On Automated Map Selection Problem in Indoor Navigation for Smart Devices

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***Abstract*—For outdoor navigation, we use unique and publicly available Google maps. For indoor navigation, we use separate maps which are not available everywhere. A challenging problem in indoor navigation is to find a method to automatically select the appropriate map in a multi-floor building. In this paper, we present a map selection model and assisted algorithms, which uses GPS (satellite number and user location) to detect indoor/outdoor transition and barometer to determine which floor we are at currently. Several scenarios are designed to collect raw data and analyze the character on different floors of the Atwater Kent Laboratory at Worcester Polytechnic Institute. A general solution with optimized parameters is made from the aspect of false alarm and time delay.**

I. Introduction

In the highly-developing society, smart phones with accurate and reliable Global Positioning System (GPS) can easily leads you to the right place. However, outdoor navigation alone cannot meets people's needs to reach certain places, especially when the destinations are located at some complicated indoor environments such as schools or hospitals, where the ubiquitous GPS is challenged.[1][2][3][4][5] To implement indoor navigation[6], not only new equipment and technologies should be used, but outdoor maps should be replaced with indoor maps. Moreover, maps of different floors in multi-floor buildings differ from each other, which makes it more complex to choose a proper map. Then here comes the map selection problem: if one is going from outdoors to indoors, or going between different floors inside a building, how can the maps be selected automatically to serve the accurate and in-time navigation?

This map selection problem can be divided into two parts: outdoor-indoor transition and multi-floor transition. For the first part, decision should be made to determine whether the user is indoor or outdoor (can be viewed as intruder detection problem)and the corresponding map should be selected as soon as the current condition changes. For the second part, detection should be made to determine which floor is the user located at a specific time and the map should be selected to represent the correct floor. Although the map selection problem seems straightforward, there still exists some difficulties in making the decision accurate and in-time:

- Different buildings have different geometry (doors, corridors, and windows) and equipment (stair and elevator), which makes it extremely complex to detect transition.
- Smart phones have various sensors, and we should decide what sensors can be used to solve the problem and whether they can be fused for better performance.

In this paper, we present a standard method which can be used to solve automated map selection problem, for either intruder or floor detection. We also design several algorithms according to the data gathered from the sensors, compare their performance, and give an general solution. We aim to develop a simple and state-of-the-art approach which can be used into smart phone application in the future.

In the following section, we will review some related works. Section III describes the methodology as well as an overview of the algorithmic components of the map selection system based on the GPS radio and barometer. Test bed, scenarios and results are outlined in Section IV while conclusion is made in Section V.

II. Related Works

Since smart phone is powerful with various embedded sensors (Barometer, Gyroscope, etc.) and other applications (WiFi, GPS), approach for intruder detection can be implemented in multiple methods. Some related work has been done related to this topic.

The work described by [7] presents an approach which detects intruder for WLAN access. Least Mean Square (LMS) and Prioritized Maximum Power (PMP) are used as two RSS-based matching algorithms. Their performance of accuracy are compared in indoor and outdoor-indoor areas and PMP algorithm provides a better performance than LMS in positioning application.

An approach using fusion of sensors, WLAN signals and building information for indoor/campus localization is developed by [8]. This method shows the possibilities of combing the measurements from different sensors and building information to obtain accurate indoor localization as well as the possibilities that sensors can aid in intruder detection[9].

Some indoor personal navigation applications are introduced in [6]. Map Matching Algorithms are implemented, which make the Pedestrian Navigation Module (PNM) have the capbility to provide localization results even with bad reception of GPS signals.

Another approach is described in [7] which fuse dead reckoning (DR) algorithm, GPS, and RFID for pedestrian positioning. This method is implemented as software module

