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B-Loc: Scalable Floor Localization using Barometer on Smartphone

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***Abstract*—Traditional fingerprint based localization techniques mainly rely on infrastructure support such as GSM and Wi-Fi. They require war-driving which is both time-consuming and labor-intensive. With recent advances of smartphone sensors, sensor-assisted localization techniques are emerging. However, they often need user-specific training and more power intensive sensing, resulting in infeasible solutions for real deployment. In this paper, we present B-Loc, a novel floor localization system to identify the floor level in a multi-floor building on which a mobile user is located. It makes use of the barometer on smartphone only. B-Loc does not rely on any Wi-Fi infrastructure and requires neither war-driving nor prior knowledge of the buildings. Leveraging on crowdsourcing, B-Loc builds the barometer fingerprint map which contains the barometric pressure value for each floor level to locate users' floor levels. We conduct both simulation and field studies to demonstrate the accuracy, scalability, and robustness of B-Loc. Our field study in a 10-floor building shows that B-Loc achieves an accuracy of over 98%.**

Keywords*—Mobile Phone Localization, Floor Localization, Barometer, Crowdsourcing.

I. Introduction

With the increasing pervasiveness of mobile phones, we have experienced an explosive growth of location based applications (LBAs), in which the location of a mobile user has to be known. In a multi-floor building environment, knowing the floor level of a mobile user is particularly useful for a variety of LBAs. For example, in a fire emergency, locating the floor level of a user quickly and accurately is critical to life saving. In a shopping mall or an airport environment, a navigation service such as Google maps can prompt a mobile user with the floor map by knowing her/his current floor level. This is known as the *floor localization* problem, which we aim to determine the floor level in a multi-floor building on which a mobile user is located.

Indoor localization [6], [17], [18] has been well studied in the literature, and they can be used for floor localization. The fingerprint-based approach leveraging on Wi-Fi or GSM appears most. SkyLoc [15] appears the first for floor localization using GSM fingerprints, however, the accuracy is far from perfect (i.e., three floor levels). RADAR [5] uses Wi-Fi signal. The idea is to war-drive the entire building to create a radio map between a physical location and its Wi-Fi fingerprint measured from nearby access points and base stations. Users can then pinpoint their locations by comparing their measured signal strength in the map. However, the main drawback is that war-driving is both time-consuming and labor-intensive for large indoor areas. Some recent approaches such as LiFS [18] use crowdsourcing to reduce the war-driving cost to some extent, but it involves a complicated training process. In reality, many mobile users may not turn on Wi-Fi all the time for energy saving, limiting the effectiveness of crowdsourcing. In addition, in developing countries, many buildings have no or sparse Wi-Fi which is not dense enough for localization. Even in developed countries, study [3] shows Wi-Fi may not be fully available in many buildings. Therefore, a cheap and scalable solution which does not need any infrastructure support is desirable.

The advancement of embedded sensors in smartphones has motivated a sensor-assisted localization approach [6], [7]. The accelerometer and compass have been used to measure the walking distance and direction of a mobile user. The user's location can be easily obtained by comparing the user moving trace and the map. However, these sensors are highly noisy [11]. The computed trajectory will increasingly diverge from the actual one. Hence, careful calibration is needed, for example, through fixed beacons [6], or landmarks [17]. Crowdsourcing has been also used to reduce the war-driving effort [4], [17]. These works rely on detecting user activities using sensors such as accelerometer. However, to ensure reliable detection, they typically require user-specific training which is costly, and the high sampling frequency which may drain the battery power quickly. In addition, the detection may be often interrupted by users making or receiving phone calls.

The increasing availability of barometer embedded in smartphones (e.g., Galaxy Nexus and Nexus 4) has motivated us to go beyond the existing work by building a simple, sensor-based, battery efficient solution for floor localization. Muralidharan's most recent paper [13] studies on the properties of mobile-embedded barometers across a number of buildings. He concludes that it is difficult to use the barometer to determine the actual floor that a user is on. In this paper, we overcome the challenges and did it with the help of crowdsourcing. We propose a novel Barometer based floor Localization system (B-Loc). B-Loc does not rely on any Wi-Fi infrastructure; it requires neither war-driving nor any prior knowledge of the buildings. In addition, it is more energy efficient as compared to other sensor-assisted approaches [17], [18]. B-Loc leverages on barometer sensing and crowdsourcing to build barometer fingerprints which contain the barometric pressure value for each floor level, and locate users' floor levels by looking up the map.

An intuitive solution may work as follows. Let's assume that the barometric pressure (a.k.a. atmospheric pressure) at the ground floor of a building is p_0. Given the barometric

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pressure decreases by 0.12 hPa for going up every 1 meter in the vertical direction, we can easily calculate the altitude of a smartphone user by $h = (p_0 - p)/0.12$ where p is the barometer reading. If each floor has the same height of h_0, we then know the floor level is $\lceil h/h_0 \rceil$. Unfortunately, in reality, it does not work in this way. First, p_0 is usually not accessible and h_0 varies for different buildings. Second, the barometer reading p from smartphone is not accurate due to sensor drift. Such as a drift for the same floor level can vary from one to three levels, which is about 2hPa (16.7 meters). In addition, the most critical issue is that the barometric pressure at the same floor of a building keeps changing in a day due to different weather conditions and time [2], [13].

In another typical solution proposed by Wang in [16]. They track the user using barometer readings. First, they assume the user's initial floor level is f_0. When the user changes floor levels, the barometer reading change Δp can be detected, and the user's new floor level is computed as $f_0 + \Delta p/(0.12 * h_0)$. In reality, h_0 varies from building to building, and each floor may have different height, so the floor height of each floor of every building is needed, limiting the scalability of this approach. More important, the initial floor f_0 is difficult to know, because users may not always enter into a building from the ground floor and they may start using the localization service at any floor level. Furthermore, a miss or wrong detection of Δp will cause serious errors in the latter localization.

