

A Floor Plan based Vision Navigation System for Indoor Navigation with Smart Device

Bei Huang and Yang Gao

Department of Geomatics Engineering, University of Calgary

Abstract

Many smart devices like smart phone and tablet nowadays are featured for hybrid sensor platform of GPS chip, inertial sensor(s), magnetic compass and other gadgets such as camera and Wi-Fi. The interest to apply those smart devices for indoor navigation is growing since a large variety of sensors on such devices enable hybrid location solutions to not only improve the availability of indoor positioning but also the accuracy and smoothness. However, in deep indoor scenario, the positioning accuracy is still seldom satisfactory due to large accumulative errors of dead-reckoning sensors. In this paper, a floor plan based vision navigation method is designed for pedestrian handset indoor application. The floor plan for buildings is an easily accessible indoor map with detailed path and room information. It can be matched with the vision measurements from the camera sensor to derive accurate and drift-free positions even in deep indoor environments. The Random Sample Consensus (RANSAC) algorithm is adopted for robust matching between floor plan and camera photo. An iPhone Demo App is developed to evaluate the performance of the designed system and the test results indicate meter-level horizontal accuracy.

Keywords: < Indoor, Vision Navigation, Floor Plan >

1. Introduction

The iPhone raw measurement of user locations is a hybrid result of GPS, cellular and Wi-Fi network. The basic scheme of assisted GPS (AGPS) is employed so that, on the one hand, the cellular and Wi-Fi network based position assists the GPS chip to lock on more satellites in shorter time period; and on the another hand, once GPS is warmed up, the network positioning performance is improved. Although the iPhone's hybrid location can be better than AGPS since signal strengths are leveraged and weighted to provide GPS/cellular/Wi-Fi integrated position, its positioning accuracy is seldom satisfactory particularly in deep indoor environments. We take the former built-in navigation App Google Map

as an example. For indoor scenarios, such as looking for a store in a shopping mall, negative reviews on Google Map from users are overwhelming and mainly attributed to two problems: 1) Google does not contain any indoor map with path and store details; 2) the hybrid location accuracy is too poor inside building. Although the iPhone's original position service partner Skyhook claims that the hybrid location accuracy is 10 m, the actual network-only position errors could be up to 200 m in deep indoor environments since GPS signal is almost totally unavailable. For the first problem, thousands of iPhone Apps focusing on indoor navigation have tried to improve their products with detailed floor plan of major shopping mall, airport and other public places. A floor plan that is available for every building is a ubiquitous and widely accessible indoor map. With partners' floor plan, navigation App can be enforced with detailed inside view along with their real scales.

For the second problem, current navigation Apps still rely on hybrid location despite that its indoor accuracy is poor at tens of meters. Consequently, with such big uncertainty, iPhone becomes not sensitive to user's movement and cannot tell if the user has arrived at a turning point or not. Currently, in addition to using floor plans, a few companies have realized the importance of refining the hybrid location accuracy to develop multi-sensor fusion platform. The accelerometer, gyro and magnetic compass in iPhone are based on MEMS technology and these low-cost sensors are implemented with dead-reckoning algorithms to improve the smoothness and accuracy of the position solutions. However, accumulative error is a significant challenge for these MEMS sensors, especially in deep indoor environment where no absolute position from GPS is available to limit the error drifts.

Unlike relative movement measurements from MEMS sensors, iPhone camera can provide absolute position information to avoid the unconstraint growth of error drifts. A successful example is a vision-based navigation system with geo-tagged photos database developed by Yuan et al (2011). In their system, the camera position and orientation is retrieved by matching a cloud of

feature points in photos that are tagged with accurate geographic information. The obtainable accuracy can be as good as 1 m. Despite of the simplicity and good accuracy of this approach, constructing a geo-reference database involves lots of field survey work, which makes this special photo database not ubiquitous as the floor plan.

