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An indoor localization solution using Bluetooth RSSI and multiple sensors on a smartphone

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Abstract In this paper, we propose an indoor positioning system using a Bluetooth receiver, an accelerometer, a magnetic field sensor, and a barometer on a smartphone. The Bluetooth receiver is used to estimate distances from beacons. The accelerometer and magnetic field sensor are used to trace the movement of moving people in the given space. The horizontal location of the person is determined by received signal strength indications (RSSIs) and the traced movement. The barometer is used to measure the vertical position where a person is located. By combining RSSIs, the traced movement, and the vertical position, the proposed system estimates the indoor position of moving people. In experiments, the proposed approach showed excellent performance in localization with an overall error of 4.8%.

Keywords Bluetooth · RSSI · Accelerometer · Magnetic field sensor · Barometer · Indoor positioning

1 Introduction

Location is one of the most important contextual factors for certain services; not only navigation services, but also social networking sites (SNSs) such as Facebook, Instagram, and even Uber, use location information. The demand for more accurate location information has increased commensurate with increases in the number of location-based services and expectations of better

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service. The Global Positioning System (GPS) is one of the most significant achievements in this respect [1]. GPS describes a walking person's location with less than 3 m error under optimal environmental conditions. However, GPS has several disadvantages, such as time delay and spatial limitations. Regarding the time delay, there is a latency in receiving location information from the satellites. Assisted GPS (A-GPS) is one solution to this problem. A-GPS uses networks to reduce the time taken to receive information from the satellites [2]. Concerning the spatial limitation, the receiver should be in an open space to receive GPS information; 3G/4G/WiFi signals can be used to complement GPS. From a basic location, where base stations or access points exist, the position of a receiver can be calculated. However, this method has a major weakness: it is simply too expensive to install sufficient base stations and access points. Thus, there is a need for accurate determination of a walking person's position in indoor space, which the GPS signal does not reach, with better cost efficiency.

This paper proposes a system that estimates the indoor position of a walking person with ease and cost efficiency. The proposed system uses three features: Bluetooth received signal strength indication (RSSI), movement, detected by an accelerometer and a magnetic field sensor, and atmospheric pressure, obtained from a barometer. As many smartphones possess all of these sensors, the proposed system provides information on the indoor position of a walking person using a smartphone and Bluetooth beacons.

The basic position of a walking person is determined by Bluetooth RSSI. This signal is easily interfered with by the particular conditions of a given space, so movement and atmospheric pressure are used to compensate for the imprecision of the RSSI-based position information. The horizontal position of a walking person is estimated according to its movement and RSSIs, while the vertical position is estimated from the atmospheric pressure. By combining these horizontal and vertical positions, the system determines the current position.

The main contributions of this paper over the previous work are as follows:

1) The proposed method executes in a smartphone and employs existing sensors in a smartphone.
2) The proposed method is an ensemble method which combines the advantages of features to estimate more accurate position of the walking person in the space.
3) The proposed method uses atmospheric pressure to estimate the horizontal position of a walking person and rule-based approach to recognize the semantics of the obtained atmospheric pressure.
4) As the estimated position of a walking person can be provided to other services and applications, applications which require to recognize the position of a walking person can be easily developed using the proposed method.

The remainder of this paper is divided into four sections: related work is described in Section 2; the methods of the proposed system are shown in Section 3; the experiments and results are discussed in Section 4; and conclusions are provided in Section 5.

2 Related work

Various studies have been concerned with the provision of accurate location information. These studies can be categorized into two types: outdoor- and indoor-related. Satellite-based positioning systems are used outdoors. GPS, GLONASS [3], Galileo [4], and BeiDou [5] fit in this category. A system used indoors is called an indoor positioning system (IPS). It is hard to use satellite-based systems in indoor spaces because the signals from the satellite may not reach the interior of buildings. Therefore, instead of using signals from satellites, IPS uses local information, which is specific to a given space. There are five IPS methods.

The first and most widely used method is a signal-based method [6–8], which uses signals from an ad hoc positioning system (AP), with the position of the receiver determined from these signals. The signal-based method has two main approaches: trilateration [9] and fingerprinting [10].

To use trilateration, at least three signals are needed. According to the received signal strength, the distances to the each generator are calculated. Using these distances, the position of the walking person is extracted. Trilateration consists of two steps: calculating the distance between the AP and the receiver, and applying the trilateration calculation. Thus, the most important factor in trilateration is to ascertain the exact distance between the AP and receiver. There are various methods to obtain the distance, such as RSSI [11], time-of -flight (TOF) [12], and time-difference-of-flight (TDOF) [13]. Although all of these methods are based on the signal, a difference lies in whether the flight time or strength of the signal is used. Thus, these methods all depend on the nature of the signal. Such signals are easily interfered with by walls, humans, and other obstacles. Diminished, reflected, or diffracted signals result in errors. To reduce such errors, compensatory methods are used. For example, APs are usually installed in the ceiling to reduce signal interference. However, the signal is dependent on the characteristics of the space, so RSSI-based distance detection should be carefully adjusted for every deployment.

For fingerprinting, a given space is divided into small cells and a radio map, which shows the strengths of signals at every cell, is made. In every cell, the pattern of signals is measured. This pattern becomes the "fingerprint" of the cell. By comparing the strengths of signals, that the walking person received, to each cell's fingerprint, the cell where the walking person exists can be located. The main disadvantage of this method is that the cost of generating the radio map is too high and whenever the devices that generate the signals are replaced, removed, or added, the radio map has to be updated. A method for generating a radio map easily is the key issue in fingerprint method-related research. The main disadvantage of any signal-based method is that the signal is easily interfered with. However, the actual process of detecting a walking person's position is simple and easy to understand [14].

The second IPS method is pedestrian dead reckoning (PDR) [15]. This method senses a pedestrian's movements. When the starting point is given, the current position of a given person can be retrieved by tracking their movement (e.g., walking). This method produces acceptable results over short distances, but errors accumulate. As the stride changes dynamically according to the height, speed, and walking characteristics of a person, ascertaining the exact step length, and the number of steps, becomes important to reduce errors. To apply PDR over long distances, a correction needs to be executed periodically.

The third IPS method uses geomagnetism [16]. The pattern of a geomagnetic field is used as the fingerprint for each space. With a premade pattern map, the position can be estimated without the need for an additional device. However, it is difficult to classify similar patterns and the geomagnetism signal is easily interfered with by minor changes such as movement of the device, nearby elevators, or cars in an underground parking lot.

The fourth IPS method uses light patterns based on LED lights [17]. This method uses a light pattern to make a fingerprint map of a given space; a camera is required, facing ceiling on which the lights are installed.

The final IPS method uses computer vision [18]. The camera can be attached on a person and from the view of walker, the position can be extracted [19]. The camera can be attached on fixed place in the given environment like CCTV [20, 21]. If the camera on the walking person's smartphone gains a view of a registered landmark, the position of that walking person can be estimated. This method requires no devices in addition to the camera and an image database. However, the image processing required with this method, is much more difficult compared to that of the other methods.

