Indoor Floor-Level Detection by Collectively Decomposing Factors of Atmospheric Pressure

Ryosuke Ichikari, Luis Carlos Manrique Ruiz, Masakatsu Kourogi, Takeshi Kurata
Human Informatics Research Institute
AIST
Tsukuba, Ibaraki, Japan

Tomoaki Kitagawa, Sota Yoshii
System Technology Development Department
Mitsubishi Heavy Industries, Ltd.
Kobe, Hyogo, Japan

Abstract—This paper presents a novel method for detecting the floor level of a smartphone user in an indoor environment based on the atmospheric pressure measured with sensors in the user’s smartphone. Atmospheric pressure is one of the most informative factors when estimating altitude, because its relative variation has a strong correlation with changes in altitude. However, it is difficult to directly estimate the altitude based on an observation of the absolute pressure via smartphones, owing to individual differences in the sensors and changes in climate. In this paper, we propose a robust method for estimating the floor level by decomposing the observed pressure into three components. The first component is the change in altitude, and this component is the primary measure. The second is the global variation, such as changes in climate. The third concerns device-dependent variation. We utilize localization infrastructure, such as beacons or Wi-Fi access points, sparsely located in the environment, because such localization mechanisms can provide floor-level information. Exploiting this mechanism, time-series references to the pressure on each floor level can be generated collectively by aggregating readings from the pressure sensors of multiple users. Using these as a reference, each output of the pressure can be decomposed into device-specific offsets, environmental trends, and the altitude-dependent component. By extracting the altitude-dependent component, the floor level of the user can be estimated robustly without relying on fixed observations of atmospheric pressure.

Keywords—floor localization, pedestrian dead reckoning, atmospheric pressure, collective method, mobile phone sensing

I. INTRODUCTION

Estimating floor level of a smartphone user is an essential part of context awareness especially in urban areas where we have many tall buildings. Although a global positioning system (GPS) is a potential source of information regarding altitude, GPS rarely practical in indoor environments, because signals can easily be blocked and attenuated by structures, and because GPS-based altitude estimations are often imprecise. Moreover, indoor localization is relatively more difficult and expensive than outdoor localization, because GPS signals cannot reach indoor environments, and because infra-structures for detecting users must be prepared by the service provider. In previous work, we developed pedestrian dead reckoning (PDR), which can track the relative movements of the pedestrians [1]. By combining PDR with the other absolute positioning methods, it is possible to complement the relationship with respect to the area of coverage and cancelation of errors. Currently, our PDR method basically tracks the users in two-dimensional (2D) space. We have investigated the detection of human locomotion, such as walking, going up and down stairs, and taking an elevator. Such detections are made with gyroscope and accelerometer. Nevertheless, other methods are needed in order to accurately detect the altitude when users move between floors.

In order to estimate the altitude of the users, accelerometers and barometers can be used, because they are embedded in most current smartphones. Accelerometers have been used to detect floor changes [2]. Meanwhile, barometers offer potential to estimate the absolute altitude, because such estimations are theoretically possible by the reference to the atmospheric pressure. The Federal Communication Commission (FCC) discussed the importance of developing barometer-based solutions for estimating altitude in order to determine the location of the emergency (911) callers, and they asked US smartphone developer to mount a barometer on smartphones for this [3]. Currently, however, the absolute value of the atmospheric pressure observed with a smartphone is not sufficiently accurate for directly estimating the correct altitude. Such estimations are affected by the device-dependent characteristics and environmental conditions. Therefore, most of the previous works used relative changes in atmospheric pressure in order to detect floor changes. However, the relative tracking of altitude with barometers or accelerometers affected by accumulated drift errors in long-term measurements.

In this paper, we propose a novel method for detecting the floor level of users. The proposed method compares the observed absolute atmospheric pressure and the time sequential pressure reference. In order to realize this, we adopt sparsely located infrastructure that can provide the absolute positional information of users. This infrastructure includes various types of beacons or Wi-Fi access points, and these are used to extract the factor of the atmospheric pressure that is related with the altitude. By utilizing the infrastructure, the observed atmospheric pressure can be decomposed into factors such as an altitude factor, an environmental factor and error factors. The purpose of the decomposition is to create the time-sequential reference table of the atmospheric pressure for each floor. During the composition procedure, constant device-
The remainder of this paper is structured as follows. In the section II, we provide an overview of localization with atmospheric pressure, while clarifying the factors related to changes in atmospheric pressure. In the section III, we describe our proposed method for detecting floors by decomposing the factors of the atmospheric pressure with sparsely located infrastructure for localization. In the section IV, we describe our evaluation of the proposed method and discuss the results of an experiment conducted in factory environment wherein we compared our proposed method and conventional methods and supported our comparative evaluation with statistical analysis. In the section V, we summarize the features of this study.

II. LOCALIZATION WITH ATMOSPHERIC PRESSURE

A. Barometers Embedded in Smartphones

Current smartphones mount several kinds of sensors, such as a GPS, gyroscope, accelerometer, barometer, and magnetic sensor, and these are used to provide location services and intuitive user interfaces. Although GPS has the ability to detect altitude itself, barometers are nevertheless mounted on smartphone in order to correct the GPS based positioning, especially when estimating altitude.

