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Sensory Landmarks for Indoor Localization

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***Abstract*—Indoor localization is important for a variety of applications such as emergency response, shopping guide, and location-based services. Localization based on smartphone inertial sensors is one of the most widely-used indoor localization techniques since it can provide continuous and real-time locations without requiring additional infrastructure. However, it suffers from the accumulated error problem, which can be addressed by using sensory landmarks. In this paper, we first introduce the concept of sensory landmarks, and then show how different types of sensory landmarks can be detected. The method for estimating the locations of sensory landmarks is also given.**

***Index Terms*—Indoor localization, sensory landmarks, landmark recognition, inertial sensors, smartphone.**

I. Introduction

Nowadays, indoor localization has attracted lots of attention from both academia and industry because of its pervasive application fields such as museum guide [1], emergency response [2], personal task reminder [3], asset tracking [4], search and rescue [5], advertising [6], [7], and location-enabled social networking [8]. Researchers have proposed a number of indoor localization solutions [9], [10], which differ from each other in terms of positioning techniques used, coverage, accuracy and cost of deployment and maintenance.

Inertial sensors-based method, also known as dead reckoning (DR), is one of the most widely-used localization, navigation and tracking techniques. This is because it can provide continuous real-time location estimation without the requirement for any additional infrastructure, given an initial location. The popularity of smartphones equipped with many kinds of sensors such as accelerometer, gyroscope, barometer and magnetometer has made the DR method become an attractive solution for indoor localization [11], [12]. Nevertheless, the DR method suffers from the accumulated error problem that its error increases over time, resulting in the inappropriateness for long time tracking tasks. This means that it needs to be periodically calibrated using other absolute localization techniques such as WiFi [13], [14] and UWB [15]. However, these absolute localization techniques are not always available and often impose extra cost on the deployment and maintenance.

An effective solution to deal with the accumulated error of DR is to make use of landmarks. Different from landmarks in linguistics, cognitive science and geographic information science [16], [17], a landmark here is defined as a location point where at least one type of sensors present a distinctive, stable, and identifiable pattern in the readings. Corners or turns, for instance, compel users to change their walking direction that can be captured by the gyroscope; a door imposes users to change their motion states that can be sensed by the accelerometer. These landmarks (e.g., doors, corners, turns, elevators, stairs) are naturally distributed in indoor spaces, and can be used to calibrate the accumulated error of the DR method.

In this paper, we first propose the concept of sensory landmarks, which are passively sensed by sensors (e.g., the built-in smartphone sensors) without any human participation or intervention. Then, we categorize the sensory landmarks and show how to detect and recognize different types of sensory landmarks in indoor environments. Finally, we introduce how to estimate the locations of sensory landmarks, the accuracy of which has a direct influence on the location accuracy of the DR method.

II. Definition of Sensory Landmarks

In the field of linguistics and cognitive science, a landmark is generally defined as everything that stands out of the background, which is easily recognizable and memorable [16]. For example, the Eiffel Tower is a globally known landmark since it is unique, easily recognizable and has a particular landscape; the Statue of Liberty is a landmark as it has special meaning and can be seen from different locations. Conventional landmarks can be classified into three types: visual landmarks, cognitive landmarks, and structural landmarks [18]. A visual landmark stands out due mainly to its contrast with the surrounding environment, prominent spatial location or easily memorable visual characteristics. A cognitive landmark is a feature or object with typical meaning or atypical characteristics. A structural landmark is defined as the one that has an important role or location in the structure of the space. However, these conventional landmarks exist in outdoor environments and are usually used for wayfinding or route directions, which require the user to find, identify and verify them, resulting in unsuitability for indoor localization.

Therefore, we propose the concept of sensory landmarks for the purpose of assisting indoor localization. A sensory

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landmark refers to a location point where at least one type of sensors present a distinctive, stable, and identifiable pattern in the readings. For instance, the accelerometer readings present a particular change pattern when the user takes an elevator, escalator, or goes upstairs or downstairs. A sensory landmark must meet the following three requirements at the same time:

• Distinctiveness. The change pattern of sensor readings must be distinctive at the sensory landmark. This feature stipulates that the sensory landmark can be distinguishable from sensor readings at other locations.