In this paper, we use a signal-based method and PDR to estimate horizontal position. The RSSIs from Bluetooth beacons are used to calculate the distance by trilateration, and PDR is used to compensate for interference in the RSSIs. The vertical position is also estimated from the atmospheric pressure obtained from a barometer.

3 Proposed system

The objective of our proposed system is to provide indoor position information with high accuracy and cost efficiency using sensors embedded in a smartphone. To achieve this, the system uses three features: Bluetooth RSSI, PDR, and atmospheric pressure. Bluetooth RSSIs correspond to the strength of signals received from the beacons [22]. Although Bluetooth beacons are easy and cost efficient to install, it is difficult to determine an exact location with RSSIs alone because of interference. PDR is a way of tracing the movement of a person. With this movement, the uncertainty of RSSIs is reduced. The atmospheric pressure is used to estimate the vertical position, i.e., the floor on which a walking person is located. By combining these features, the indoor position of the walking person can be calculated.

3.1 Bluetooth RSSI

As mentioned previously, the Bluetooth RSSI denotes the strength of signals received from the beacons in a given space. The Bluetooth RSSI has several advantages compared with WiFi and radio frequency identification/near filed communication (RFID/NFC). A Bluetooth beacon can send additional data. According to the iBeacon specification (Fig. 1), 4 bytes, which are assigned for Major and Minor factors, can be used to send data without any additional process of data transmission [23].

If this specification is not used, then the 9 bytes for the iBeacon Prefix can also be used for private purposes. This paper is concerned with the iBeacon specification; the 4 bytes of additional data are used only to represent the location of the beacon. The location of the

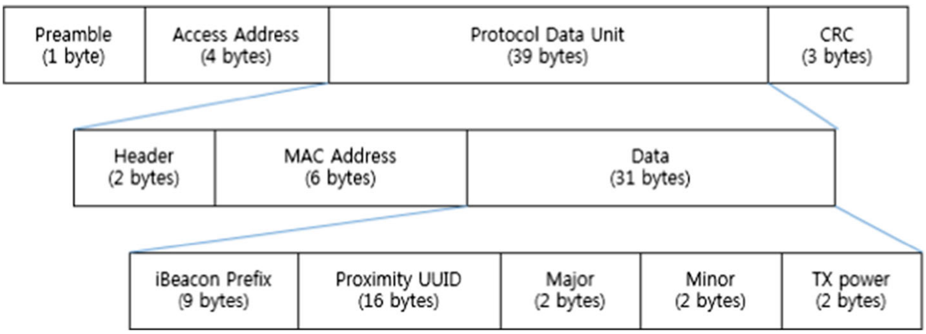


Fig. 1 The information structure of iBeacon

Fig. 2 Modified data format for representing a beacon's location

Floor (7 bits)	Area Radius (11 bits)	X position (7 bits)	Y position (7 bits)

beacon is represented in the format shown in Fig. 2. The first 7 bits represent the floor on which the beacon is located and we assume that most buildings have fewer than 128 floors. The next 11 bits represent the total area of the building and we assume that the area of most building is less than 4000 m^2. The next two values represent the x, y position of the beacon (data provided as percentages).

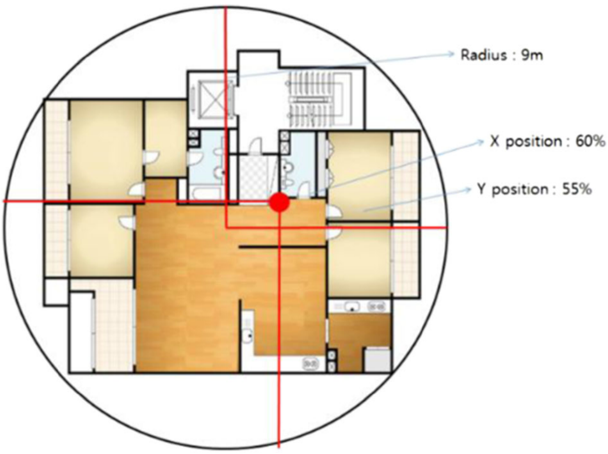
For example, if a beacon is placed in a certain indoor space (Fig. 3), the location data will look like this: "0000001 (first floor) 00000001001 (radius 9 m) 0111100 (x position: 60%) 0110111 (y position: 55%)." The x-axis represents the east-west direction. The y-axis represents the north-south direction. The distances between beacons and the receiver are calculated using RSSIs and, by combining the beacons' locations, the receiver's location is obtained. At least three beacons are used, for trilateration.

Using the beacon's RSSI and its location information, the distance between the receiver and the beacon is calculated using the Friis eq. [9]. To use this formula, we apply the following constants: 300,000 km/s for speed, and 2.4 GHz for frequency. With three distances, trilateration determines the position of the receiver. However, this method does not consider interference with RSSIs resulting from the particular characteristics of a given space.

As shown in Fig. 4, the RSSI is influenced even by the location of the smartphone. The results are the average of six experiments conducted with an iPhone 5 (Apple Inc., Cupertino, CA, USA). Apple Inc., which designed the iBeacon protocol and its specifications, recommends not using RSSI-based distances, but instead employing categorized tags such as 'Immediate,' 'Near,' and 'Far.', where 'Immediate' means less than 1 m; 'Near' is less than 3–5 m; and 'Far' is further than 'Near.' However, these approximated distances are insufficient to determine an indoor position accurately.

In this paper, we use the beacons, which announce their own position with the protocol in Fig. 2. However, RSSIs are easily interfered with and are not sufficient to detect the correct position of a walking person. To reduce ambiguity, the system uses two additional features: traced steps and atmospheric pressure.

Fig. 3 Example of the position of a beacon



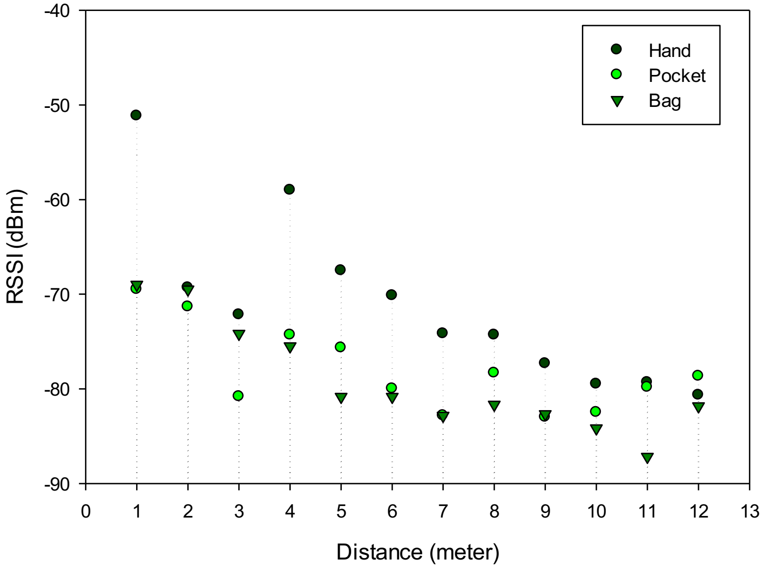


Fig. 4 Changes in received signal strength indications (RSSIs) according to distance and carrying position

