Fusion of Barometric Sensors, WLAN Signals and Building Information for 3-D Indoor/Campus Localization

Hui Wang, Henning Lenz, Andrei Szabo, Uwe D. Hanebeck, and Joachim Bamberger

***Abstract*—Location estimation in indoor/campus environments has attracted much interest for its broad applications. Many applications (e.g. personnel security) require not only the 2-D coordinate but also the floor index where the mobile users are situated. However, most of the current location systems cannot provide the floor information accurately and robustly. In this paper, we propose a 3-D localization scheme which fuses the barometric sensor with Wireless LAN (WLAN) signals and building information. Our experiments show that this fusion scheme can both identify the floor index without errors and improve the horizontal localization accuracy. Moreover, since the barometric sensor is quite simple and cheap, it would bring almost no increase in system costs.**

I. Introduction

LOCATION estimation in indoor/campus environments has attracted more and more research efforts in recent years. It is the basis of many applications such as personnel security, tracking of assets and people, routing, navigation, location-aware multimedia services and many others [1]-[4].

Some systems over the years have already tackled the localization problem. In general, these systems can be categorized into three groups: satellite based systems, sensor based systems and communication network based systems. The satellite based system, such as GPS, is widely used for outdoor navigation [5] [6]. But for indoor environments the satellite signals cannot be used because they are highly attenuated by the walls of the buildings. Furthermore, GPS signals that could be received have propagated via a very complex propagation channel, i.e. not through a line of sight path, such that the propagation time cannot be directly transformed into a distance.

The first generation indoor location systems are mostly based on various dedicated sensors. Examples include magnetic sensors, radar, laser sensors, ultrasonic and infrared sensors [7]-[9]. These systems can usually achieve a very high accuracy, but the drawbacks are also obvious: (a) they scale poorly because of the limited propagation range; (b) they incur significant installation and maintenance costs, and (c) some systems suffer from other interference, e.g. IR based systems are strongly influenced by the direct sunlight.

Recently emerging and promising indoor localization techniques use the existing indoor communication infrastructures, such as WLAN or DECT [10]-[12]. The received signal strength (RSS), propagation time (time of arrival, time difference of arrival) and angle of arrival are typically used to infer the user's location. The biggest advantage of such kind of systems is that it makes use of available wireless networks and does not need additional hardware, thereby keeping the installation and maintenance cost at a very low level. Unfortunately, current systems suffer from the noisy characteristics of wireless channel, leading to a coarse accuracy.

For indoor/campus location based services, a crucial parameter is the floor index. The localization systems and their applications are very sensitive to the choice of the floor. For instance, if a wrong floor would be identified, a wrong map is selected to display the position. This kind of wrong localization is independent of the horizontal precision. Furthermore, in many cases, e.g. personnel rescue, the change of a floor is more involved than the inspection of a neighboring room. Therefore, in some sense, floor accuracy is more critical than horizontal precision. However, the communication network based systems alone do not provide very accurate floor information because of the large variations in the field strength measurements.

In this paper, we aim to develop a localization approach which can provide the 3-D location, especially the accurate floor index. Our solution is firstly to estimate the floor index by fusing the noisy altitude obtained from a barometric sensor with the building information. To compensate for the measurement fluctuation caused by the environmental changes, an *adaptive* fusion algorithm is proposed. Then the floor index is combined with the estimated location from WLAN signals, finally giving an accurate 2-D coordinate and very robust floor identifications. The structure of our proposed method is shown in Figure 1. In our experiments, the floor information could be inferred without errors by this fusion scheme. Additionally, we find that the 2-D location accuracy in some special scenarios (e.g. in the elevator) could also be remarkably improved.

The rest of the paper is organized as follows. In Section II, we briefly introduce the localization algorithm based on the received power of WLAN signals and evaluate the 3-D localization performance. In Section III, we present our adaptive fusion algorithm between the barometric sensor and

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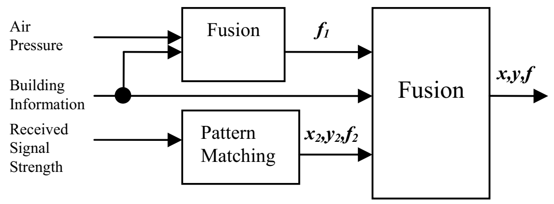

Fig.1. Fusion structure. f_1 is the floor estimation by fusing barometric sensor with building information. (x_2, y_2, f_2) is the 2-D coordinate and the floor index estimated using the WLAN signal. (x, y, f) is the final estimated 3-D location.

building information. We report the results using this adaptive algorithm in a complex indoor/campus office environment. Section IV introduces methods of fusing WLAN based localization with barometric measurements and building map information to obtain an accurate 3-D location. Section V concludes the paper.

