Adaptive context-agnostic floor transition detection on smart mobile devices

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***Abstract*—We present a technique for detecting floor changes in an indoor environment and improving pedestrian indoor localization and navigation. Our technique relies on barometric pressure sensors commonly available on smartphones and tablets. We developed an algorithm running on smart mobile devices that can be integrated in any indoor localization system to improve accuracy and support 3D navigation. The main novelty of our technique is that it can work in any type of environment, without any prior knowledge of the building layout, it does not require calibration and it is adaptive. Experimental results show that our method can accurately detect floor changes in any condition without requiring any additional work.**

***Keywords*-3D localization; barometric pressure**

I. Introduction

Indoor localization and navigation services are becoming widespread thanks to the diffusion of more and more powerful mobile devices (i.e., smartphones). Most of the approaches used for indoor localization are based on empirical measurements of access point signal strength (RSS-based), which are stored offline. These techniques comprise an online mapping of the stored scans with the current ones, and assume that access points are located in the same 2D location. Unfortunately, these methods are not suitable for multi-level buildings, especially if open spaces exist, because the similarity of received signal strength of access points, can determine incorrect mappings of positions located in adjacent floors. The direct consequence of these mismatching is the ping-pong effect in the visualization of the floor associated to the device position. Therefore, a method for extending 2D indoor localization with information about height is required.

This paper proposes a practical approach to estimate altitude changes that can be combined with any 2D localization technique to generate a 3D indoor localization system. Our approach is adaptive, independent from the layout of a building and works for any type of transport mode (stairs, elevators, etc.). We started from the theoretical work made by Misra et al. [1], who used classification strategies based on measurements provided by phone-embedded barometric sensors to identify the number of floor traversed by users. We used an empirical approach, and implemented and validated an algorithm that uses barometric pressure sensors available on off-the-shelf smartphones for detecting floor transitions and mapping floors in a multi-floor environment. Information about floor mapping can be used to improve the accuracy of RSS-based indoor localization systems a/o to provide 3D navigation support.

II. Related Work

This work focuses on the integration of context information collected using mobile phones' built-in sensors into localization systems to provide more accurate indoor location. Recently, in [2] we have been exploiting the sensing capabilities of smartphones (i.e., accelerometer, compass and gyroscope) to provide alternative tracking techniques, which come in support of standard localization methodologies when they are not available. Here, we propose to use barometric pressure sensors to infer floor-level information in localization systems.

Despite the number of solutions for 2D localization, only a few works deal with mapping of multi-floor buildings, but they use dedicated hardware. In [3], for example, authors use multiple robots, while in [4] a single robot provided with a barometric pressure sensor explores a multi-floor building and in [5] a high precision barometric sensor mounted on a van is used to perform vehicle localization in an outdoor environment. In [6], fixed dedicated sensors provide reference measures, which are used in conjunction with measurements obtained from tags equipped with barometric pressure sensors to determine the floor. In [7] an external air pressure sensor was attached to a smartphone via Bluetooth for identifying the storey where a device is located: the technique proposed strongly depends on information about the layout of the building (i.e., the altitude of each floor, the distance between every two storeys and the attenuation of signal due to the penetration through the floors). Fingerprinting methods [8], which use correlations between locations and radio-signal patterns, are inaccurate to detect floor changes because radio-signal fluctuations/attenuations are high in the areas where elevators /staircases are located. Recently, smartphone manufacturers have started selling models with integrated barometric pressure sensors. Given the novelty of these sensors, there is little prior work that has applied them to the problem of determining indoor floor information. In [9] for example, authors unsuccessfully attempted to use a barometer to help users find where their car was parked. To the best of our knowledge only

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few authors started studying solutions that use barometric pressure sensors installed on off-the-shelf smartphones to infer floor-level location, but they have not published their results yet.

III. Rationale

Barometric pressure is defined as the force per unit area exerted against a surface by the weight of the air above that surface. The standard unit for pressure is the pascal (Pa), which is equal to one Newton per square meter (N/m^2). In meteorology, the hectopascal (hPa) unit is mainly used; 1 hPa corresponds to 100 Pa.

