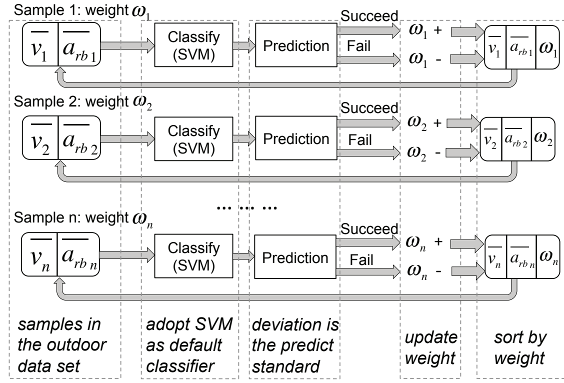


Fig. 4 The procedure of transfer learning in `iLoom`**.**

Algorithm 1 Algorithm of Transfer Boosting

Input:
T, S, $\mathbb{R}_i(R_{\overline{v}}, \overline{a_{rb}})$, $\mathbb{R}_o(R_{\overline{v}}, \overline{a_{rb}})$
Output:
The updated $\mathbb{R}_i(R_{\overline{v}}, \overline{a_{rb}})$ including the transferred instances
Set weight vector $w^1 \leftarrow (w_1^1, ..., w_{n+m}^1)$.
while N>0 **do**
  $N--$;
  Let $p^t \leftarrow w^t/(\sum_{i=1}^{n+m} w_i^t)$.
  Call SVM/SVMt;
  (T with distribution p^t over T) $\cup$ S.
  Get back to hypothesis: $h_t : X \rightarrow Y$.
  Estimate the error of h_t on T_s:
  $\epsilon_t \leftarrow \sum_{i=n+1}^{n+m} \frac{w_i^t \times |h_t(x_i) - mf(x_i)|}{\sum_{i=n+1}^{n+m} w_i^t}$
  Set $\beta_t \leftarrow \epsilon_t/(1-\epsilon_t)$, $(\epsilon_t < 0.5)$ and $\beta = 1/(1+\sqrt{2lnn/N})$.
  Update the new weight vector:
  $$w_i^{t+1} \leftarrow \begin{cases} w_i^t \beta_t^{|h_t(x_i)-mf(x_i)|}, 1 \le i \le n \\ w_i^t \beta_t^{|-h_t(x_i)-mf(x_i)|}, n+1 \le i \le n+m \end{cases}.$$
  sort instances in $\mathbb{R}_o(R_{\overline{v}}, \overline{a_{rb}})$ by the latest w_i^{t+1}
end while
transfer p% instances with higher weights in T to $\mathbb{R}_i(R_{\overline{v}}, \overline{a_{rb}})$

distribution training data. Hence, it is necessary to reduce its training weight w to decrease its effect. We multiply the weight by the factor $\beta^{|h_t(x_i)-mf(x_i)|}$, which is in the range of (0,1]. In the next round, the misclassified diff-distribution training instances will have less effect for the transfer learning procedure than the current round. By iteration, the diff-distribution training instances in $\mathbb{R}_o$ that are proximate to the same-distribution instances will have higher training weights, whereas the diff-distribution training instances that are dissimilar to the same-distribution ones will have lower weights. Thus, the instances having large training weights in $\mathbb{R}_o$ can help the learning algorithm to train better classifiers. The noises of acceleration values on the three orientations will be reduced effectively.

After executing the transfer boosting, we only transfer the $p\%$ instances with higher weights to assist the classification approach. The probability of transferred instances in $\mathbb{R}_o$ is determined by the experience. The theoretical analysis and proof of transfer boosting algorithm are in the literature [16].

Via transferring the same-distribution instances from $\mathbb{R}_o$ to $\mathbb{R}_i$, we obtain a new relation $\mathbb{R}_c(R_{\overline{v}}, \overline{a_{rb}})$ ($\mathbb{R}_c$ for short) in the combined dataset. Thus, a user can employ the constraint made by the newly generated $\overline{a_{rb}}$ to enhance dead reckoning localization.