Android smartphones have included barometers for some time, whereas Apple smartphones have started to include barometers in the iPhone 6 and iPhone 6 Plus. PressureNET [4] is a smartphone application for crowd-source barometric data reporting, which aims to collect global atmospheric pressure data for weather forecasting.

Popular micro-electromechanical system (MEMS) barometers embedded on smartphones are piezoresistive, and these utilize calibration methods, temperature compensations, and over-samplings in order to reduce noise and errors [5]. MEMS barometer nonetheless suffer from inevitable errors in terms of the absolute accuracy when they used directly for estimating altitude.

B. Behavioral Estimations with Atmospheric Pressure

Barometers can be also be used to estimate the behavior of users. Sankaran et al. proposed a method for using atmospheric pressure to determine whether a user is idle, walking, or traveling in a vehicle [5]. They found the value of the barometers in its low-power consumption and its characteristics of orientation-independent and position-independent.

We found that even changes in the user’s posture can be detected via the atmospheric pressure. Floor detection and the decomposition of factors related to atmospheric pressure can thus be used as the basis for further investigations in behavioral analysis.

C. Altitude Estimation with Barometers

1) Using the Absolute Pressure Level

Methods that rely on the absolute atmospheric pressure to detect the floor level are not affected by drift errors, and the altitude of the initial point is not required. However, the absolute accuracy of smartphone barometers is not sufficiently accurate for directly estimating altitude. Moreover, the absolute pressure varies depending on the weather.

2) Using Relative Change of the Pressure

The relative accuracy of a smartphone barometer is more precise than the absolute accuracy. Indeed, the relative change in atmospheric pressure has been proposed for detecting movement between floors [6]. We have previously implemented an altitude-estimation method based on the relative change in atmospheric pressure [7]. To convert the change in atmospheric pressure into an alteration in altitude, we employed a standard atmosphere model [8]. The relative accuracy of smartphone barometers is sufficiently accurate for detecting changes in atmospheric pressure caused by the user
going up and down stairs or escalators. A suitable equation for the relationship between the atmospheric pressure and changes in altitude can be defined as follows:

\[ h_{\text{diff}} = 8.0 \times p_{\text{diff}} \]  

(1)

where \( h_{\text{diff}} \) is the difference in altitude (m), and \( p_{\text{diff}} \) is the difference in atmospheric pressure (hPa).

This kind of relative tracking of the floor level requires data regarding the difference in altitude or atmospheric pressure between each floor, and it requires the floor level of the initial point. However, such data is not always available. Moreover, a failure to detect changes in floors cannot be corrected without external positioning methods.

3）Using Reference Data

In order to accommodate low-accuracy barometers, high-accuracy reference barometers have been integrated to correct errors [9]. The Japan Meteorological Agency (JMA) publishes hourly atmospheric pressure reports and other data measured at the JMA’s observatories. JMA’s data is unsuitable as a dynamic reference for the atmospheric pressure, however, because the pressure varies considerably within any given hour. However, it is possible to arrange a fixed barometer for each environment, if costs permit. In any case, reference data is required in order to adjust for the offset between a fixed barometer and smartphone barometer.

In addition to utilizing other physical barometers, the measured atmospheric pressure can be also utilized as reference data [10]. The difference in the atmospheric pressure between floors can be saved and utilized subsequently as a reference.

D. Main Factors in Atmospheric Pressure

In order to investigate the characteristics of barometers mounted on smartphones, we conducted a preliminary experiment to capture atmospheric pressure with four Android smartphones (Nexus5) carried together at the same time. The results from this experiment are shown in Fig.1. These results show that the absolute values of atmospheric pressure reported by each phone differ significantly. By contrast, the relative change was precisely synchronized. When the user traveled up and down stairs during the experiment, this behavior was clearly recognized in the graphs as peaks. We conducted another experiment with different models of smartphones: Samsung’s Galaxy S5, Galaxy’s Note Edge, and Motorola’s Nexus 6. Again, the results (see Fig. 2) show little relative difference, despite slight variations as a result of noise. Using the results of these preliminary experiments, we can summarize the characteristics of atmospheric pressure observed with smartphones as follows.

1) Altitude

The altitude is a dominant factor in atmospheric pressure. This factor changes according to the base altitude of the building (i.e., its elevation above sea-level) and the floor level of the user in the building. One of the aims of our method is to extract this factor, especially insofar as it changes with movements between floors.

The change in atmospheric pressure caused by the altitude, when users move up and down stairs, for instance, can be observed in Figs. 1 and 2. We confirmed experimentally that even small changes in altitude can be measured, even when a device is elevated a mere 50 cm. We assume that the factor by the altitude changes frequently according to the user’s movement. The limits to such changes can be used to determine the type of human locomotion.

By using Equation (1), altitudinal factors can be estimated and predicted, provided that the actual differences of the altitudes between the target floors are known. Moreover, it is possible to automatically estimate the reference atmospheric pressure between each floor by the measured data. We refer to this as the floor-dependent offset.

