An Integrated Indoor BLE-SLAM System

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***Abstract*—The presentation of Bluetooth Low Energy (BLE; e.g., Bluetooth 4.0) makes Bluetooth based indoor positioning have extremely broad application prospects. We propose a received signal strength indication (RSSI) and Dead Reckoning (DR) based Bluetooth positioning method and design a fancy SLAM algorithm integrating the training and locating procedures into a non-divided system. In order to reduce the influence of positioning accuracy due to the abnormal RSSI, we implement a particle filter to help pre-process the signals. Besides, K-NN algorithm is utilized to construct maps of indoor environments.**

I. Introduction

Recent years, We have seen a lot of SLAM algorithms being used in indoor positioning system as Wi-Fi SLAM. However, there is seldom no SLAM algorithm based on Bluetooth Low Energy. In our work, we present a novel SLAM algorithm based on BLE. Our main contributions are:

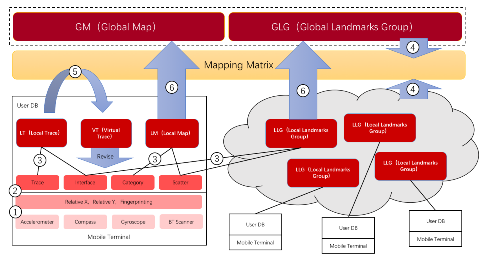
1) Propose a fancy algorithm which fuses training and location phase into a whole part.
2) Propose a algorithm to increase the accuracy of users' traces detection.
3) Exploit presented algorithm like Most-likelyhood, K-NN and particle filtering algorithms in our system.

In the next few sections, I will introduce them in detail.

II. Integrated System

Wi-Fi based indoor positioning algorithm are widely researched by many universities and Institutes. While BLE based system are broaded applied to indoor localization, the SLAM algorithm are seldom designed at the best knowledge we have. Basically, the reason is that the RSSI is unstable not only due the multipath effect but also its trade-off on power efficiency and low cost. However, we can utilize other methods to make up for the unstability. Intuitively, we design a system using sensors in the smartphones to cooperate with BLE. The integrated system is as Figure 1. The block gives a clear explain of our system.

The brief procedure of our system is as follow: 1) The BLE access points are deployed randomly in an indoor environment(e.g our laboratory). The initial phase begins as the training phase. 2) Users with their smartphones enter the indoor envrionments, then our system will collect smartphones' data to form the trace of users in their own reference system. Our system will distinguish where the access points are during walking and give a weight of the accuracy of the access points' positions. 3) Online synergy will gather all the user' traces to unify the reference system to get a GM. We also design a fancy



The left part of the block stands for the local database (i.e. users' databases). The right part which evoloped by a cloud means the server. They are transformed by Mapping Matrix to further form GM and GLG. GM is the integrated map of current indoor environment and GLG contains the coordinates of the anchors in GM.

Fig. 1. Integrated System

algorithm to determine when and which access points can get to work(i.e. to leave the training phase and modify user's trace) 4) User's localization is determined by Dead Reckoning and Modification of access points which get enough weights to work.

Here are several challenges to overcome in our system:

1) How to reduce the effect of the unstability of RSSI from BLE access points due to multipath effects and itself's limitation?
2) How to determine whether a certain BLE access point is ready to work(i.e. to leave the training phase and modify user's trace)?
3) How to cooperate with each user's trace on the cloud server?

In the next section, I will give a clear explaination to each challenge.

III. Online Synergy

My contribution to the whole system is on the online synergy part which is the key to our system. The challenge described above are explained here clearly.

A. How to reduce the effect of the unstability of RSSI from BLE access points due to multipath effects and itself's limitation?

Actually, the unstability does have a great influence on our system. The method we use to determine an access point's location is firstly to set a threshold and then judge if the RSSI exceeds the threshold to determine where there exist an access point. In this scenario, a fluctuation of RSSI will give a possibility to have a bad determination over true points. Considering these challenges, we give each determination a weight to show the credit.

$$Weight(i,j) = \frac{|RSSI(j) - RSSI_{max}(j)|}{\Delta t(i)}$$

$Weight(i,j)$ stands for the credit for $AccessPoint_j$ in $User_i$'s trace, $RSSI_{max}(j)$ means the global maximum of RSSI of $AccessPoint_j$ and $\Delta t(i)$ is the interval between the current time point and the latest modified time point.
Then we use centroid method to get the final coordinates of the access points.

$$(x,y)_j = \frac{\sum_{i=1}^{n}(x,y)_j Weight(i,j)}{\sum_{i=1}^{n} Weight(i,j)}$$

$$Weight(i,j) = \frac{\sum_{i=1}^{n} Weight(i,j)}{n}$$

As for multipath effect, we know that the largest RSSIs are usually got from signals from a reflection of obstructions. However, it does not matter our system. Because our scheme is to utilize BLE access points as anchors, we do not accurately know the location of access points. Without big changes of indoor environments the RSSI distribution will not change too much.

