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Abstract

Pedestrian navigation services guide people to reach their destinations as the vehicle navigation services do. However, the moving way of people differs from that of vehicles, and hence the assumptions for car-navigation services are not suitable for pedestrian navigation. People may walk through the place without GPS signals due to the shelter in the sky. In some space, the accuracy of GPS may not be enough for pedestrian navigation. In this situation, localization ability is necessary in this space, we call it as a special interest zone (SIZ), to assist the GPS-navigation systems. This paper proposes a system by offering a navigation service on general routes and a localization service to SIZ. For navigation service, GPS and GIS technologies were used for guiding, and a modified A* algorithm was developed to implement the path planning function. Because the accuracy of GPS is insufficient to offer the precise localization needed at SIZ, ZigBee-based sensor networks were applied and deployed around SIZ. When the user is close to SIZ, a dynamic swap mechanism enables the localization function to provide higher localization results. The localization algorithm, using an extended Kalman filter to fuse the data of ZigBee and GPS, achieved the localization error less than 1 m, when the error compared to ZigBee-only or GPS-only approach. Both services were successfully implemented on an embedded platform and evaluated on the real environment.

Keywords: Navigation, Localization, ZigBee, GPS

1. Introduction

Localization is a fundamental function for navigation, and GPS is the most promising technology used in the outdoor navigation. For vehicle navigation, some technologies such as map matching [1], and dead reckoning [2] are used to enhance the localization accuracy. However, for the situation needed higher localization accuracy, like a person walks through a pedestrian crossing, a normal localization result from GPS may not distinguish whether the person is inside the region of crossing or not. GPS is available on many navigation devices or consumer electronics, but the accuracy is about 15 to 30 m and insufficient to deal with the application requiring higher accuracy. To supply the above demand, a more accurate localization technology than GPS has to be adopted when people enter these special zones. In general, the localization methods are divided into range-free and range-based schemes [3]. Range-free localization algorithms assume that the transmission range or the deployment distribution is known before the localization phase. This assumption is not always easy to achieve in the desired environment. On the other hand, range-based methods such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength indicator (RSSI) assume that the distance to the known reference is a priori, and can be used to estimate the position. Unfortunately, for the methods of TOA, TDOA, and AOA, a little error of the measurements causes a dramatic difference of the final result, so they need precision instrument to satisfy the conditions of measurement. The review of wireless network localization techniques includes cellular network and wireless local area network (WLAN) environments. Cellular network has coarse estimation of position, while WLAN is preferred to be employed in the indoor environment. Wireless sensor network (WSN), with features of small, inexpensive, and cooperative, is another technique used for localization [4-6]. WSN is more appropriate to achieve our purpose in outdoors. To transform the information of the signal strength to the real distance, the relationship between these two values has to be built first. Many
methods such as radial basis function (RBF) [7], fuzzy modeling [8], and piecewise modeling [9] have been used to establish the model. However, the models in [7] and [8] are used in the range-free localization methods, as known fingerprinting, and the accuracy is relied on the presetting of reference nodes in the offline stage. The piecewise linear model is established by large numbers of field measures, which let only linear operation when estimating ranges from RSSI. Although the complexity is simplified, the model error also increases compared to a log-distance path loss model. After the model is acquired, the position can be estimated by localization methods such as trilateration [10], Min-Max method [8], and maximum likelihood estimation (MLE) [11]. Trilateration is the process of determining absolute or relative locations of points by measurement of distances, using the geometry of circles, spheres or triangles, and is the main localization technique in GPS. The Min-Max method has the similar concept of trilateration with a simplified processing, and MLE method adds the probability to decrease the noise influence. If the measured distances between the target and the senders are accurate, the estimated position by trilateration achieves an accurate result. However, in the RSSI-based localization methods, the distance is mapped by the model and the raw estimated position can be influenced by the variation of RSSI.

This paper proposes a system using GPS for navigation on general routes and ZigBee-based WSN for localization at a zone, called a special interest zone (SIZ), requiring higher accuracy. This design aims on the requirement of SIZ for pedestrian navigation. When a user enters SIZ, the ZigBee transmitters deployed around SIZ enhance the GPS only system to provide higher precision positioning data. The signal-distance models were built in the offline stage with carefully measurements. To increase the estimated accuracy, three enhancements of continuity, variation, and outlier tests were applied for data preprocessing, which decrease the inference of unreasonable data. The absolute position accuracy of GPS is insufficient for SIZ. The velocity information of GPS offers a reasonable trendy of movements and is fused with the ZigBee data by an extended Kalman filter (EKF) to provide higher position accuracy. Compared to the methods such as trilateration, Min-Max, and MLE, the proposed approach with EKF and preprocessed ZigBee signals has the least localization error. Although there are many studies on localization algorithm designs [12-14], few researches address the cooperating of the navigation and localization. Therefore, a smart swap mechanism between these two major functions is also presented in this paper. The proposed system was implemented on an embedded platform and tested on the real environment to evaluate the practicability for pedestrian navigation.