The change in atmospheric pressure caused by changes in posture, for example, can be regarded as one factor related to the altitude, because such changes do in fact result in slight changes in altitude. However, provided that the resolution of the altitude estimation is calibrated to the floor level, such changes can be regarded as errors.
2) **Environmental Condition**

Another strong factor that affects atmospheric pressure is the environment. This factor corresponds to time-series behavior of the atmospheric pressure at the same point and same altitude. Atmospheric pressure at the base altitude of a building is the product of both altitudinal and environmental factors. However, it is practical to regard both factors as integrated environmental factors, because they are closely related and difficult to decompose. Environmental factors are mainly affected by weather conditions such as cyclones (low atmospheric pressure) and anticyclones (high atmospheric pressure). Other environmental conditions are related to temperature. These conditions remain the same in a localized area, provided that there is no change in the altitude within that area. Most of the time, the smartphones were not touched on the same floor during the preliminary experiment. One effect observed during the experiment was due to environmental changes, resulting in a gradual increase in pressure, as seen in Fig.1. Also actual records of the atmospheric pressure from the JMA’s data changed similarly.

We assume that environmental factors remain constant within the same building, and that they change more slowly than the dynamic changes resulting from changes in altitude, such as when the user moves between floors or proceeds up or down stairs.

3) **Error**

a) **Absolute Error**

The remaining of factors can be classified as errors. The first error factor is absolute error which is relevant to the difference between the measured absolute value and actual atmospheric pressure. The difference can be separated into a device dependent static offset and residual error. In this paper, we regarded latter one as absolute error. The amount of the device dependent offset is not negligible. For example, the difference between the Device 1 and Device 4 in Fig 1 is more than 0.5hPa which is almost equivalent to the difference resulting from the user moving between two floors. We assume that the device dependent offset is constant in the short term. In this paper, we do not estimate the absolute error. Only device dependent offsets are estimated for correcting the difference of altitudes at the same altitude by different devices.

b) **Relative Error**

The other error factor is relative error which is the difference between relative change of the measured atmospheric pressure and the actual change of the atmospheric pressure. This error can be regarded as minor error, because the shape of lines in the graph was very similar in Fig.1 and 2. The noises, denoted by the thickness of the lines in the graph in Fig 1 and 2, can easily be filtered out. Most previous works adopt the relative change in atmospheric pressure based on the high relative accuracy of the atmospheric pressure. The specification sheets for the smartphone sensor show that the relative accuracy is much more precise than the absolute accuracy. According to these observations, we assume that the relative error can be disregarded. As described in Section II.D.1, above, the effect from changes in posture is a relative error, given that the target resolution in terms of altitude is used to determine the floor level.

### III. FLOOR-LEVEL DETECTION BY DECOMPOSITION

#### A. Overview of the Proposed Method

Based on the above observations, we propose a method for decomposing the factors related to atmospheric pressure. In order to address the variance of the device dependent offset, auxiliary localization methods are used to align the absolute level and to help the detection process by working as anchor references for altitudinal information. The proposed method is designed as a correction method for indoor altitude estimations localized with PDR. In this scenario, other localization methods should be used in order to render the entire system more practical. One requirement for these localization methods that are used alongside the proposed method is the ability to provide information for the area where the user is located. It is unnecessary to continuously and accurately track the users’ exact location. To this end, beacons or Wi-Fi access points are suitable. Beacons [11] and WiFi access points [12] have been proposed for indoor localization. In this paper, we use Bluetooth Low Energy (BLE) beacons for localization, because current smartphones have the ability to detect BLE signals and because beacons inexpensive. To detect BLE beacons, our proposed method merely checks whether the received signal strength indication (RSSI) values are above a certain threshold. PDR also can be integrated with BLE beacons based position correction. Therefore, the proposed method can be integrated with this method without requiring any additional devices. The proposed method can be developed independently as a floor-localization method.

Fig. 3 is a conceptual image of the proposed method combining beacons and smartphone barometers for indoor floor localization. This method is designed to use the same smartphone with PDR at the same time for gathering the required data. When the users change floor as shown in the left of Fig.3, the observed atmospheric pressure are changed as shown in the right of Fig.3. The main idea of the proposed method is to utilize beacons as the reliable positional clues for estimating the reference of the atmospheric pressure of each floor as shown as “Estimated ref *F” in the Fig.3 while estimating the relevant offsets. When an user’s smartphone (hereafter referred to simply as the “device”) n credibly detects beacon b on the floor f at time t, observed atmospheric pressure $P_{b,n}$ can be registered into the reference table as the reference atmospheric pressure on floor f at time t. By comparing the observed pressure with the reference table constructed in advance, floor level $f_{t,n}$ which is the floor-level of device n at time t can be detected as follows.

$$f_{t,n} = \arg \min_f \text{Diff}(P_{t,n} + O_{\text{dev},n}, \text{Ref}(f,t))$$

where Diff(a,b) is a function for calculating the absolute value of the difference between a and b, $O_{\text{dev},n}$ is the device-dependent offset for device n, and Ref(f,t) is a function for acquiring the reference pressure on floor f at time t from the reference table. Decomposition is then carried out in order to register the reference values for each floor in the reference table by considering all of the offsets. Note that time t is discretized with time window in order to generate the reference table.
B. Assumed Conditions and Targets for the Proposed Method.