II. Localization Based on the Received Power of WLAN Signals

A. Pattern Matching Algorithm

In communication network based localization systems, RSS is most often used as the input of the positioning algorithm because it is easier to obtain compared with the time or the angle information. The popular localization algorithm for the RSS based systems is so-called pattern matching or the nearest neighbor (NN) [10]. This algorithm includes two steps.

1. In the ***offline step***, the received power vectors from several base stations (BSs) at calibration points are measured and recorded as the fingerprints of the calibration points.

2. In the ***online step***, the received power vector is then compared with the fingerprint of calibration points. The calibration point which has the closest distance with the received power vector is then chosen as the estimated position. This is shown analytically in (1) [13].

$$\hat{\underline{w}} = \underset{\underline{w}}{argmin} \quad E\left\{\left(P_q^{\,m} - P_q\left(\underline{w}\right)\right)^2\right\}, \qquad (1)$$

where $\hat{\underline{w}}$ is the estimated position, $P_q^{\,m}$ is the measured power from base station q, $P_q(\underline{w})$ is the fingerprint at the position of the calibration point $\underline{w}$. E is the mean operator over all the measured BSs.

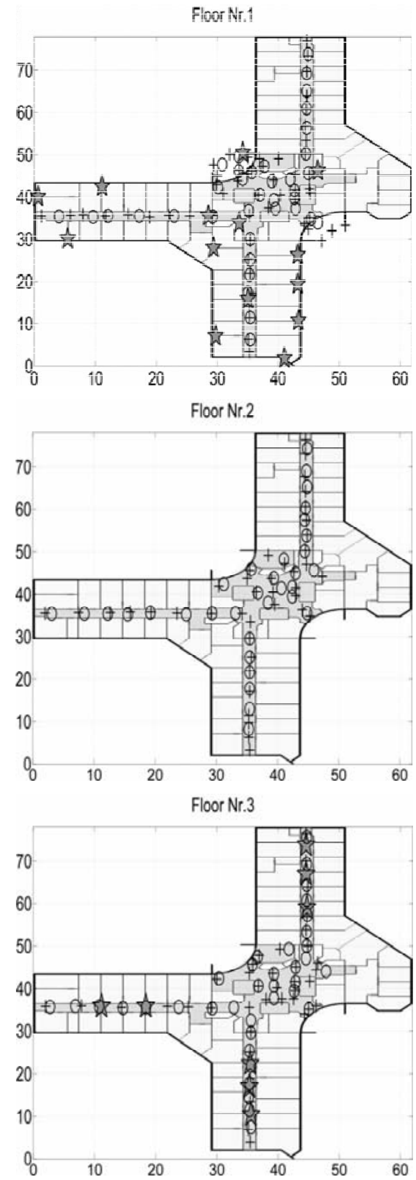

Fig.2. The test environment. The BSs are marked with pentagrams; the calibration points are marked with '+' and the test points are marked with 'o'.

B. Performance Evaluation

Our experimental network is placed on 3 floors of a standard office building. Each floor has a similar structure with an area of 62×78 m^2, as depicted in Figure 2. There are 14 WLAN base stations installed in the first floor and another 8 base stations in the third floor (marked with pentagrams). There is no base station in the second floor.

Our laptop used for measuring and testing is equipped with a Lucent Orinoco 802.11b WLAN card. In the offline step, we measured the received power at 143 different calibration points (55 in the first floor, 41 in the second floor and 47 in the third floor; shown in Figure 2, marked with '+'). At each calibration point, we measured 10 samples and took the mean value as the fingerprint. In the online step, we walked around in the building with the same laptop and recorded the received power at 107 test points (37 in the first floor, 33 in the second floor and 37 in the third floor; shown in Figure 2, marked with 'o'). In real life, people typically don't stay in a place too long. So we only took 3 samples for each test points and took the mean as the received power vector.