B. How to determine whether a certain BLE access point is ready to work(i.e. to leave the training phase and modify user's trace)?

Here is the key to our system. We propose a simple but efficient method to determine whether a BLE access point is ready to work. I have presented the defination of $Weight(i,j)$, It is intuitive that when the weight exceed a threshold, It may be ready to work. However, we propose another factor which is the total number of anchors n. We also require n exceeds a certain threshold.

$$s.t. Weight(i,j) > \lambda; n > \mu$$

When the constraint is satisfied. The access point begins to modifying user's traces(i.e. location). We can see that our system does not seperate the training phase and location phase but fuse them into a whole procedure. When several access points start to work. $\Delta t(i)$ in last section will be shorten. In consequence, it makes other access points getting to work sooner. It is like users light the access points when they pass it and the light will lead to light other access points, too, rendering all access points lighted soonly.

C. How to cooperate with each user's trace on the cloud server?

Firstly, we utilize most-likelyhood algorithm to do the matrix transform. Since our access points are deployed relative compactly, every trace will pass some access points and record them in their traces as anchors. Then we could unify all users' traces based on anchors using a transformational matrix.

$$argmin H = \|HA - B\|^2$$

H is the transform matrix, A is the GM belongs to a certain user's and B is the global GM. Here I will present two novel algorithm designed by me.

1) Optimization on enclosed traces: If the trace is like a closed loop like Figure 2. Our system can detect users'

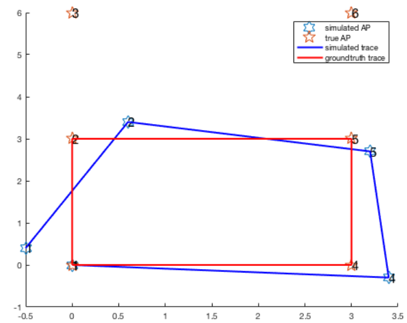


Fig. 2. Enclosed Trace

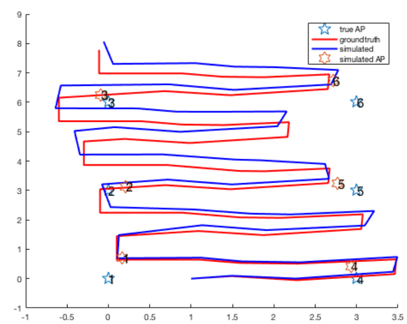


Fig. 3. Simulated Trace

traces which are enclosed. If detected, the algorithm will be triggered.

Algorithm 1: Optimization On Enclosed Traces

Input: GLG,$UserTrace$
Output: $ModifiedUserTrace$

n = Numberof(AP in $UserTrace$);
for $j = 1; j \leq n; j++$ **do**
  $flag = true$;
  $(x,y)_{Global(j+1)}$=Coordinates in GLG;
  while $flag$ **do**
    Adjust $(x,y)_{Local(j+1)}$;
    if *argmin* $(x,y)_{j+1} = (x,y)_1 - (x,y)_n$ **then**
      $flag = false$;
  $(x,y)_{Local(j+1)} = (x,y)_{Global(j+1)}$;
Connect $(x,y)_{Local}$ form $ModifiedUserTrace$;
return $ModifiedUserTrace$;

IV. Implementation & Evaluation

I have not deployed the BLE access points in the real environment, however, we have simulated it on MATLAB. We use 6 access points scenario as an example. Figure 3 shows one of the trace I simulated.
I use 50 traces simulated by myself to draw a whole picture of access points. Figure 4&5 and Table 1 show the location and weights.
We could find that the Weights can truly reflect the similarity between simulated locations and ground-truth locations of access points.

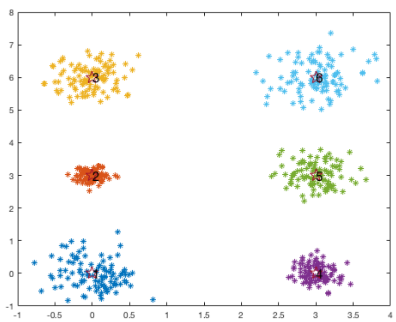


Fig. 4. Distribution of Simulated Access Points

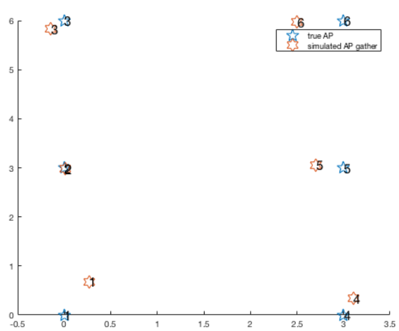


Fig. 5. Final Simulated Access Points Location

TABLE I
Weights & Numbers of Each Access Point Location

MAC	1	2	3	4	5	6
Number	26	30	22	19	30	21
Weight	13.3055	106.6153	83.5447	55.6379	58.6071	14.4855

V. Future Work

We will soonly deploy the BLE access points in our laboratory in the next week. I am responsible for building up the database in the server and using cloud computing to realize the algorithms above.

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