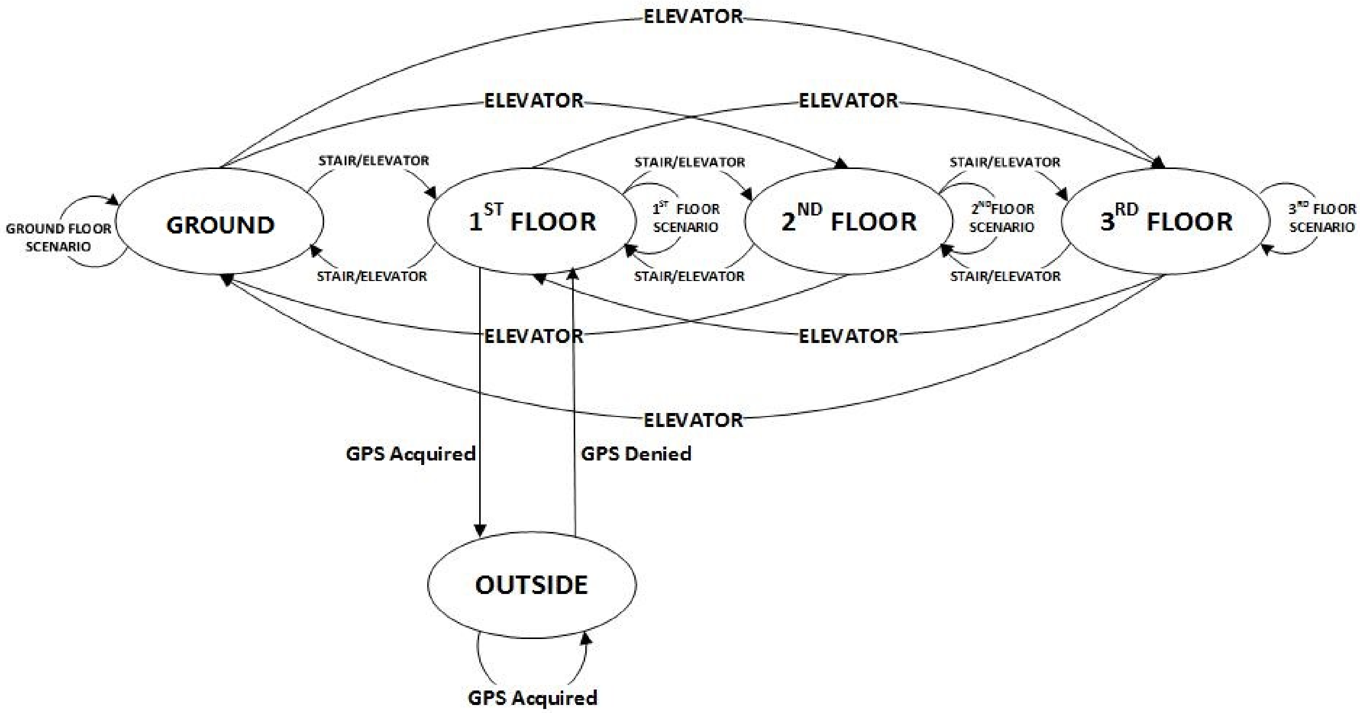

Fig. 1. State Machine

with web-based APIs on computing systems which shows that GPS and the active RFID tag system can seamlessly and effectively adjust estimation errors in DR as well as possibilities for sensor fusion localization.

III. Methodology

A. State Machine Model

Since the map is selected according to the current state (indoor/outdoor or different floors), a state machine model satisfies the problem perfectly. We design a state machine with five states: outdoor and indoor (ground floor, 1st floor, 2nd floor and 3rd floor). Now that the five states are determined, we should find suitable sensors from which data can be provided to predict the transition between different states. Commonly, modern smart phones are integrated with various sensors, such as embedded GPS radio, accelerometer, gyroscope, barometer, and etc. We tested all the sensors in outdoor, indoor and multi-floor scenarios and found GPS radio the best to determine indoor/outdoor transition while barometer the best to determine multi-floor transition.

Detection of indoor/outdoor transition will be made according to the availability of GPS radio. It's well recognized that GPS provides great accuracy in outdoor localization. But the signal is lost in most indoor environments which are hostile to GPS radio. So we can roughly determine the user is outdoor when GPS is acquired and indoor when GPS is denied. But the detection is not accurate enough in all cases, so some methods are discussed to improve the performance in the next section.

As for detection of floor transition, we exploit the properties of barometric pressure since it is tightly related to the altitude of each floor (can be calculated by using certain equations). When the user is going upstairs or downstairs, he can choose either walking the staircase or taking the elevator. These two methods show different characters in the barometric pressure readings, so we should treat them differently. More exploration will be presented in the pressure-height model.

With all the five states and triggering conditions for transition, the entire state machine is depicted in Figure 1.

B. Detecting Outdoor-indoor Transition

As is mentioned above, GPS radio is considered the best for detecting outdoor-indoor transition. From the embedded GPS radio, we can get both the Line-Of-Sight (LOS) satellite number and the estimated location at a certain moment. From these two types of data, we can design algorithms to realize transition detection.