Pressure and altitude are strongly related. It is well known that the higher the storey the lower the barometric pressure, and vice versa. The relationship between pressure P and altitude h up to 11.000 meters can be defined as:

$$h = (1 - (P/P_0)^{(k*R/g)}) * (T_0/k) \quad (1)$$

where P_0 and T_0 are the pressure and temperature at sea level (1013.25 hPa and 288.15° K), R is the universal gas constant (287.052 m^2/s^2), k is the lapse rate/drop in temperature with altitude (0.0065° K/m), g is the gravitational constant (9.82 m/s^2). In the real world, barometric pressure and temperature are not constants. Furthermore, buildings' floors have different heights and the pressure across different floors of the same building may vary due to pressurization artefacts. These factors make the problem at hand very challenging.

IV. Experiments

We conducted preliminary experiments using different mobile phones in order to investigate the characteristics of barometric pressure in different scenarios. For our tests, we used two Android mobile phones models: Samsung Galaxy Nexus and Samsung Galaxy SIII. The first phone is equipped with a Bosch Sensortec BMP180 digital barometric pressure sensor, while the Samsung Galaxy SIII mounts an STMicroelectronics LPS331AP chip. The relative accuracy pressure is ±0.12 hPa for the BMP180 and ±0.1 hPa for the LPS331AP chip. The empirical data we collected had been used to derive and develop our practical method for detecting floor changes.

First, we analyzed raw pressure readings characteristics. For all experiments, data was recorded with a sample rate of approx. 1 Hz. Android allows to listen to pressure events: the rate events are delivered is only a rough indication as they are specified with values such as "DELAY_FASTEST" or "DELAY_NORMAL". For this reason we decided to get sensor data as fast as possible (using the "DELAY_FASTEST" rate), to select the median value of three samples for minimizing the impact of transient values, and then to wait 1 s. for the next three values to be read.

The first consideration we made is about the absolute value of pressure readings: in the same place and at the same time, there was a gap of about 1.7 hPa in the measurements provided by the two phones. This means that absolute pressure readings of a mobile phone cannot be used neither for directly associating pressure to altitude nor for inferring altitude based to reference values provided by *e.g.* fixed sensors at known positions. The second consideration is that, in the same position, absolute pressure values are not constant but vary with time because of atmospheric events (cloudy/sunny). Our conclusion was that we cannot rely on absolute pressure values for correlating pressure to altitude and classify floor-level location.

Raw pressure graph presents some peaks related to distorted readings, even when the phone is resting on a support. To produce unbiased pressure values, we decided to use a technique for producing smoothed data in a noisy time series. The approach we used is double exponential smoothing, which is also an excellent approach in following the data when there is a trend. If x_t is the raw data sequence of observations starting at time $t = 0$, s_t is used to represent the smoothed value for time t, and b_t is the best estimate of the trend at time t. The following two equations are associated to Double Exponential Smoothing:

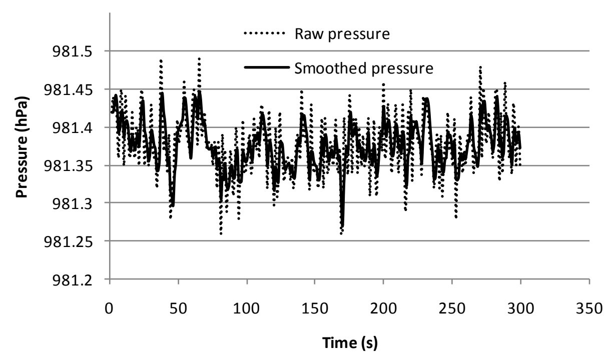

Figure 1. Raw and smoothed pressure data.

$$\begin{aligned} s_t &= \alpha x_t + (1-\alpha)(s_{t-1} + b_{t-1}) \\ b_t &= \gamma(s_t - s_{t-1}) + (1-\gamma)b_{t-1} \end{aligned} \quad (2)$$

where α is the *data smoothing factor*, $0 < \alpha < 1$, and γ is the trend smoothing factor, $0 < \gamma < 1$. The initial values can be taken as $s_1 = x_0$ and $b_1 = x_1 - x_0$. The smoothing factor, for both data and trend, represents the importance applied to the most recent period (1 means that the latest period is more important). We used 0.5 for both factors. Figure 1 shows raw and smoothed pressure readings when the phone is on a table.