The 3-D location error and the percentage of false floor estimations for each floor can be found in Table I. We can see that although the pattern matching algorithm can achieve a good performance in the sense of localization error, it cannot guarantee the high accuracy on floor estimation. The false floor estimation tends to occur especially in the following cases.

1. The mobile user enters some place where the received signal is highly attenuated, e.g. in the elevator.
2. The mobile user is situated in a place where the number of measurable BSs is small, e.g. some floor where no BS exists.
3. Sometimes the connection to BSs is blocked because of high data load or the fault of BSs.
4. The radio separation between floors is bad, i.e. the reference points at different floors can not be accurately differentiated. This can happen for example in stair cases or if the floors are merging together in a tall hall.

As we have stated in Section I, for many applications, the false floor estimation is unacceptable. Therefore, a 3-D indoor localization system should provide the floor index as accurate as possible. Obviously, the system based on the received signal alone can not satisfy this requirement.

TABLE I
RESULTS FOR RSS BASED LOCALIZATION ALGORITHM

	1st Floor	2nd Floor	3rd Floor	All Floors
3-D Location Error (m)	4.7	6.1	8.7	6.5
2-D Location Error (m)	4.2	5.5	7.1	5.6
Percentage of False Floor Estimation	2.7%	3%	8.1%	4.7%

III. ADAPTIVE FUSION OF BAROMETRIC SENSORS AND BUILDING INFORMATION

Section II has shown that the very robust floor estimation cannot be obtained using only the received power of WLAN signals. Other approaches to sense the floor information should be considered. One good candidate we found is to fuse the barometric sensor with building information.

A. Altitude Estimation by Barometric Sensors

As is well-known, the atmospheric pressure is a physical property strongly related with the altitude and the height above a certain level. We can use barometric sensors to sense the value of the pressure and then transform the pressure to the altitude. For example, (2) is the transformation formula between the pressure and the altitude to the sea level under the standard conditions (temperature is 15 °C, i.e. 288.15 K; the reference pressure at sea level is 1013.25 hPa; temperature gradient is 0.65 K per 100 m.) [14].

$$P_{abs} = 1013.25\left(1 - \frac{0.0065 \cdot h}{288.15}\right)^{5.255} \text{hPa}, \qquad (2)$$

where P_{abs} is the pressure measured by the barometric sensor with the unit of hPa; h is the sea level altitude in meter.

In the following, we use the altitude h directly without stating verbosely the transformation from pressure to altitude.

B. Building Information

Building information is another useful information source. Typically, the building information can be obtained from a CAD system or in an image format (e.g. .jpg or .bmp file). A lot of location-related data can be extracted from the building structure information, such as the distance between floors, the position of walls, doors or elevators. In our algorithm for floor identification, we will use the observation that the height of the floors is discrete and that the floor separation distance is known.

C. Adaptive Fusion Algorithm for Floor Identifications

In order to determine the floor on which the mobile device is situated we can fuse the altitude determined by the barometric sensor with building information. For example, if we know the altitude above sea of the building and the altitude difference between two floors, we can tabulate the altitude for each floor. Then the floor index can be easily determined by comparing the measured altitude and the calibration for each floor.

However, due to the environmental changes, the measured altitude varies with time. This causes a non-trivial problem for floor identifications, because in many cases the range of variance is already larger than the floor height of the building. Therefore, the calibration of the barometer must be updated in short periods to compensate the altitude fluctuations.

One simple idea is to calibrate a barometer using reference sensors and meteorological information to determine the altitude. One or more barometric sensors are used as reference sensors, which are put in fixed places and use their measurements to calibrate the moving sensor. But this calibration scheme has several drawbacks: (a) it needs extra cost for reference sensors; (b) Due to the complexity of indoor environment, the pressure recorded by the calibration sensor is not always consistent with that recorded by the mobile device. For example, Figure 3 shows one of our records by two barometric sensors. The thick curve records the altitude by a calibration sensor which is fixed on a desk in the 1st floor. The thin curve records the altitude by another sensor moving on the same floor. At the beginning, these two curves coincide. Later, there is a big difference between the mobile sensor (whose altitude must be estimated) and the reference sensor, which can result in false floor estimations.