The first arithmetical design is based on the availability of the GPS radio. State is recognized as outdoor if GPS is acquired while indoor if GPS is denied. To get a precise location estimation, more than 4 LOS satellites should be available. So at the beginning of the algorithm, we should make sure that more than 4 LOS satellites is acquired. If not, the algorithm will not work until the LOS satellite number meets the requirement. To detect the transition, we should also consider the building geometry. Since entrances of a building are the access between outdoor and indoor world, we should pay special attention to the data gathered around

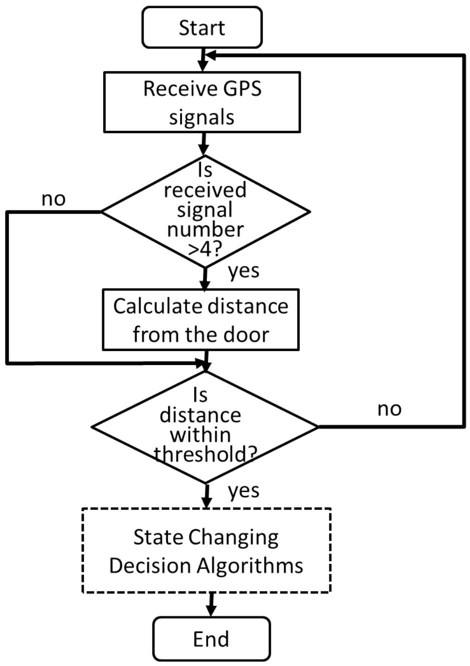

Fig. 2. Basic structure of the algorithm

the door. Consequently, the location should be around the entrance before we make a transition detection and we will ignore all the changes of the GPS status when we are far from the entrance.

The basic structure of the algorithm is shown as Figure 2. It starts by receiving the GPS signal from the phone, and compares the received LOS satellites number with 4. If the LOS satellite number is more than 4(including 4), we have enough number of signals to estimate our current location and calculate the distance from the door. If so, the value of distance will be updated and we will compare the calculated distance with a predefined threshold. If the distance is within the threshold, then we can go to the next step and the system attempts to make a decision to change the state.

The state change problem is similar to the handover problem in cellular network [10], so we design two handover algorithms for this part.

The easiest and most direct way to make a handover decision is using the availability of the GPS signal. The steps of Algorithm 1 are depicted in Figure 3. The state will change if the GPS status changes. If GPS signal is available, we decide the state as outdoor; If GPS signal is denied, we decide it as indoor.

Algorithm 1 is simple and straight, but it has great disadvantage since it will introduce numbers of false alarms, especially when the device is around the door and the GPS signal keeps changing frequently. We add some improvement in Algorithm 2 (shown in Figure 4) and the state will not change until GPS status stays the same for a certain period of time. The decision not only depends on the current status of GPS signal, but the maintenance of the GPS signal.

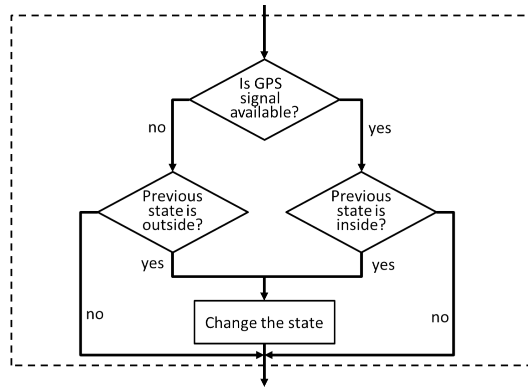

Fig. 3. Decision algorithm 1: using only GPS access to make the decision

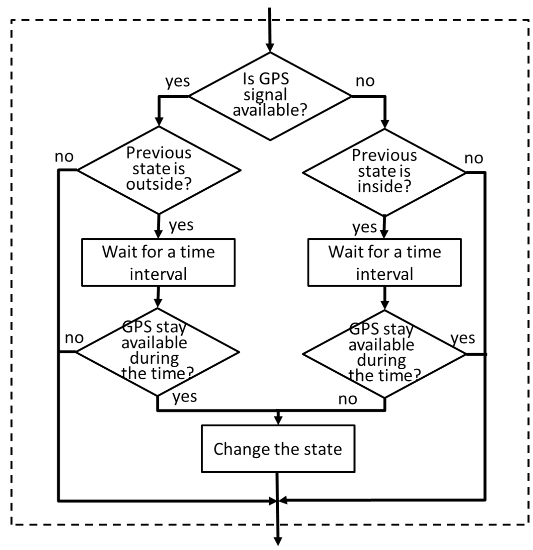

Fig. 4. Decision algorithm 2: using GPS access and time delay to make the decision

