Improving Accuracy of WLAN-Based Location Estimation by Using Recursive Estimation

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Abstract

We propose a method of improving accuracy of WLAN-based location estimation. The WLAN-based location estimation is a convenient method once a dense map of access points (APs) is prepared by AP hunting such as war-driving/walking. However, the density of the APs cannot be always high. Rather, it is still low such that less than three APs are found even in urban areas. We propose recursive estimation methods and experimentally compare to the existing method, where the estimation accuracy was improved from 41.6 meters to 31.1 meters at a low density area best case.

1. Introduction

Physical location of a user is one of the most useful contextual information of personal experience log in a ubiquitous computing environment for ubiquitous experience media [1] applications such as lifelog. People have started using 802.11 LAN beacons because of its wide deployment indoors and outdoors in urban areas [2]. It can provide a fairly good location estimation of a client by using the received signal strength indicator (rssi) from the access points (APs) nearby when a good and dense AP location map is available. However, the radio characteristics across walls and the density of AP vary depending on locations.

We propose new *recursive algorithms* of the location estimation by using past estimates of the client location to compute a current estimation, which shows good performance with low density APs. Two algorithms are presented, experimentally compared with the existing method, and showed 10 to 20 % improvement when the number of observed AP is only one to three.

2. Related Works

There are many research efforts and working systems on Radio LAN based location estimation. As the coverage of 801.11 beacons is expanding throughout countries, location aware services are becoming feasible. However, the simple location identification of AP is still erroneous [3] due to the difficulty of massive AP hunting with reasonable ground truths in convenient ways. Matsuzawa et al. [4] proposed to use AP's virtual location that takes into account radio characteristics in order to make a reasonable map of AP locations by war walking. They showed that better accuracy is achieved when multiple AP signals are used with rssi based weights, in particular, in an AP dense area. Our proposal is based on the observation to increase the number of anchoring information.

3. User Location Estimation

In this research, we refer to the RSSI Density Weighted Centroid (RDWC) method [4] and make comparison with our proposed method. We propose two recursive location estimation methods using the preceding estimated location.

(1)RSSI Density Weighted Centroid (RDWC) [4]

The existing method, RDWC, computes a weighted centroid of whole observed APs by weights w_i (i: the identical number of each AP at a location, $i=1,\ldots,k_n$) derived from the signal strength and the density of APs. The n-th estimated user location $(lat, lon)_n^T$ is given by the following equations.

$$(lat, lon)_n^T = \frac{1}{\sum w_i} \sum_{i=1}^{k_n} w_i (x_i, y_i)_n^T, \quad w_i = \frac{10^{(rssi_{ni}+a)/b}}{c_i},$$

where k_n is the number of observed APs at n-th observation. $(x_i, y_i)_n^T$ is the known *latitude* and *longitude* data of the i-th AP (AP_i), respectively. $rssi_{ni}$ is the signal strength of AP_i at n-th observation and c_i is the registered number of APs within 10 m from i-th AP in the preassembled map. $()^T$ represents the transpose of a matrix. The constants a and b of the weight w_i indicate the relation between signal strength and distance, which are computed using learning samples. In this experiment they are set to $a=35.47$ and $b=24.42$.

(2) Recursive RDWC (R^2DWC)

The first proposed method, R^2DWC, recursively computes a weighted centroid of whole observed APs taking into account the preceding estimated location. The weight w_i for AP_i is same as RDWC. An additional weight for the preceding estimate, $d^{-1}{}_n$, is derived from the moving distance since the preceding estimation.

$$(lat, lon)_n^T = \frac{1}{d^{-1}{}_n + \sum w_i}\left(d^{-1}{}_n (lat, lon)_{n-1}^T + \sum_{i=1}^{k_n} w_i (x_i, y_i)_n^T\right),$$

$$d^{-1}{}_n = \frac{1}{v(t_n - t_{n-1})},$$

where t_n is the time at n-th observation and v is the moving speed of wearable client. In this experiment it is predefined as $v=1.34$[m/s] by assuming a constant speed of human walking.

(3) Weighted Recursive RDWC (WR^2DWC)

WR^2DWC is the second proposed method, which is the same as R^2DWC except that the weight of the preceding estimated location, $d^{-1}{}_n$, is adjusted according to the number of observed APs according to the following equation.

$$d^{-1}{}_n = \frac{1}{v(t_n - t_{n-1})k_n}$$

4. Experimental Results

We did a war-walking session around a university campus and obtained 801.11 radio observations at 7,326 points (3,707 point for APs map creation, while 3,529 for estimation experiment). Each point observation consists of several AP's MAC address, their radio strengths and a GPS location as a ground truth. We used a Wireless Embedded Card Model 0504 built into a Panasonic CF-T1 laptop PC and a SONY GU-BT1 GPS receiver (5 m accuracy).

Table 1 shows the mean errors per the numbers of observed APs and the overall mean error. The recursive R^2DWC and DR^2DWC show better results than RDWC. Because the estimation accuracy was greatly improved to 31.1 m by using R^2DWC in the case with 1-3 APs, the recursive estimation using preceding location can be said to be useful information at a low density area. Figure 1 shows the mean error for each number of APs. With a few APs (1-6 APs), DR^2DWC is better than R^2DWC. However, DR^2DWC is worse than R^2DWC for dense area (13 or more APs). It suggests that R^2DWC and DR^2DWC can be used adaptively according to the observed number of APs. Figure 2 shows the estimated route by RDWC and DR^2DWC using the Google Map toolkit. The route by DR^2DWC (Fig.2 (b)) is smoother and closer to actual walking route than by RDWC (Fig.2 (a)).

Table 1 User Location Mean Estimation Errors [meters]

Estimation method	The number of observed APs			Overall
	1-3	4-9	10-	
(1) RDWC	41.6	34.9	36.4	37.7
(2) R^2DWC	36.4	33.6	<u>33.8</u>	34.7
(3) WR^2DWC	<u>31.1</u>	<u>31.0</u>	35.6	32.1
The number of observations	1316	1416	797	3529

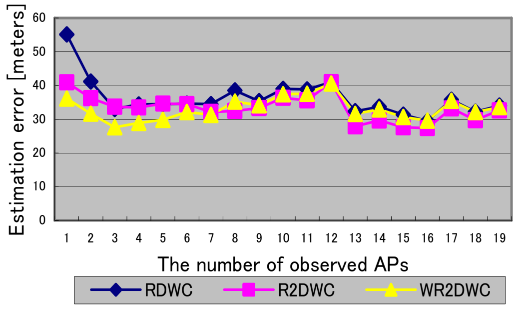
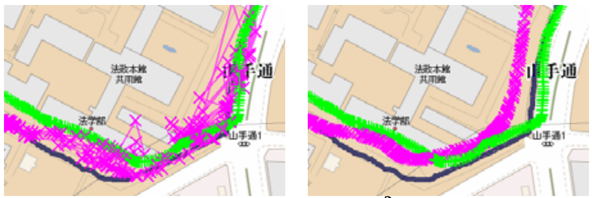


Figure 1 Estimation Errors of Each Number of APs



(a) RDWC[4] **(b) R^2DWC**(proposed)

×: estimate +: GPS trace *: walking route

Figure 2 Estimated Routes

5. Conclusion

We proposed new location estimation methods using a recursive algorithm and obtained better results. Since the proposed algorithm is a recursive one, obtaining an accurate initial estimate is essential. Periodical check with a reliable beacon will be helpful to keep accuracy as well. Their source can be different from the 801.11 signals. Future work includes considering a distribution model of AP signals by employing Kalman filtering. This work is supported by the cc-Society Program, MEXT Japan.

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