To overcome the bad impact of measurement fluctuation,

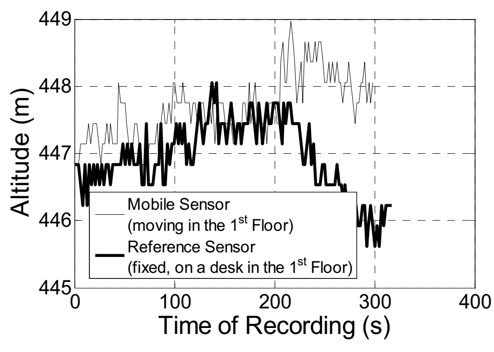

Fig. 3. Comparison between the altitudes by two sensors

we propose a novel adaptive self-calibrating algorithm. This algorithm does not use calibration sensors, but is based on two observations. Firstly the heights of the floors are discrete, so that normally the mobile device is at a constant altitude. Secondly, the environmental changes are much slower than the time needed for changing the floors. Consequently, with an adaptive recursive filtering we can identify when device is situated on the same floor and the barometer can be self-calibrated. Then the changes between the floors can be recognized by more sudden changes of the barometric measurement.

As shown in Figure 4, the algorithm recursively detects the floor index by building two filter windows in the time domain. The first window is called the *ahead window* and is positioned at the current time. The second window is called the *back window* and is positioned in the past, delayed by a time Δt. The *back window* can be regarded as the calibration window, which is used to update the calibration. Since it moves with time, the pressure changes due to the weather influence can be compensated. Finally, by comparing the difference of the averaged altitude in the two windows with the height difference between floors, it can be decided if a floor was changed between the first window and the second window, or not. The algorithm is presented in detail by the following steps:

1. Initialize the experiment introducing the start floor as $Floor(t_0)$.
2. Build *ahead* and *back* filter windows in the time domain. The length of *back window* is denoted as t_2, the filtered altitude by *back window* is denoted as a_2. The length of the *ahead window* is denoted as t_1. The filtered altitude by the *ahead window* is denoted as a_1. The distance between two windows is denoted Δt.
3. At each time t, compute the difference between the filtered values a_1 and a_2.

   If the difference is larger or equal than the threshold H, the object is regarded as moving vertically. Mark that there is a floor change by setting the floor level to 0 (notice: in our experiment the floor number 0 does not exist. Otherwise the marking of the floor change can be done with any other value or flag) and continue with Step 4.

   If the absolute value of the difference between a_1 and a_2 is smaller than H, the device is regarded as remaining at the same floor. Move both windows ahead and go back to Step 3.
4. If a vertical movement is detected, the *back window* remains static and the *ahead window* is repeatedly shifted with Δt_{shift} until two consecutive average altitudes from the *ahead window* remain stable, i.e. the difference is less than the threshold H_s.
5. Compute how many floors the device moved by dividing the difference between the latest a_1 (after the vertical movement stopped) and a_2 by the height difference of the floors, Δf. Update the user's position with the new floor index. Finally move the *back window* to the new floor and go back to Step 3.

D. Physical Meaning and Sensitivity of Parameters

In the above algorithm, several parameters should be given a priori. The final performance is related to the choice of the parameters' values. However, our experiments also indicate that the algorithm is robust, i.e. in some range the choice of parameters' values would not affect the validity of the algorithm. In the following, we explain the physical meaning and sensitivity of the parameters. And in sub section E, we give the empirical range of the parameters' values.

t_1 and t_2 are the length of the *ahead* and *back window*, respectively. They should take several samples to smooth the noise of the barometric measurements and must be short enough in order not to interfere with the identification of a floor change. In some special cases where people stay shorter than the window size on some floor, this short staying will be neglected by the algorithm.

Δt is the time delay between the *ahead window* and the *back window*. It must be longer than the time needed for a person to climb or to descend a floor on foot or with the elevator, but shorter than the time in which the barometric pressure is changed due to weather changes. Also, this delay must be shorter than the period a person spends on a floor.

Δf stands for the relative altitude difference between two floors. It is usually constant and can be obtained as a prior, e.g. by inspection of the building plan.

Δt_{shift} is the time shifting to identify the stopping of the vertical movement state. It should be short to track the vertical movement precisely. But it cannot be too short in order to avoid the wrong identification when people move slowly.

H is the threshold to identify the change of one floor. It should be a little smaller than Δf to tolerate remaining measurement noise.

H_s stands for the threshold to identify whether the vertical movement stops. It should be a value larger than the measurement noise, but smaller than the vertical movement of the device in Δt_{shift}.