3.2 Traced steps of a person

Here, the movement of a person is detected using an accelerometer and a magnetic sensor. As these sensors are present in many smartphones, the system does not require any additional device. These sensors generate two kinds of information: the direction and number of steps. To determine direction, a compass, which comprises the accelerometer and magnetic sensor, is used together with information regarding changes in RSSIs. The magnetic field signal obtained from the magnetic sensor changes continually according to the position of the smartphone. Thus, the compass is not guaranteed to accurately record direction information unless the smartphone is placed flat with its display side pointing up. Because this paper does not cover the method for making a robust compass, we assume that a person carries a smartphone in a fixed position. As shown in Fig. 5, the direction varies according to the steps taken by the walking person. Figure 5 is the result of four right-angle turns after four steps. The standard deviation of this vibration is less than 20°. Thus, the direction is determined as the average of direction changes when the rotation is less than the standard deviation. After the direction is determined, whether the movement is forward or backward is determined by comparing the changes in RSSIs.

To detect the moving distance, data on the number of steps and the direction of every step are used. The number of steps is calculated using the signals obtained from the accelerometer. According to the position in which the walking person holds the smartphone, and their physical state such as bending, turning, kneeling, or jumping, different signals are obtained. Despite this variation, the number of steps can be estimated by counting the peaks that exceed a threshold of activity, which is calculated as the root of the sum of the squared accelerations of the x, y, and z axes. Figure 6 shows an example of acceleration over 20 s of walking. The participant took four steps on four occasions during the 20 s period plus a right-angle turn. To estimate the final position after walking, it is necessary to obtain not only the step count, but also the length of each step. The step length differs according to the ambulation situation. For example, steps taken to avoid obstacles, and steps taken by someone who has a limp, is in a

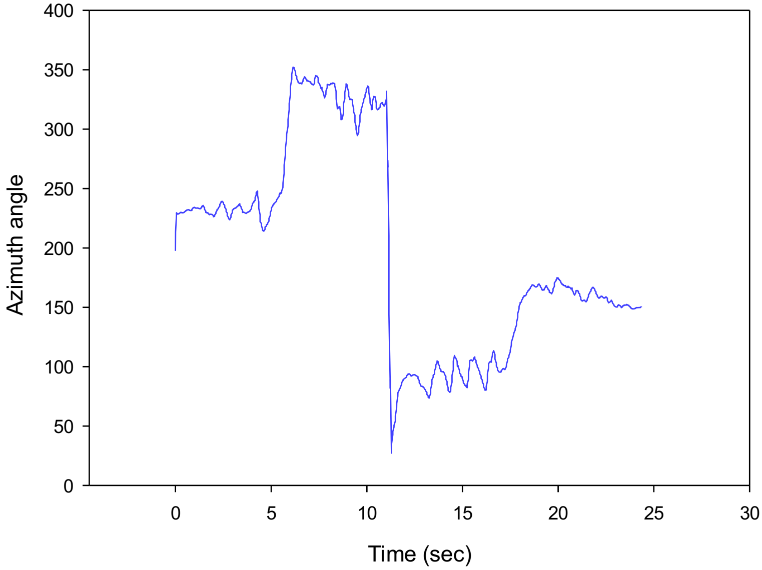


Fig. 5 Noise in the direction signal while a subject is ambulating

hurry, is tall or short – as well as steps taken in various other situations – are characterized by different stride patterns. It is beyond the scope of this paper to determine the exact step length, so we assume that every step has a fixed stride, which is determined by subtracting 100 from the walking person's height.

Using the data on moving direction and distance, this system can infer the walking position of a person. The traced position is reset whenever the smartphone receives an 'Immediate' RSSI signal. Because an 'Immediate' signal means that the current position is equal to the beacon's position, the

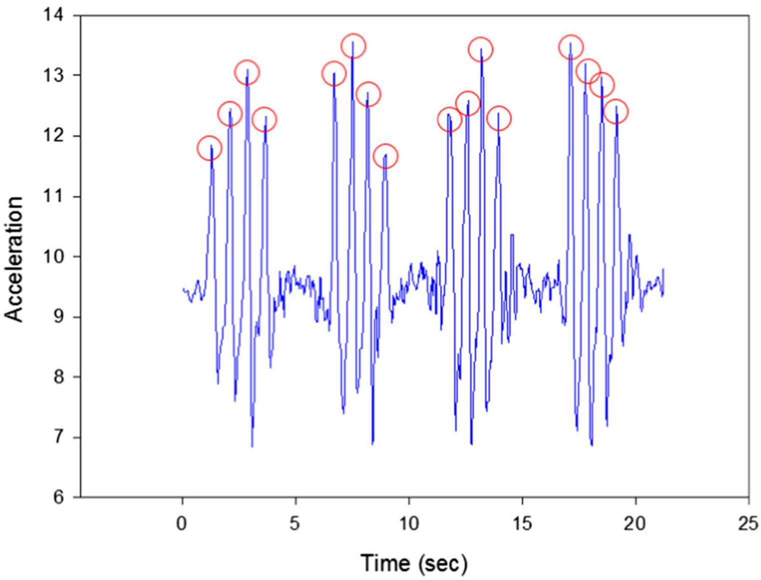


Fig. 6 Detected walking motion using the accelerometer

beacon's position becomes the base position for tracing the person's movement. Figure 7 shows how the process flows to trace the walking position of a walking person.

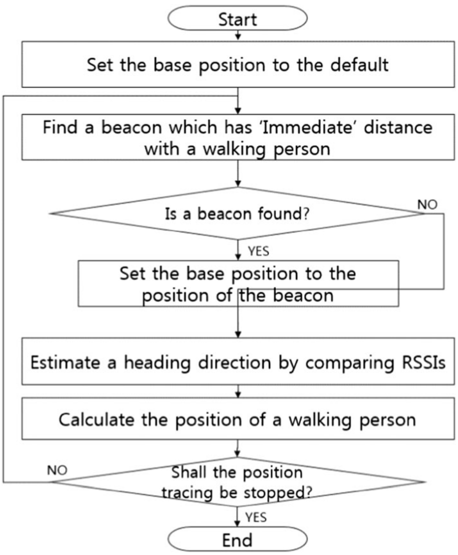
3.3 Atmospheric pressure

The vertical location is an important feature in determining the current position of a walking person. Atmospheric pressure, which is obtained from a barometer in the smartphone, is used to determine the vertical position of the person. To achieve this, three issues need to be resolved.