In B-Loc, we propose several novel solutions to address these issues. First, we design a scalable, transitive calibration algorithm to automatically calibrate different smartphone users' barometers. The calibration makes use of user encounters and crowdsourcing, and it is done in a transitive way with more users involved. Second, to solve the issue that the barometer reading at the same floor changes over time, we propose time-based projection to project the barometer readings collected from different floors at different time to a common timestamp. It is based on the observation that although the barometer reading at the same floor may change over time, the difference of the barometer readings between any two floors keeps constant. If we obtain the barometer reading of a floor at a timestamp, the readings of any other floor can be estimated by computing the difference. Third, leveraging on crowdsourcing, we cluster the barometer readings for each floor to generate a barometer fingerprint map which contains the barometer readings of every floor at any time.

In summary, we make the following contributions:

1) We propose a novel barometer based approach for floor localization. B-Loc makes use of barometer on smartphone only, and does not require any infrastructure and the prior knowledge of buildings.
2) We design several novel techniques to calibrate barometers for different smartphone users in a scalable way, project barometer readings to a common timestamp, and cluster crowdsourced barometer readings to generate real-time barometer fingerprints.
3) We conduct both extensive simulations and field studies to analyze the performance of B-Loc. We deploy B-Loc in a real situation to demonstrate its superiority over existing solutions.

The rest of this paper is organized as follows. Section II gives an overview, followed by the detailed design of B-Loc. Our evaluation is reported in Section III. Section IV discusses the related work, and finally, Section V concludes the paper.

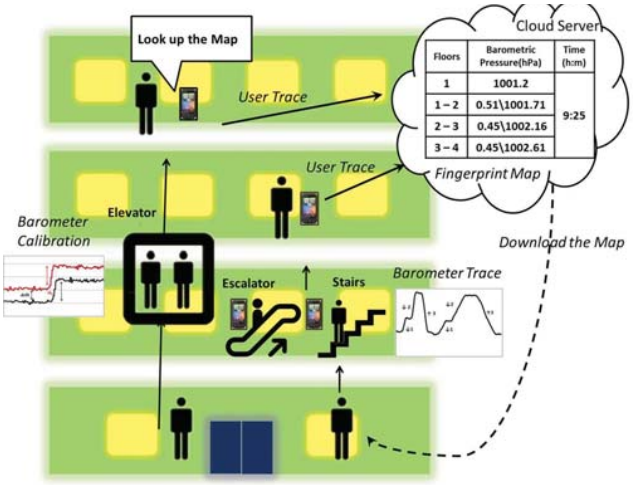

Fig. 1. Overview of B-Loc

II. System Design

We give an overview of B-Loc in this section, as shown in Fig. 1. The system operates in two phases. In the first phase, B-Loc builds the barometer fingerprint map automatically. When a user travels up and down in the building (e.g., taking elevators/escalators and climbing stairs), as illustrated by the solid line arrows in Fig. 1, the mobile client software running on the phone collects barometer readings in real-time. The activities of changing floors are detected and captured by our activity recognition algorithm. We design a robust technique to recognize such activities using barometer on smartphone. The recognized activities, together with real-time barometer readings, will be uploaded to the cloud server as a user trace. Different traces may contain the barometer readings of different floor levels, these readings have to be calibrated before we make use of them. We calibrate barometers on different smartphones based on user encounter, which can be detected when two users enter in an elevator. The calibration is done in a transitive way with more users involved, and eventually propagated to all possible users in a scalable way. After calibration, barometer readings in each trace will be projected to a timestamp t_0, making the readings from different users comparable. In the end, we cluster the barometer readings using a clustering algorithm based on CURE [9] to generate the barometer fingerprint map which contains the barometer readings of each floor at t_0. By projecting the readings in the map from time t_0 to the current time t_{now}, we obtain the real-time barometer fingerprints.

In the next phase, a mobile user first downloads the barometer fingerprint map of the building and the calibrate information from the cloud server, and then scan the barometer reading around. B-Loc calibrates the readings, and compares the reading with the barometer fingerprints. The nearest barometer reading in the map will conclude the right floor level for the user.

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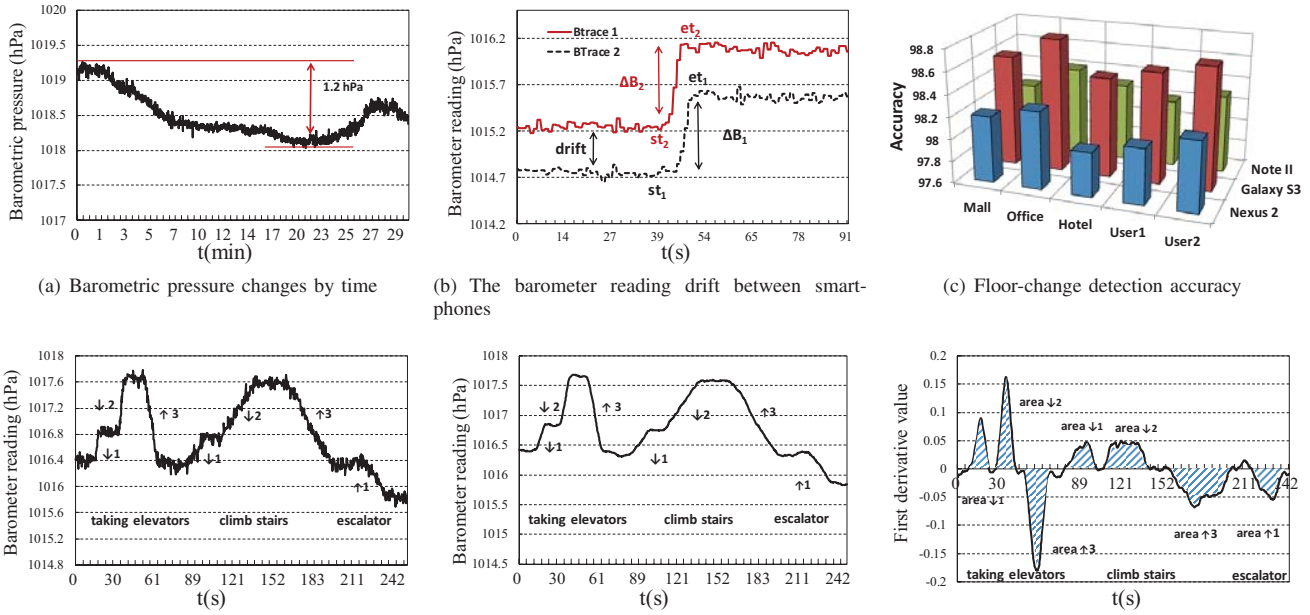

