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A Localization Method for Smart Phones by Detection of Walking Using an Accelerometer in Indoor Environments

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Abstract: This paper proposes a new localization method for smart phones using an accelerometer. Although the global positioning system (GPS) is applied in various fields, it has a disadvantage in that it cannot be used effectively in indoor environments. To overcome this problem, many localization methods in indoor environments exploiting Wireless LANs have been proposed, but few systems achieve high accuracy. On the other hand, the smart phones with many sensors and powerful CPUs are becoming wide spread. We examined a localization method specialized for smart phones, and evaluated our proposed method by implementing a prototype system and conducting experiments with it.

Keywords: localization, smart phone, accelerometer, Wireless LAN

1 INTRODUCTION

Currently, the Location-Based Services (LBS) are spreading widely. Using GPS is one way to obtain position information, and it is being used for variety of LBS, including car-navigation systems. However, this approach is difficult to use in indoor environments where electromagnetic waves cannot reach. Then, many systems utilizing variety of wireless equipment for indoors have been proposed[1][2], but they require constructing an infrastructure specifically for the service. Therefore, they may not be the best policy because of the cost. Some systems using existing Wireless LAN(WLAN) access points to solve that problem. If a WLAN is used for localization, a simple and widely used way to estimate distance is based on Received Signal Strength Indicator (RSSI), which do not require complex hardware. Unfortunately, RSSI is environment-dependent, and the wireless channel is very noisy in indoor environments. A radio frequency signal can suffer from reflection, diffraction, and multipath effects, making the signal strength a complex function of the distance. Therefore, the many existing methods exploiting RSSI cannot provide results high accuracy.

On the other hand, over the last few years, smart phones with many sensors have become widely distributed and are expected to increase in the future. Nevertheless, almost all existing localization methods for mobile phones are for non-smart phones, there are few or no methods specialized for smart phones.

Based on this background, we propose a localization method achieving greater accuracy with smart phones by making the best use of the its advantage. The smart phone has features such as usability, powerful computing ability and many sensors. We attempted to use the accelerometer in smart phone for localization. In this study, we exploit existing wireless access points for localization to avoid the cost of custom system.

2 LOCALIZATION METHOD

In this study, we use the RSSI received by a smart phone for position estimation using existing WLAN access points. Generally, the RSSI value will vary in the same place because the radio signal emanating from an access point is affected by shadowing and multipath fading. Therefore, it is hard to accurately estimate distance or position based on the RSSI . Assuming an office environment as the situation requiring the LBS, users will be stationary most of the time. If the user is not moving, it is reasonable to use all signals during the period the user remains stationary to estimate the position rather than using only the last signal. In general, the signal strength follows a Gaussian distribution, so we can improve overall accuracy by using the average value in our estimation.

2.1 Models for localization

The system estimates the user's position using the RSSI from WLAN access points. As the localization algorithm, we use least-squares approach, which is the most common and easiest using RSSI.

2.1.1 Distance estimation using RSSI

We assume a localization model comprising a set of access points as anchors $A \ni a_i$, which have well-known positions on the map and are identified by the pair (x_i, y_i), a smart phone designated as the target T and a localization server. Generally, a smart phone can obtain RSSI from WLAN access points. As mentioned above, though the RSSI value is very noisy, when defining d_i as the true distance between a_i

and T, the variation in RSSI can be well modeled with the following[3]:

$$\overline{P}_i = \alpha d_i \tag{1}$$

where $\overline{P}_i$ denotes the average signal power received at the ith access point, and α and β are two channel parameters representing the attenuation factor and the power decay factor, which are uniquely determined by the location estimation area.

2.1.2 Localization model

Generally, the localization model using least-squares approach is defined by the following[4]:

$find\ \varphi = (x, y)\ which\ minimizes$

$$E(\varphi) = \sum_{a_i \in A} w_i^2 \left(\hat{d}_i \quad d_i(\varphi)\right)^2 \tag{2}$$

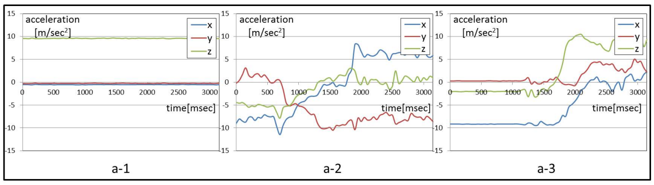
where $\hat{d}_i$ is the estimated distance between a_i and T, or in other words between the ith access point and the smart phone using the model in Eq. (1), and $d_i(\varphi)$ is the distance between a_i and a coordinate (x, y). the w_i term represents the weight applied to each equation. For simplicity we assume that $w_i = 1$. This equation allows us to find a coordinate (x, y) that minimizes $E(\varphi)$ and exhibits a non-linear continuous function about φ. As a result, the localization problem can be viewed as a problem of minimizing a non-linear continuous function with no constraints.