H. Pedometer Improves Dead Reckoning

Most common smartphones can support and run a pedometer application. Samsung Galaxy Smartphones provide an off-the-shelf application named S Health to count the number of a person's walking steps. Some brands of wearable devices, such as Fitbit, Jawbone, etc, also contain electronic pedometers. The inaccuracy of current pedometer monitors has been shown to be around 9% [13].

In the procedure of transfer learning, the average speed ($\overline{v}$) is the bridge to connect the outdoor and the indoor information. In an indoor environment, the average speed not only can be computed by acceleration, but also can be obtained by leveraging the third-party pedometers. Based upon the two types of obtained average speeds, `iLoom` calculates two types of corresponding $\overline{a_{rb}}$. For each speed range, we update the Acceleration Range Box by averaging the values of the two $\overline{a_{rb}}$. Then, we employ the updated Acceleration Range Box to calibrate the dead reckoning approach.

Algorithm 2 illustrates how `iLoom` exploits pedometers to optimize the existing Acceleration Range Boxes. Li, et al. proposed that step frequency and step length has a linear relation [17], we conduct curve fitting for collected data and compute the factor values of a and b. Thus, if we obtain the step frequency of people by pedometers, we can estimate the step length of people. Also, once a user inputs his/her known step length, he/she could calculate his/her step frequency according to the linear relation. Based on these information, we can modify the $\overline{a_{rb}}$ via pedometers on the mobile devices by algorithm 2. The experimental performance of this approach will be displayed in the evaluation section.

I. Indoor GPS Exception

Anchor Points were applied in location service systems [18]. They are the positions in the environment with unique sensing signatures. Anchor Points can be used to reset the motion traces if a user reaches one of them. They are classified to two categories: 1) the points can be recognized by inertial sensors,

Algorithm 2 Pedometers Improve Acceleration Range Box

Input:
$\overline{v}_i$, L_i - average speed, length steps of the pedometer user i
n_p, n_A - number of pedometers, number of $\overline{a_{rb}}$
Output:
The updated $\overline{a_{rb}}$ for each sample

```
for i=0; i < n_p; i++ do
    L_i ← a×F_i + b (or F_i ← a×L_i + b)
    // step frequency F_i and step length L_i has a linear relation
    Initialize: v̄_i ← F_i×L_i, j ← n_A, cnt ← 0;
    while j > 0 do
        if |v̄_i-v̄_j| < ΔSR
        // if the average speeds are in the same range, merge the
        different a_rb. ΔSR is the threshold.
         then
            a_rb_i ← a_rb_i + a_rb_j, cnt ← cnt+1;
        end if
        // Calculate the average value of different a_rb
        a_rb_j ← a_rb_j / cnt , j ← j-1;
    end while
end for
```

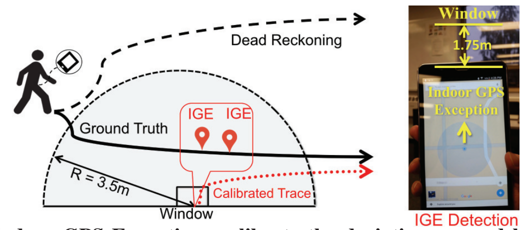


Fig. 5 Indoor GPS Exceptions calibrate the deviations caused by dead reckoning. The generated motion trace using IGE is closer to the ground truth.

such as stairs, elevators, etc; 2) the points could receive GPS on smartphones, as building entrances and windows.

In `iLoom`, we focus on the second type of Anchor Point. For some entrances in an indoor building, by obtaining the position information through GPS, they are often marked as the initial positions of motion traces.

We have discussed the indoor/outdoor detection in Section II.B. There exists an interesting phenomenon: although indoors, sometimes people receive GPS samples from the windows or other places near the outdoors. When we predict whether the environments are indoors or outdoors, these samples are seen as false information and should be disposed. These samples, named Indoor GPS Exception (IGE), provide an accuracy of better than 3.5 horizontal meters [14]. They also can be employed for calibrating some obvious deviation caused by dead reckoning: while a user is conducting dead reckoning for building the motion trace, when he/she is near the window and gets a IGE, if the estimated position by dead reckoning is out of the range of IGE, we can assume the estimated position has a serious deviation, thus, we will adopt the position of IGE to replace it.