The vision-based system is still inspiring because the floor plan database has the potential to be integrated with camera to retrieve camera position. We have investigated the integration scheme of camera photo and geo-reference database and we found that the floor plan is able to provide sufficient 3D geo-reference information. A passive ranging algorithm proposed by Hung et al (1985) has demonstrated that if a quadrangle pattern formed by four features is given with its true scale, their 2D locations on photo can be used to derive their ranges to camera, therefore 2D photo features can be reconstructed to a 3D world. A floor plan contains the true scale of a building and perfectly meets our need. Now, we are very close to the goal of retrieving 3D position from 2D photo and floor plan, though the direct output of the passive ranging is still the feature ranges to the camera. In order to obtain more interpretable navigation solution, we expect outputs about the camera pose, the computer vision community has defined it as ‘‘Perspective N Points’’ problem, and a close form solution has been demonstrated in Horn et al (1988).

In this paper, a novel indoor navigation method is proposed. Our goal is that on the basis of an initial hybrid location, by matching a user’s single shot of hallway with a floor plan database, the user will receive an absolute position with improved accuracy. In order to demonstrate the feasibility and accuracy, indoor tests were conducted with an iPhone Demo App developed at The University of Calgary. Integrated with camera photo, the floor plan is found able to not only significantly improve the hybrid location accuracy from 74 m to 2.8 m on average, but also provide user an innovative navigation experience and augmented navigation reality.

2. System Design

2.1 Definition of frames

Shown in Fig. 1 are three frames used in the proposed system and their definitions are described below: a) Camera frame: this is the camera body frame with respect to origin at camera perspective center (red axes); b) Image frame: a 2D frame of camera imaging plane (blue axes); c) Floor plan frame: a local origin is chosen on the floor plan, with X axis defined along the hallway, Y axis in the traverse direction, and Z axis pointing up. This frame is also referred as navigation frame.

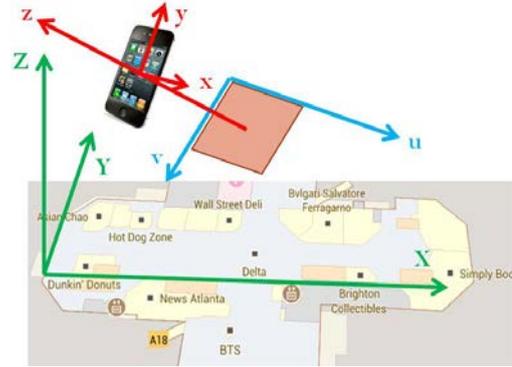


Figure 1: Image frame (blue); Camera frame (red) or body frame; Floor plan frame (green).

2.2 System overview

Shown in Fig. 2 is an overview of the proposed system. The only equipment required at the user-end is an iPhone camera. The indoor scenario is expected to have open Wi-Fi access. Since the processor of most smart devices nowadays is extremely powerful, the main navigation algorithm can probably be carried out at the user end efficiently. To simplify the software development effort, in our current prototype design, a remote server has been set up to support the main navigation calculations whereas the iPhone is merely used to upload the required inputs of the initial hybrid location, accuracy and indoor photo, and to download the expected resources of floor plan and refined position results. The server will conduct the following two tasks:

- Execute the main navigation algorithm;
- FTP service allowing user to upload required inputs for the main navigation algorithm and download floor plan resource and results feedback.

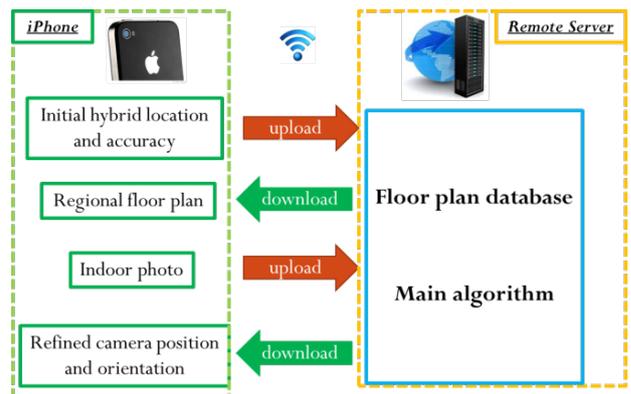


Figure 2: System overview

2.3 Main navigation algorithm structure

Shown in Fig. 3 is the structure of the main navigation algorithm to be executed by the remote server, which consists of the following five components:

- iPhone’s raw measurements of initial hybrid location and accuracy;

- Floor plan database: to centre the floor plan around the initial hybrid location and determine the region of interest by referring to the current accuracy level; and to generate the floor plan database in the region of interest, which contains all floor plan features with their real scales;
- Feature detection: an indoor photo is first captured by iPhone camera and the feature detection algorithm is applied to extract photo features, specifically the hallway features which can be found correspondence in the floor plan, for example, the corner of walls and doorways;
- Robust matching: with outputs from the previous two steps, the Random Sample Consensus (RANSAC) algorithm is applied to match photo features with the floor plan database, and to identify reliable photo-to-floor plan correspondences;
- Camera position and orientation determination: first implement a passive ranging method and then retrieve camera position and orientation. The detailed mathematical derivations of these two steps will be described in the following.

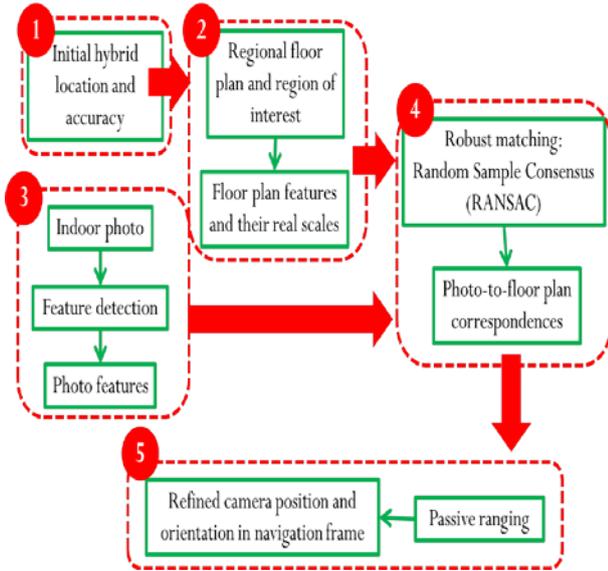


Figure 3: Structure of the main algorithm

2.4 Passive ranging

An iPhone camera follows the projective imaging rules. When a feature in a 3D world is projected and scaled down to a 2D planar imaging sensor, the scale information is lost, which directly leads to an unknown range between the feature and camera. Hung et al (1985) provided a solution, known as “passive ranging” method, to solve the unknown range, hence to reconstruct the feature from a 2D monocular image to a 3D space. In their paper, four coplanar features consisting quadrangle pattern are needed: if the shape of the quadrangle is constrained by their coplanar relationship, the possible 3D positions of these four features can be narrowed

down to a series of similar quadrangles’ vertices; additionally, if one side length is known which can be applied to fix the size of the quadrangle, the features’ positions can then be uniquely determined. We extend the minimum four feature points required for passive ranging to a more general case where more than four features are available. Two types of constraints, namely coplanar and length are needed for passive ranging. To be specific for our case, the length constraints are easily obtainable by referring to the true scales from the floor plan, while the coplanar constraints are obtainable from hallway parallelism.

The following derivation provides details of how to implement the passive ranging. Each photo feature determines a line of sight (LOS) as shown in Eq. (1), and the feature 3D position must locate along the corresponding LOS with a unique scale, as shown in Eq. (2). These scales form the vector of unknowns in Eq. (3) and the passive ranging aim to derive a unique solution. Eq. (4) and (5) describe the length and parallelism between features, respectively. Apparently, the entire mathematical model is not linear so recursive iterations are required to update the vector of unknowns in order to finally converge to a solution.