• Stability. A sensory landmark must be stable for a period of time, which means that it has to be detected by some sensors every time a user passes it. For example, a door is a sensory landmark if the user has to change his or her motion states every time he or she passes through the door. However, if the door is sometimes open but sometimes closed, it cannot be regarded as a sensory landmark since the corresponding change pattern in sensor readings is unstable.

• Identifiability. A sensory landmark must be detectable by one or more types of sensors at the location point. The intuition of proposing the concept of sensory landmarks is to free users from manually recognizing landmarks (e.g., visual landmarks, structural landmarks, or cognitive landmarks), which is troublesome especially when the user is not familiar with the environment.

Fig. 1: Types of sensory landmarks

III. Detection of Sensory Landmarks

Sensory landmarks can be categorized by the types of sensors that are able to detect them, as shown in figure 1. So far, we define nine types of sensory landmarks according to these sensors that are built in most smartphones, namely GPS (Global Positioning System), WiFi, NFC (Near Field Communication), accelerometer, gyroscope, barometer, audio, camera, and magnetometer. With the development of sensor technology, it is expected that more types of sensory landmarks will become available for indoor localization. We regard location points that meet the distinctiveness and identifiability feature requirements as potential sensory landmarks, and introduce an algorithm in section IV to verify their stability. Only location points that satisfy the defined three feature requirements can be taken as sensory landmarks. All the sensory landmarks can be detected by checking where an abnormal change of one or more types of sensors arises or where the user is forced to perform certain activities or movements [19], [20].

A. GPS Landmarks

The status of GPS signal changes when a user enters or exits a building or is at the vicinity of a window, as shown in figure 2. Therefore, an entrance or a window can be regarded as a GPS landmark if it possesses the three characteristics defined in section II. As a GPS landmark, the GPS sensor must be able to detect a change in the number of visible GPS satellites as the user passes or approaches it, e.g., from 3 to 0 or vice versa.

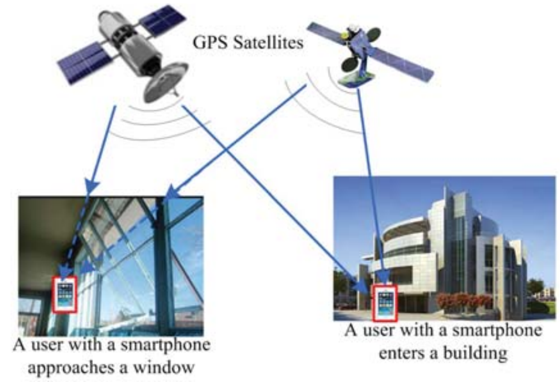

Fig. 2: An example of GPS landmarks

B. WiFi Landmarks

The WiFi landmarks can be detected based on the similarity of signal strength received from WiFi access points. Let A_1 and A_2 represent the sets of WiFi access points (APs) whose signals are received at two locations l_1 and l_2, respectively. Then, a similarity S between locations l_1 and l_2 can be defined as follows [21]:

$$S = \frac{1}{|A|} \sum_{\forall a \in A} \frac{min(f_1(a), f_2(a))}{max(f_1(a), f_2(a))} \tag{1}$$

where $A = A_1 \cup A_2$, $|A|$ is the total number of access points whose signals are received at either location, and $f_i(a)$ is the received signal strength (RSS) of AP a overheard at location l_i. If AP a is not overheard at l_i, then $f_i(a)$ will be set to zero. The range of the similarity S is between 0 and 1. Then, small areas (e.g., 4 m^2) that have low similarity (e.g., $S < 0.4$) with all locations outside that area can be chosen as WiFi landmarks.