The first issue is that the atmospheric pressure will differ according to a building's location; for example, the atmospheric pressure on the first floor on a mountain is higher than that on a beach. Buildings that are situated on a slope may have multiple entrances that lead to different floors. In such cases, setting the base atmospheric pressure for the 'first' floor of the building is ambiguous. The second issue is that the height of floors differ among buildings; in fact, even within the same building, the height of the floors may differ. In Korea, the average height of floors is around 4 m. However, the average height of floors in residential buildings is only around 3 m. Thus, it is not possible to infer the current floor, where a person exists, with only the atmospheric pressure difference between the ground floor and the current floor. The final issue is that differences in the barometers used by different smartphones in turn result in differences in the data obtained. Figure 8 shows example signals obtained from different barometers according to floor. Fig. 8 is made with three smartphones; the HTC One (HTC Inc., Taoyuan, Taiwan), the Galaxy Alpha (Samsung, Suwon, Korea), and the LG G3 (LG Electronics, Seoul, Korea).

Thus, the system proposed herein uses additional rules for interpreting the floor on which a person is located according to the atmospheric pressure data. Table 1 shows the heuristic rules. From these rules, we get the atmospheric pressure on each floor. For example, when we get values such as (10) from Rule 1, and (8, 16, 18) from Rule 2, then Rule 3 will infer that the height of each floor is two units and a person moves to the lower floor and then to the third and fourth floors. Because we cannot be sure that the base floor is the first floor, this result does not guarantee accuracy regarding floor location; instead it shows only the relative change in the vertical position of a walking person.

Fig. 7 Process flow for tracing the walking position of a walking person



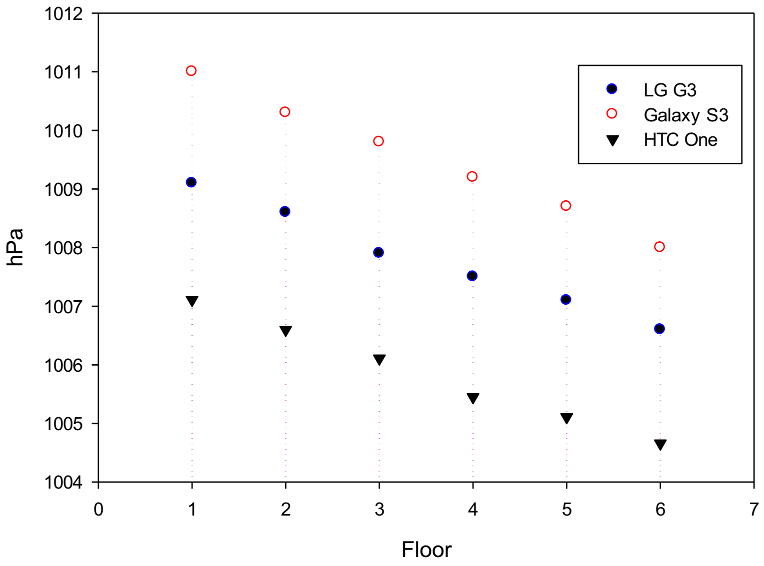


Fig. 8 Atmospheric pressure data obtained by the barometers used in different smartphones

3.4 Integration of the three features

The proposed system uses three different features to estimate the indoor position of a walking person. As the indoor position cannot be determined by a single feature, integration of these features becomes an important issue. The Bluetooth RSSI identifies persons near beacons but

Table 1 Heuristic rules for estimating atmospheric pressure of each floor

Rule 1: Base Atmospheric Pressure
GPS signal cannot be obtained indoor. Therefore, we can assume that when GPS signal is lost, the person who has GPS device enter a building. When GPS signal is lost, the current atmospheric pressure becomes the base atmospheric pressure.
Step 1. Check whether GPS signals can be obtained or not.
Step 2. If GPS signals are not obtained, set base atmospheric pressure to current atmospheric pressure.
Rule 2: Detecting Floor Change
If an atmospheric pressure is not changed for a given time, we can assume the atmospheric pressure as a current floor's atmospheric pressure.
Step 1. Let t_1 = current time when current atmospheric pressure is changed and t_1 is empty.
Step 2. Let t_2 = current time when current atmospheric pressure is changed and t_1 is not empty.
Step 3. If $(t_2 - t_1)$ > threshold, let atmospheric pressure of the current floor as current atmospheric pressure.
Rule 3: Detecting Floor Height
With Rule 2, the change of floor is detected. However, the number of floors which have been changed is not detected. In order to determine the number of floors, base floor's atmospheric pressure and difference of atmospheric pressures for each floor are required. The base atmospheric pressure is acquired from Rule 1. The current floor's atmospheric pressure is acquired from Rule 2. The minimum difference among atmospheric pressures obtained from Rule 1 and Rule 2 becomes the standard atmospheric pressure difference for a floor change.
Step 1. Let *MDV* as a minimum difference value among the atmospheric pressure of each floor
Step 2. Let n^{th} floor's atmospheric pressure as base atmospheric pressure + $(n\text{-}1) * MDV$
Step 3. Compare the atmospheric pressure calculated from Step 2 and the obtained atmospheric pressure.
Step 4. If two values are not equal, remove the calculation result and wait until Rule 2 is fired to add new atmospheric pressure.

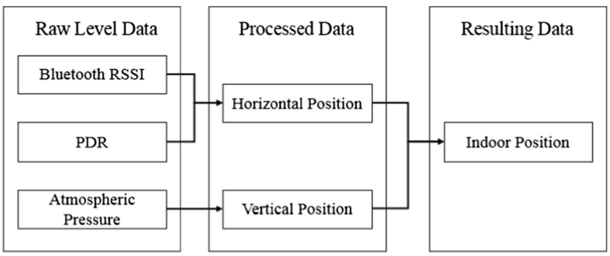
it is not reliable enough to estimate the distance to each beacon. Figure 9 shows how the features are combined to estimate the position of a walking person accurately. Bluetooth RSSIs are used to estimate the distances from beacons to a person and PDR shows the traced movement of a person among beacons. With these two features, the horizontal position of the walking person is estimated. The atmospheric pressure determines the vertical position of the walking person. By combining horizontal position and vertical position, the system determines the indoor position of the walking person.

3.5 Architecture of the proposed system

Figure 10 shows the architecture of the proposed system. Bluetooth Beacon Information Parser (BBIP) finds the nearest beacon and identifies the map as described in Fig. 3. Each beacon deployed in the area broadcasts its location as defined in Fig. 2. By parsing this message, BBIP identifies nearby beacons and the beacons location. When the distance from a beacon is short enough to be classified as ‘Immediate’, the beacon’s position is referred to make a base position of a person. Once the base position is determined, PDR Module starts to trace the walk. PDR Module calculates the number of steps using accelerometer and the direction of each step using magnetic field sensor. With these data, the position of a person from a base position is extracted. Horizontal Position Detector (HPD) has a responsibility of determining this horizontal position. When a person walks around the given space and passes by other beacon which is near enough to be classified as ‘Immediate’, the base position of the person is updated with the beacon’s position. By updating the base position and refreshing the PDR Module, the distortion of tracing PDR is restored. The cooperation of components in Fig. 10 follows the process shown in Fig. 7.