C. Detecting Multi-floor Transition

Detection of floor transition should be considered in another way since the barometric pressure readings has a different property from the satellite data. A pressure-height model is constructed so that we can calculate the altitude of a certain location from which the floor transition can be determined. What's more, new algorithms are explored to eliminate the effect of some factors (noise, bias) in the pressure-height model and analyze the transition progress. The following two sections will discuss more about these two aspects.

1) Pressure-height Model: Barometric pressure is exploited for detecting multi-floor transition since it is related to the altitude of the current location. According to the International Standard Atmosphere Model formulated by International Civil Aviation Organization, their relation can be represented and derived by equation 1.

$$p = p_0 \times (1 - \frac{L \times h}{T_0})^{\frac{g \times M}{R \times L}}$$
$$\approx p_0 \times (1 - \frac{g \times h}{c_p \times T_0})^{\frac{c_p \times M}{R}} \quad (1)$$
$$\approx p_0 \times exp(\frac{-g \times M \times h}{R \times T_0})$$

All the parameters used in the pressure-height equation is shown in Table I. From the equation above, altitude can be calculated from barometric pressure, which is derived as follow:

TABLE I
PARAMETERS USED IN PRESSURE-HEIGHT EQUATION

Parameter	Description	Value
p_0	Standard atmospheric pressure	101325 Pa
L	Temperature lapse rate	0.0065 K/m
c_p	Constant pressure specific heat	1007 J/kg*K
T_0	Sea level standard temperature	288.15 K
g	Gravitational acceleration	9.80665 m/s^2
M	Molar mass of dry air	0.0289644 kg/mol
R	Universal gas constant	8.31447 J/(mol*K)

$$h = -\frac{R \times T_0}{g \times M} \times ln(\frac{p}{p_0}) \quad (2)$$

Basically, we can calculate altitude from air pressure according to equation 2, however, data gathered from the smart phone suffers great noise, bias, and time difference, which will affect the precision of the transition detection. The following three sections will have a deeper look at these three factors.

Noise causes the change of raw pressure readings in a fixed floor. This change is slow with a small range, and after fitting it into different distributions (shown in Figure 5), we find it an ideal Gaussian-distributed noise with zero mean (white noise). To eliminate the effect of noise, we use a simple low-pass filter, which will be discussed later.