Besides, the location point that experiences the strongest WiFi RSS to an AP within a certain region can be also regarded as a WiFi landmark. This is because there is usually only one location point that can receive the strongest RSS within the coverage of that AP and it is stable, distinctive, and identifiable. For example, in figure 3, the location point P_2 is a WiFi landmark if it receives the strongest RSS from the corresponding AP compared to other location points.

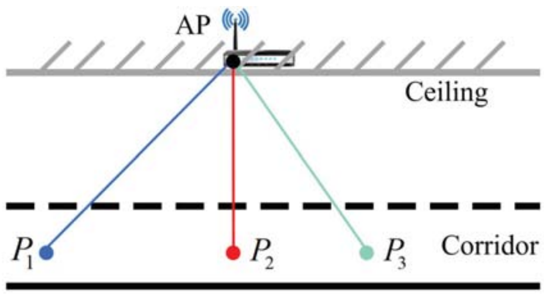

Fig. 3: A type of WiFi landmarks

C. NFC Landmarks

Near field communication technique (NFC) has been integrated into most modern smartphones, which is a specialized subset within the family of Radio-frequency Identification (RFID) technology. NFC readers can act as a type of landmarks as long as they are fixedly installed or do not change their location for a period of time. When a NFC tag (e.g., a smartphone) touches on a NFC reader or is within the range of the NFC reader, the location of the tag can be calibrated. Nowadays NFC technique has been widely used for payment, check-in or check-out, etc. The NFC readers are usually placed at some fixed location points like a cashier's desk or a door, as shown in figure 4, which possess the three features of being a landmark.

Fig. 4: An example of NFC landmarks

D. Accelerometer Landmarks

The motion state of a user changes at certain locations in an indoor environment, which can be sensed by the accelerometer. For instance, when a user is opening a door, his or her motion state would change from Walking to Still, and then to Walking. The location of the door can be regarded as an accelerometer landmark if the user has to experience this change every time he or she passes through the door. The motion state change also happens when a user goes upstairs or downstairs, or takes an elevator upward or downward.

Figure 5 shows the change in the magnitude of acceleration when a user passes through a door. The accelerometer readings can be inputed into a classifier (e.g., a decision tree) that classifies the user motion states (e.g., Walking, Still, Going upstairs). More details about motion state classification can be found in our previous work [22]. The change pattern of "Walking $\longrightarrow$ Still (for a few seconds) $\longrightarrow$ Walking" can be regarded as a condition that checks whether a door is a potential accelerometer landmark.

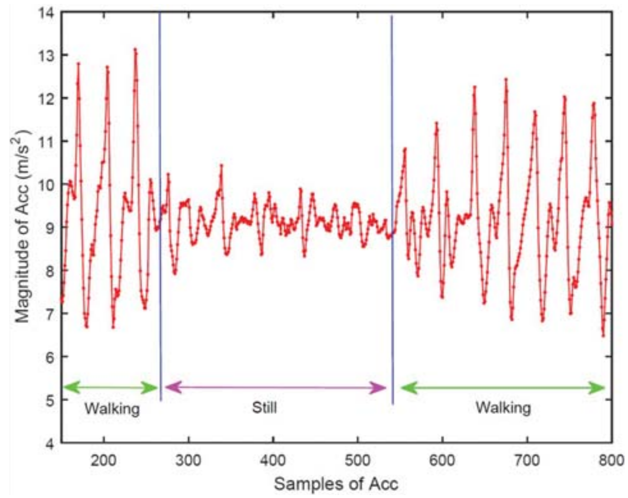

Fig. 5: The change in the magnitude of acceleration when a user passes through a door