In order to clarify the target of the proposed method, the section addresses problems and assumptions related to the proposed method.

First, the target devices for this method comprise mobile devices such as smartphones that have a barometer and the capability of detecting BLE/RFID beacons or Wi-Fi access points. No additional barometer is needed in the environment.

The various x-y-z global coordinates for the infrastructure must be provided in advance. For example, the x-y-z coordinates for the beacons are required. Other information, such as the altitude at the base of the building and the difference in altitude between floors is not mandatory. Moreover, the devices do not require calibration. This information can be estimated automatically by decomposing factors related to atmospheric pressure.

Given that the proposed method can be applied to real-time navigation inside a building, the method must be capable of estimating floors in real-time. In the case of offline processing of the method, the accuracy of these estimations will increase, owing to the fact that all of the data can be referred to.

In order to reduce drift errors, our method utilizes the absolute value of atmospheric pressure by creating a reference table for the time-series atmospheric pressure on each floor. The atmospheric pressure does not need to be observed frequently on each floor, because the proposed method can separately estimate the environmental trends and offsets between floors.

The area of coverage for each reference table is the area wherein environmental trends can be regarded as the same. In this paper, the coverage area is assumed to extend to the boundaries of a single building. The expected result of the estimation of the environmental factor by our method is more frequent and more locally adapted than the reference by JMA.

C. Collective Method for Creating Time-Series Reference Table of the Atmospheric Pressure

As described in the previous section, the proposed method can be applied to both single and multiple users. These two cases differ with regard to the quantity of learning data needed. By adopting the device-dependent offset to cancel the difference in absolute values between devices, the same reference table can be shared among multiple users. Therefore, the estimated environmental trend and the floor-dependent offsets can be shared with the users. With input data from multiple users, a more accurate reference table for atmospheric pressure can be generated. This characteristic is the one of the most important contributions of this paper. In the next section, we introduce a procedure for estimating the offsets and creating the reference.

D. Estimating Device-dependent Offset

The device-dependent offset \(O_{\text{dev},n}\) is assumed to be constant. To estimate the device-dependent offset \(O_{\text{dev},n}\), the same beacon must be credibly detected by multiple devices in the same time window. One of the devices is regarded as a reference device. The difference between the atmospheric pressure observed by device \(n\) and the reference device can be measured multiple times as time advances. These differences are used to estimate \(O_{\text{dev},n}\). Ideally, estimations of \(O_{\text{dev},n}\) should be sophisticated and robust. Indeed, we obtained promising results with a simple median filter. With a single user, the reference device is the user’s device, and \(O_{\text{dev},n}\) is set to 0.

If different beacons are detected in the same time window, the equivalent pressure level on the same floor can be calculated by adding or subtracting the floor-dependent offsets, (discussed in the next section). If the reference device is not always in the building, another user’s device can be used as the reference device, or statistically estimated trends in the atmospheric pressure can be assessed with data from multiple users. Although a fixed barometer in the building is not mandatory for the proposed method, if one is available, it also can be used as the reference device when estimating the reference atmospheric pressure.

E. Estimating the Floor-dependent Offset

The atmospheric pressure offset between floors is assumed to remain constant. Prior knowledge regarding the actual height between floors is not essential for the proposed method. The offset between the \(f^\text{th}\) floor and the ground floor \(O_{\text{floor},f}\) can be estimated by collecting observed data when the beacons on different floors are detected in the same time window by deferent users. \(O_{\text{floor},f}\) can be calculated in the same manner as the device-dependent offset. The device-dependent offsets are referred to during this process. Therefore, they must be estimated beforehand. If there are few users, or only a single user, it is difficult to collect this data simultaneously. In such cases, the atmospheric pressure on the \(f^\text{th}\) floor at that time can be interpolated with same device’s data at the different times. Alternatively, these offsets can be set manually.

F. Estimating Environmental Trend and Registering into the Reference Table

We assumed that the environmental trend is varying slowly. Therefore, it can be estimated as time series pressures of the reference floor in each time window. When atmospheric pressure \(P_t\) is measured with device \(n\) that has also detected beacon \(n\) on floor \(f\), then it is converted to the atmospheric pressure \(P_{\text{ref}}\) which corresponds to the equivalent atmospheric pressure of the reference floor as follows.

\[
P_{\text{ref}} = P_{t,n} + O_{\text{dev},n} + O_{\text{floor},f}
\]

\[
P_{\text{ref}} = \sum W_{t} P_{t,f}
\]

\(P_{\text{ref}}\) is obtained after each detected beacon at time \(t\) on floor \(f\). The average pressure (i.e., the average of \(P_{t,\text{ref}}\)) is used as the final \(P_{\text{ref}}\). Moreover, \(P_{\text{ref},f}\) can be estimated separately for each floor. Finally, the weighted sum of \(P_{\text{ref},f}\) from all floors \(P_{\text{ref}}\) is regarded as the environmental trend for time \(t\) and is registered into the table \(\text{Ref}(f)\). The weight for each floor \(W_t\) is assigned a with certainty factor for \(P_{\text{ref},f}\). We used the number of detected beacons on the floor within a certain time window to determine this certainty. An interpolation technique for \(P_{\text{ref},f}\) might be required when content is missing from the table, owing to a
lack of detected beacons or a low number of users. In the case of online processing, interpolation cannot be used to estimate $P_{ref}^t$. Rather, extrapolation can be used. Whether $P_{ref}^t$ is estimated by interpolation or extrapolation, the weight $w_f$ for the floor is set as a smaller value.