We carried out a series of experiments at our main building, which is located at 341 meters above sea level, in five different scenarios. In the first scenario, we recorded pressure and acceleration in the Z axis while the phone was laying on a support (stationary mode). In the second scenario, pressure measurements were made while a user was walking on the same floor of our building (walking mode). In the third and fourth scenario, pressure was recorded while the user was stepping up and stepping down the stairs between the basement and the second floor of our building. Finally, in the fifth scenario, we moved from the basement to the second floor using an elevator and monitored pressure.

As it can be seen from Figure 3, pressure and acceleration in the Z axis remain stable when the user is in stationary mode. Standard deviation of barometric pressure for both phones was less than 0.1 hPa. Furthermore, standard deviation for the Galaxy SIII was higher than the one for Galaxy Nexus. This result complies with data about accuracy provided from both chip manufactures. Acceleration is displayed in the charts in a secondary axis (with a dashed line), and is comprised between $\pm 0.25 m/s^2$.

When the user is in walking mode (Figure 4), pressure is relatively stable, while acceleration in the Z axis oscillates frequently ($\pm 3.5 m/s^2$), and the amplitude of oscillations varies as a function of user's speed, phone's orientation and phone's position (e.g., in pocket or hand). Thus we concluded that the stationary state is the only one that can be well characterized by fixed bounds of pressure and acceleration.

Figure 5 shows the evolution of pressure while user was stepping up the stairs between the ground and the second floor. The exploration starts at the ground floor. The user takes the stairs and goes to the first and then to the second floor, where the pressure is lower as expected. The amplitude of the acceleration measurements is high at the start and at the end of the graph (where the user was stepping up the stairs), while it is limited in the middle of the graph because there is a landing between the two floors. We do not report the graph here, but we checked that (similarly) pressure increases as the user moves from the second, to the first floor, and then to the basement. Floor transitions are clearly observable from the pressure data: they are identified by discontinuities in the pressure graph. Furthermore, pressure values on different floors are clearly separated.

Finally, Figure 6 shows pressure graph when riding the elevator from the basement to the second floor. The two spikes in the acceleration measurements, showed in the graph (elevator up and arrival), are related to the initial acceleration of the elevator and to the deceleration at floor arrival. There is roughly 1 hPa pressure difference between floors. Furthermore, the rate pressure varies over time is higher than in the two previous scenarios.

To sum up, the most important considerations that can be made from the set of experiments are:

- pressure difference between consecutive floors is approximately the same for both phone models;
- the dynamics associated to pressure variations are the same for both phones and they do not depend by external factors like *e.g.* the speed of the movement.

This means that floor changes can universally be identified by observing pressure differences.

V. Algorithm

The detection of floor transitions is based on the relative difference of pressure readings and on the identification of the user dynamics mode ("stationary", "walking" on the same floor or "stepping up/down" the stairs, "elevator up/down"). The detailed detection algorithm is presented in Figure 2. It takes as input the smoothed pressure readings and first checks the difference between its value and the mean value for pressure of the current time window. This check is made to identify if the user is in stationary/walking mode. The mean value is updated only if this difference is less than the PRESS_ACC threshold, which reflects the accuracy of the pressure measurements we found during the experiments. PRESS_ACC is first assigned a fixed value and this value is automatically adjusted by combining pressure measurements with accelerometer data when a user is in stationary mode. The standard deviation of the pressure when user is in stationary mode is used to update the value of PRESS_ACC as:

$$PRESS\_ACC = k * pressure\_std\_dev, \text{ where } k = 3$$

The rationale for the above equation is that we assumed that pressure in stationary mode is normally distributed. Therefore, from the three-sigma rule of normally distributed data [10], we can state that nearly all values lie within 3 standard deviations (σ) of the mean (μ):

$$P(\mu - 3\sigma \leq x \leq \mu + 3\sigma) \approx 0.9973$$

To identify when a user is in stationary mode, we periodically read the Z axis acceleration and check if it is less than a specified threshold T_STATIC [11]. If the amplitude of the oscillations is higher than the T_STATIC threshold and there is a minimum number of samples for calculating the standard deviation of pressure, PRESS_ ACC is updated. If the user is in one of the other dynamics mode ("walking", "stepping up/down" or "elevator up/down"), pressure will exceed the PRESS_ACC threshold and continue to increase/decrease until the user commutes to the stationary or walking mode. As said, by using the smoothed pressure value, we are sure to follow the trend. A floor transition will then be clearly identified by a change of sign in the smoothed pressure difference between adjacent readings.