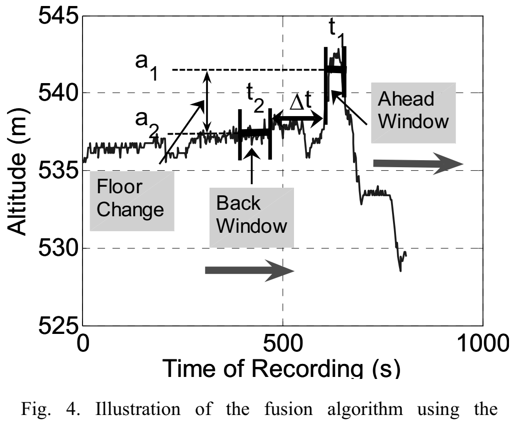

Fig. 4. Illustration of the fusion algorithm using the barometric sensor and building information

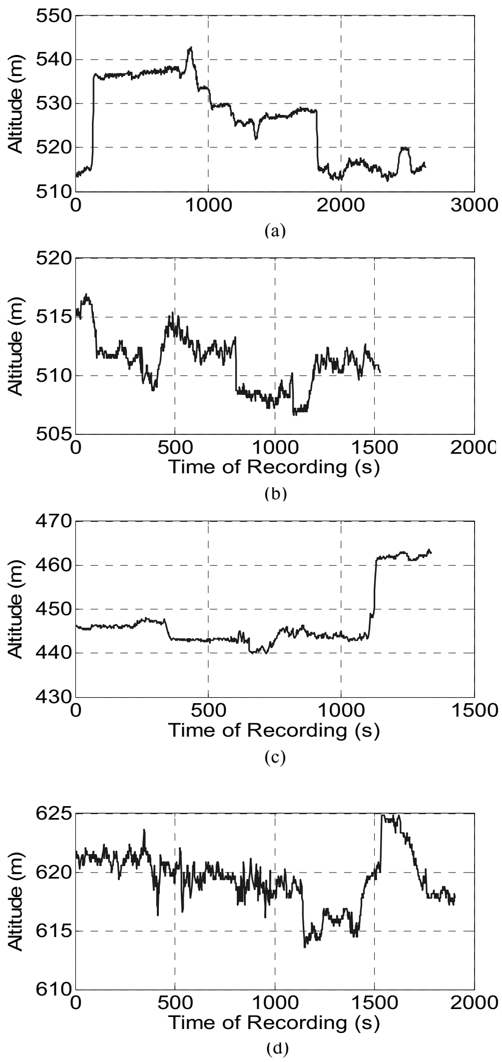

Fig. 5 Different Measurement Data Sets. (a) noon of Jan. 27, 2006. (b) afternoon of Jan. 27, 2006. (c) noon of Jan. 30, 2006. (d) afternoon of Feb. 9, 2006 when it snowed heavily.

E. *Performance Evaluation*

In order to evaluate the above algorithm, we walked with a barometric sensor along several traces, including moving up and down inside buildings by stairs or elevator, going into and out of the building and walking around the campus. In addition, to get a more fair evaluation, we made experiments at different time of a day, on different days and under different weather conditions. Some of the altitude measurements are shown in Figure 5. In all the experiments, we started to walk from the same floor. But as we see in Figure 5, the altitude of the starting point for each experiment differs a lot. This demonstrates the big influence of environmental change in the long term. On the other hand, we can also observe that in a short time, the altitude change caused by the environment is relatively slow, which makes our adaptive calibration possible.

We applied our adaptive fusion algorithm to the four measurement data sets in Figure 5. Table II gives the parameter values used for the calculations presented before. In addition, tests have been performed with different values to determine the range of parameters for which the algorithm performs correctly, i.e. perfect floor identification. In this way, empirical range for the parameter values has been found (see Table II). Here we take the typical movements as consideration, some special cases, such as people stay very short in a floor or people run extremely fast or slow are not considered. Figure 6 shows the comparison between the real and the estimated floor index (The points in floor zero mean that at that time the object is estimated to be moving vertically). We observe that the result of our floor identification approach is very good. It gives very accurate floor estimations, even under bad weather conditions.