(a) Barometric pressure changes by time

(b) The barometer reading drift between smartphones

(c) Floor-change detection accuracy

(d) Raw barometer readings

(e) Smoothed barometer readings

(f) First derivative value of the readings

Fig. 2. The properties of smartphone's barometer and Floor-change activity detection by barometer readings

TABLE I. BAROMETER SENSOR PARAMETERS

Property	BMP180/182	LPS331AP
Absolute accuracy	-4.0 ... +2.0 hPa (-33...+17m)	- 3.2...+2.6hPa (-27...+22m)
Relative accuracy	± 0.12 hPa (± 1m)	± 0.2 hPa (± 1.7m)
Noise	0.06 hPa (0.5m)	0.06hPa (0.5m)
Used in smartphone	Galaxy Note 2/3, Xaiomi M2, Sony Ericsson Active, Nexus 3/4	Galaxy S3,S4

A. Barometer on Smartphone

We now move to study the barometer sensor on smartphones. Barometer sensor has become increasingly popular on smartphones today. Most commonly used barometer sensors are BMP180/182 and LPS331AP. Table I gives their technical specifications. From the table, we observe that while the absolute accuracy[1] is about ± 20 meters (which is low), the relative accuracy[2] is high. This implies that the barometer sensor has a high level of sensitivity, and it is good enough to detect the change of the barometric pressure when users go up or down in a building. Motivated by this observation, we use barometer to detect the activities when users change their floor levels.

We used a professional digital pressure gauge to measure the barometric pressure at a fix location in an office building over a period of half an hour. Figure 2(a) plots the result. From the figure we observe the barometric pressure measurements change with a variation of $1.2hPa$ which is equivalent to about 10 meters in altitude. This variation may result in a detection error ranging up to three floor levels. Hence, directly applying the barometric formula to calculate the floor level is not feasible. In another study, we sampled the barometer readings of two smartphones of the same type at the same indoor location. Figure 2(b) shows that a constant drift of sensor readings which may result in an error ranging up to three floor levels. It is clear that appropriate calibration needs to be done.

[1]The accuracy of a sensor reading compares to the real barometric pressure.

[2]The accuracy of the change of a sensor reading compares to the change of real barometric pressure.

B. Floor-change Activity Detection

We first present a novel technique to recognize the activities of changing floors using barometer. We represent a barometer sample P by $B = \{t, Baro\}$, where t is the time for sampling, and $Baro$ is the barometer reading at time t. The barometer samples arriving in time order form a barometer trace, which is represented by $BTrace = \{ID, B_1, B_2, ..\}$, where ID is the identity of the user. Users typically change their floor levels by taking elevators/escalators and walking up or down the stairs. The barometer sensor is inherently noisy. Figure 2(d) shows the raw barometer readings which apparently contain many spike noise. In B-Loc, we first filter these noise, and then smooth the values with a reasonable window size of 1000 ms (i.e., the value at time t is the average value from $t - 500$ to $t + 500$ ms), as shown in Fig. 2(e). In our previous study, we observe that barometer readings on smartphones don't change much in a short period of time unless users change their floor levels. Hence, the change of barometer readings can be used to recognize the floor-change activities. To do this, we extract the first derivative of the barometer readings and the resulting curve is shown in Fig. 2(f). We can see from the figure that the change of barometer readings is transformed to crest when going up and trough when going down. The crest and trough are sharp when taking elevators and smooth when taking escalators and stairs. The start and end time of the activity is the time of the left and right edge of each crest or trough.

To detect these activities, we calculate the area size of each crest or trough. If it meets certain conditions, a change-floor activity is detected. In detail, each area is defined as a

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continuous and closed region formed by the x axis and the curve. The region is located below or upon the x axis, which should meet the following conditions: 1) Lasted time between 3 and 120 seconds, 2) Area size bigger than 1.0. Figure 2(f) shows the areas of different ways of floor changing. In B-Loc, we do not impose any constraint on the ways users carry or use their smartphones. A smartphone can be held on hand, placed into a pocket or bag, or used to make/receive a phone call, etc. This certainly offers a great advantage over the accelerator based activity recognition [4]. We define an floor-change activity as $A = \{STime, ETime, SBaro, EBaro\}$, where $STime$ is the start time of an activity, $ETime$ is the stop time of an activity, $SBaro$ and $EBaro$ is the barometer reading at $STime$ and $ETime$, respectively. The user's moving trace can be then defined as $MTrace = \langle ID, A_1, A_2, \ldots \rangle$, where ID is the identity of the user. The detection is done in the smartphone and the resulting $MTrace$ will be uploaded to the cloud server. We conducted experiments with two users using three different smartphones under real-life situations in three different buildings. Figure 2(c) shows the accuracy of detecting floor changes. The results show the average accuracy using barometer is about 98.3%.

It is worth knowing that barometer readings at this stage are used for real-time activity detection on smartphone. We will show at a later stage how barometer readings are used for generating the barometer fingerprint map in the cloud server.

C. Transitive Calibration Algorithm

The objective of barometer calibration is not to calibrate each smartphone's barometer to the real barometric pressure, but use any smartphone's barometer as a reference point and find the drift between each of other user's barometer and the reference. Before we introduce our calibration algorithm, we first introduce the property of the drift between sensors. We define $drift_{AB}$ as the drift between barometer A and B, and $drift_{AB} = Baro_A - Baro_B$, where $Baro_A$ and $Baro_B$ is the reading from barometer A and B, respectively, under the same barometric pressure. The barometer drift holds the following properties: 1) $drift_{AB} = -drift_{BA}$, 2) $drift_{AB} + drift_{BC} = drift_{AC}$. These properties clearly demonstrate the transitive relationship. We define barometer calibration as follows: 1) For two smartphones, they are calibrated when the drift of the two barometers is known by the cloud server. 2) For more than two smartphones, they are calibrated when the drift between every two barometers is directly known by encounter in elevator or indirectly known by the transitive relationship.