While HPD determines the horizontal position, Vertical Position Detector (VPD) determines the vertical position of a person. Rule Engine executes rules which are mentioned in Table 1. When the GPS signal lost, the atmospheric pressure obtained is set to the base atmospheric pressure as defined in Rule 1. With Rule 2 and Rule 3, VPD determines the difference of atmospheric pressure according to the floor and vertical position. The floor information is also acquired by parsing beacons’ broadcasting message. When various beacons broadcast different floor information, VPD’s vertical information is used to determine which beacons are in the same floor with the person. The combination of a horizontal position and a vertical position is the responsibility of Current Position Detector (CPD). CPD determines final position and sends the determined position to other services. As shown in Section 4.4, a remote application can acquire a person’s position by communicating with CPD which is installed in the person’s smartphone.

Fig. 9 Three features used to calculate the indoor position of a walking person



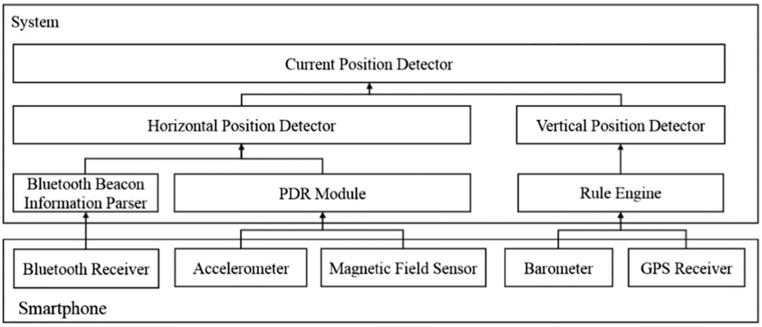


Fig. 10 Architecture of the proposed system

4 Experimental results

To evaluate the proposed system, several experiments were conducted. The experiments had four objectives: to measure the accuracy of the RSSIs, traced movements, and obtained atmospheric pressure data, as well as the combination of these three features. Five participants were recruited to the experiments and they used two smartphones: the HTC One and the Galaxy Alpha. First, they walked around a six-story building to obtain the atmospheric pressure map shown in Table 1. Then, they moved to the sixth floor, on which the beacons were installed. Each participant walked from Path 1 to Path 4, as shown in Fig. 11. Each walk was repeated five times for each smartphones.

4.1 Experiment on Bluetooth RSSI

Using the Friis equation, we estimated the distance from the phone to the beacon. Even though the RSSIs differed from ideal RSSIs according to the characteristics of the space, relative RSSIs were obtained. When a smartphone is near to a specific beacon, its RSSI is strong enough to recognize that it is located at the 'Immediate' distance. However, the RSSI of a more distant beacon is weaker than that of a nearer beacon. The HTC One and Galaxy Alpha devices were used for detecting RSSIs at distances of 1 to 14 m. The average distance of 10 tests is shown in Fig. 12.

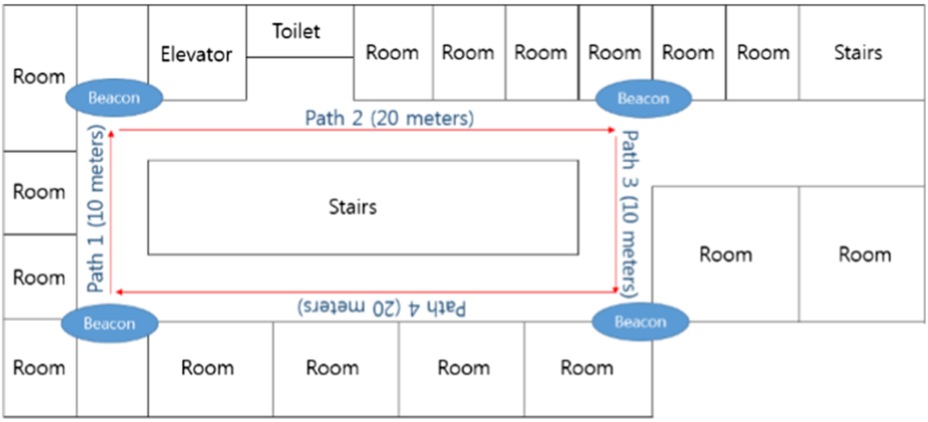


Fig. 11 The space in which the experiments were conducted

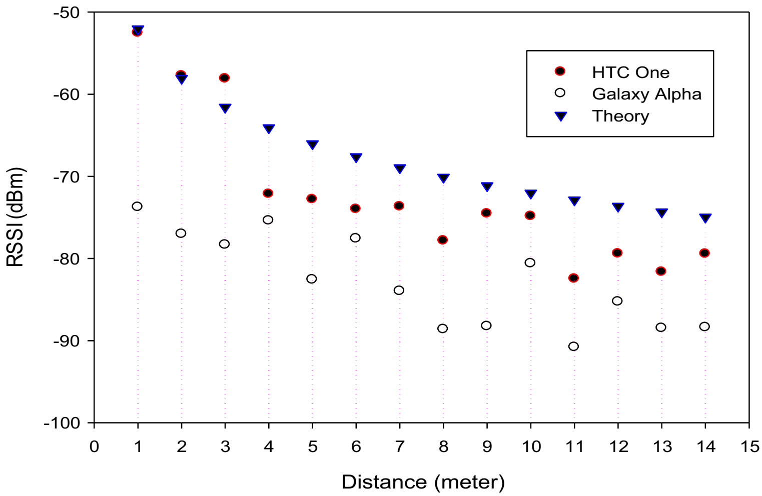


Fig. 12 The RSSIs suffered from interference according to the characteristics of a given space

Depending on the type of smartphone, signals may be stronger at farther distances. Due to interference, it is impossible to determine the position of a walking person accurately with RSSIs alone. However, an 'Immediate' distance, which is less than 1 m, can be correctly determined. Whether a person is approaching or moving away can be known by tracing RSSI changes.

From this result, we adjusted BBIP in Fig. 10 to activate PDR module when a person in 'Immediate' distance. Therefore, the horizontal position is interpreted as the distance from a specific beacon. The distance is calculated by PDR module and the beacon for basis is determined by BBIP.