Here we conducted an experiment: a user of `iLoom` walks and stops arbitrarily in a room for 10 minutes. He receives 12 indoor GPS samples from the window. The GPS has a range of errors within 3.5 meters. As illustrated in Fig. 5, two samples in the 12 IGE are helpful for dead reckoning. Therefore, IGE samples can calibrate the obvious deviation.

J. Reduce the Training Burden

So far, our analysis is based on a single user. Before a person uses `iLoom` to obtain his/her locations, a procedure of light-weight training is required. If we extend our approach to more users, the training task can be further reduced. In the multi-user model of `iLoom`, we provide an approximate solution for reducing the training load: People with the similar ages and heights often have the similar movement habits [19]. We categorize users into different groups by ages and heights. For each group of people, after data collection and transfer boosting we construct a special $\mathbb{R}_c$. The relation is stored in a hash map on the remote server. When the user logs in the `iLoom` system, after inputing his/her age and height, he/she will get a correlated $\mathbb{R}_c$ to assist the indoor localization.

III. Evaluation and Case Study

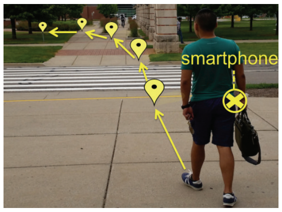
A. Experiment Setup

We build a prototype of `iLoom` on the Android platform (version 5.0) and evaluate its performance on two types of smartphones (Samsung Galaxy S7 and Google Nexus 5). The smartphones are equipped with standard sensors that include GPS, accelerometer, barometer, light and magnetic sensors. We adopt DynamoDB on Amazon Web Services (AWS) as the remote server to store data. The frequency of data uploading is 1 Hz. Initially, we focus on the single-user model. The user conducted the experiments on the campus of Michigan State University. A user of `iLoom` walks arbitrarily and stores sensing data in both the outdoor and the indoor environments. Fig. 6 depicts the scenarios and routes from which the user collects data. For the outdoor scenario, the user carried the smartphone and walked and stopped for 4 hours. The time period of each sample is 10 seconds. Since we expect the outdoor training data can profile the user body's walking behaviors, the smartphone was in the user's pocket to avoid the noise that includes making a phone call and swinging the hand with the smartphone. For the indoor scenario, the user walked 10 minutes with the smartphone. The smartphone was in the user's pocket or on the user's hands, which includes dead reckoning noise. The sampling frequency is 0.2 HZ. After collecting data indoor and outdoor, we built the $\mathbb{R}_o$ and $\mathbb{R}_i$ for people's motion behaviors. The Euclidean distance between the ground truth and estimated position is defined as the metric of localization error.

B. Acceleration Range Box Evaluation

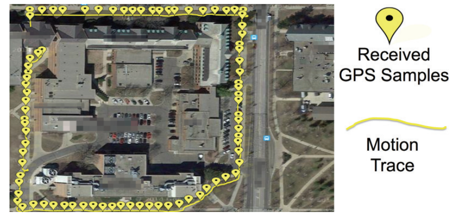
Fig. 7 (a)-(b) represent the distributions of average speed for outdoor and indoor collections. Although most samples are between the range from 1.2m/s to 1.6m/s, the two distributions have some differences. After applying the transfer learning approach on them, the combination data distribution varies as Fig. 7 (c).

We first validate the effectiveness of the Acceleration Range Box. When the user is walking in the indoor scenario, `iLoom` records the average error of distance within the growth of time. The user adopts the Average Acceleration Range Box



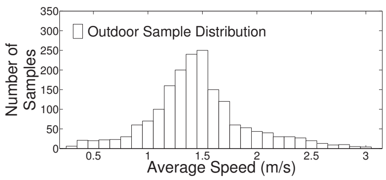
(a) Data collection in an outdoor environment.

(b) Data collection in an indoor environment.