1) Calibration for Two Barometers: Calibration is done by analyzing barometer traces. The idea is to calibrate users' barometers when they encounter each other. Elevator is very common in buildings now and users often encounter each other in elevators. We observe that if users encounter each other in an elevator, the time and value of their barometer change are the same. In another word, if we detect two floor-change activities from both users' barometer traces, these activities start and end at the same time, and the barometer readings change is the same, we conclude that the two users encounter in the same elevator, Fig. 2(b) is an example. This is formalized as follows.

1) I_1: $A_i.STime = A_j.STime$; *2)* I_2: $A_i.ETime = A_j.ETime$; *3)* I_3: $A_i.SBaro - A_i.EBaro = A_j.SBaro - A_j.EBaro$; and *4)* I_4: $A_i = A_j$; where A_i and A_j is the floor-change activity for user i and j, respectively. The rule is then formulated as follows.

$$R_1 : I_1 \wedge I_2 \wedge I_3 \rightarrow I_4.$$

If we have $A_i = A_j$, the drift is then calculated by the following formula.

$$drift_{ij} = \frac{\sum_{t=A_i.STime}^{A_i.ETime}(B_i(t) - B_j(t))}{n} \quad (1)$$

where $B_i(t)$ and $B_j(t)$ is the barometer reading of user i and j, respectively, at time t, n is the total sample size.

We analyze a case that when two users enter into different elevators at different floors and experience a floor-change activity with the same barometer change at the same time. The above rules will conclude they are in the same elevator. To handle this case, we first observe that when users encounter in an elevator, they often experience more than one floor-change activity together. For example, user i and j encounter each other at the ground floor and go up to the 8th and 10th floor, respectively. Before arriving at level 8, the elevator stops at levels 3 and 5. In this scenario, user i and j experience 3 floor-change activities (i.e., from 1 to 3, 3 to 5 and 5 to 8). Based on this observation, we detect consecutive floor-change activities between two users to minimize the probability of this fault case. We formalize it as follows.

1) I_5: $\exists A_1, A_2, .., A_k \in MTrace_i$; *2)* I_6: $\exists A_1, A_2, .., A_k \in MTrace_j$; *3)* I_7: $A_{m+1}.STime - A_m.ETime < 30$ holds in $MTrace_i$ and $MTrace_j$; *4)* I_8: $MTrace_i.A_m = MTrace_j.A_m$; *5)* I_9: user i and j are in the same elevator and the confidence is k. The rule is then formulated as follows.

$$R_2 : I_5 \wedge I_6 \wedge I_7 \wedge I_8 \rightarrow I_9.$$

where $MTrace_i$ and $MTrace_j$ is the trace of user i and j, respectively, and k is the confidence that user i and j is in the same elevator.

2) Calibration for All Barometers: In the previous section, we present barometer calibration for two smartphones. To calibrate all smartphones' barometers, while the same principle will be applied, the calibration propagates from phone to phone in a transitive way. We model this process using a graph shown in Fig. 3(a). In this graph, each barometer is represented by a node. If two barometers are calibrated by an encounter in elevator, we draw an edge between the two nodes, and the weight of the edge represents the confidence value of the calibration. Since there may be more than one calibration done between two users (e.g., two users may encounter each other multiple times), we choose the calibration with the highest confidence value. Since barometer calibration is transitive, in theory, any two barometers can be calibrated if this graph is connected. To select a root barometer, a trivial approach is to randomly choose a node as root and find a spanning tree from the graph as shown in Fig.3(b). Any node in the spanning tree can be calibrated following the path from the node to the root. For example, to get the drift of barometer j, we find a path between node f and j, $f - k - j$, and obtain the drift by $drift_{fj} = drift_{fk} + drift_{kj}$.

There are two factors affecting the accuracy of our calibration algorithm. The first one is the confidence values of

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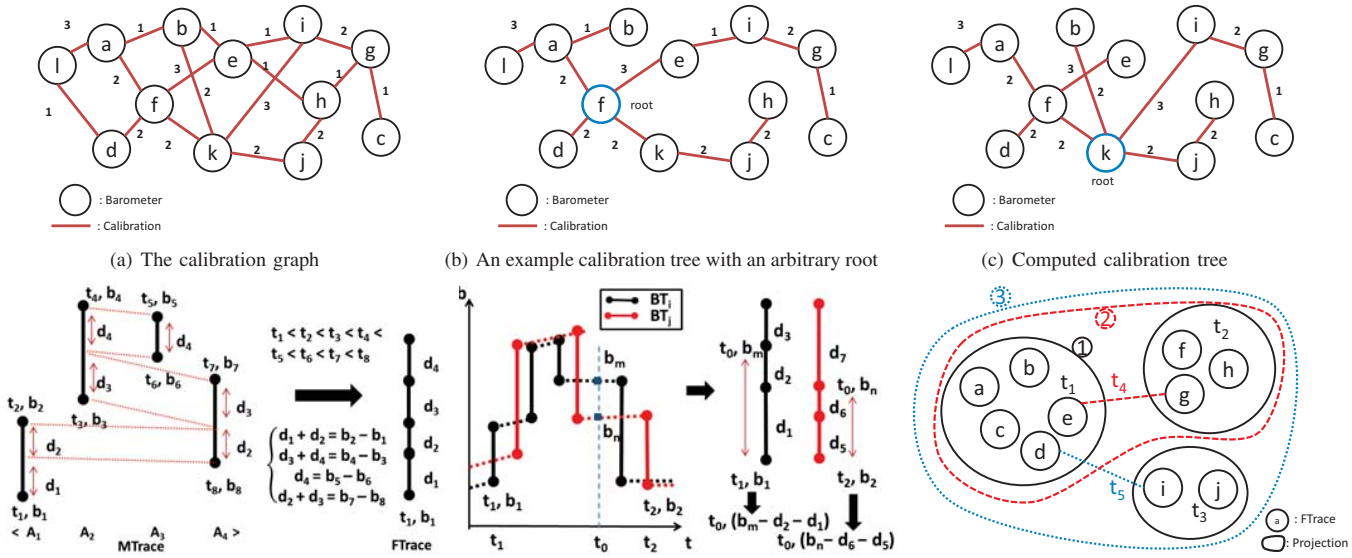