4.2 Experiments on ambulation

To determine the position of a walking person using ambulation data, the system needs a base position. When a smartphone receives any signal, it infers a base position. As Bluetooth beacons broadcast their positions according to the protocol delineated in Fig. 2, a smartphone can detect nearby beacons. If the 'Immediate' distance is calculated, the position of the beacon that broadcast the signal becomes the base position for calculating ambulation. Thus, in this experiment, we deployed one of the beacons at the entrance to the building. By comparing the RSSIs, the heading direction can be determined. The steps taken by a walking person are counted by comparing the activity obtained from the accelerometer with a threshold. Rotation, which indicates how the moving direction changes, is determined with the accelerometer and the magnetic field sensor. The equations for calculating ambulation are as follows.

$$\mathrm{EP.X} = \mathrm{BP.X} + \sum_{i=0}^{n} SL*SC_i*\cos\theta_i \quad (1)$$

$$\mathrm{EP.Y} = \mathrm{BP.Y} + \sum_{i=0}^{n} SL*SC_i*\sin\theta_i \quad (2)$$

where EP is the estimated position of a walking person which have x-position and y-position, *SL* is a step length, and *SC* is a step count

The formula for calculating the distance error between current position and estimated position of a walking person.

$$D_e = \frac{d(EP, CP)}{d(OP, CP)} \tag{3}$$

where EP is the estimated position, CP is the current position, and OP is the original position. $d(P_1, P_2)$ is a function that calculates Euclidian distance between P_1 and P_2.

When a participant gets into the 'Immediate' distance of each beacon, the beacon's position becomes the current position and the participant's estimated position which is calculated by (1) and (2) is compared. When a participant walks into the area within a beacon's 'Immediate' distance, the base position of a participant is replaced with the position of a beacon.

The experiment was conducted with five participants and each participant walked around the given space 10 times. Each participant carried two smartphones, i.e., the HTC One and the Galaxy Alpha. As shown in Figs. 13 and 14, acceleration and rotation differed according to the type of smartphone. Thus, it is important to customize the sensitivity thresholds for step counting and rotation detection. These customizations were performed for each participant before running the experiments. Table 2 shows the customized features for each participant.

Table 3 shows the experimental results of position error and step error. The position error shows the ratio of difference between an actual position and a calculated position. The track which the participant follows in the experiment is composed of four paths. Beacons are deployed at the end of each path and the position of each beacon becomes the actual position of each path as shown in Fig. 11. The step error is calculated by dividing obtained step count by actual step count.

The participant's position is calculated with the direction obtained from magnetic field sensor and the number of steps obtained from an accelerometer sensor. The position error is calculated when the participant reached at the end of the path by comparing the calculated

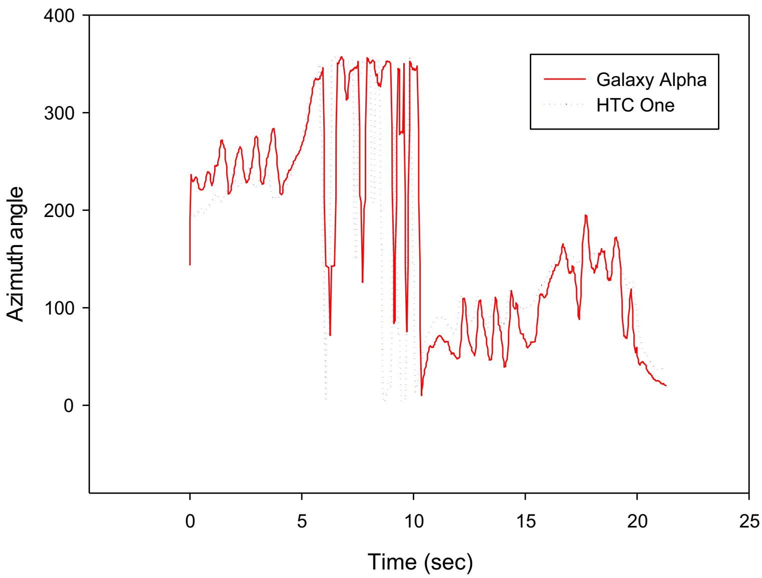


Fig. 13 Variation in the rotation data obtained by the two smartphones

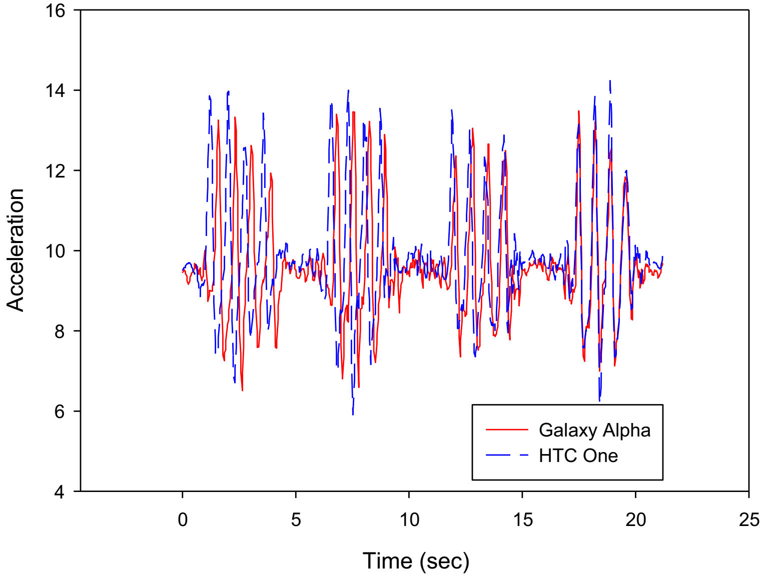


Fig. 14 Variation in the acceleration data obtained by the two smartphones

position and the beacon's position. The number of steps was detected with an error of 2% averagely. The position error is 4.8% averagely.

This result is compared with PDR and RSSI. Table 4 shows the result of the comparison. When PDR is used, the position error is 39% averagely. The main reason for the low result of PDR is that the direction is easily distorted. Therefore when the path is not straight and the variation of steps is big, the error of PDR increases. In the proposed method, the restoration of distortion in walking is executed whenever the participant go through any beacons. The error of RSSI is 28% averagely. Even though the resulted accuracy is similar to PDR, 32% of the cases are failed to calculate the position because the signal strength is too weak.

The proposed method is an ensemble of PDR and RSSI. PDR and RSSI show inaccurate result as long as they are used independently. However, by composing such insufficient methods, the proposed method traces the reliable position of a person.