The rest of this paper is organized as follows: Chapter 2 addresses the system overview. The designs of navigation and localization modules are detailed in Chapter 3 and Chapter 4, respectively. Chapter 5 introduces the flow of the dynamic swap between the navigation and the localization modules. The experimental results and the comparisons are presented in Chapter 6. Finally, a conclusion is given in Chapter 7.

2. System overview

Figure 1 shows the functional structure of the proposed system. The system includes two major modules, one is the navigation module, and the other is the localization module. In the navigation module, GIS map and path planning are two components used to display the map and the planned path results. In the localization module, the mapping between RSSI and distances has to be built first by RSSI-distance modeling, and then the EKF [15] is used to acquire the estimated position.
The SIZ, a pedestrian crossing in our study, is defined as the area employed with ZigBee transmitters. In the navigation module, the current position is obtained by GPS and the shortest path is determined by A* algorithm [16]. The navigation module comprises three main functions, GIS data fetching, path planning, and navigation. GIS data fetching uses the open source GIS library to fetch the data of digital maps, and the acquired information is used to display the map or plan the path. After the user selects a beginning and a destination on the map, the path planning function uses node information of roads to determine the shortest path by A* algorithm. Once the path is planned successfully, the system starts navigation function. On the other hand, in the localization module, the signal strength data is collected from ZigBee transmitters and the user’s position is estimated by EKF. The localization module executes three steps to obtain the estimated position. First, the received signal strength data is enhanced by continuity, variation, outlier tests to refine raw RSSI, and then pre-trained models are used to map RSSI to real distances. Finally, three mapped distances from ZigBee transmitters with maximum RSSI are picked and fused with the velocity from GPS to estimate the position at SIZ by EKF.

3. Navigation module

3.1. A* algorithm

Path planning function is the most important function in the navigation module. A* algorithm, a computer algorithm, is widely used in path finding and graph traversal [17]. It uses a best-first search and finds a least-cost path from a given initial node to one goal node. This achieves better performance by using a distance-plus-cost heuristic function, denoted $f(x)$, as described in Equation (1).

$$f(x) = g(x) + h(x)$$  \hspace{1cm} (1)

where $f(x)$ represents an estimate of the total cost of the path from the start, through $x$ to the goal. $g(x)$ is the path-cost function, which is the cost from the start node to the current node $x$, and represents the actual distance at which the node $x$ has been found in the graph. $h(x)$ is an admissible heuristic estimate of the distance from $x$ to a goal node. To be admissible heuristic, $h(x)$ must not overestimate the distance to the goal. In our design, $h(x)$ represents the straight-line distance to the goal, since that is physically the smallest possible distance between any two points or nodes. If the heuristic $h(x)$ satisfies this additional condition, A* can be implemented more efficiently because no node needs to be processed more than once.

3.2. A modified A* algorithm-based path planning

Unlike common applications using “point” as a basic unit to solve problems, GIS data use “feature” as a basic unit, in the form of a line or a polyline. Some definitions in A* algorithm are modified and explained in the following.

- Relationship between points and features
  - The starting point and the terminal point are not just a “point”. Actually, they are extended to a “feature”, which maybe a line or a polyline, as a basic unit in GIS data. Similar to the concept by using points in the algorithm, features are used in the searching processing instead.

- Heuristic function
  - The Euclidean distance is used as the heuristic function in our system. The first node of a feature (FNODE) or the tail node of a feature (TNODE) is selected as one node, and the destination is selected as the other node. The distance is calculated between these two nodes.

- Cost function
  - The cost function is defined as Equation (1). $g(x)$ is the real distance from the point of departure to the searched feature, and $h(x)$ is the value calculated from the heuristic function. Particularly, the cost of movements does not contain the length of the current searched feature, because the final path may not contain this feature.

Figure 2 shows the flow chart of the path planning algorithm. First, the user selects the beginning and the destination on the map, and the features belonging to the selected points are further determined.
as the start and target features, respectively. Next, every connected road segment on the start feature, which are candidate features, is calculated its cost according to Equation (1). The candidate feature with the minimum cost is picked as the best feature, which means this road segment is the best choice from the current start feature. If the best feature is not the target feature, the best feature in this stage is set as the next start feature to continue the searching process. Once the chosen best feature is equal to the target feature, all former picked best features generate the final planning path.