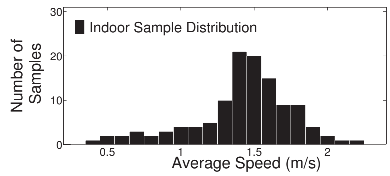


(c) A 200×200 area for data collection. Each yellow mark represents a sampling of GPS.

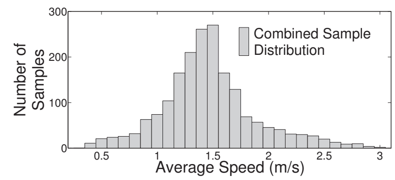
Fig. 6 Collect data in different scenarios while a user of smartphone is walking.



(a) Sample distribution in outdoor environments



(b) Sample distribution in indoor environments



(c) Combined distribution after transfer boosting

Fig. 7 The procedure of transfer learning. The bars in each figure represent the average speed range and the associated acceleration range box. After adding parts of samples from (a) to (b), the combined samples in (c) have more useful samples.

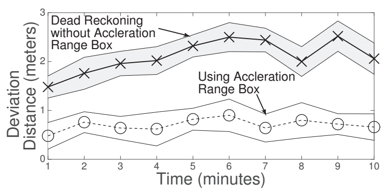


Fig. 8 Acceleration Range Box improves the accuracy of dead reckoning approach.

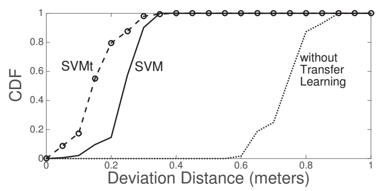


Fig. 9 Transfer Learning improves the accuracy of dead reckoning approach.

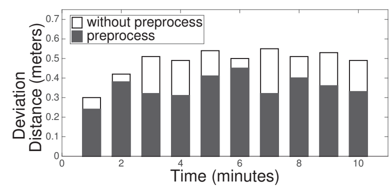


Fig. 10 The comparison result of preprocessing and not taking preprocessing.

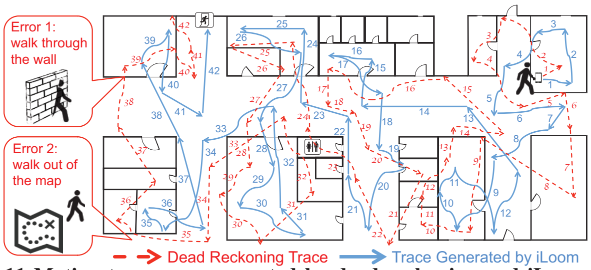


Fig. 11 Motion traces are generated by dead reckoning and iLoom.

TABLE IV THE RELATION BETWEEN EACH USER'S LOCALIZATION ERRORS AND THE DURATION OF OUTDOOR DATA COLLECTION.

Duration (Hours)	0.2	1	2	4	8
Deviation (Meters)	0.532	0.432	0.399	0.388	0.384

TABLE V SUCCESSFUL RATES OF TWO INDOOR/OUTDOOR DETECTION METHODS UNDER DIFFERENT SCENARIOS.

	Dining Hall	Residence Hall	Library
IODetector	87.24%	88.61%	91.43%
GAPO	94.32%	95.05%	95.15%

($\overline{a_{rb}}$) as a constraint while computing the motion trace by dead reckoning [5]. As Fig. 8 shows, the localization accuracy is greatly and consistently improved by approximately 60%. We repeat the comparison 8 times and the results remain the same. The shadow areas in Fig. 8 refers to the confidence intervals.

Based upon the results in Fig. 8, we measure the performance of transfer boosting. We use the transferred $\overline{a_{rb}}$ to replace original $\overline{a_{rb}}$ trained from the indoor environment. Fig. 9 provides the experimental results of the comparison: although all three groups can enhance dead reckoning, the two groups using the $\overline{a_{rb}}$ combined with transferred outdoor and indoor data outperform the group just using $\overline{a_{rb}}$ from indoor environments. In `iLoom`, we choose SVM and SVMt [15] as the classifiers. In Fig. 9, both of the two classification algorithms fit the transfer learning approach, and SVMt performs better than SVM. By repeating the experiments 10 times, the final error of indoor localization is less than 0.35 meter.