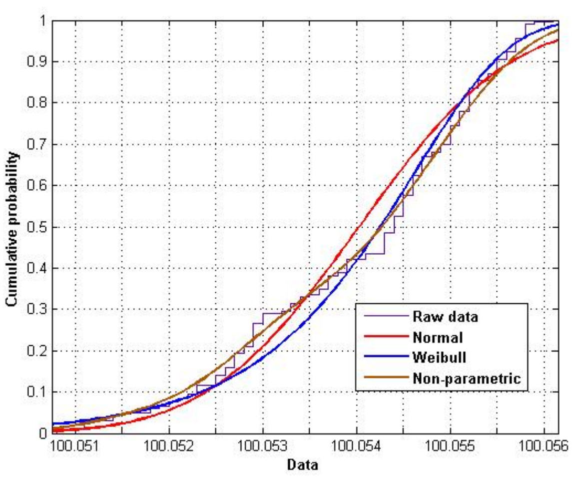

Fig. 5. Distribution fit for noise

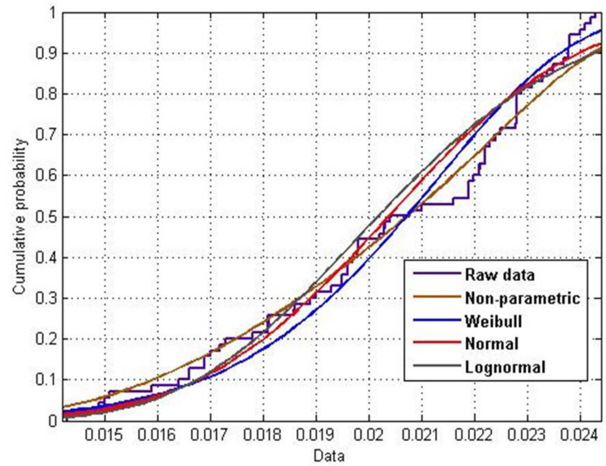

Fig. 6. Distribution fit for bias

Bias is the difference of raw pressure reading caused by different devices. In our experiment, we use two different barometers to measure the air pressure and fit their difference with different distributions (shown in Figure 6). We find that bias is also Gaussian-distributed with a certain mean value. Note that although we can model bias between different devices, in reality we don't need to put it into consideration in localization. The reason is that during the navigation, the device is fixed and we don't need to know the difference.

Time difference is the most uncertain part in the pressure-height model. From equation 1we can see that some physical factors will affect the barometric pressure, such as temperature and humidity (which will change during the time), then at different time, we will get pressure data with extremely great difference. For example, the barometric pressure in winter is much higher than that in summer in a fixed place at the same time during a day.

Fortunately, when we are using the model to deal with localization, we can assume that the time duration is so small that we don't need to consider time difference anymore.

When noise, bias and time difference are considered, the equation should be written as follow:

$$h' = -\frac{D \times R \times T_0}{g \times M} \times ln(\frac{p + N + B}{p_0}) \quad (3)$$

Where N represents noise, B represents bias and D represents time difference.

2) Smoothing: Since raw pressure reading contains some noises, which may distort the result and affect threshold value choice, and thus influence the detection of floor transfer. To eliminate those noise, we adopt double exponential smoothing to produce smoothed data. The basic idea of double exponential smoothing is to take account of the trend estimation, this technique works as follows: x_t is the raw data set, $s_t$is the smoothed value set, $b_t$is the best estimation value of the trend.

For initial value,

$$\begin{aligned} s_1 &= x_1 \\ b_1 &= x_1 - x_0 \end{aligned} \tag{4}$$

And for $t > 1$,

$$\begin{aligned} s_t &= \alpha \times x_t + (1-\alpha) \times (s_{t-1} + b_{t-1}) \\ b_t &= \beta \times (s_t - s_{t-1}) + (1-\beta) \times b_{t-1} \end{aligned} \tag{5}$$

α is the data smoothing factor, $0 < \alpha < 1$, and is the trend smoothing factor, $0 < \beta < 1$. The smoothing factor means how much recent changes weights to result. In this case, factor values close to zero have more smoothing effect and are more responsive to recent changes. Considering the distortion and calibration, we use 0.3 for α and 0.2 for β. It effectively removes the noisy peak and showed smoothed readings.

3) Algorithms for Detection: The algorithm used for transition detection is quite similar with the ones used for intruder problem, the difference lies in that we use the pressure readings variance as the parameter that used as the threshold to determine floor transition.

To identify whether it is a floor transition mode or not, we just need to figure out prominently pressure variance, which can be realized by applying 1st derivation to pressure reading and setting thresholds. After smoothing the derivative result, there is still some noise and transient oscillation, which might cause bias and effect detection accuracy. The main basis of floor detection is comparing derivative result with threshold, therefore identifying the transition. According to that, we should compare period result behavior with threshold value and avoid transient oscillation influence. And setting a D_buffer, which to store 1st derivative value in a 15 seconds period, could effectively solve our problem. The D_buffer is triggered every 5 seconds. And after analysis the result data, we find both in stair mode and elevation mode, the threshold could be 1.3. If there are 10 data value in the buffer are larger than threshold, then transient value influence minimized and floor transition identified. The algorithm is shown in Figure 7 in detail.

IV. Test-bed, scenarios & Data Collection

A. Test-bed

Test-bed is inside and outside the Atwater Kent (AK) building in Worcester Polytechnic Institute (WPI). The experiments are mainly composed two parts: the first is mainly focusing on the spots around three doors (shown and labeled in Figure 8) on the first floor; the second part is mainly measuring barometric pressure on different floors under different mode and detecting floor changing using pressure-height formula.

We conducted several experiments using different mobile phones. Android phone (version 4.3) is used in this experiment to collect GPS data, iPhone 6 and iPhone 6 plus is used to collect barometric pressure data(the M8 motion coprocessor offers elevation data from new barometer), and Matlab is used to do data analysis.