To avoid false floor transition detections, we check if the pressure measured afterwards does not exceed the PRESS_ACC threshold for at least MIN_SAMPLES samples. To get the final confirmation that there has been a floor transition, we check that the difference between the last mean pressure value and the pressure when a floor transition has been detected is higher than a DELTA_PRESS_MIN constant. DELTA_PRESS_MIN is first initialized to PRESS_ACC and its value is updated in an adaptive way by computing differences between stored pressures values at floor changes. After a floor transition has been detected, the pressure mean value is recalculated from scratch.

The main advantage of this approach is that floor transitions can be identified without any prior knowledge of the building layout. The detection algorithm does not include information about floor heights, which can be different for different buildings, but even for the same building; therefore it can work in any type of environment. Furthermore, our technique does not depend on the transport mode used (stairs or elevator). Finally, it does not need any additional HW nor any complicated preliminary calibration of the barometric sensor to correct the sensor device error component.

```
Input: pressure p, previous pressure prev_p, acceleration a
Output: floor transition is_floor_changed
PRESS_ACC←1.2
MIN_SAMPLES ←4
change_in_sign ← FALSE
threshold_exceeded ← FALSE
if (a < T_STATIC)
    update pressure_std_dev
end if
else if (num_samples_pressure_std_dev > MIN)
        PRESS_ACC= k * pressure_std_dev
end if
deltaPress ← (p – meanPressure)
adjacentDeltaPressure ← (p – prev_p)
if |deltaPress| > PRESS_ACC
        threshold_exceeded ← TRUE
end if
if threshold_exceeded
        if(n_boundaries==MIN_SAMPLES)
                if (p – last_press > DELT_PRESS_MIN)
                        is_floor_changed ← TRUE
                        last_press = p
                end if
        end if
        if change_in_sign
                if |deltaPress| < PRESS_ACC
                        n_boundaries← n_boundaries+1
                end if
                else
                        change_in_sign ← FALSE
                end if
        end if
        else if (adjacentDeltaPressure change sign)
                re-compute meanPressure
                change_in_sign ← TRUE
        end if
else
        update meanPressure
end if
return is_floor_changed
```

Figure 2. Algorithm for detecting floor transitions.

VI. Results

To validate our floor detection algorithm, we deployed an application implementing it. Since we demonstrated in Section IV that the behaviour of the two smartphones is identical, we used only one phone for tests (the Galaxy Nexus) and conducted a number of experiments first at our main building, and then in a different building.

In the first experiment, the user started walking from the basement, and then took the stairs, exited at the first floor, walked and entered into our office. Finally, he did the reverse path. The experiment was repeated 50 times. We initially used a small value for the MIN_SAMPLES parameter: it was set to 2. With this value, as expected, we achieved an accuracy of 82% in exactly identifying floor transitions. More precisely, 9 over 50 times, pressure decrease was not linear and the algorithm detected a false floor transition because there was a change of sign in the difference of pressure between adjacent readings, followed by short pressure variations within the PRESS_ACC interval, and then by a subsequent decrease in pressure values. For this reason, we decided to set the value of MIN_SAMPLES to 4. Then, we repeated the experiment again for 50 times and no longer got false floor transitions.

In the second experiment, the user stepped into the elevator from the basement, went to the first floor and finally stepped out from the elevator. We repeated the experiment 50 times. Our algorithm was always successful because the elevator context is characterized by a distinct linear variation of pressure until a new floor is reached.

In the third scenario, we combined the paths followed in the previous two: the user waited for the elevator, took the elevator at the ground floor, stepped out at the first floor, walked along the corridor and finally went downstairs by stairs. In 7, which refers to this scenario, the elevator context can be easily identified from the measurements since the rate of change of pressure over time is very fast. Staircase environment is instead characterized by a slow rate of change in pressure. The value of PRESS_ACC - automatically calculated by the application when the user stood in front at the elevator (stationary mode) - was 0.11 hPa. We repeated the experiment 10 times: our application was always able to correctly detect floor transitions.