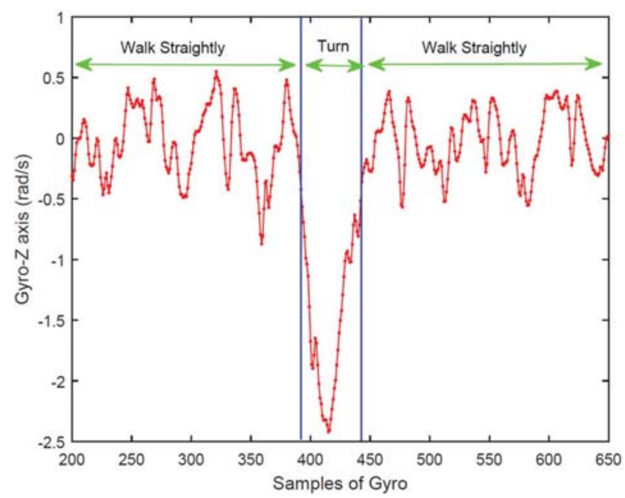

Fig. 6: The change in the gyroscope readings on the Z-axis when a user takes a turn (The user holds the phone in the hand)

E. Gyroscope Landmarks

The gyroscope can measure the angular displacements without the effect from ferromagnetic materials or other devices. When a user takes a turn, there is a significant change in the gyroscope readings, as depicted in figure 6. To detect a gyroscope landmark, we define d_{gyro} as the difference in the average value between two neighboring windows of gyroscope readings, namely

$$d_{gyro} = |\bar{\theta}_{i+1} - \bar{\theta}_i|, i = 1, 2, 3, ... \quad (2)$$

when d_{gyro} is greater than a certain threshold ϵ_{gyro}, we consider this location point as a potential gyroscope landmark and record the sensor readings and corresponding position at this point.

F. Barometer Landmarks

The barometer is able to measure the air pressure, which changes with the height. This means that it can be used to detect the vertical movement of a user (e.g., going upstairs or downstairs, taking an elevator). Figure 7 shows the change in the barometer readings when a user walks horizontally, goes upstairs or downstairs, and takes an elevator downward or upward.

It is easy to recognize these motion states by using the pressure derivative feature proposed in [22]. Stairs and elevators can be regarded as barometer landmarks, provided that they satisfy the distinctiveness, identifiability and stability conditions.

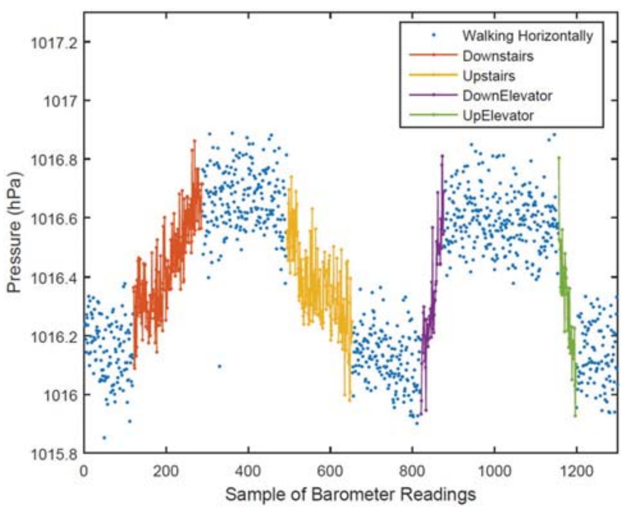

Fig. 7: The change in the pressure when a user takes stairs or an elevator

G. Visual Landmarks

Traditionally, visual landmarks are recognized by their facade area, shape, color, and visibility [23], and this recognition needs human's attention and participation. Nowadays, the camera, which has been integrated into modern smartphones, can assist human to recognize these visual landmarks.

However, continuously using the camera reduces the battery run time dramatically. A promising type of visual landmarks is quick response (QR) code, which can be seen everywhere (e.g., supermarkets, shopping malls) today. These QR codes are good potential visual landmarks if they are attached at fixed locations. The detection of QR codes is easy, as shown in figure 8, and they can be quickly recognized by scanning with the camera.

Fig. 8: An example of visual landmarks (QR code)

H. Audio Landmarks

The microphone can capture the human voice as well as the sound from environment. Some machines that are placed at some fixed locations may produce a particular sound, which is different from environment noise and human voice. If this sound is stable, then the location of the machine can be an audio landmark.