G. Absolute Floor-level Estimation with the Pressure Reference Table

According to Equation (2), the floor level of the user can be estimated via pressures measured by the devices. Once the table is created, newcomers can begin obtain monitoring their altitude, and they can contribute to the joining the creation table after estimating the device-dependent offset.

Even though the reference table is generated discretely, the user can obtain floor-detection results at each time-frame in the atmospheric pressure data.

IV. EVALUATIONS

A. Evaluation in a Factory Environment

In order to evaluate the proposed method, we conducted experiments in an actual factory. In the target environment, there were four floors, and height of each floor from the ground was approximately 0m, 1.5m, 3m, and 5m, respectively. The sizes of the floors from 1st floor to 4th floor are roughly 80m×45m, 15m×3m, 20m×3m and 5m×15m respectively. We asked two employees to walk around imitating the normal behavior of workers in the area for approximately 25 min. As a result, the distance traversed totaled approximately 1150m each. We used two Nexus5 smartphones to record the data, and we asked the employees to carry them in their chest pocket. The simplified appearance of the target area is shown in Fig. 4. The total size of the area was approximately 80m × 45m × 5m.

![Fig. 4. Simplified appearance of the target area](image)

The proposed method was evaluated by comparing its results with those from a relative-pressure-based method. We also compared the proposed method with different configurations for creating the reference tables. We tested its performance with both single and multiple users. To present our evaluation, we visualized the results, the estimated references, and the input pressures. We also conducted a numerical evaluation by comparing the results with the ground truth.

- Evaluating the Method using as a Correction Method for 2.5 dimensional Position Tracking

In order to evaluate the proposed method in more practical situations, we evaluated it by using it as a correction method for PDR based employee tracking in the target area. We integrated the method with other correction methods for PDR by using our sensor data fusion (SDF) framework. For numerical evaluation, we evaluated each combination of correction methods by calculating the three dimensional positional errors compared with the ground truth.

Furthermore, we conducted a statistical analysis to confirm the significance of the proposed method. First, we extracted information related to BLE, because this positioning method exerts considerable influence on the error reduction. Thus, we analyzed the interaction between positioning methods with our proposed methods.

Finally, we calculated the interaction between all the above-mentioned positioning methods by generalized linear models (GLMs). We calculated the P-value for all the methods in each combination as well as the AIC correspondent value.

A GLM can be described as a log-linear model [13] in the following manner:

$$
\mu = E[y \mid x_1, \ldots, x_r] = e^{\beta_0 + \beta_1 x_1 + \cdots + \beta_r x_r}
$$

(5)

$$
\log(E(Y_i)) = \text{const} + x_i^T \beta
$$

(6)

where $Y_i$ is a response that depends on a different regressor variables such as: $x_1, \ldots, x_r$.

In order to estimate the parameters for the previous model, maximum likelihood estimation must be calculated as follows:

$$
L(\beta, \sigma) = \prod_i e^{\frac{-\mu}{\sigma}} \frac{\mu^{y_i}}{y_i!}
$$

(7)

where $\mu$ is defined by Equation (5). In order to calculate these models, we used R software version 3.2.0 [14].

B. Evaluation of the Estimation of Floor Levels

1) Detailed Procedure of the Evaluation

The results from the proposed method were compared with those from a conventional method based on the relative change in atmospheric pressure. The latter method detects changes in floors when the difference between the maximum and minimum pressure is more than certain threshold within a set amount of time. The threshold and time window were set properly (threshold: 0.18 hPa, time window: 10 seconds).

To evaluate the collectively generated table, we compared results between those with the table created by using two employees’ data and the one with the table created by only using an input data. In order to verify the reference table works...
for both single and multiple users, the results from the estimating floors were visualized for both users with the reference, the ground truth is recorded for only one user through. For a numerical evaluation, we compared each method with the ground truth for a single user’s input. We recorded the percentage of correct floor detections for each record in the ground truth.

2) Results
The visualized results for the proposed method with data from multiple users is shown in Figs. 5-7. Figs. 5, 8, and 10, show the reference table and input atmospheric pressure. Ref *m represents the reference atmospheric pressure on each floor, which is calculated using time-series environmental trends and constant floor-dependent offsets.

In Fig 6, 7, 9, 11 show the results of floor detection by each method. The ground truth of the floor detection is also shown in the same manner in Fig. 13. In these graphs, the results of floor-detection were visualized as the altitudes of the floors from the 1st floor.

The atmospheric pressure observed by User 1’s device was corrected with the automatically derived device-dependent offset using the reference table shared with User 2 (see Fig. 5). As the result, the reference pressure for each level was correctly fitted to the data from both users, despite inevitable environmental change. Fig 8 and Fig 9 show the result of the creation of the reference table and the result by only learning with user 1 data. By comparing the graphs between Fig 5, Fig 8 and Fig 13, Fig 5 looks more similar with Fig 13 than Fig 8. The effect of the collective method can be confirmed by this comparison. Fig 10 and Fig 11 show the result of the creation of the reference table and the result by only learning with user 2 data.