(a) The calibration graph (b) An example calibration tree with an arbitrary root (c) Computed calibration tree

(d) Extract $FTrace$ from $MTrace$ (e) Project two $FTrace$ to a timestamp t_0 (f) Project all $FTrace$ to a timestamp t_5

Fig. 3. Calibration and projection

the edges in the path. The other one is the length of the path. The confidence determines the probability of correct calibration. The length of the path determines the calibration accuracy because errors may be accumulated along the path. This turns out to be an optimization problem—find a spanning tree, choose a root to minimize the sum of nodes' depths, and maximize the weight of the edges in the path. It has been proven to be a NP-complete problem [8], hence, finding this spanning tree is not realistic. In B-Loc, we propose a heuristic solution based on the observations that the confidences of edges in the path are important and the calibration errors accumulate slowly. We first find a maximum spanning tree which maximizing the edge confidences in the tree, we then choose a node as the root which minimizes the average depth of all other nodes. As an example, we run the algorithm on the graph shown in Fig. 3(a) and the resulting graph is shown in Fig. 3(c). The complexity of the algorithm is $O(NlogN)$.

It is also important to notice that the calibration graph is not limited to only one building. When a user appears in different buildings, the calibration graphs are merged. So, ideally all users using B-Loc can be calibrated in a huge graph, the structure is similar to a social network. More important, the calibration process is once for all, once a user's barometer is calibrated, the calibration information is recorded and can be used when the user is in any other buildings.

D. Time Based Projection

After calibration, we update all the barometer readings in $MTrace$ by adding their drifts. The barometer readings in $MTrace$ are collected by different users at different time, and each trace may only contain a partial view of barometer fingerprints of the building. To have a complete view, we have to combine them. To do so, we first project $MTrace$ to a timestamp. We define a new data structure called $FTrace$. A $FTrace$ contains the barometer reading distance between some floors and a reference barometer reading point extracted from a $MTrace$. As shown in the left-hand side of Fig. 3(d), in the $MTrace$, there are floor-change activities of going up and down. Since the barometer reading distance between every two floor levels is constant, we can extract the barometer distance between floors from $MTrace$ as shown in the right-hand side of Fig. 3(d). For example, if we know b_4 and b_5 are the barometer reading at the same floor (we assume no miss detection), and $b_4 - b_3 = b_5 - b_6 + d_3$, we can then infer that b_6 is scanned on a higher floor than b_3 and d_3 is the barometer reading distance of the two floors. In this way, we extract all the barometer reading distance between floors from $MTrace$. The structure of $FTrace$ is defined as $\{\langle d_1, d_2, ..d_{k-1}\rangle, \langle t, b\rangle\}$, where d_i is the barometer distance of two floors (which floors still unknown at this stage). b is the barometer reading at timestamp t in the lowest floor of $FTrace$, and $\langle t, b\rangle$ is called the reference point of $FTrace$.

Next, we project two $FTrace$ to the same timestamp, making them comparable. Consider two $FTrace$ FT_i and FT_j from user i and j, respectively, b_i and b_j is not comparable because $t_i! = t_j$. As shown in Fig. 3(e), we first choose a reference time t_0 in the overlap time zone of the two $BTrace$ from user i and user j, and get sample $\langle t_0, b_m\rangle$ in BT_i and sample $\langle t_0, b_n\rangle$ in BT_j. For every sample, we get the barometer reading distance between the floor level of the sample and the floor level of the reference point, e.g., $\langle t_0, b_m\rangle$ is sampled at a higher floor level than t_1, b_1 and the distance is $d_2 + d_1$, we can then infer that, at time t_0, the barometer reading at the floor of the reference point is $b_m - d_2 - d_1$, and the barometer reading of the reference point of FT_j at t_0 is $b_n - d_6 - d_5$. Therefore, both the references of FT_i and FT_j are projected into the same timestamp t_0.

We present Algorithm 1 to project all $FTrace$ into the same timestamp, as illustrated in Fig. 3(f).

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Algorithm 1 Project all $FTrace$ into the same timestamp.

Input:
The set of all FTrace, C; An empty set, C';
Output:
The set of all projected FTrace, C';

1: Find a biggest subset C_1 of C, where the intersection of their time intervals is not empty. Remove C_1 from C, and put C_1 to set C';
2: Choose a timestamp t from the intersection time interval of C_1, project all $FTrace$ to timestamp t;
3: Repeat 1 and 2 until C is empty;
4: Choose two biggest set C'_1 and C'_2 from C', choose a $FTrace$ from C'_1 and C'_2 respectively, project them to timestamp t_1, and project all $FTrace$ in C'_1 and C'_2 to t_1, union set C'_1 and C'_2;
5: Repeat 4 until C' become an one element set;
6: **return** C'.

E. Barometer Reading Clustering

After calibration and projection, we are now able to compare barometer readings in $FTrace$, and relay them to each floor level in the building. As shown in Fig. 4, we first transform $FTrace$ from $\{\langle d_1, d_2, d_3, ..d_{k-1}\rangle, \langle t, b\rangle\}$ to barometer reading points $\{b, b + d_1, .., b + d_1 + .. + d_{k-1}\}$, where each element represents the barometer reading of a floor level. Each $FTrace$ contains some barometer readings at different floors of the building at the same timestamp t. Ideally, for a n-floor building, we should have n different barometer readings. However, errors may be introduced during calibration. To eliminate errors, we use clustering. We apply the hierarchical clustering algorithm named CURE [9]. Initially, each barometer reading is a cluster. The CURE algorithm merges two closest clusters in each step until a certain number of clusters are formed. CURE fits well in this situation because it is less sensitive to outliers. However, we cannot apply CURE directly because the resulting number of clusters f (should be the same to the floor numbers n) is unknown. In B-Loc, we adapt the CURE algorithm by designing the distance function and determining when to stop clustering. We use the Euclidean distance as distance function to calculate the distance between two clusters of samples. In each cluster, we choose m median samples to calculate the distance. The distance function between cluster C_i and C_j is computed as follows.

$$Distance(C_i, C_j) = \sqrt{\sum_{k=1}^{m}(B_{ik}.b - B_{jk}.b)^2} \qquad (2)$$

where $B_{ik}.b$ is the barometer value of the kth middle value sample of cluster C_i.