Algorithms for floor transition detection

```
        Num_sample <-- number of qualified samples in 15-sec-
ond buffer
        DEM <-- Double exponential smoothing
        DEV <-- 1st derivation
Inputs:  P <-- raw pressure value
    D-raw <-- 1st pressure derivation value
    D_buffer <-- 15 second buffer of 1st pressure derivation
value
Outputs:  FLOOR_CHANGED state
THRESH1 <-- 1.3(threshold of 1st pressure derivation value)
THRESH_EXCEED <-- false
C_Dev <-- DEV(P)
D_filt <--DEM(C_Dev)

IF (D_filt > THRESH1)
    THRESH_EXCEED == TRUE
END IF
(Every five seconds triggers D_buffer starts from current
second, during the buffer period)
FOR i=1:1:15
     IF(THRESH_EXCEED)
     Num_sample = Num_sample + 1
     END IF
  IF Num_sample >=10
  THEN return FLOOR_CHANGED
  END IF
```

Fig. 7. Floor detection algorithm

B. Scenarios & Data Collection

We designed five different scenarios for these three doors. The first three scenarios are designed for movement nearby the doors without crossing them and movement across the doors (shown in Figure 8):

- Scenario 1: Door 1 (In-Out, In, Out)
- Scenario 2: Door 2 (In-Out, In, Out)
- Scenario 3: Door 3 (In-Out, In, Out)

The other two scenarios are designed for some special spots (dirty spots) since in some part around the building (near Door 3 in this experiment), sometimes we have GPS access indoor and sometimes we cannot get any signal outdoor.

- Scenario 4: Outdoor/ GPS signal denied
- Scenario 5: Indoor/ GPS signal available

Fig. 8. Scenarios at Three Doors

With the five scenarios above, we collect data from the Android phone in every 10ms and create a database around the three doors. We can have two sets of data, which are LOS satellite number and estimated location at one specific position. Given the database, we can evaluate the error performance at different positions and use algorithms described in the previous section to make intruder detection.

We also carried out four different scenarios for multi-floor detection. In the first scenario, we record barometric pressure while the user was walking and collecting data in the same floor with the mobile phone. In the second scenario, the pressure data was collected while the user walked upstairs and downstairs. In the third scenario, we moved between different floors by elevator and measured pressure data. In the fourth scenario, the same phone was laid in four different places in third Floor and collecting pressure. The fourth scenario is designed to detecting time errors as a component of our pressure-height model.

- Scenario 1: collecting pressure data in same floor
- Scenario 2: collecting pressure data while changing floors in walking mode
- Scenario 3: collecting pressure data while changing floors in elevator mode
- Scenario 4: collecting pressure data in different spots on same floor under stationary mode

With the four indoor scenarios mentioned above, the raw pressure data set is built. By filtering and applying statistical analysis to the data, we get the noise and bias distribution model of the pressure reading and the characteristic of the trend. Given these analysis, together with the existing physical pressure-height formula, the pressure-height model of this paper could be built, including noise and device bias components, which helps floor detecting and supports indoor mapping selection research.

V. Results & Analysis

A. Histogram, Error Range & CDF of Estimation Error

The histogram for different LOS GPS satellite number is shown in Figure 9. We can see that three doors show different GPS signal characters in the histogram. The difference comes

