Self-positioning System for Indoor Navigation on Mobile Phones

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***Abstract*--This paper presents a positioning system for indoor navigation which can run independently on a mobile phone by using only its basic equipped sensors such as a camera and a compass. The system outperforms existing mobile phone positioning methods by reducing the error of position estimation to around 0.7 meters.**

I. INTRODUCTION

Recently, due to the impressive development of mobile phones, navigation on mobile phone has received lots of attention. Since GPS signal is not available in indoor environments, many other localization methods have been proposed using other signals such as WiFi [4, 5], RFID, ultrasound [6], Bluetooth, accelerometer [2, 3], compass [2], etc. Considering the popularity of modern mobile phone equipped with a camera and a compass, we combine these sensors to develop a positioning method for navigation applications which can run on mobile phones independently without the requirement of additional hardware (e.g. central servers) or external infrastructure.

II. THE PROPOSED POSITIONING SYSTEM

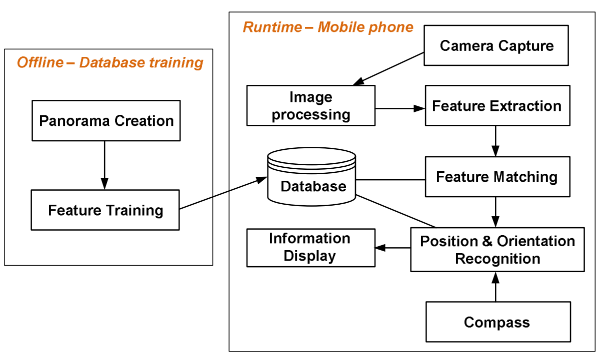

Fig. 1. System's workflow

The proposed system is structured as in Fig. 1. In training phase, a database of reference images is created based on panoramic images of targeting environment. During runtime phase, mobile device's position and orientation are estimated based on captured images and compass orientation.

Feature training and matching: We slightly modify Histogrammed Intensity Patch (HIP) matching scheme [1] for our system: In our situation, we often face a zoom-in problem than a zoom-out situation. Therefore, in training phase, we reduce number of scales to 5 that will not affect the system's robustness while decreasing the number of features stored in database. Moreover, to solve the zoom-in problem more effectively, we add multi-scaling scheme in runtime matching phase.

Database creation: We divide the targeting indoor environment into 3m x 3m cells and take one 360^o panoramic image in the center of each cell. The position and orientation are recorded with each panoramic image. Next, we divide horizontally each panoramic image into four sub-images. That means one sub-image covers 90^o of the horizontal view (*HAoV*) and it is easy to calculate the orientation of each sub-image based on the orientation of the original panoramic image. Finally, we run HIP feature training on each sub-image and then store HIP features with corresponding positions and orientations into database.

Update 2D-features: Since we take one panoramic image on every 3m x 3m cell, neighbouring panoramas often have overlap areas. We take an advantage of those overlaps for estimating user phone's position more precisely: If any match is found between two neighbouring sub-images, 2D reference coordinates of matched features are calculated and then updated into the database.

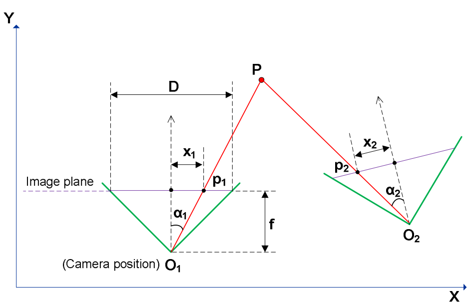

Fig.2 Simulation of camera views of 2 sub-images in 2D reference coordinates

Assuming that each sub-image is a perspective image, then for each one we can simulate a corresponding virtual camera's view in 2D reference coordinates. Fig. 2 shows a simulation of two reference images. "*D*" is the horizontal camera sensor size of the virtual camera, while "*f*" is the effective focal length. To calculate 2D coordinates of point "P", we only need to calculate two angles α_1 and α_2 since position and orientation of two camera's view are known. Using perspective projection mode, we have:

$$r_1 = \frac{x_1}{D} \quad (1)$$

$$\alpha_1 = \arctan\left(\frac{r_1 D}{f}\right) = \arctan\left(2r_1 \tan\left(\frac{HAoV}{2}\right)\right) \quad (2)$$