When we transfer the instances with higher weight in outdoor dataset T to $\mathbb{R}_i(\overline{v}, \overline{a_{rb}})$, the proportion of the transferred instances ($p\%$) is significant. If we do not transfer enough instances in T to $\mathbb{R}_i(\overline{v}, \overline{a_{rb}})$, `iLoom` cannot achieve the optimal localization accuracies. If `iLoom` transfers excessive instances to $\mathbb{R}_i(\overline{v}, \overline{a_{rb}})$, the instances that are not similar to the instances in $\mathbb{R}_i(\overline{v}, \overline{a_{rb}})$ may include noise. In our evaluation, the optimal $p\%$ value is 74.8% for SVMt and 73.5% for SVM.

Depending on the above experiment conditions, we concentrate on the relations between indoor localization errors and the duration of outdoor data collection. By measuring the average indoor deviations of `iLoom` users under different time lengths of outdoor data training, Table IV supports our claim 1) as the

(a) Indoor localization results of user1 walking in different indoor/outdoor scenarios. The indoor localization accuracies increase gradually.

(b) Indoor localization results of user2 walking in different indoor/outdoor scenarios. The indoor localization accuracies increase gradually.

Fig. 12 Evaluation results of iLoom over three days.

duration of outdoor data collection increases, a user's indoor localization accuracy improves gradually; 2) `iLoom` is able to enhance indoor positioning without long-term and extensive pre-training.

Fig. 11 illustrates that, in a real indoor scenario (160m $\times$ 40m), the user of `iLoom` walked on the path that was preset. The trace generated by dead reckoning includes errors such as walking through the walls and leaving the map of building. Via adopting transfer learning, the trace provided by `iLoom` rectifies the localization errors caused by dead reckoning.

C. Performance of GAPO

In this subsection, we analyze the approach of preprocessing (GAPO) in detail. The function of GAPO is to distinguish data samples' environments. To validate GAPO is efficacious, we provided a control group. One group is the experiment result adopting GAPO and the other group does not use it. As shown in Fig. 10, we can conclude the group without preprocessing the false data cannot achieve the improved performance. To further explore the performance of GAPO, we execute the environment detection for three different buildings by receiving data samples both indoors and outdoors. Table V provides the comparison of P_e values between GAPO and the other classical detection approach (IODetector). GAPO attains higher successful rate than IODetector. Although GAPO may cost more energy for smartphones due to the usage of GPS, the GPS is not working all the time for a user. The energy consumed is within a reasonable range.

D. Multi-User Model

`iLoom` supports two working models: single-user and multi-user. We have evaluated the single-user model in the above discussion. For multi-user model, the users' heights are highly related to the users' average speeds [19]. In this paper, we did such an experiment: we collected 15 volunteers' average speeds, accelerations and heights. The heights of these volunteers are approximately categorized to five levels: 1.65m, 1.70m, 1.75m, 1.80m, 1.85m. All the volunteers are 20-30 years old. For each user, we obtained the corresponding $\mathbb{R}_c$ for them. The person with higher height has a larger range of accelerations. The relation from height to $\mathbb{R}_c$ is stored in the `iLoom` system. Once a user inputs his/her height, `iLoom` will choose the approximate height for him/her and provide a related $\mathbb{R}_c$ for the user.

In practice, the multi-user model is not as accurate as the single user model. For example, a person with 1.69m will be assigned the 1.70m type's $\mathbb{R}_c$, but there still exists some differences. We compare the differences of the two models: for single-user model, we adopt the above experiment (the height of user is 1.73m); for multi-user model, we let the user with the height of 1.73m choose the type of 1.75m's information and did the control group measurement as what the user did in single-model. We choose 6 observation points to record the deviations of the two models. The differences between the single-model and multi-model are listed in Table VI. Even though the multi-user model has more errors than single-user model, the localization results of multi-model is still convincing.