The clustering algorithm stops when the distance of the nearest two clusters is smaller than a threshold. We set the threshold to the two-third (0.3hPa) of the minimum barometer distance between floor levels in $FTrace$ (the one-third 0.15hPa is for tolerating the error of the barometer reading). After clustering, we obtain a set of clusters. For each cluster, we compute the average of their m median samples as the value of this cluster. We then order all the clusters by this value from high to low. The ordered sequence has an one-to-one mapping

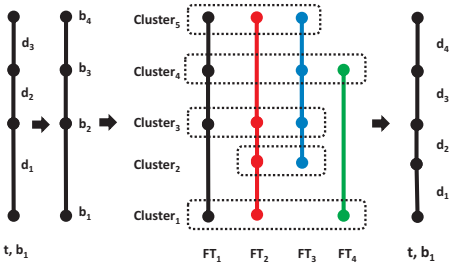

Fig. 4. Clustering barometer readings

to floor levels. The highest value maps to the ground floor, and the lowest value maps to the top floor level. In the end, we obtain the barometer reading of each floor at timestamp t, and also the barometer reading distance of every pair of floor levels. A barometer map with a reference point $\langle t, b\rangle$is generated, and it is defined as: $Map = \{\langle d_1, d_2, d_3, ..d_{n-1}\rangle, \langle t, b\rangle\}$, where d_i represents the barometer distance of floor i and $i + 1$, n represents the floor number, b represents the barometer reading at the ground floor at timestamp t. Using the barometer fingerprint map, we can know the barometer readings at each floor. For example, the barometer reading at floor level 3 is $(b + d_1 + d_2)$.

F. Real-time Barometer Fingerprint Map

After obtaining the barometer fingerprint map at timestamp t with the reference point $\langle t, b_1\rangle$, we now convert the reference point to the current time (i.e., t_{now}). In the first scenario, when the users are still in the building. Our idea is to find a $BTrace$ which contains readings at both time t and t_{now}. We first get the floor level f_1 of user at time t by comparing the barometer reading at time t with the barometer fingerprint map. We then detect if the floor-change activities occurred between time t and t_{now}, and obtain the floor change which is Δf. The current floor level of the user is $f_2 = f_1 + \Delta f$, we then obtain the barometer reading b_2 at time t_{now}, and the reference point is now $\langle t_{now}, b_2 - d_{f_2-1} - d_{f_2-2} - ... - d_1\rangle$. In this way, we convert the barometer fingerprint map from time t to t_{now}.

In the second scenario, all users leave the building and arrive the building in the next day, now we only need to update the reference point $\langle t, b\rangle$ to now (t_{now}). Since users are all calibrated, the approach is to get and cluster the barometer readings of the users at t_{now}. Only if there is at least one user in the ground floor, the cluster with the biggest barometer reading value must be the reading of the ground floor. Hence, the reference point gets updated.

G. Locating Users

Users can now download the barometer fingerprint map and the calibration information from the cloud server. For each barometer reading sampled from a smartphone, the reading will be adjusted based on the calibration information, and look up the map to find the floor level of the user.

The barometric pressure of the ground floor may change by time, and B-Loc is able to dynamically update the reference point of the map. The way we do is to append the barometric

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pressure change to the reference point ($\langle t, b\rangle$). For example, the barometric pressure changed Δb after 60 seconds, the reference point will be updated to $\langle t + 60, b + \Delta b\rangle$. In this way, the application does not need to download the map again if the user stay in the building. At the same time, the application will upload the reference point to the cloud server periodically, where the barometer fingerprint map is updated.

III. Evaluation

We now move to evaluate B-Loc using both simulation and field studies.

A. Simulation Methodology

We design a simulator to evaluate the efficiency and scalability of B-Loc. In the simulation, we aim to evaluate how well B-Loc performs calibration and how fast the barometer fingerprint map can be built. The simulator models the process of user taking the elevator up and down in a multi-floor building. It works as follows. The simulation process is divided into cycles of elevator going up or down (which occurs with an equal probability). For elevator going up, each cycle simulates the process that the elevator goes up from the ground floor, with people entering and leaving the elevator from or to any levels, until the elevator is empty. We model the process of people entering the elevator from the ground floor as the Poisson distribution. The expected number of the Poisson distribution is set to 1/4 of the maximum load of a typical elevator (i.e., four persons). People on the ground floor may go up to any floor with a probability of $1/(n-1)$, where n is the number of floors of the building. From any other floor f_i, some people may enter the elevator, and go to the rest $(n-i)$ floors with an equal probability $1/(n-i)$. Each cycle starts from the ground floor, we first compute the number of people entering the elevator and which floors they are going to, the elevator goes up from the ground floor, and stops when people exiting or entering, until there are no users in the elevator. For elevator going down, every time the elevator starts from the top floor, users in every floor may enter the elevator, and will go to the rest n' floors with an equal probability of $1/2(n'-1)$, except to the ground floor which is $1/2$. When people enter or exit the elevator from a floor, the number of people on that floor gets updated, and the trace of every user is recorded. Based on our observation from real-life situations, in our simulation model, we assume that when an elevator passing a floor, the probability of a user in that floor entering the elevator is p (1% in our setting).

Given a number of floors n and a number of users u, we simulate cycles of elevator going up and down until a certain number of user-elevator trips m is reached (a user-elevator trip is defined as the process of a user entering and leaving the elevator). At the end of each simulation cycle, we combine the ground truth from the floor-change activity detection to get the $MTrace$ of every user. We will evaluate how well the barometer sensor of the users can be calibrated. We then build the barometer fingerprint map using the calibrated $MTrace$, and show how fast it can be built.The parameters of the simulator are listed as follows.