Because $HAoV = 90^o$, then

This research is supported by Ministry of Culture, Sports and Tourism (MCST) and Korea Creative Content Agency (KOCCA), under the Culture Technology(CT) Research & Development Program 2011.

$$\alpha_1 = \arctan(2r_1 \tan(45^o)) = \arctan(2r_1) \quad (3)$$

Originally, "*D*" and x_1 are in mm. Since r_1 is a ratio measurement, it can be calculated in pixels dimension instead. Similarly, we can calculate the value of α_2.

Position and orientation estimation: Each runtime captured image is compared to database. If any match is found, the position and orientation of mobile phone is calculated. At this point, there are two possible situations that can happen:

Situation 1: The captured image is matched but no matched feature in the database has 2D reference coordinates. In this case, corresponding position and orientation of the matched image in the database are considered as the position and orientation of the mobile phone. To get real orientation, we use RANSAC algorithm to calculate the error of the orientation using the following equation:

$$\Delta\beta = \left(\frac{\Delta x * 90}{Ws}\right) \quad (4)$$

where *Ws* is the width of reference image in captured image's frame and Δx is a difference of 2 central points' x-coordinate in captured image's frame.

Situation 2: The captured image is matched and there are at least 2 matched features in the database that have 2D reference coordinates.

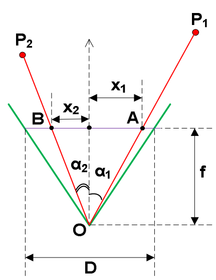

Fig.3 Mobile phone's position estimation using compass

In this case, we use two 2D-features and compass's orientation to get mobile phone's position. To estimate mobile phone's position "O", we only need to determine two angles α_1 and α_2 using equation (2) because camera phone's orientation is known using the digital compass attached to the phone. Note that if there are more than 2D-features, each pair of 2D-features will be used to calculate the phone's position. The final phone's position is considered as the center of the set of estimated ones.

Position tracking: To reduce matching time, a previous position tracking mechanism is employed: Each captured image is first compared to reference images which have positions (or coordinates) close to the previous position. This mechanism can avoid comparing to all database images.

III. Experimental Results

For performance evaluation, we have implemented the proposed system on an iPhone 3GS. First, we implemented and tested the modified version of HIP method on the iPhone. The speed of wide baseline matching on the iPhone is about 9 fps. Then we take an evaluation on the correctness of position estimation for a mobile phone in a museum's floor having 5 rooms. In this experiment, 75 panoramic images captured from 5 rooms are used to create database. In runtime test, 60 positions were examined and estimated coordinates were then compared to the corresponding real coordinates which are considered as ground-truth data for calculating errors. In summary, the mean error of our method is 0.68 m and the standard deviation of error is 0.40 m. Compare to other existing positioning methods our method performs best with the lowest mean error.

TABLE I
Comparision of Positioning Methods

Methods	Accuracy (*m*)		Signals
	Mean error	Std. Dev.	
Adaptive dead reckoning[2]	2.60	Not reported	GPS + compass accelerometer
User activity modeling [3]	Floor-level	-	GPS + accelerometer
Fingerprinting [4]	1.5	-	WiFi
EZ localization[5]	2.0	-	WiFi
Our method	*0.6*	*0.4*	*Camera+compass*

To check the responding time, the proposed positioning system is then tested in the museum. The testing results show that the system can navigate successfully a user to a destination with response time less than 1 second in tracking mode.

IV. Conclusions

The main contribution of our paper is that the proposed system combines two consumer-grade sensors of modern mobile phone and utilizes panoramic images to localize users in indoors without the requirements of extra hardware or external infrastructure. Experimental results show that our solution outperforms other existing methods working on mobile phones. In this paper, we have not investigated initialization problem that would be our future works.

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