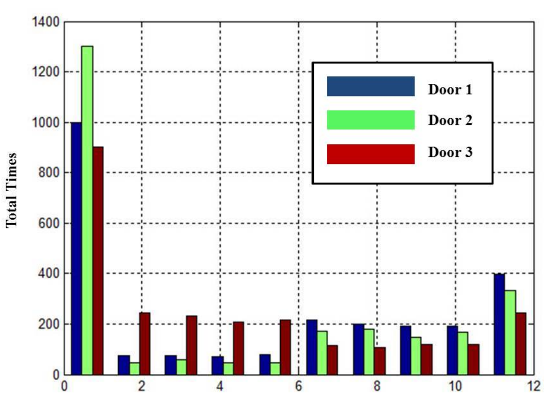

Fig. 9. Histogram of the GPS signal in the database

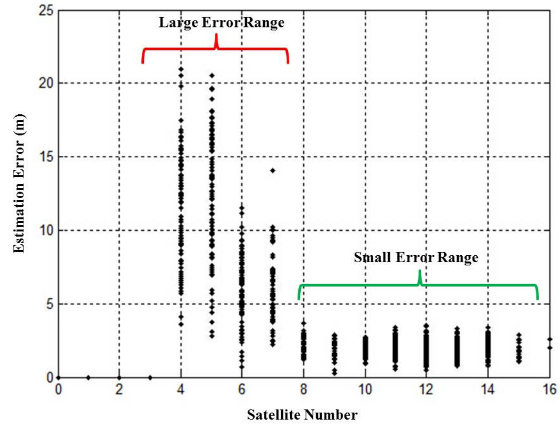

Fig. 10. Error range of the estimation by using different number of satellites

from the different geometry of these doors. There are various factor which affects the geometry: the number of doors, the opening shape and the surroundings (especially windows).

From estimated location in a certain location, we can find the estimation error in this position and relate the error to the LOS satellite number in the position we can have the error range shown in Figure 10. From the plot we can see that when we only get 4 or 5 LOS satellites in one position, the estimated location becomes inaccuracy while we have more than 6 LOS satellites, the error range falls and accuracy increases.

Plot cumulative distribution function (CDF) of the estimation error vs LOS satellites number in Figure 11. We make satellite number into two groups, one with more than 4 LOS satellites while the other only has 3 or 4 LOS satellites. We can see in the plot that with greater LOS satellite number, we have better estimation error performance.

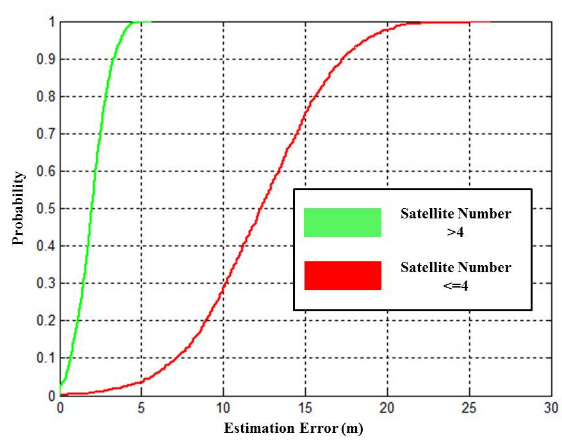

Fig. 11. CDF plot of the estimation error by using different number of satellites