I. Magnetic Landmarks

A magnetic landmark is a location point where the magnetometer presents an outlier due to the effect of ferromagnetic materials. It can be detected by checking whether the average value of a window of magnetometer readings exceeds a threshold.

IV. Location Estimation of Sensory Landmarks

To use sensory landmarks for calibrating the accumulated error of inertial sensors-based localization method, we need to first obtain the locations of sensory landmarks. While the locations of some landmarks (e.g., those at the location of stairs, elevators) can be obtained from the map information, other landmarks can be inferred from users' trajectories. Here we provide the method for estimating the locations of sensory landmarks from the trajectories obtained by the DR method. The basic equations of the DR method are as follows:

$$\begin{cases} x_{t+1} = x_t + s_t \sin\theta_k \\ y_{t+1} = y_t + s_t \cos\theta_k \end{cases} \quad (3)$$

where (x_t, y_t) and (x_{t+1}, y_{t+1}) are the locations of a user at time t and $t + 1$, respectively. s_t is the corresponding displacement and θ_k is the heading at step k (which corresponds to the time period from t to $t + 1$. Given an initial location (x_0, y_0), we can infer the user's real-time location by making use of the collected readings from accelerometer, gyroscope and magnetometer. To do this, we need to compute the user's step length and heading at each step.

A. Step Length Estimation

It is observed that the step length of a user is relatively fixed during a period of time. Thus, we can use the following formula to calculate the user's step length at each step.

$$s_t = s_{t-1} + \Delta s_t \tag{4}$$

where s_t is the value of the step length whose initial value can be empirically determined (e.g., 0.65 meters according to [24]). Δs_t is the deviation at time t between the ground truth and the estimated value of step length.

To estimate the value of Δs_t, we need to know how many steps a user takes from a known point to another known point (which can be inferred from map information). This can be done by utilizing the repetitiveness and periodicity of a user' walking to check the number of peaks in the accelerometer readings. Suppose the user takes n steps traveling this distance d between these two points, then we can compute Δs_t as follows:

$$\Delta s_t = (d - n \cdot s_{t-1})/n. \tag{5}$$

B. Heading Estimation

Both the magnetometer and the gyroscope in the smartphone can be used to provide the user's heading. However, the magnetometer is affected by the ferromagnetic materials, and the gyroscope has the drift problem. To address these problems, we can use the Kalman filter to combine the magnetometer readings and gyroscope readings, which can eliminate the magnetic effect on the magnetometer and the drift problem of the gyroscope [12]. The main equations of the Kalman filter are as follows.

Prediction:

$$\theta_k^- = \theta_{k-1}^- - \dot{\theta}_k \cdot \Delta T \tag{6}$$

$$P_k^- = P_{k-1} + Q \tag{7}$$

Update:

$$\theta_k = \theta_k^- + K_k \cdot (\theta_k^{'} - \theta_k^-) \tag{8}$$

$$K_k^- = P_k^- / (P_k^- + R) \tag{9}$$

$$P_k = (I - K_k) \cdot P_k^- \tag{10}$$

where θ_k is the heading computed at the k_{th} step, $\theta_k^{'}$ and $\dot{\theta}_k$ are the angle from the magnetometer and the gyroscope reading along the movement direction, respectively. ΔT indicates the sampling interval, K_k denotes the Kalman gain, and P_k represents the error covariance matrix. Q and R are the process noise covariance and measurement noise covariance, respectively.

C. Location Refinement of Sensory Landmarks

Given an initial location, we can use the DR method to infer and record the locations of a user, including potential sensory landmarks where some sensors present the defined feature patterns. However, the coordinates of these potential sensory landmarks that are inferred from the user's trajectories are coarse and inaccurate, which need to be further refined. Also, as we mentioned before, potential sensory landmarks need to be verified on their stability to be considered as sensory landmarks. This ensures that we can eliminate some false sensory landmarks. For example, the accelerometer might present the features of an accelerometer landmark when a walking person runs to another person at the corridor and stops for a short chat, which cannot be considered as a sensory landmark since it does not satisfy the stability requirement.