However, in many cases, distance $\hat{d}_i$ estimated by RSSI is unreliable because of large amount of noise, made worse by using only a single RSSI measurement. Since $\overline{P}$ in the model of Eq. (1) denotes an average of RSSIs, we need to measure many times and calculate the average for a proper estimation. Clearly the more measurement made the more accurate $\hat{d}_i$ will be. The best approach is to have the system calculate the average from all RSSIs during periods the user does not move.

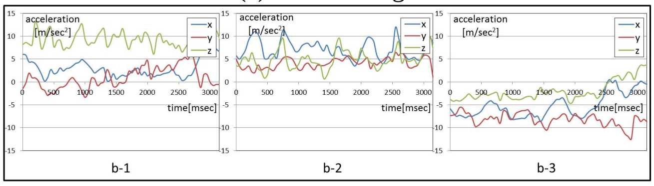
2.2 Movement detection

In order to detect whether or not user is moving, specifically whether or not the user is walking in this study, we utilize information from the accelerometer in the smart phone. The accelerometer must always be running while the position is being estimated, raising the issue of battery drain. However, for examining the effectiveness of using the accelerometer for localization, we are not concerned with this. Almost all smart phones can obtain acceleration data in three dimensions, but it is impossible to calculate the distance that a user has moved from this data because of the amount of noise. To detect whether the user is walking based on noisy acceleration data, the system needs to check the data directly and its time frequency. For example, if the user shakes his legs while his smart phone is in his pocket, the system must determine that he is not in fact walking. Fig. 1. presents examples of acceleration while a user is walking and not walking. There seems to be a slight difference between (a) and (b) in that when the user is walking the acceleration changes at a constant frequency. We transformed the composite acceleration data into its frequency components using the Fast Fourier Transform (FFT) , and this clearly shows the difference (Fig. 2.). In generating a classifier based on the transformed data, we found it inadvisable to classify simply according to a threshold and determined that we should utilize supervised learning because of the diversity of situations. We subsequently generated a classifier using a K-nearest neighbor algorithm (K-NN) for the detection.

Acceleration data obtained at intervals of 50[ms] by a smart phone and transformed into frequency components, which are classified once 64 data have been stored. Therefore the system indicates whether or not a user is walking at intervals of 3.2[s]. The classifier is generated from 200 samples used as a training data set, and evaluated by 200 other samples used as a test data set. Fig. 3. presents the results of this test. According to the K-NN algorithm, an unclassified sample is assigned to the class represented by a majority of its k nearest neighbors in the training data set. With $k = 5$, we achieve a precision of 100.0[%] and recall of 94.0[%] for

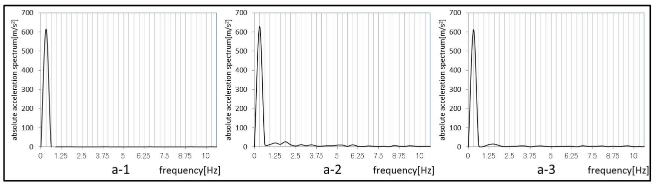


(a) Not walking

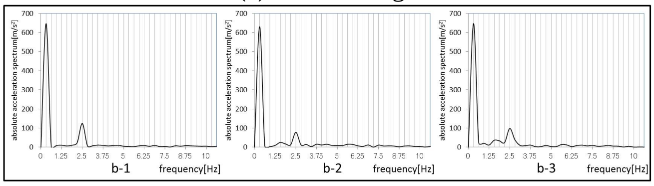


(b) Walking

Fig. 1. Examples of acceleration



(a) Not walking



(b) Walking

Fig. 2. Examples of spectrum

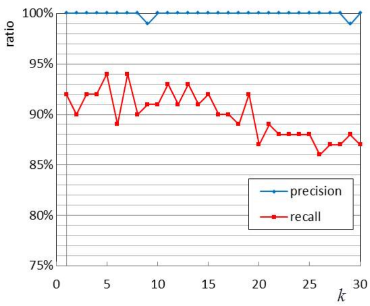


Fig. 3. Precision and recall ratio vs. k

classification of whether or not a user is walking, using the accelerometer in a smart phone.