Finally, we tested the convergence of our algorithm. We initially set the value of PRESS_ACC to 5 hPa, reproduced stationary mode conditions (amplitude of acceleration oscillations lower than T_STATIC) and checked if the algorithm was able to adjust the PRESS_ACC value in order to detect a floor transition in two scenarios: when the user stepped upstairs from the ground to the first floor, and when he went from the first to the second floor and then again to the first by the elevator. Note that with PRESS_ACC set to 5 hPa, even if there is a big drop/rise in pressure (hence the floor is presumably changed), the algorithm is not able to distinguish it because the margin of tolerance to discriminate between stationary and walking mode is high. In both scenarios, our algorithm detected the initial stationary mode conditions and computed the standard dev. of pressure during that period. The value was calculated right after the amplitude of the acceleration oscillations was higher than the T_STATIC threshold (0.35 m/s^2).

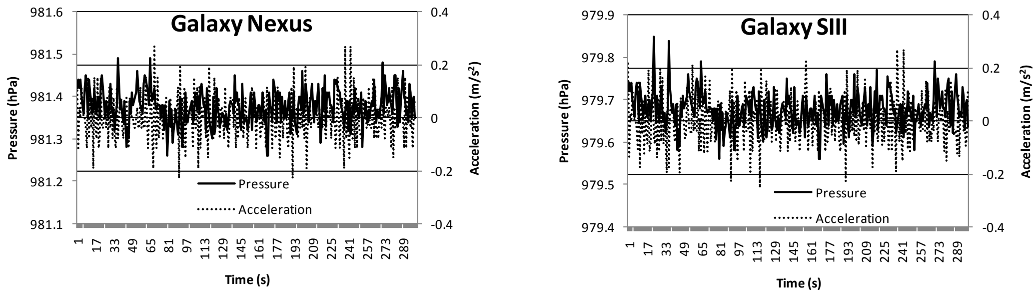

Figure 3. Barometric pressure and acceleration in stationary mode.

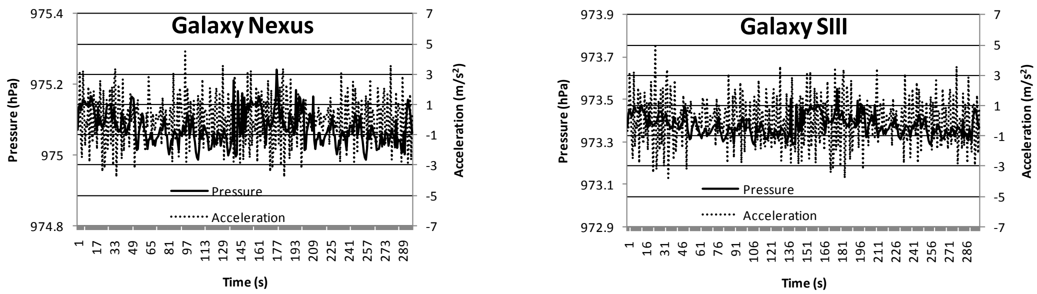

Figure 4. Barometric pressure and acceleration walking on the same floor.

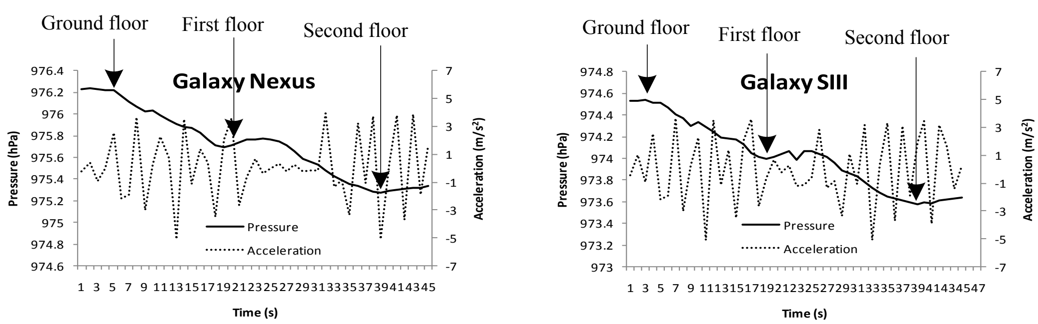

Figure 5. Barometric pressure and acceleration stepping up stairs.