$$v_i = [x_i \quad y_i \quad C]^T \quad (1)$$

$$P_i = K_i v_i \quad (2)$$

$$K = [K_1 \quad K_2 \quad \dots \quad K_n]^T \quad (3)$$

$$d_{ij} = \sqrt{(P_i - P_j)^T (P_i - P_j)} \quad (4)$$

$$(P_{i_1}^L - P_{i_2}^L) / d_{i_1 i_2} = (P_{j_1}^R - P_{j_2}^R) / d_{j_1 j_2} \quad (5)$$

where,

v_i pixel location of feature point in image frame

C focal length

P_i feature point’s 3D coordinates in the camera frame

K_i the scale of feature point along the line of sight

L the left hallway feature points

R the right hallway feature points

A linearization of Eq. (4) – (5) leads to the coefficients of the Jacobian matrix as shown in Eq. (6). As the floor plan correspondences provide true measurements of the feature lengths and coplanar relationship, the residuals in Eq. (7) are applied to update the unknowns in each iteration.

$$M = \begin{bmatrix} M_{\text{coplanar}} \\ M_{\text{length}} \end{bmatrix} \quad (6)$$

$$\delta K = (M^T M)^{-1} M^T Z \quad (7)$$

where,

Z the residual between the predicted coplanar relationship and length and the true measurements from the floor plan correspondences

M_{coplanar} the coplanar constraints coefficients matrix of the differential of Eq. (4)

M_{length} the length constraint coefficient matrix of the differential of Eq. (3)

2.5 Camera orientation and position determination

The passive ranging method reconstructs ranges of 2D photo features and expresses the features' 3D coordinates in the camera frame. However, we expect a more interpretable navigation solution for the camera position and orientation. Till now, we have obtained two sets of 3D coordinates, features' position in the camera frame and their corresponding floor plan points' positions in the floor plan frame. These two sets of coordinates should be mutually transformable through a rotation and translation. In computer vision, the derivation of the transformation between the two correspondence sets is well known as the "Perspective N Points (PnP)" problem. In PnP problem, the transformation is the result of a camera perspective change, therefore, the rotation should be computed from the camera orientation and the translation vector is exactly equivalent with the camera position.

After the passive ranging, the second step is to find out the rotation matrix and translation vector. Horn et al (1988) derived a close-form solution, which has perfectly enforced the orthonormality property of the camera orientation matrix. Further considering the fact that photo features and floor plan points are extracted from different data sources, it is impossible to derive a transformation that can make the two sets perfectly coincide. Another remarkable merit of Horn's solution is that the derived transformation is by nature based on the least square method which makes the two sets of correspondences best fit with each other.

2.6 Robust matching using Random Sample Consensus (RANSAC)

The real scale for the photo features is obtained by referring to the corresponding points in the floor plan. However, to find correct correspondence for each photo feature from a large pool of floor plan points, this should be solved before the passive ranging. A robust matching is implemented to automatically identify photo-to-floor

plan correspondences. We assume that in the region of interest, hallway features such as doorway and wall corner form unique pattern. This unique pattern acts like "finger print" of hallway features. The robust matching then aims to find those floor plan points that have the same "finger print" with the photo features. The classical least square based robust matching techniques are not employed here, because the least square is an averaging technique for redundant observations. In other words, the least square is to best fit between the photo and floor plan. But when the photo and floor plan cannot agree on a universal "finger print", the disagreement due to mismatch will be inappropriately smoothed out. As a result, a least square based matching is not efficient to distinguish mismatches.

Unlike the least square, RANSAC uses a sample dataset as small as feasible to work out an initial guess of a camera pose, and then enlarges this set with consistent correspondences whenever possible. In our case, we need a minimum of four points to obtain a camera pose. The RANSAC routine is summarized as follows:

- Randomly select four feature points and floor plan points, noted as S_1 . Use the initial guess to derive camera position and orientation, noted as P_1 .
- In order to demonstrate P_1 is not only agreed by the initial guess sample set, but also agreed by the majority of other features, project the rest of the floor plan points to it. Comparing with feature points, if the projection falls into the error tolerance circle specified by a predefined threshold t , enlarge the initial sample set S_1 with consensus correspondence.
- When the number of correspondences in the redundant consensus set (noted as S_1^*) exceeds a predefined threshold m , recalculate the camera pose, noted as P_1^* .
- Otherwise, if the size of S_1^* fails to reach the threshold, it means the entire dataset can hardly agree on P_1 . Then repeat from the first step, until the maximum number of trials has been reached.