TABLE II
VALUE OF PARAMETERS

Parameter	Value	Empirical Range
t_1	4 s	4~16s[1]
t_2	20 s	4~30s
Δt	60 s	60~120s
Δf	4.5 m	From the building plan
Δt_{shift}	10 s	1~20s
H	$0.75\Delta f$	$0.6\Delta f$~$0.9\Delta f$
H_s	$0.2\Delta f$	$0.1\Delta f$~$0.25\Delta f$

IV. FUSION OF BAROMETRIC SENSORS, THE RECEIVED POWER OF WLAN SIGNALS AND BUILDING INFORMATION

A. *Fusion Algorithm*

Since the algorithm in Section III can provide a very accurate floor index, a natural idea is to combine the estimated floor in Section III with the estimated location in Section II. Generally speaking, fusion of barometer sensors, the RSS based localization and building information can benefit each other from the following aspects.

Firstly, the barometric sensor based floor identification was demonstrated to be very robust in the various examples presented. Hence, by combining it with WLAN signals we can get an accurate 3-D localization.

Secondly, not only the floor estimation but the 2-D location performance can also be improved. On one hand, with accurate floor information, we can make a pre-selection of the reference patterns on the correct floor which improves the localization performance. On the other hand, we know that the received signal is highly attenuated and will cause quite a large error in some special areas, like inside elevators or staircases. By combing the barometric sensor, the received

[1] In our experiments, the sampling rate of barometer is 0.5 sample/s. So the 4s (2 samples) is the shortest period for averaging. If a higher sampling rate is used, the range can be extended to 1s or even shorter.

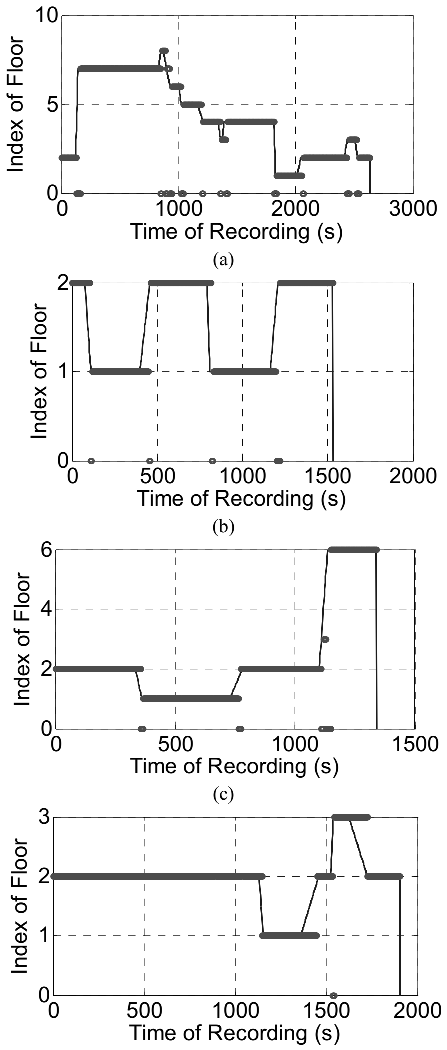

Fig.6. Floor estimation by adaptive calibration based algorithm. (a) - (d) correspond to the four measurement data sets in Figure 5 respectively. The lines stand for the real trace in floor level. The series of points stand for the estimated trace in floor level.

signal and the map information, we can identify the period when people stay in an elevator. Therefore, the elevator related location error can be reduced.

Thirdly, since the estimated location with WLAN signals has usually a good 2-D accuracy, it can be combined with the building map to enhance the barometric sensor based floor identification in the following cases: a) in a campus environment, different buildings often have different building parameters such as the floor height. We can use the RSS based algorithm to locate the building first and choose the correct building parameters for the floor identification; b) although we did not observe the false floor estimation by barometric sensors, theoretically this might happen when people enter a special place where the pressure changes suddenly, e.g. nearby air conditioners. In that case, the 2-D coordinate by WLAN signals can help to identify such a kind of areas; c) the barometric measurements can be performed only at the mobile device and are not available in the network without a communication system to transfer the data. It is beneficial to send the barometric measurements to a central server for several reasons, like monitoring applications and joint processing of the measurement information from several users.

In out test environment we have tested the following fusion algorithm that interactively checks the barometric measurements and the RSS ones to obtain an increased accuracy of the 3D localization, as shown in Figure 1:

1. Initialize the parameters of barometric based floor identification algorithm, i.e. the initial floor using RSS based location estimation and the height of the floors using the building map information.