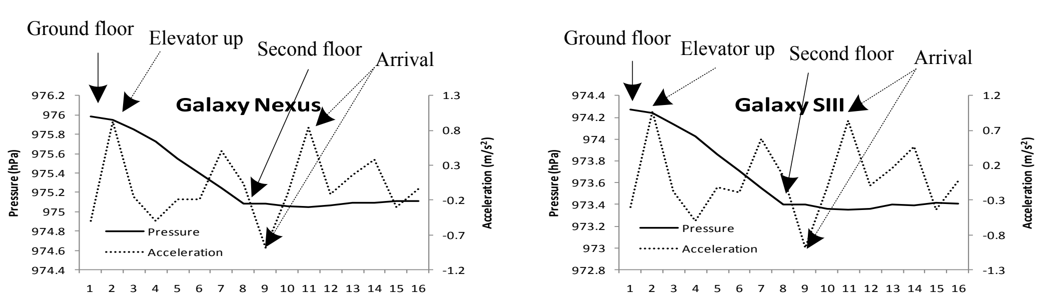

Figure 6. Barometric pressure and acceleration riding the elevator to the second floor.

To discard the influence of external factors (*i.e.*, related to the structure of the building, to weather conditions or to altitude), we performed a second set of experiments in a different building, with a different layout (3 floors with lower heights, connected by two staircases), located at 210 meters, under good and cloudy weather conditions.

The first consideration is that, as expected, pressure values

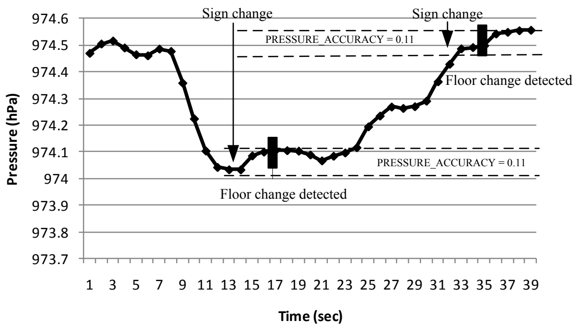

Figure 7. Floor changes taking the elevator and stepping down the stairs.

were higher than those measured at our main building because altitude is lower. Our algorithm correctly detected

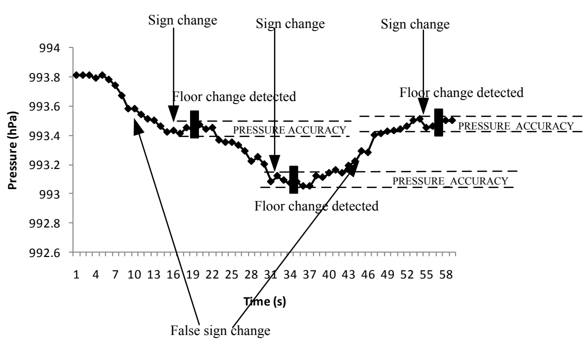

Figure 8. Floor changes under low pressure conditions in new building.

floor changes along the route basement→first→second→ first floor (Figure 8). The two false changes of sign indications were ignored as pressure respectively had been decreasing/increasing and exceeded the PRESS_ACC threshold, meaning that the user was not in stationary mode.

The final consideration is that the capability to detect floor changes from the barometric sensor observations was unaffected by changes in the phone's positioning and orientation. In our experiments we intentionally didn't care about the positioning of the phone, as it happens in a daily usage pattern: under this "flawed" condition, the accuracy to detect floor transitions didn't change.

VII. Conclusion

We presented a mechanism for detecting floor transitions using barometric pressure measurements provided by widely available off-the-shelf smartphones. We use measurements provided by embedded accelerometers to adapt the behaviour of our algorithm to the environment. Our approach is context-agnostic, thus can work in any type of environment; and does not require any external hardware or preliminary calibration of the barometric sensor to fix the sensor error component. The experiments show that our algorithm can accurately detect floor transitions in any type of indoor environment and for any type of transport mode used (stairs or elevators).

Future work includes: the investigation of the power consumption of our algorithm and its integration into our ELS solution [2] to provide a continuous localization service while reducing the resources consumption; the conversion of the algorithm into an add-on that can be easily integrated into any 2D indoor localization system to provide 3D localization; the integration with our PROMO indoor localization platform [12] for a large-scale evaluation of accuracy.

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