The proposed method successfully generated the reference table and detected floor changes with the reference table only from a single user. The floor-dependent offset for the floors that were 3.0 m high and 5.0 m high, using the table based on User 1’s data, appeared slightly smaller in Fig. 8. By contrast, it appears slightly bigger in Fig 10. Compared with the results from a single user’s data, the results with a reference table generated from multiple users’ data were more accurate, as shown in Fig 5.
Fig. 12 shows the results from floor detection with the conventional relative-pressure-based method. The conventional method could not accurately track floor changes. It was especially difficult to estimate the exact change in height.

The comparisons of the graphs with the ground truth show that the proposed method outperformed the conventional method. The results from the conventional method were poor, because whenever the method failed to track a floor change, it could not subsequently recover. The method proposed by Muralidharan et al. [6] suffers from a similar drawback, because it is also based on the relative change in pressure. The proposed method records the difference in pressure between floors, as do previous methods [6][9][10]. However, by virtue of the reference data, the results from the proposed method are more accurate. Compared with the ground truth shown in Fig. 13, the results from the proposed method do contain some temporal errors. However, these errors were immediately corrected by the reference table. Therefore, the overall results were not affected by drift error. To further improve the performance, these temporal errors must be filtered out.

The results from the numerical evaluation also demonstrate that the proposed method outperforms the conventional method in the scenario considered for the experimentation. The proposed method works well by learning from the data of multiple users. In terms of accuracy of the detected floor, the proposed method correctly detected more than 90% of the ground-truth data. Therefore, the proposed method is sufficiently accurate for practical use; the effectiveness of the collective method has thus been demonstrated by these results.

C. Evaluation of the Proposed Method’s Ability to Correct the PDR Method for 2.5 Dimensional Positional Tracking

1) Detailed Procedure of Evaluation

In addition to an evaluation of the estimated altitude, we conducted a 2.5-dimensional evaluation by integrating the proposed method with PDR based on our SDF framework. This evaluation aimed to verify the feasibility of the method for correcting the results of PDR. The method is used exclusively to correct estimations of the altitude. It is not practical simply to change the altitude, because there is no guarantee that the floor exists on the corresponding floor. We selected the other method. When the proposed method detects a floor change, it searches for the most appropriate stairs, according to the estimated current position and the estimated floor level. By identifying the stairs, rather than merely the altitude, the three-dimensional position can be corrected. The difference between the proposed method and the conventional method is that the proposed method recognizes both the destination level and the departure level during a floor change, whereas the conventional method exclusively recognizes the relative change in floors. In order to verify the effectiveness of the atmospheric-pressure-based correction method, we compared the methods by changing the combination of correction methods, as shown in Fig. 15. In order to calculate the errors, we used the same ground-truth data that was used in Section IV.B, above. The errors were calculated as the three-dimensional Euclidean distance between the reference frames and the nearest-neighbor frames of the input trajectories.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Percentage of the check points detected floor level correctly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Method (learning 2 users’ data)</td>
<td>91.8367</td>
</tr>
<tr>
<td>Proposed Methods (learning 1 user’s data)</td>
<td>90.4762</td>
</tr>
<tr>
<td>Relative Tracking Method</td>
<td>35.7143</td>
</tr>
</tbody>
</table>

2) Configuration of PDR Based Relative Positional Tracking with Correction Methods

The core technology used to track users is PDR, which is a relative tracking method with sensors including gyroscopes, accelerometers, and magnetic-field sensors. Currently, a barometer is not used for PDR. Our PDR method tracks only two-dimensional movements on the same floor, and the floor level must be detected or defined with other methods. SDF calculates the user’s position and orientation by combining the PDR’s relative tracking method with other absolute position/orientation-detection methods.

The following correction methods were used to evaluate PDR combined with floor detection via atmospheric pressure.

- Orientation correction using the earth’s magnetic field

Tracking orientation with PDR suffers from errors in drift, owing to the fact that it relies on relative tracking. The earth’s magnetic field (EMF) can be used to correct the orientation, because the EMF indicates north. In this experiment, EMF-based correction was used in all cases.

- BLE beacons for absolute position correction

Furthermore, we corrected the absolute position with BLE beacons. Corrections are sent to the SDF if the RSSI of a BLE beacon remains stronger than a certain threshold for a set period of time. We arranged 30 beacons in the area. Apart from a barometer, only BLEs can correct altitude, among the available methods.

- Map matching

After all of the correction methods are integrated to generate the final trajectory, map-based constraints can be applied. For our purposes, we define the following elements of a map.

- Floors: floors define the total possible area within which a user can move.
Walls: walls are denoted by lines, and represent a spatial limitation through which users cannot move.