4.3 Experiment on atmospheric pressure

The experiment on atmospheric pressure was conducted using the barometer installed in the smartphones. Using the heuristic rule set shown in Table 1, the intended semantics were extracted, pertaining for example to the signals that were obtained from the beacons located on the same

Table 2 Customized features for each participant

	P1	P2	P3	P4	P5
Gender	Male	Female	Female	Male	Male
Height (cm)	175	163	157	180	180
Step Length (cm)	75	63	57	80	80
Acceleration Threshold for Steps (m/s^2)	10.6	11.0	10.3	11.7	11.6
Rotation Range (degree)	6.29	4.53	7.46	5.09	12.47

Table 3 The experimental results of position error and step error

	Test	Position Error				Step Error
		Path 1	Path 2	Path 3	Path 4	
P1	1	0.02	0.01	0.02	0.01	0
	2	0.02	0.01	0.02	0.01	0
	3	0.02	0.01	0.02	0.01	0
	4	0.02	0.01	0.02	0.01	0
	5	0.02	0.01	0.02	0.01	0
P2	1	0.01	0.01	0.01	0.01	0
	2	0.01	0.01	0.01	0.01	0
	3	0.01	0.01	0.01	0.01	0
	4	0.01	0.01	0.01	0.01	0
	5	0.01	0.01	0.01	0.01	0
P3	1	0.03	0.26	0.77	0	0.04
	2	0.03	0	0.03	0	0
	3	0.03	0	0.03	0.26	0.08
	4	0.03	0	0.03	0	0
	5	0.03	0	0.03	0	0
P4	1	0.04	0	0.28	0	0.04
	2	0.04	0	0.04	0	0
	3	0.28	0	0.04	0	0.04
	4	0.04	0.24	0.04	0	0.08
	5	0.28	0	0.28	0	0.08
P5	1	0.28	0	0.04	0	0.04
	2	0.04	0	0.04	0	0
	3	0.04	0	0.04	0	0
	4	0.04	0	0.04	0	0
	5	0.04	0.24	0.04	0.24	0.17
		0.06	0.03	0.08	0.02	0.02

floor as the person. In the experiment, we found that the two smartphones sensed the pressure differently (Fig. 8). The signals obtained from the HTC One were weaker than those obtained from the Samsung Galaxy S3 and the LG G3. As the Galaxy Alpha does not have a barometer, no atmospheric pressure data were obtained from it. Thus, it was impossible to compare the atmospheric pressure data for a given building among all of the smartphones; for this each smartphone requires its own atmospheric pressure data for that building. Therefore, a walking person needs to walk around the building before using the rules in Table 1 can be applied.

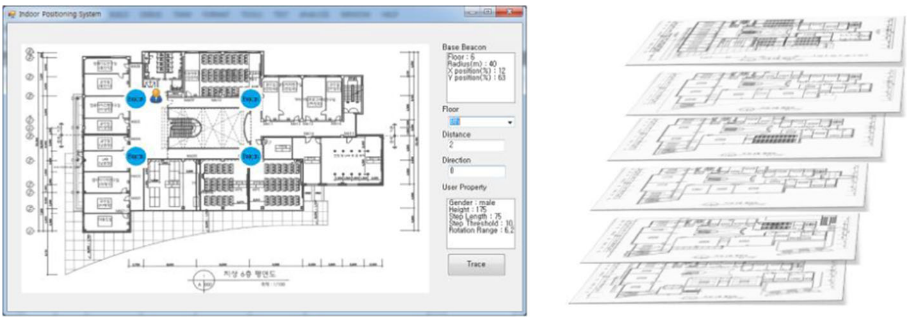
4.4 Experiment on feature combination

To determine the indoor position of a walking person, the proposed system uses three features. The first feature is the RSSI, which provides two kinds of information: the base position and the heading direction. A base position is acquired when the RSSI is translated into an 'Immediate' distance. If a person is nearby to any beacon, that beacon's position becomes the person's current position. The heading direction is used to trace the movement of the walking person. As the strength of the signals indicates the beacons to which the walking person is getting close, the moving direction is inferred from the change in RSSIs. The second feature is a step count and the step direction. Using the accelerometer and magnetic field sensor, the moving position is traced from the base position. As all smartphones have different sensors, the accuracy of the signals obtained also differ. Thus, the proposed method, which

Table 4 Comparison between the proposed method and existing methods based PDR and RSSI

	Test	Position Error		
		Proposed Method	PDR [15]	RSSI [12]
P1	1	0.01	0.59	0
	2	0.01	0.66	NULL!
	3	0.01	0.59	0
	4	0.01	0.64	0.12
	5	0.01	0.51	0.41
P2	1	0.01	0.48	0.99
	2	0.01	0.44	0.58
	3	0.01	0.46	0.12
	4	0.01	0.43	0.25
	5	0.01	0.34	0.58
P3	1	0.26	0	NULL
	2	0.01	0.01	0.25
	3	0.08	0.09	NULL
	4	0.01	0	NULL
	5	0.01	0.05	NULL
P4	1	0.08	0.08	0.41
	2	0.02	0.06	NULL
	3	0.08	0.08	0.41
	4	0.08	0.01	0
	5	0.14	0.03	0
P5	1	0.08	0.37	0.77
	2	0.02	0.33	NULL
	3	0.02	0.36	0
	4	0.02	0.4	0.11
	5	0.14	0.27	0
		0.05	0.29	0.28

processes the signals, needs to be adjusted according to the smartphone. Table 3 shows the result of this adaptation. The number of steps was estimated with an error of 2%. The distance from a given beacon was estimated with an error of 4.8% which is the mean of position accuracies in Table 3. However, when the direction of ambulation changes, accuracy decreases markedly. This is due to the unreliability of the signals arising from the magnetic field sensor; this will be discussed in Section 5. The third feature is the atmospheric pressure. The



(a) Prototype of Indoor Positioning System (b) 2D map for the given building

Fig. 15 Demo view of desktop application which shows detected position in the given space

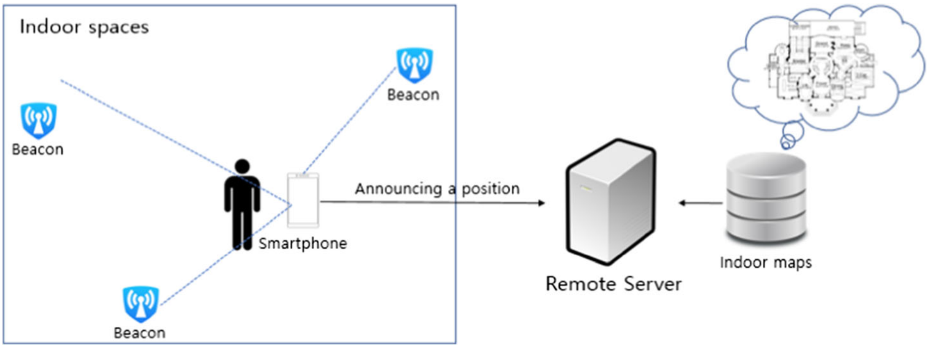


Fig. 16 System overview of the demo application

atmospheric pressure data also varied according to the smartphone. We used the relative pressure instead of the exact pressure, as shown in Table 1. With this information, the system knows whether or not the person has changed floors.

This detected position is transmitted to a server which shows the position of moving people in the give space as shown in Fig. 15. In order to show the position of people, the server shows the map of each floor of the building and the location of beacons in each floor as well as the profile registered people. The mobile application in a smartphone sends its ID, nearest Beacon ID, PDR data, and the inferred number of floor in JSON format. Figure 16 shows the system overview of the demo application in Fig. 15. We made the test sets available at https://sites.google.com/site/yynams/.