2. At each time interval, we receive a WLAN signal power vector and an altitude by barometric sensor. Estimate the floor index using the adaptive fusion algorithm in Section III. The result is denoted as f_1. Estimate the 3-D location by pattern matching. The result is denoted as (x_2, y_2, f_2).

3. If f_1 is the same with the previous floor f, use f_1 to choose the floor map and calibration points, and then compute a new 2-D coordinate (x, y) with the RSS based pattern matching algorithm. Return to Step 2.

4. If f_1 is not the same with the previous floor f, (x_2, y_2) should be checked. If (x_2, y_2) is close to stairs or to elevators, we conclude that the mobile device is going up or down by stairs or elevator. Update f with f_1 and the estimated position (x, y) with the position of the stairs or the elevator. Return to Step 2.

5. If f_1 is not the same with the previous floor f, and meanwhile the user is estimated to be close to some pressure breaking point, we use the floor f_2 estimated by the RSS based algorithm as the current floor f. (x, y) is set to (x_2, y_2). Return to Step 2.

B. Experimental Results

We tested the above fusion algorithm inside the building depicted in Figure 2. We walked in the building and recorded the received power and altitudes by the barometric sensor simultaneously. The walking trace is shown in Figure 7. Firstly, we walked in the corridor of the 1st floor and then went up to the 3rd floor by elevator, walked around in the 3rd floor and finally took another elevator down to the 2nd floor.

Table III shows the comparison between the RSS based location estimation and our fusion algorithm with respect to the 2-D and 3-D mean localization error, location error in the elevators and floor identification error. It can be remarked that both the 2-D and the 3-D localization performances are improved by our fusion algorithm. Especially, the large location errors due to the bad radio receiving in the elevators are corrected. This encouraging result indicates that it is a good choice to combine the barometric sensor, RSS of

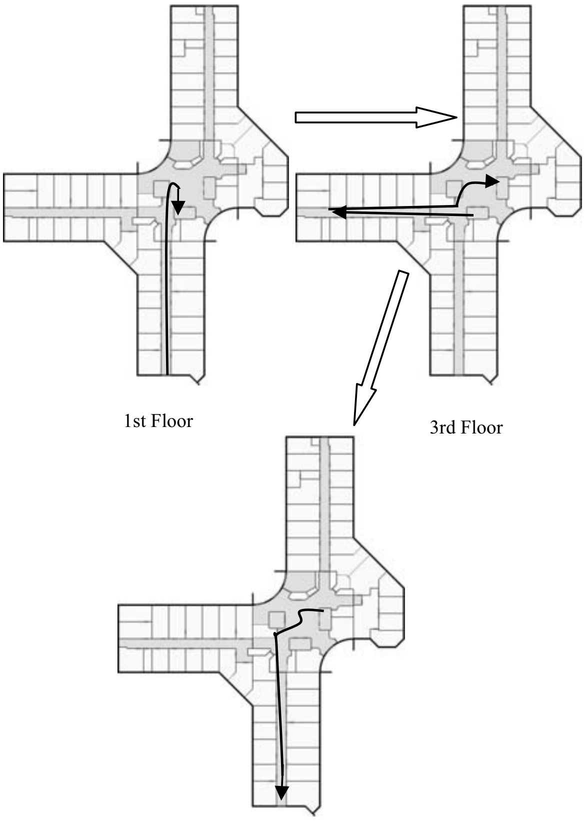

Fig.7. The walking trace where the measurements are taken.

WLAN signals and the building map information to infer 3-D indoor locations.

TABLE III
RESULTS OF FUSING RSS, BAROMETRIC SENSORS AND BUILDING MAP INFORMATION

	RSS Based Algorithm	Fusion Algorithm
3-D Location Error (m)	7.71	3.54
2-D Location Error (m)	4.96	3.54
Location Error in the Elevators (m)	8.70	1.28
Percentage of False Floor Estimation	8%	0

V. CONCLUSION

In this paper we investigate the possibilities of combing the measurements from a barometric sensor with WLAN received signal power and building information to obtain an accurate 3-D indoor localization. We propose two novel fusion algorithms. The first one is an adaptive self-calibrating method to fuse the barometric sensor measurement with the building information, i.e. the floor height, to accurately identify the floor on which the mobile device is situated. The second step is the fusion of the results from the barometric sensor based algorithm and the RSS based localization algorithm. Our experiments indicate that by the above fusion, not only a floor index can be inferred without errors, but the horizontal location accuracy can also be improved remarkably.

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