3) Results

By integrating the correction method with PDR, we obtained the trajectories shown in Fig. 14. Fig. 15 provides a comparison of the errors in 3D among various combinations of methods. “AtmosMulti2” here denotes the proposed method using a table generated by multiple users, and “AtmosMulti1” denotes the proposed method using data from only a single user. “AtmosSingle” is the conventional relative-position-based method. The combination that resulted in the fewest errors was PDR combined with BLE and AtmosMulti2. The best results with respect to the correct-answer rate for floor detections were attributed to the same combination (i.e., PDR + AtmosMulti2). Because of the constraint related to stairs, AtmosSingle also achieved better results than the results shown in Table 1. These results indicate that the performance of any method depends to a considerable extent on the correction method and constraints. Significant improvements were made in cases with major errors, such as PDR (only) and PDR + MAP. Indeed, it was possible to obtain somewhat accurate results without relying on changes in atmospheric pressure. However, the proposed method further improved the results in cases where minor errors were found—e.g., for methods integrated with BLE. We believe that the reason for this improvement is that the proposed method can detect stairs more accurately, owing to the absolute altitude.

In order to calculate the statistical difference between each group, we used GLMs. Thus, we analyzed the influence of the absolute positioning methods integrated with PDR.

The model to describe the interaction between absolute positioning methods can be written as follows:

$$\log(\text{error}) = a \cdot \text{Atmos}_{(M1,M2,S)} + b \cdot \text{Map}$$

where \(\log(\text{error})\) denotes the logarithm for the error calculated using different positioning methods, \(\text{Atmos}_{(M1,M2,S)}\) represents whether AtmosMulti1, AtmosMulti2, or AtmosSingle was implemented, and MAP refers to map matching. Previous positioning methods were set as binary variables. Finally, \(a\) and \(b\) denote the coefficients for each model.

First, we evaluated how the different GLMs interacted without the BLE positioning method. This is because the latter method more effectively corrects the user’s position than other methods. As explained above, however, the interaction of the methods helps to reduce the accumulated errors, and thus corrects the user’s position. By comparing the GLMs (Table 2) between the models AtmosMulti1 and AtmosMulti2 (i.e., 1 and 2), it is evident that AtmosMulti2 is more important than AtmosMulti1.

The Wilcoxon rank-sum test and the Kruskal-Wallis test were used to evaluate the differences between the models. In comparing models that used AtmosMulti1 with those that did not, there was no significant difference between the groups (W = 7, p = 0.120), with a confidence level of 0.1. By using the Kruskal-Wallis test, we confirmed these results (Chi-squared = 1.98, p-value = 0.158). For AtmosMulti2, however, the results from the Wilcoxon rank-sum test (W = 8 and p-value = 0.05) show that there is indeed a significant difference. Moreover, the Kruskal-Wallis test confirmed this result (Chi-squared = 3.53 and p-value = 0.06). The confidence level remained the same for all tests.

On the other hand, when the methods were combined with BLE, they performed differently, as expected. The GLM that describes the interaction with BLE is defined as follows:

$$\log(\text{error}) = a \cdot \text{PDR} + b \cdot \text{Atmos}_{(1,2)} + c \cdot \text{Map} + d \cdot \text{BLE}$$

### Table 2. P-values for each positioning method through generalized linear models without BLE

<table>
<thead>
<tr>
<th>Models</th>
<th>AtMH1</th>
<th>AtMH2</th>
<th>AtmosSingle</th>
<th>MAP</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AtmosMulti1</td>
<td>0.350</td>
<td></td>
<td></td>
<td>-6.838</td>
<td></td>
</tr>
<tr>
<td>AtmosMulti2</td>
<td>0.133</td>
<td></td>
<td></td>
<td>-8.302</td>
<td></td>
</tr>
<tr>
<td>AtmosSingle</td>
<td></td>
<td>0.881</td>
<td></td>
<td>-5.779</td>
<td></td>
</tr>
<tr>
<td>MAP</td>
<td>0.355</td>
<td></td>
<td></td>
<td>-6.816</td>
<td></td>
</tr>
<tr>
<td>MAP +</td>
<td>0.356</td>
<td>0.361</td>
<td></td>
<td>-6.073</td>
<td></td>
</tr>
<tr>
<td>AtmosMulti1</td>
<td></td>
<td></td>
<td></td>
<td>-7.809</td>
<td></td>
</tr>
<tr>
<td>MAP +</td>
<td>0.132</td>
<td>0.309</td>
<td></td>
<td>-4.850</td>
<td></td>
</tr>
<tr>
<td>AtmosMulti2</td>
<td></td>
<td></td>
<td></td>
<td>-3.497</td>
<td></td>
</tr>
<tr>
<td>MAP + AtmosSingle</td>
<td></td>
<td>0.884</td>
<td>0.397</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: P-values 0 – 0.001: (***) , 0.001 – 0.01 (**), 0.01 – 0.05 (*), 0.05 – 0.1 (.)
where \(a, b, c,\) and \(d\) denote the coefficients for each respective factor.

From Table 3, the best model was the combination of PDR + AtmosMulti2 + BLE + MAP, with an AIC of -31.89. MAP, AtmosMulti2, and BLE resulted in significant p-values: 0.05, 0.013 and 0.025 respectively. Indeed, the most significant variables in these models are those with a low p-value—those with a p-value between 0.01 and 0.05 (*). All GLMs integrated the BLE positioning method.