1) *floor number*: the number of floors. *2*) *total trip number* : the number of user-elevator trips for all the users. *3*) *average trip*: the average number of user-elevator trips for each user.

The performance metrics used in the paper are summarized as follows. *1*) *average weight*: The average weight of all edges in the calibration tree. *2*) *average hop*: The average hop of all nodes to the root in the calibration tree. *3*) *percentage calibrated*: The percentage of users who have been calibrated.

B. Simulation Results

Figures 5(a) - 5(f) show the simulation results when the user number at each floor is 10 and the average number of users in elevator is 4. Figure 5(a) shows the *percentage calibrated* in three different buildings under different *total trip number*. It shows that all users can be calibrated after about 150/300/1000 trips in a 5/10/40-floor building. When the *total trip number* is changed to the *average trip* as shown in Fig. 5(b). We find that in the three buildings, all users can be calibrated when each user takes the elevator for about 2.5 times on average. Figure 5(f) shows the *percentage calibrated* in the 10-floor building with different *average trip*. The different colors in each column represent the calibrated groups, from the largest to the smallest. It shows that when *average trip* grows from 1 to 1.3, the size of the largest calibrated group grows fast and almost 95 percent of users are calibrated when the *average trip* is 1.5.

Figure 5(c) shows the number of floors found in the barometer fingerprint map with different *average trip*. It shows that B-Loc builds the map for the 5/10/40-floor buildings when the average trips of users are less than 1.5. Compare to the result in Figure 5(a) and Figure 5(f), it shows that B-Loc builds the map before all users are calibrated, and locates most of the users quickly (e.g., 95 percent of users when *average trip* is 1.5). Figures 5(d) and 5(e) show the *average weight* and *average hop* in the calibration tree, respectively. Figure 5(d) shows that the average calibrate weight is about 2/3/5 in the 5/10/40-floor building. In Fig. 5(e), the hops is about 3/4.5/8 in the three buildings when all users are calibrated.

C. Field Study

To evaluate B-Loc under the real-world situations, we implemented a prototype system and publish it on a website [1]. We encourage users to download and try B-Loc in our 10-floor computer science building. A total number of 67 users downloaded our application to their mobile phones (e.g., Samsung, Google Nexus, Sony Ericsson, etc). Out of 67 mobile phones, only 28 have both barometer sensors and a mobile network data connection (i.e., GPRS or 3G). We developed a mobile application named "Talking to Strangers (up/down stairs)" which is built on top of B-Loc. The application finds users from other floors of a building for message chatting. This is similar to other chat applications such as find strangers around, but we incorporate B-Loc into our application for floor localization.

When the application runs, it continuously collects barometer readings at a rate of 2 samples per second, and all the samples will be logged in a data file which will be uploaded to the cloud server every 2 hours. The floor-change activity detection is done in real-time and the $MTrace$ will also be uploaded to the cloud server. The client also performs time synchronization with the sever by computing the round-trip delay time and the offset. If the barometer fingerprint map is

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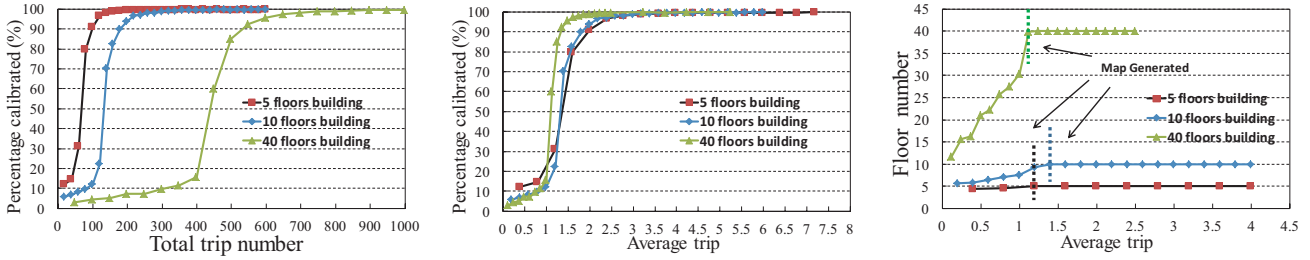
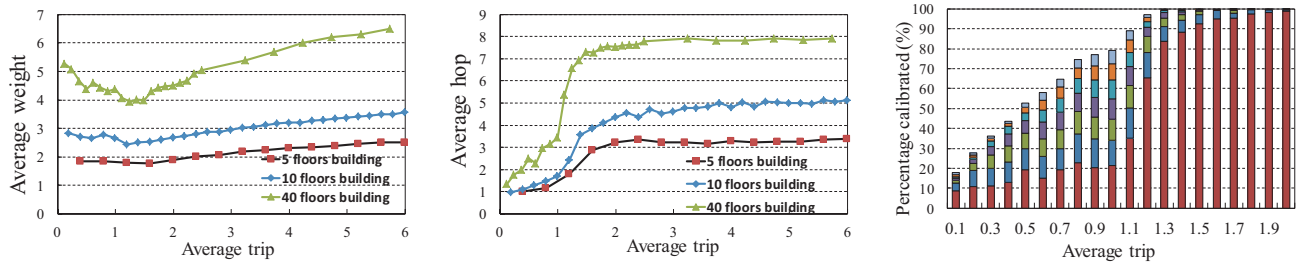


(a) The *percentage calibrated* with different *total trip number*

(b) The *percentage calibrated* with different *average trip*

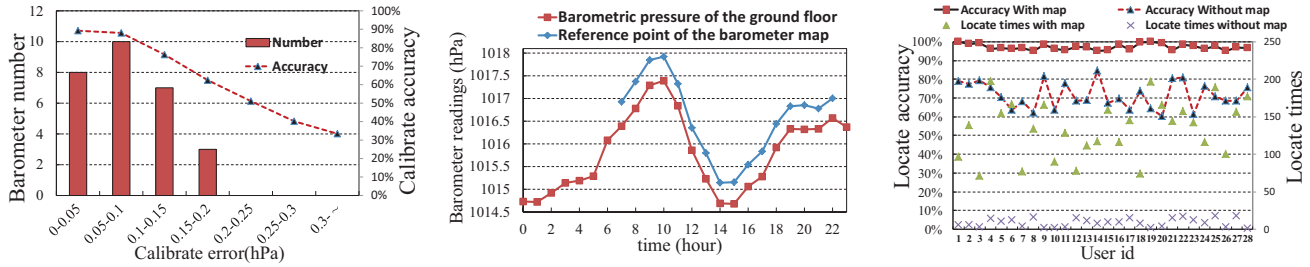
(c) Floor numbers detected with different *average trip*