2.3 Proposed system model

The system estimates position using this classifier and the model of Eq. (2). Consider the set $\mathbf{P}_i$, defined as the set of significant RSSI. $\mathbf{P}_i$ is updated by the following steps:

1. measure RSSI of the ith access point at time t : $\stackrel{\text{def}}{=} p_t$
2. if the classifier determines the user is moving, $\mathbf{P}_i = \{\emptyset\}$
3. $\mathbf{P}_i = \mathbf{P}_i + \{p_t\}$

The number of elements $|\mathbf{P}_i|$ thus varies dynamically, and the average value $\overline{P}_i$ of Eq. (1) is given by

$$\overline{P}_i = \frac{1}{|\mathbf{P}_i|} \sum_{p_t \in \mathbf{P}_i} p_t \quad . \tag{3}$$

Furthermore, $\hat{d}_i$, defined as the distance estimated by RSSI, is

$$\hat{d} = exp\left(\frac{1}{\beta} ln\left(\frac{\bar{P}}{\alpha}\right)\right) \tag{4}$$

by deformatting Eq. (1). Therefore, the localization problem is given by the following:

$$find\ \varphi = (x, y)\ which\ minimizes$$

$$E(\varphi) = \sum_{a_i \in A} w_i^2 \left(\hat{d}_i \quad d_i(\varphi)\right)^2$$

$$where$$

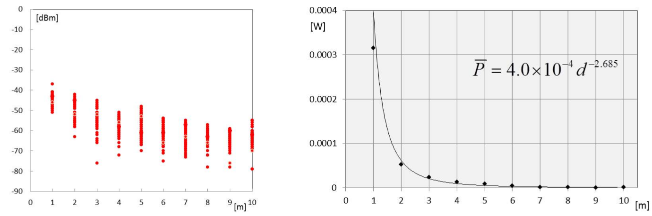
$$\hat{d} = exp\left(\frac{1}{\beta} \ln\left(\frac{\frac{1}{|\mathbf{P}_i|}\sum_{p_t \in \mathbf{P}_i} p_t}{\alpha}\right)\right) \tag{5}$$

3 IMPLEMENTATION FOR EVALUATION

We implemented a localization system using the model given above.

3.1 System configuration

The system consists of a module in the smart phone and a localization server. The smart phone measures the RSSI from multiple access points at even intervals, while in parallel obtaining acceleration information from its accelerometer. The obtained acceleration data are transformed, and then a classifier determines whether or not a user is moving based on data taken at regular intervals by the smart phone. The smart phone sends the RSSI data for multiple access points along



(a) RSSI measurement (b) RSSI propagation model

Fig. 4. RSSI measurement

with the result of the determination of whether or not the user is moving to the localization server. The server estimates the smart phone's position from the received data using the proposed method and displays the result on the screen.

3.2 Preparatory experiment

We measured the RSSI 100 times at each 1[m] intervals to determine the constants of Eq. (1), . Fig. 4.(a) presents the result. Using the average value for each distance, we determine the constants by the least-squares method after converting the units form dBm to W. In this case, we obtained $\alpha = 4.0 \quad 10^{\ 4}$ and $\beta = 2.685$.

3.3 Solution for least-squares problem

As mentioned above, the localization problem can be viewed as a problem of minimizing a non-linear continuous function with no constraints, or what is called least-squares problem. Several algorithmic solutions for this problem have been proposed, and in this study, we use the Levenberg-Marquardt algorithm[5]. This is a cross between the Gauss-Newton direction and the steepest descent direction, and is the most popular method for least-squares. We need to note, however, that it may not converge to a best fit solution if the initial value is far from the optimum value.

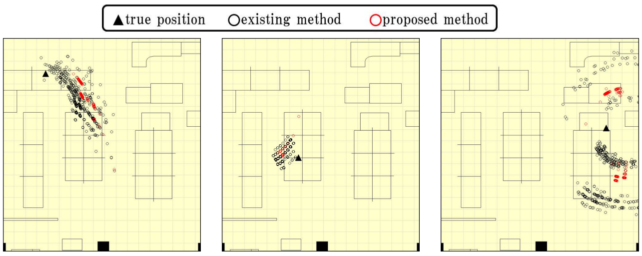
4 EXPERIMENT AND EVALUATION

4.1 Outline of experiment

We conducted an experiment with the system in order to evaluate the effectiveness of the proposed method. In this experiment, we compare the proposed method and the classical method using RSSI that simply uses the last signal to estimate distance. The room in which the experiment was conducted is a space of 8.75[m] by 9.4[m], and there are many desks in the room. Imagine a user sitting at his desk, the system estimates his position 500 times in two different ways. The experiment was conducted at three positions in the room.