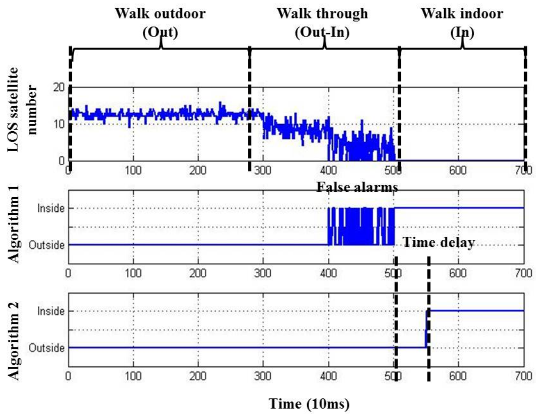

Fig. 12. State decision when going around Door 1

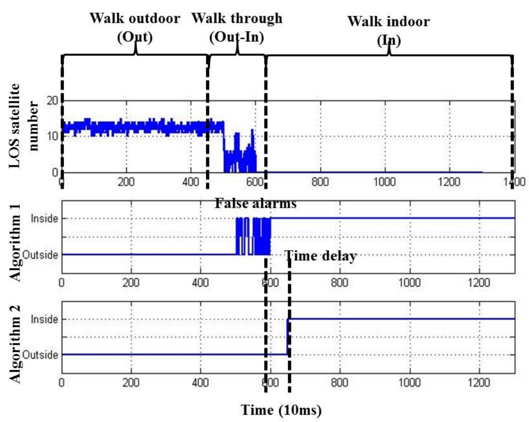

Fig. 13. State decision when going around Door 2

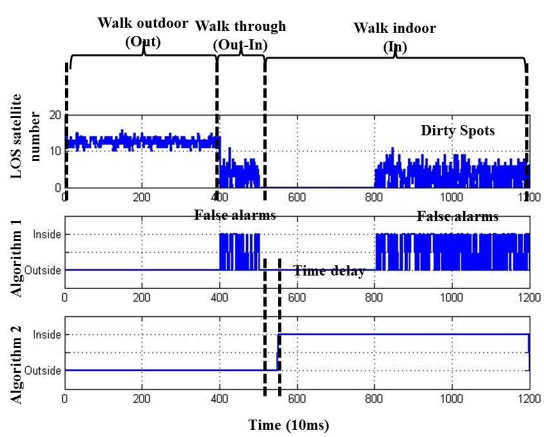

Fig. 14. State decision when going around Door 3

B. Performance Comparison of Algorithms

Figure 12-14 show the intruder detecting progress. The first plot in every figure shows the original data (LOS satellite number) at every position while walking in the scenario. The second and third plots are the detection results of Algorithm 1 and 2 respectively. We can see clearly that for Algorithm 1, there are always great number of false alarms since the GPS status changes frequently while we are walking through a door. Algorithm 2 shows significant improvement in eliminating the false alarms. However, it introduces some delay, which degrades the continuity of the system.

Dirty spots in the scenario of Door 3 greatly affect the detection accuracy. We can see in Fig. 11 that even if we are indoor, the LOS satellite number remains to a certain scale that which brings lots of false alarms. To eliminate the effect, we should make a large wait time to make sure that the current state is stable. As long as the state is decided as stable, we can make a accurate detection.

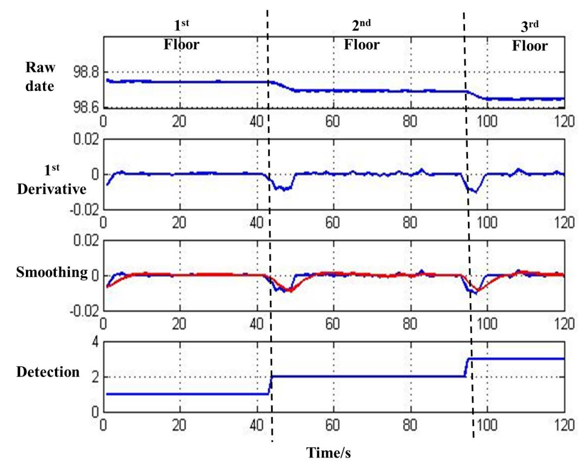

Fig. 15. Floor decision for elevator

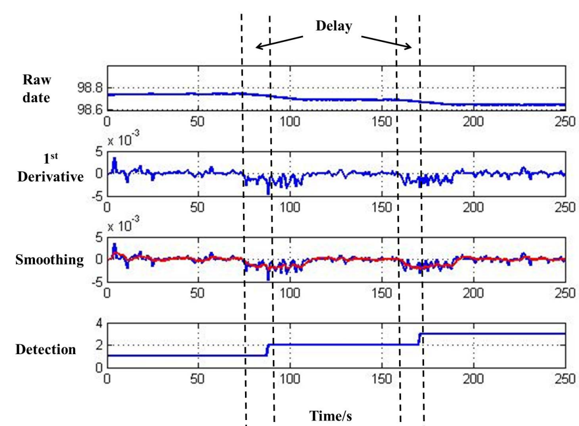

Fig. 16. Floor decision for stair

Figure 15 and 16 show the multi-floor detection progress for elevator and stairs. The first plot in every figure shows the original data (air pressure) at every position while walking in the scenario. The second and third plots are first derivative and its smoothing respectively. We can see clearly that after smoothing, it is more clear for us to see the transition between two floors. The fourth plot shows the detection results by using the algorithms described above.

VI. Conclusion

In this paper, we present an approach to make intruder detection by analyzing GPS data and make multi-floor detection by using barometer in smart devices. We design scenarios on different floors in Atwater Kent laboratory and conduct series of experiments to collect data. By relating the estimation error with the LOA satellite number, it shows that estimation becomes more accurate as the LOS satellite number becomes greater. Based on the pressure-height physical law, we take the first derivative of the barometer and use pressure variance to detect floor transition. The handover algorithms are used to automatically detect intruder and multi-floor transition, and the experiment show that the algorithm performs well in indoor building and for any type of transport modes(stairs and elevators). To precisely identify which floor, we also consider noise, device bias and time difference in our pressure-height model.

Future work includes: To expand our system to other kind of building, such as hospital, shopping mall, airport, and develop a more general solution. Fully combining the intruder detection, floor transition detection and floor identification technique, and try to provide a continuous indoor map selection system. Refine our pressure-height model, and bring up a precise time difference model. Integrate our technique into 2D indoor localization system to provide 3D localization.

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