Some important quantities remain to be determined before the implementation of RANSAC, including the pixel error threshold t (to determine whether or not a correspondence is compatible with current camera pose), the consensus sample size threshold m (the number of compatible correspondences that a correct camera pose will accept) and the maximum number of trials. Fischler and Bolles (1981) have provided the relationship between the maximum number of trials and the consensus sample size on the basis of *a priori* probability. The pixel error threshold, theoretically, is a function of the error associated with the camera location

error and misalignment, and the pixel error due to feature detection. However, it is not straightforward to derive those complicated mathematics. Instead, a more efficient method is to estimate the bounds of the error tolerance experimentally, for example to check the sample deviation by perturbing the correct sample set.

3. Indoor Tests and Results

3.1 Experiment description

The floor plan database used in our experiments is generated from The University of Calgary's interactive online map with a scale accurate within decimeter level. In order to demonstrate that the derived camera position has a better accuracy than the initial hybrid location, 42 photos are taken at different indoor landmarks. Each photo is matched with the floor plan to derive camera position and orientation. For reference purpose, the horizontal positions of the landmarks are measured on the interactive online map with decimeter level accuracy, while the height to ground has used an empirical value of 1 m. In the following, the performance of the main navigation algorithm is evaluated as follows:

- Paradigm of how to use this iPhone Demo App is illustrated;
- RANSAC matching process is shown to assess how well and fast RANSAC can identify reliable matches between photo and floor plan;
- After photo-to-floor plan correspondences are identified, the passive ranging method is applied. A set of feature ranges converges to their correct value, and we hereby reconstruct 2D photo features' 3D coordinates in the camera frame;
- PnP solution is then implemented to compute the camera position and orientation. The features' coordinates in the camera frame are then transformed to the floor plan frame and compared with their floor plan correspondences. The average residuals between them are examined to validate if the derived camera pose is correct and robust to make the two sets of correspondences mutually transformable and best fit.
- The derived camera positions are compared with the reference landmark positions for accuracy analysis.

3.2 iPhone demo App

An iPhone Demo App has been developed and tested with an iPhone. For Demo App, however, the remote server is simulated by an online storage Dropbox. Except that Dropbox does not have capability to execute the main navigation algorithm, the communication with Dropbox for uploading and downloading can fully represent a FTP service by the remote server. To carry out the main navigation algorithm in a post mission, a software system is developed in C++ and Matlab, and results are loaded to Dropbox for download. Fig. 4 shows some screen shots when the Demo App is tested

in the Engineering Building of The University of Calgary and the following steps elaborate the paradigm of using this App:

- At the moment of a screen shot, the GPS/Cellular/Wi-Fi based indoor location is obtained with an accuracy of 74 m. "Link to server" button is also shown at the bottom of the screen. See Fig. 4.1.
- After connecting to the remote server, the floor plan centred around the initial location is downloaded and overlaid on the Google Map. See Fig. 4.2.
- User takes a photo of the hallway and touch on features like doorway and wall corner (shown as red dots in Fig. 4.3). With this step, the feature detection will detect feature points in the search area specified by the red dots as accurate as a few pixels.
- After execution of the main navigation algorithm including robust matching, passive ranging and retrieving camera position and orientation, an improved position result is sent back and pinned on the floor plan (shown as red dot in Fig. 4.4). Meanwhile, user can type in a destination room.
- The feedback in the last step contains improved camera position and orientation, which enable the software to rotate the floor plan and navigation arrow to user's perspective and overlaid on a camera view. Therefore, the augmented navigation reality is of the first time brought to the pedestrian indoor navigation. If an up-to-date database of room inventory is available, event in the destination room can also be displayed. See Fig. 4.5.



Figure 4: Screen shots of iPhone demo App

3.3 RANSAC matching results

In the previous section, RANSAC routines are described in details. In Fig. 5, the yellow circles show the pixel error threshold t ; red stars are photo feature points. The camera position and orientation P_1 are at first calculated from the initial guess sample set S_1 . Other floor plan points are projected to the image frame using P_1 . Once a projection of the floor plan point falls into a yellow circle, it is successfully matched with a photo feature,

and the pair of photo-to-floor plan correspondences are marked in green and yellow stars, so called consensus points. Apparently, the pixel error threshold t shown as the radius of the yellow circles should be dependent on the feature range. To be specific, larger pixel errors are resulted when closer floor plan points are projected to the image frame, and vice versa.