5 Conclusion and discussion

5.1 Conclusion

In this paper, a system that provides information on the indoor position of a walking person with accuracy and cost efficiency is proposed. This system uses three features: Bluetooth RSSIs, the traced movement (ambulation), and atmospheric pressure. Although no single feature is sufficient to estimate the position of a walking person accurately, by using a combination of these features we can determine the indoor position of that person.

With the Bluetooth RSSI, we determine the position of each beacon and its signal strength. Then, the ambulation data are used to reduce ambiguity with respect to the RSSI signal strength. The ambulation data has two aspects: the moving direction and the number of steps taken in that direction. Using this information, the ambiguity of RSSIs can be reduced. The final feature, i.e., the atmospheric pressure, is used to determine the floor on which the person is located. Walking up or down stairs, which causes an error in the calculation of moving distance, is detected from the atmospheric pressure. By combining these three features, the indoor position of a person can be determined with an error of 4.8%.

5.2 Discussion

The accuracy of the proposed system is not yet sufficient to be applied to the real-world environment. The main reason for the errors is not the method or the algorithm, but the devices themselves. Smartphones have various sensors, of which four were used in our investigation: the Bluetooth receiver, accelerator, magnetic field sensor, and barometer. These sensors obtain different signals in the same situation. Bluetooth RSSIs are easily interfered with by the characteristics of a given space. The atmospheric pressure data obtained differed according to the smartphone used. Thus, an atmospheric pressure map needs to be generated beforehand. The magnetic field sensor represents the most sensitive sensor, in which errors can result depending on the way in which the smartphone is carried during walking. Especially, when a subject turns and walks at the same time, it is impossible to determine the number of steps and direction of movement. The errors listed in Table 3 were due to this reason, where the proposed method failed to determine the direction of the steps taken by the walking person.

Smartphones have various functions, but we cannot rely on them for accuracy. In the future, methods for extracting reliable data from unreliable sensors will be investigated to improve the accuracy of the proposed system. An embedded PDR detection system which is equipped in shoes can make more accurate result than that in smartphones [24]. WSN can replace the Bluetooth beacons which are used in our work [25]. Even though Bluetooth beacons announce more reliable information, WSN is easier and more efficient way to apply in various spaces. More accurate and more flexible method for detecting indoor position is the objective of our future work.

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References

1. Welcome to GPS.gov. Available at: http://www.gps.gov/. Accessed 21 Apr 2016
2. The Qualcomm/SnapTrack Wireless-Assisted GPS Hybrid Positioning System and Results from Initial Commercial Deployments,. Available at: https://www.ion.org/publications/abstract.cfm?articleID=2037. Accessed 21 Apr 2016
3. Glonass. Available at: http://www.glonass.it/eng/. Accessed 21 Apr 2016
4. Galileo | European GNSS Agency. Available at: http://www.gsa.europa.eu/galileo. Accessed 21 Apr 2016
5. BeiDou Navigation Satellite System — Home. Available at: http://en.beidou.gov.cn/. Accessed 21 Apr 2016
6. Müller P, Raitoharju M, Piché R (2014) A field test of parametric WLAN-fingerprint-positioning methods. In: 2014 17th International Conference on information FUSION (FUSION), pp 1–8
7. Loeffler A, Wissendheit U, Gerhaeuser H, Kuznetsova D (2010) A multi-purpose RFID reader supporting indoor navigation systems. In: 2010 I.E. International Conference on RFID-Technology and applications (RFID-TA) 43–48. doi:10.1109/RFID-TA.2010.5529857
8. Fischer G, Dietrich B, Winkler F (2004) Bluetooth indoor localization system. In: proceedings of the 1st workshop on positioning, navigation and communication
9. Friis HT (1946) A note on a simple transmission formula. Proc IRE 34:254–256
10. Chan S, Sohn G (2012) Indoor localization using wi-fi based fingerprinting and trilateration techiques for lbs applications. ISPRS - International archives of the photogrammetry. Remote Sens Spat Inf Sci XXXVIII-4(C26):1–5
11. Quan M, Navarro E, Peuker B (2010) Wi-fi localization using RSSI fingerprinting. Comput Eng
12. Li WW-L, Iltis RA (2013) A smartphone localization algorithm using RSSI and inertial sensor measurement fusion. 3335–3340. doi:10.1109/GLOCOM.2013.6831587

13. Lanzisera S, Zats D, Pister KSJ (2011) Radio frequency time-of-flight distance measurement for low-cost Wireless sensor localization. IEEE Sensors J 11:837–845
14. Barshan B, Ayrulu B (1998) Performance comparison of four time-of-flight estimation methods for sonar signals. Electron Lett 34:1616–1617
15. Ojeda L, Borenstein J (2007) Personal dead-reckoning system for GPS-denied environments. In: 2007 I.E. International workshop on safety, security and rescue robotics 1–6. doi:10.1109/SSRR.2007.4381271
16. Shahidi S, Valaee S (2015) GIPSy: geomagnetic indoor positioning system for smartphones. In: 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN) 1–7. doi:10.1109/IPIN.2015.7346761
17. Nakazawa Y, Makino H, Nishimori K, Wakatsuki D, Komagata H (2013) Indoor positioning using a high-speed, fish-eye lens-equipped camera in visible light communication. In: 2013 International Conference on indoor positioning and indoor navigation (IPIN) 1–8. doi:10.1109/IPIN.2013.6817855
18. Jayatilleke L, Zhang N (2013) Landmark-based localization for unmanned aerial vehicles. In: systems Conference (SysCon), 2013 I.E. International 448–451. doi:10.1109/SysCon.2013.6549921
19. Liang JZ et al (2013) Image based localization in indoor environments.Computing for Geospatial Research and Application (COM. Geo), 2013 Fourth International Conference on. IEEE
20. McKenna SJ, Gong S (1997) Non-intrusive person authentication for access control by visual tracking and face recognition. International Conference on audio-and video-based biometric person authentication. Springer, Berlin
21. Clarke R (2001) Person location and person tracking-technologies, risks and policy implications. Inf Technol People 14(2):206–231
22. Bohonos S, Lee A, Malik A, Thai C, Manduchi R (2007) Universal real-time navigational assistance (URNA): an urban bluetooth beacon for the blind. ACM Press, p 83. doi:10.1145/1248054.1248080
23. iBeacon for Developers - Apple Developer. Available at: https://developer.apple.com/ibeacon/. Accessed 21 Apr 2016
24. Viani F, Rocca P, Benedetti M, Oliveri G, Massa A (2010) Electromagnetic passive localization and tracking of moving targets in a wsn-infrastructured environment. Inverse Prob 26(7):074–003. doi:10.1088/0266-5611/26/7/074003
25. Faulkner W, Alwood R, Taylor D, Bohlin J (2010) GPS-denied pedestrian tracking in indoor environments using an imu and magnetic compass. Proceedings of the 2010 International technical meeting of the Institute of Navigation (ITM), pp 198-204

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