(d) The *average weight*

(e) The *average hop*

(f) The size of the calibration groups



(g) The calibration error and accuracy

(h) The reference point of the fingerprint map

(i) Accuracy of B-Loc

Fig. 5. Simulation and Field study results

available in the cloud server, it will be downloaded to locate the user. The indoor/outdoor detection is done by scanning GPS signals. Before obtaining the map, the application uses a simple tracking approach to locate the user. It has a low accuracy because it assumes users enter the building from the ground level (i.e., the initial floor is 1) and the height of each level is fix (i.e., the barometer reading change of every floor is about 0.45), floor localization is then done by detecting user activities of changing floors. We did not give special instructions to the users during our study. Users ran the application as they like. To get the ground truth, we first manually get the drift to the real barometric pressure for all the 28 smartphones, then placed a barometer logger at each floor to get the ground truth by comparing their readings with the ground truth. The field study ran for eight days. In each mobile client, the history of floor location is logged. In the cloud server, all calibration results and the barometer fingerprint map generated are logged. We analyze the performance based on the logged data in both the client and the cloud server.

D. Field Study Results

The calibration error is shown in Fig. 5(g). The left vertical axis shows the number of barometers in different error regions. The right vertical axis shows the accuracy of the calibration in each region. The accuracy is defined as the ratio between error and the barometer reading distance of one floor. An accuracy of higher than 50% is the necessary condition to locate the user to the right floor. Figure 5(h) shows the real barometric pressure of the ground floor and the reference point of the map in 24 hours. The reference point is available from 8 AM to 11 PM when there are users in the building. The reference point updates the same way as the barometric pressure change, which shows that the map is accurate. The root of the calibration tree is not calibrated by real barometric pressure and caused a constant drift between the two curves.

We get the accuracy of floor localization by comparing the ground truth with the barometer loggers and the floor location history of B-Loc. It is shown on the left vertical axis of Fig. 5(i), where the accuracy is more than 98% for every user when they are calibrated and the barometer fingerprint map is generated. When the users are not calibrated or at the beginning of every day when the reference point of the map is not found, using the simple tracking approach the accuracy is about 70%, which appears in about 3% of all location cases as shown in the right vertical axis of Fig. 5(i).

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IV. Related Work

Many fingerprint based techniques for indoor localization have been proposed such as [5], [12], [14], [15]. They mainly rely on Wi-Fi signal strength, and they are capable of achieving a high accuracy in an indoor environment. However, like RADAR [5] has to war-drive the entire building in order to obtain the radio map. War-driving is very time-consuming and labor-intensive, and it may have to be done periodically since the Wi-Fi signature at the same location may be changed over time. Hence, this solution is not scalable. The fingerprint based technique has been used in floor localization. SkyLoc [15] uses GSM fingerprints to locate a user's floor level in a multi-floor building. They report an accuracy of 73% for locating a user to the right floor, and 95% within 2 floors. But the GSM signals vary significantly in indoor environments, and the training process in SkyLoc is time-consuming. It has a poor scalability since war-driving and training are required for every building. Some recent approaches such as LiFS [18] use crowdsourcing to reduce the war-driving cost to some extent, but it involves a complicated training process. In reality, many mobile users may not turn on Wi-Fi all the time for energy saving, limiting the effectiveness of crowdsourcing. Different from these systems, B-Loc makes use of the new barometer sensor appears in recent smartphones. It does not require war-driving to build the fingerprint database, B-Loc relies on crowdsourcing and intelligently build the barometer fingerprint map to locate users' floor level.

Sensor-assisted localization methods [6], [7], [10] have been proposed, making use of embedded sensors available on smartphones. These systems typically use accelerometer and electronic compass. However, careful calibration is needed from time to time due to the limitations of the sensing technology. For example, Escort [6] leverages on fixed beacons for calibration. Crowdsourcing has been also used to reduce the training effort [4], [17]. These works rely on detecting user activities using sensors such as accelerometer. However, to ensure reliable detection, they typically require user-specific training which is costly, and the high sampling frequency which may drain the battery power quickly. In addition, the detection may be often interrupted by users making phone calls. FTrack [10] using accelerometer for floor localization. The main problem of this approach is that they cannot handle some practical issues such as different user walking patterns and a variety of ways to carry/use mobile phones, which may affect the accuracy and limit the feasibility. Muralidharan's most recent paper [13] study on the properties of mobile-embedded barometers across a number of buildings. But failed to solve the problem of using the barometer to determine the floor of a user. In another solution proposed by Wang in [16] before the mobile-embedded barometers appear, using a barometer sensor to track user's floor level. As we discussed in the introduction, this approach need the detail information of the building and need to know a initial floor of every user, which is hard to get. Furthermore, a miss or wrong detection will cause serious errors in the latter localization. While B-Loc is not a tracking system and it does not rely on the previous location information. B-Loc detects user activities of changing floor by a novel barometer based technique, and it has no assumption of users walking pattern or the ways to carry/use mobile phones.

V. Conclusion and Future Work

This paper presents a novel, scalable floor localization scheme. Leveraging on mobile phone sensing and crowdsourcing, B-Loc requires neither any infrastructure nor any prior knowledge of the building. Different from similar approaches, B-Loc does not require war-driving, and rely on barometer only. B-Loc provides high accuracy of activity recognition and minimum energy consumption, making it more realistic for real-world deployment. Our simulation and prototype system demonstrate the performance, scalability, and robustness of B-Loc. For our future work, we will further improve B-Loc by enhancing the calibration algorithm. We also plan to offer a full version of B-Loc as a free service to the play store for public use, and test B-Loc under real-life situations.

VI. ACKNOWLEDGMENT

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