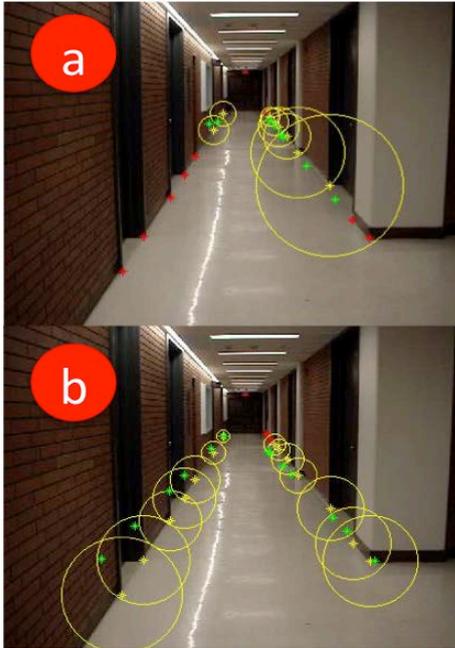


Figure 5: Pairs of green and yellow stars are consensus floor plan points and photo features, respectively; yellow circles are pixel error threshold; red stars are photo features those fail to match with any floor plan point

In Fig. 5(a), only 8 photo features out of 16 detected features find their consensus floor plan points. Since the consensus set S_1^* does not pass the threshold of consensus size m , the initial guess sample set S_1 is probably mismatched, resulting in incorrect camera pose P_1 . Therefore, the RANSAC starts a new iteration from the first step and another four points sample set are selected as initial guess S_2 . After n iterations, sufficient consensus points forming S_n^* is found as shown in Fig. 5(b), 14 out of 16 photo features are matched with the floor plan points. It indicates that the initial guess sample set S_n is correct and the derived camera pose P_n is not only agreed by the sample set but also agreed by the majority of the entire dataset. Moreover, for better redundancy, an improved camera pose P_n^* will be recalculated with the consensus set.

Another important performance of RANSAC matching is the speed. Since 42 camera photos are taken in different places during the indoor test, the RANSAC

processing speed for each photo is studied. With a maximum number of iterations set to be 500, 2 photos are found in failure because RANSAC cannot identify sufficient consensus matches within 500 trials. The iteration numbers to process each of the rest 40 photos are investigated and the histogram is shown in Fig. 6. The average number is 41, which is quick enough for real time application.

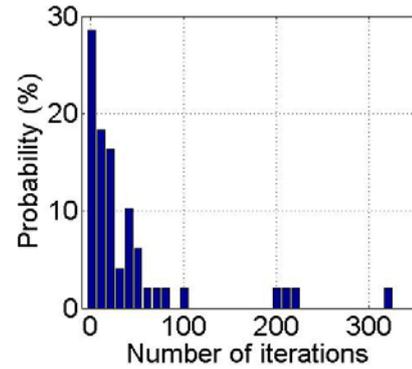


Figure 6: Histogram of number of iterations

3.4 Passive ranging results

Fig. 7 connects each photo-to-floor plan correspondence identified by RANSAC. It is obvious to discover that, not all of points are correctly matched which will affect the passive ranging accuracy. Fortunately, improved camera pose is recalculated from this redundant consensus set, and errors due to a few mismatches will be smoothed out so will not affect the accuracy.