In addition to the models that did not interact with BLE, we evaluated the statistical difference between groups using the Wilcoxon rank-sum and Kruskal-Wallis tests. For models that interacted with MAP, there was a significantly difference after running the Kruskal-Wallis test (Chi-squared = 5.11, p-value = 0.02). Moreover, there was a statistical difference for the models using the AtmosMulti2 positioning method. The Wilcoxon rank-sum test resulted in \(W = 29\) and p-value = 0.05, and the the Kruskal-Wallis test resulted in Chi-squared = 2.89 and p-value = 0.089. Finally, we compared the various methods with and without the BLE-based positioning method. The Wilcoxon rank-sum test revealed a significant difference, with \(W = 56\) and p-value = 0.03. This was confirmed by the Kruskal-Wallis results: Chi-squared = 3.70 and p-value = 0.05.

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed a novel floor-detection method for indoor environments based on the atmospheric pressure measured by sensors in smartphones. We decomposed three factors that affect readings of the atmospheric pressure: a device-dependent factor, the altitude, and the environment. To decompose these factors, we utilized localization infrastructure sparsely located in the environment. The proposed method more precisely detects floor changes without errors in drift, because it generates a reference pressure table to mitigate variations in the pressure caused by environmental trends, floor offsets, and device-dependent offsets. We confirmed the effectiveness of the proposed method by comparing it with relative-pressure-based methods in terms of the change in altitude, and also by conducting the Wilcoxon rank-sum and Kruskal-Wallis tests.

Furthermore, the proposed method is applicable to both single and multiple users. With multiple users, a collective method offers advantages in terms of accurately estimating the offsets and environmental trends, because more data is used.

In terms of localization infrastructure, we used BLE beacons. However, these might be replaced with other infrastructure, such as Wi-Fi access points, ultrasonic sensors, or vision-based human-identification methods, among others. As an idea for further improvement of the proposed method, the atmospheric pressure can be used to filter errors resulting from the positional infrastructure. We expect that the proposed method can be further improved by adopting such a recursive cycle between the atmospheric pressure and the infrastructure.

Only two participants were used to evaluate the proposed method. To further evaluate the scalability of the method, experiments with more participants might be required. If information can be gathered from several users, the absolute atmospheric pressure might be estimated with considerably more accuracy, and with a higher temporal resolution for the estimated environmental trends. With many users, moreover, the proposed method has the potential to be used for crowd-sourced weather forecasting.

REFERENCES


Table 3. P-values for each positioning method through generalized linear models with BLE

<table>
<thead>
<tr>
<th>Models</th>
<th>PDR</th>
<th>AtmosMulti1</th>
<th>AtmosMulti2</th>
<th>AtmosSingle</th>
<th>MAP</th>
<th>BLE</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDR</td>
<td>0.445</td>
<td>0.351</td>
<td>0.370</td>
<td>0.416</td>
<td>0.430</td>
<td>0.892</td>
<td>-24.123</td>
</tr>
<tr>
<td>PDR + AtmosMulti2 + BLE</td>
<td>0.449</td>
<td>0.352</td>
<td>0.403</td>
<td>0.431</td>
<td>0.403</td>
<td>0.392</td>
<td>-24.697</td>
</tr>
<tr>
<td>AtmosMulti2 + MAP</td>
<td>0.425</td>
<td>0.127</td>
<td>0.403</td>
<td>0.437</td>
<td>0.403</td>
<td>0.392</td>
<td>-24.697</td>
</tr>
<tr>
<td>AtmosMulti2 + MAP</td>
<td>0.460</td>
<td>0.899</td>
<td>0.403</td>
<td>0.437</td>
<td>0.403</td>
<td>0.392</td>
<td>-24.697</td>
</tr>
<tr>
<td>AtmosSingle + MAP</td>
<td>0.414</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-25.603</td>
</tr>
<tr>
<td>AtmosSingle + MAP</td>
<td>0.416</td>
<td>0.352</td>
<td>0.403</td>
<td>0.437</td>
<td>0.403</td>
<td>0.392</td>
<td>-24.697</td>
</tr>
<tr>
<td>PDR + AtmosMulti1 + BLE</td>
<td>0.386</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-26.877</td>
</tr>
<tr>
<td>AtmosMulti2 + MAP</td>
<td>0.386</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-26.877</td>
</tr>
<tr>
<td>PDR + AtmosMulti2 + MAP</td>
<td>0.430</td>
<td>0.892</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-23.627</td>
</tr>
<tr>
<td>PDR + AtmosMulti2 + MAP</td>
<td>0.418</td>
<td>0.889</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-24.532</td>
</tr>
<tr>
<td>PDR + AtmosMulti2 + MAP</td>
<td>0.353</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-29.161</td>
</tr>
<tr>
<td>PDR + AtmosMulti2 + MAP</td>
<td>0.351</td>
<td>0.286</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-28.699</td>
</tr>
<tr>
<td>PDR + AtmosMulti2 + MAP</td>
<td>0.306</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-31.89</td>
</tr>
<tr>
<td>PDR + AtmosMulti2 + MAP</td>
<td>0.372</td>
<td>0.878</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-27.195</td>
</tr>
</tbody>
</table>

Note: P-values 0 – 0.001: (***), 0.001 – 0.01 (**), 0.01 – 0.05 (*), 0.05 – 0.1 (.)