4. Localization module

4.1. RSSI-distance modeling

The log-distance path loss model is also widely used for describing the signal strength over distance decay [18]. Many RSSI-based localization algorithms have been proposed utilizing this model. In general, the model is expressed as follows:

\[ P_d = P_{d0} - 10 \cdot n \cdot \log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \]  

where \( P_d \) represents the received signal strength in dBm at distance \( d \), \( P_{d0} \) represents the received signal strength in dBm at reference distance \( d_0 \), \( n \) represents the path loss exponent that shows the rate of increase of path loss with distance, \( X_\sigma \) follows a zero-mean normal distribution with standard deviation \( \sigma \), which is also an indication of how well the model fits the RSSI measurements. In our work, \( d_0 \) in Equation (2) is assumed as 1 m for simplicity, and the following formula is used to compute RSSI.

\[ \text{RSSI} = -10 \cdot n \cdot \log_{10}(d) + A \]  

where \( d \) is the distance from the sender and \( A \) is the received signal strength at 1 m of distance.

By collecting the RSSI values at the specific distance to the sender in the off-line stage, we can determine the parameter \( n \) and \( A \) by using least squares estimation. Thus, in the on-line stage the localization module can use the models to transfer the measured RSSI values to the corresponding distances. In our experimental environment, 6 ZigBee transmitters were deployed around SIZ. In order to build correct models, we recorded RSSI for 100 times with 1 m interval at the distances of 1-15 m away from each ZigBee transmitters. In Figure 3, the mean and standard deviation of RSSI is plotted.
with an error bar chart, and 6 curves represent the measured results of 6 ZigBee transmitters. Six curves have the similar trends, which show RSSI varies between -35 and -75 dBm, and become flat when the distance increases. The flat curve represents that the different distances are mapped to the same RSSI value, which means when the user is far away from ZigBee transmitters, RSSI cannot reveal the difference. These observations lead to a result that the RSSI value lower than -65 dBm has low discrimination of distance, and is not used to process the estimation of location.

![Graph showing RSSI vs. distance with 6 curves](image)

**Figure 3.** RSSI-distance modeling

### 4.2. Data preprocessing

Three enhancements of data, continuity, variation, and outlier, are done for refining the raw RSSI. The flow of three enhancements is depicted in Figure 4. First, the continuity prevents a sudden change due to the signal brokenness by Equation (4). The value at the last time is kept for short brokenness, but if the signal is not received twice, the RSSI value is set to -90 dBm. Because RSSI ranges from -35 to -75 dBm, the value of -90 dBm is set to represent that the transmitter of ZigBee is unavailable.

\[
x_k = \begin{cases} 
  x_k & \text{if } x_k \neq -90 \\
  x_{k-1} & \text{if } x_k = -90 \text{ AND } x_{k-1} \neq -90 \\
  -90 & \text{otherwise}
\end{cases} \quad (4)
\]

where \( x_k \) is RSSI at time \( k \), and \( x_{k-1} \) is the one at last time \( k-1 \). Next, the variation determines RSSI with large variance by Equation (5). If \( \sigma^2 \) is bigger than 16, \( x_k \) is set to \( x_{k-1} \) to reserve smoothness, where 16 is an empirical threshold from experiments.

\[
x_k = \begin{cases} 
  x_{k-1} & \text{if } x_{k-1} \neq -90 \text{ AND } \sigma^2 > 16 \\
  x_k & \text{otherwise}
\end{cases} \quad (5)
\]

Finally, an outlier test is applied to eliminate the unreasonable RSSI values by Equation (6). From the results of RSSI-distance modeling, we have known that the RSSI value lower than -65 dBm has low discriminability. Therefore, a threshold of -70 dBm is adopted to identify whether the obtained RSSI is reliable or not. If \( x_k \) is smaller than -70, the RSSI value is identified as unreliable and is not used by setting its value to -90.
4.3. Position estimation

With the prebuilt model of each ZigBee transmitter, every input of signal strength is mapped into the distance online, and the extended Kalman filter further processes the information of distance to estimate the position. There are two inputs in EKF. One is the distance mapped from the model of ZigBee signal strength. The other one is the velocity of the user from the GPS module. The state is the position vector containing two variables, the coordinates in $x$-axis and $y$-axis. Equation (7) shows the state equation.

$$x_k = x_{k-1} + u_{k-1} \times \Delta t + w_{k-1}$$  (7)

where $u_k$ is the input of velocity from the GPS module, $\Delta t$ is the sampling period, and $w_k$ is the noise with normal probability distributions $p(w) \sim N(0, Q)$, where $Q$ is the covariance of the process noise. The measurement equation is determined in Equation (8).

$$z_k = Hx_k + v_k$$  (8)

where $z_k$ is the measurement vector containing a set of distances mapped from ZigBee signal strengths, and $v_k$ is the noise with normal probability distributions $p(v) \sim N(0, R)$, where $R$ is the covariance of the observation noise. The $H$ matrix establishes the relationship between the measurements and the states. Equation (9) shows the relation between the position and the distance.