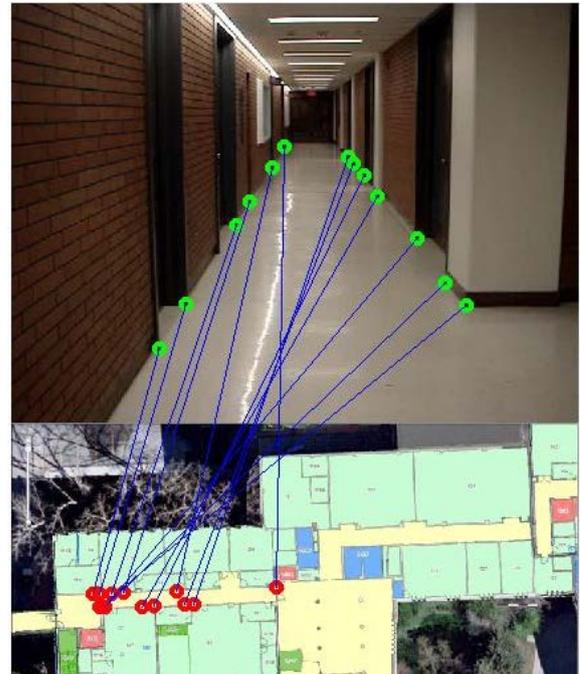


Figure 7: Example of feature-to-floor plan correspondences identified by RANSAC

The passive ranging implement the coplanar and length constraint obtained from the floor plan correspondences and successfully converges to a set of feature ranges as shown in Fig. 8. With them, it is easy to interpret feature positions in the camera frame, as shown in Fig. 9. Till now, by integrating the floor plan with monocular image, the remarkable effect of the passive ranging to reconstruct 2D photo feature to 3D space is clearly illustrated.

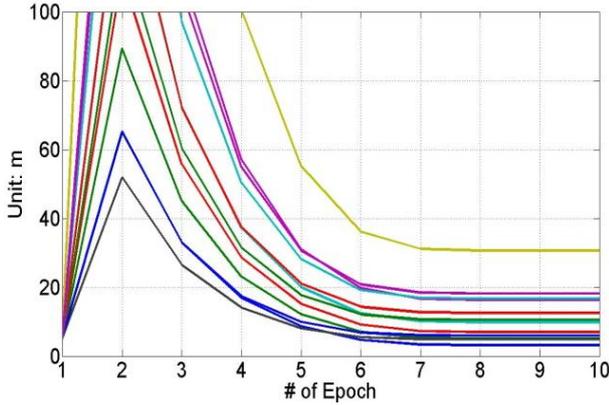


Figure 8: Passive ranging converges to a set of feature ranges

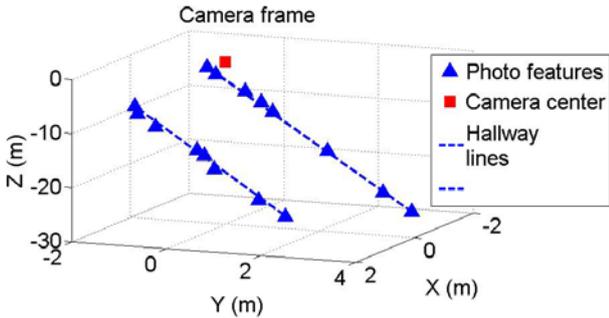


Figure 9: Reconstructed photo features' 3D coordinates in camera frame. The red rectangle is the origin of camera frame

3.5 Camera orientation and position results

PnP solution is implemented on the two corresponding sets of feature positions and floor plan points, and the camera position and orientation are produced. By using the derived camera pose, features are transformed to the floor plan frame and compared with their correspondences as shown in Fig. 10. Apparently, these two sets of points do not perfectly coincide with each other after transformation, but the residual between them is reasonable. Error sources causing the residual are summarized as follows:

- Camera calibration error due to, for example, inaccurate estimation of the camera perspective centre and focal length;
- Feature detection error
- Floor plan scale error
- Remaining mismatch

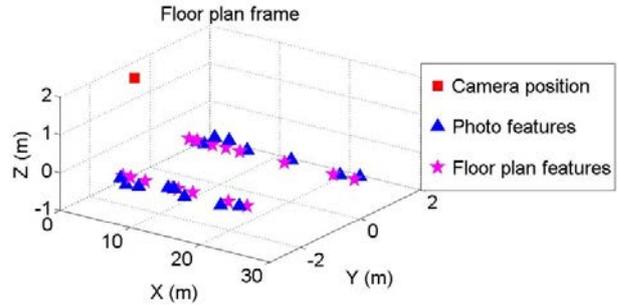


Figure 10: Camera position in the floor plan frame with both reconstructed photo features and floor plan points