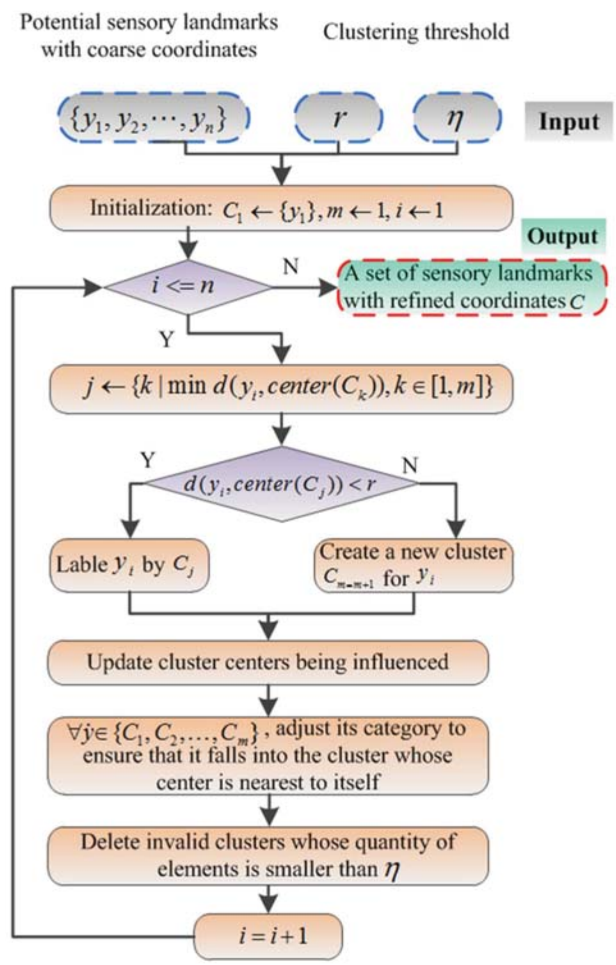

Fig. 9: Refining locations of sensory landmarks

In the following, we introduce the distance constraint-based K-Means clustering method [12] to determine sensory landmarks by checking the stability condition and further refine their locations. This algorithm takes as input a sequence of potential sensory landmarks with coarse coordinates (denoted by $Y = \{y_1, y_2, \cdots, y_n\}$), a distance constraint threshold r (which is an empirical value, e.g., 2 meters based on [12]), and a quantity threshold η. It outputs a set of sensory landmarks with refined coordinates, denoted by $C_1, C_2, \cdots, C_m$. Each of them represents a sensory landmark and the clustering center is the refined coordinates. The procedure of the algorithm is described in the flowchart 9, where d represents the function to compute the Euclidean distance, and $center$ is the function to compute the clustering center.

The algorithm starts by randomly or sequentially selecting a potential sensory landmark y_1 from Y and putting it into an empty cluster of sensory landmarks denoted by C_1. Then repeat this process under the constraint of the distance threshold r: if the distance between a newly-selected element y_i from Y and the center of any existing clusters of sensory landmarks is smaller than r, then put y_i into the existing cluster whose center is nearest to y_i and recalculate the center of this cluster; otherwise, create a new cluster and put y_i into this newly-created cluster. After this, update all cluster centers being influenced. Once all elements in Y have been assigned, we need to check and adjust all elements in each cluster to make sure that each element falls into the cluster whose center is nearest to itself. To stipulate the stability of a sensory landmark, we only consider those clusters whose quantity of elements is greater than a threshold η as sensory landmarks.

V. Conclusion

In this paper, we propose the concept of sensory landmarks, which not only can be used to assist indoor localization, but also are useful for navigation, tracking, and other location-based services. Different types of sensory landmarks are defined and the corresponding detection methods are given. In addition, we show how to estimate the locations of the proposed sensory landmarks. In the near future, we will investigate how to use sensory landmarks for assisting indoor localization and navigation.

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