$$d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2}$$  (9)

where $d_i$ is the distance between the user and $i$ represents the index of ZigBee transmitter located at $SIZ$. $x_i$ and $y_i$ are two values of the state $x$, and $x$ and $y$ represent the position of $i$th ZigBee transmitter. By linearizing Equation (9), we can obtain $H$ as shown in Equation (10).

$$H = \begin{bmatrix} \frac{x_i - x_x}{d_x} & \frac{y_i - y_y}{d_x} \\ \frac{x_i - x_b}{d_b} & \frac{y_i - y_b}{d_b} \\ \frac{x_i - x_c}{d_c} & \frac{y_i - y_c}{d_c} \end{bmatrix}$$  (10)

where the indexes $a$, $b$, $c$ are used to distinguish different ZigBee transmitters. At least three ZigBee transmitters have to be selected to complete the calculation.

5. Dynamic swap module

Figure 5 shows the flow chart of the dynamic swap module. After the user decides the beginning and the destination, the system immediately plans the shortest path and starts the navigation service.
The navigation service continues until the user arrives at the destination. If there is a SIZ on the way of the planned path, the system detects the user entering SIZ and swaps to the localization module. Once the system enables the localization service, it starts to query RSSI of surrounding ZigBee transmitters and converts the values to the distances. Then the distances and the GPS information are processed by EKF to estimate the user’s position. Meanwhile the position is also checked with the digital map information. After confirming that the user leaves the SIZ, the system swaps to the navigation module to continue the navigation service.

Figure 5. The flow chart of the dynamic swap module

6. Experimental results

The test scenario was set in our campus, and a pedestrian crossing was chosen as SIZ. Six ZigBee transmitters were employed on the ground around the area of 5 × 15 m². The system prototype was implemented on an embedded platform, with a 600 MHz ARM processor and Linux kernel 2.6.18, and programmed with Qt/Embedded 4.6.2. The peripherals included a Bluetooth GPS module and a ZigBee receiver. Our purpose is to associate the GPS navigation with the WSN localization. We have the path planning service with GPS in the normal situation, and also have the fine localization service with ZigBee sensors at SIZ. Figure 6 shows the interface of the map with a starting position and an end set by the user, and the dialog with a picture indicates the position of the SIZ. Figure 7 displays the path planning result used to guide the user. When the user was approaching SIZ, in our case, was the pedestrian crossing, the system checked the status of the environment as demonstrated in Figure 8-9. Once the system confirmed the user entered SIZ, the system automatically swapped the display interface and showed the user’s trajectory as illustrated in Figure 10-11.
The trajectories of localization using trilateration and EKF are shown in Figure 12 and Figure 13, respectively. The red squares indicate the positions of the ZigBee transmitters. The user walked through SIZ along the center line, and recorded the estimated position every 1 m at the ground truths, symbolized by blue crosses. The estimated positions are marked with green dots, and the red lines between the blue crosses and the green dots indicate the estimated results with corresponding ground truths. Figure 14 presents the positioning error of 15 ground truths for trilateration and EKF from the record data. The red line with squares represents the error of trilateration while the blue one with triangles is for EKF. The average localization error of trilateration and EKF is 0.92 m and 0.59 m, respectively.

Moreover, Table 1 shows the comparison of localization error using the same signal model but with different localization methods, trilateration, Min-Max, MLE, and EKF. The trilateration and Min-Max has the similar results, and the difference comes from the error of simplified computation by Min-Max. MLE performs not well when there are less sensor nodes in the field. The experimental results match the conclusion in [9]. The proposed three enhancements of data preprocessing reduce the noise inference and EKF fuse the user’s motion to further decrease the effect of RSSI variation. It shows that our system has the best performance by using the EKF method.
Table 1. The comparisons of localization error for different methods

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7. Conclusion

The proposed system comprises navigation and localization functions, and a dynamic swap mechanism is designed to cooperate these two functions. In the normal situation, only GPS is enough for guidance with the planning path. However, when people enter some special areas requiring higher accuracy, such as the pedestrian crossing, the localization service with WSN can warn and avoid the person from exceeding this SIZ. The proposed approaches were successfully implemented and fully tested on an embedded platform. The testing scenario in the real campus environment has demonstrated the correct navigation/localization function swap. The experimental results show the localization error is less than 1 m, which implies the proposed system can be realized in the real world to achieve the goal of reducing localization errors. In the future, a central server for managing the location data of SIZ can be integrated with the system. Then the system will not need to store all the location data of SIZ, and become more practical for location-aware applications.

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9. References