Among these errors, remaining mismatches account for the major part of the residuals, which deteriorate the camera position accuracy. Unfortunately, it is impossible to find out correspondences free of mismatch from a large pool of candidates but within a limited number of iterations. Although we have not found an effective method to further detect the remaining mismatches, we have applied the transformations described above to examine residuals when processing the 40 photos. A histogram of residuals is shown in Fig. 11. Since all residuals are less than 1 m, it confirms that the derived camera position and orientation are reliable even with the presence of a few mismatches.

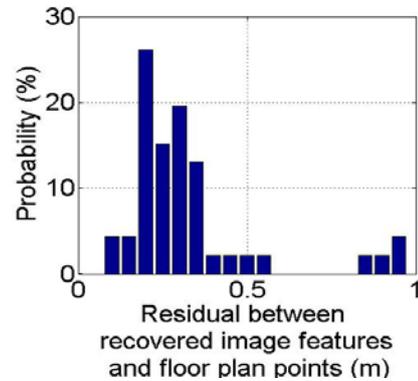


Figure 11: Histogram of residual

3.6 Camera position accuracy

Verifying the camera position accuracy is the final step of our analysis. The initial hybrid location accuracy was as bad as 74 m during the indoor test. The final derived camera position is expected to have much better accuracy. Among the 40 photos, each is successfully matched with the floor plan and derives camera position independently, and the result is compared with the reference landmark position. Histograms for the horizontal and height errors are displayed in Fig. 13. On average, the camera height RMS error is 0.7 m and 82.5% height RMS errors are less than 1 m, while the horizontal RMS error is 2.8 m, with 90% horizontal errors less than 5 m.

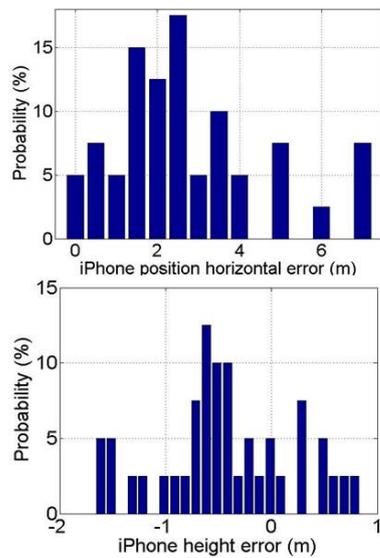


Figure 12: Histogram of iPhone position horizontal and vertical error

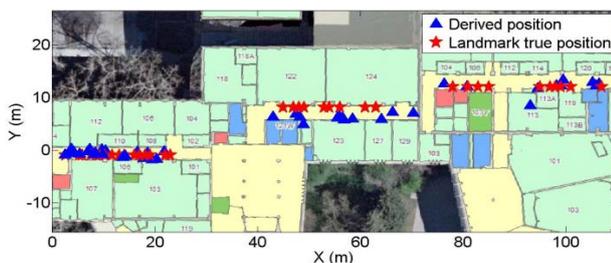


Figure 13: Derived iPhone position with landmark positions

4. Conclusions

A monocular vision navigation system integrated with a floor plan database has been proposed to improve the current GPS and network based pedestrian indoor navigation service. Any Wi-Fi enabled camera phone and tablet can enjoy the benefits of the proposed system. The system robustness has been enforced by a robust matching method and reliable camera position and orientation. An augmented reality navigation application is exhibited as well based on an iPhone Demo App.

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Biography

Bei Huang is an MSc student in the Department of Geomatics Engineering at the University of Calgary. She achieved her Bachelor degree in 2009 in the Department of Electrical Engineering at the Huazhong University of Science and Technology, Wuhan, China. Her current research involves multi-sensor integrated navigation methodology.

Dr. Yang Gao is a Professor in the Department of Geomatics Engineering at the University of Calgary. His research expertise includes both theoretical aspects and practical applications of satellite positioning and navigation systems. His current research focuses on high precision GPS positioning and multi-sensor integrated navigation system.