TABLE VI LOCALIZATION DEVIATION IN DIFFERENT SITES.

Model / Site	Entrance	Exit	Hallway	Office	PC Lab
Single-user	0.424m	0.476m	0.392m	0.287m	0.398m
Multi-user	0.454m	0.503m	0.422m	0.314m	0.423m

E. Long-Term Observation of iLoom

We extended the procedure of outdoor data collection to 3 days. Users walked, stopped, and kept smartphones out of their pocket in their daily life. IFig. 12 indicates 1) the indoor localization accuracies increase with profiling more outdoor motion data and 2) the indoor positioning accuracies are within 0.4m even in challenging conditions where a user walked in different indoor/outdoor scenarios. We believe the transfer boosting approach reduces the influence of the samples that cannot represent user's normal walking styles.

IV. RELATED WORK

A. Traditional Indoor Localization

Traditional indoor localization methods can be categorized by two types: device-based and device-free. For device-based approaches, the user often carries a specific receiver to communicate with the sender. Cricket [2] estimates the distance of the corresponding beacons by using the differences in propagation speeds between RF and ultrasound. Other systems such as Bat [20] and SpotFi [21] are all based on certain infrastructures. Although these systems have accurate results, the costs of systems and inconvenience of the devices limit the further development. For device-free approaches, it often uses signal fingerprinting to locate people [3], [22]. In the training phase, RSSI signal strengths are collected at each location when a person moves around an indoor environment. When the system begins to localize a person on line, matching is conducted by using the maximum likelihood standard: the system will chose highest probability position by comparing with the known training data. Unfortunately, these approaches often need a long-term and complex training procedure.

B. Smartphone Based Approaches

Dead reckoning [5] is a common method to estimate user's current location by physical formulas. But the accelerations obtained from sensors often include some noise, for example, the direction obtained from accelerometer is different from the people's real direction. The accumulative errors grow sharply within the time increase. To address the problem, Unloc [6] employs a virtual landmark to assist dead reckoning. The landmark is the sensing signatures naturally existing in an indoor environment. Dead reckoning tracks locations between different landmarks. Other approaches use computer vision and sensing approaches [7], [8], [23], [24] to do indoor localization on smartphones. Although all of these above methods do not require other devices, they need complex signal processing and recognition in indoor environments.

C. Transfer Learning

Transfer Learning [9], [16] is learning in a new task through the transfer of knowledge from a related task that has already been studied. Transfer learning has been applied in many research areas, such as web document classification, emotion detection, and computer vision recognition. For indoor localization, Pan [25] uses regression modeling to locate people. It identifies several cases of knowledge, and transfers localization models over time, across space and clients. Nevertheless, WILP is a traditional infrastructure approach and requires lots of context-aware analysis. Compared to the related work, `iLoom` does not rely on any extra device except for a smartphone. The procedure of off-line training for a certain scenario is not necessary. Just turning on the GPS option on a smartphone, by transferring learning the accurate and sufficient GPS information from outdoors, the motion behavior model stored on the smartphone can help dead reckoning.

V. Conclusion

In this paper, we propose one key conjecture: could we transfer a user's worthwhile outdoor motion information to indoor movement data and enhance indoor localization? We present `iLoom`, an indoor localization mechanism that utilizes the users' outdoor walking features. `iLoom` selects the dead reckoning approach to locate people indoors and introduces an Acceleration Range Box to optimize the user's received accelerations. To build an accurate Acceleration Range Box, the sensed data from indoor and outdoor environments are processed: since certain people's moving behaviors are proximate in indoor and outdoor environments, we combine the data describing the outdoor motion by accurate GPS and the data of the indoor movements via transfer boosting. Experiments and simulations from 15 users and 3 real buildings demonstrate `iLoom` not only improves dead reckoning with unattended mode but also does not need extra infrastructure and data training for certain scenarios. Based upon the real environment studies, the accuracy of indoor localization reaches up to 0.28$\sim$0.51 meter.

Acknowledgment

This paper was supported in part by the National Science Foundation grant No. CNS–1320561.

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