4.2 Result and evaluation

Fig. 5. presents the graphical result of the experiment. The triangle indicates the true position in the room, and the black and red circles indicate the estimated position by the classical and proposed methods. These observations may suggest that the proposed method has a smaller variance than the classical method. In fact, we see from Fig. 6. that the more times the system estimates the position, the smaller the share of error in the position estimated by the proposed



position A position B position C

Fig. 5. Graphical result

method becomes. It is reasonable to assume that the influence of any one distance measurement on the estimation becomes small and that the estimation result becomes more accurate as a result of using more measurement data. Note that a position estimated by the proposed method uses only the average value of the overall RSSIs measured before, and not the average position from among all the positions estimated before. Therefore the error in Fig .6. is not an average of overall precious performance either. Something else notable is the earliest few values in the graphs of positions B and C. The values are very high, but this is caused by the Levenberg-Marquardt algorithm. As mentioned in Section 3.3, the initial value is significant for this algorithm, and if it is far from the optimum value, the result may converge to a local optimal solution. We set the initial value of the first estimation to the center of the room and designed the system so that the initial value after the first one is the last estimated value, but it is nevertheless likely that earliest few values converge to a local optimal solution.

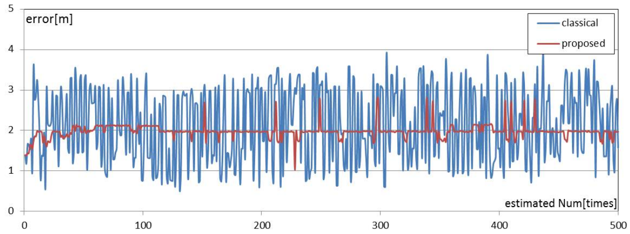
In addition, we use the Root Mean Square Error (RMSE) as a numerical measure for evaluation. RMSE is a frequently used measure of the difference between true values and values which are actually observed in the environment being modeled and estimated. Looking at Table 1.,the RMSE of the proposed method is smaller than that of the classical method in all positions, and therefore the proposed method is superior to the classical method, which simply uses the last signal for position estimation.

Table 1. RMSE

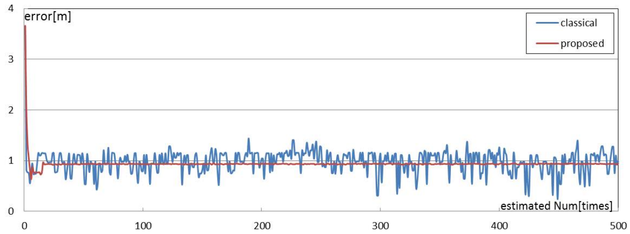
	classical	proposed
position A	1.90[m]	1.75[m]
position B	1.01[m]	0.95[m]
position C	1.93[m]	1.74[m]

5 CONCLUSION

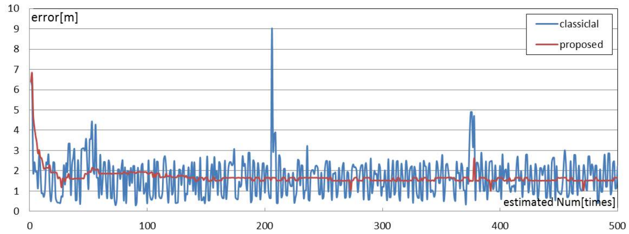
This paper proposes a new indoor localization method for smart phones which are becoming more popular. We focused on the fact that smart phones feature an accelerometer, and introduced a classifier that detects whether or not a user is moving into a classical localization method using least-squares. Our experiment clearly demonstrates that the



position A



position B



position C

Fig. 6. Comparing error between classical and proposed methods

proposed method is superior to the classical method from an RMSE standpoint.

A future study will combine this classifier with a "finger printing" approach in order to achieve greater accuracy. In this study we used the least-squares approach for indoor localization, but generally, this approach is not so accurate. In fact, though the proposed method achieved greater accuracy than the classical method in our experiment, it did not achieve the required accuracy. Therefore, we need to use another approach superseding the least-squares, e.g. a "finger printing" approach, for indoor localization with smart phones.

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