POSITIONING THE NODES WITH ACTIVE BEACONS USING BLUETOOTH BLE.

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Abstract—The indoor positioning of users, using a network of Bluetooth Low Energy (BLE) beacons deployed in a large wholesale shopping store. Our objective is to accurately determine which product sections a user is adjacent to while traversing the store, using RSSI readings from multiple beacons, measured asynchronously on a standard commercial mobile device. We further wish to leverage the store layout (which imposes natural constraints on the movement of users) and the physical configuration of the beacon network, to produce a robust and efficient solution. We introduce our node-graph model of user location, which is designed to represent the location layout. We also present our experimental work which includes an investigation of signal characteristics along and across aisles. We propose three methods of localization, using a "nearest-beacon" approach as a base-line; exponentially averaged weighted range estimates; and a particle-filter method based on the RSSI attenuation model and Gaussian-noise. Our results demonstrate that the particle filter method significantly outperforms the others. Scalability also makes this method ideal for applications run on mobile devices with more limited computational capabilities.

I. Introduction

Our project is concerned with enhancing the experience of users whilst hill climbers at nearby mountain. The mountain is part of a national chain and users already have access to a mobile app which has been widely adopted by its customer base, across the UK. The objective is to add location-dependent services and data, including navigation information, which can be configured by the user depending on their requirements. We have experimented with a number of positioning systems, but the work we report here is concerned with determining the position in the store, using a network of BLE Beacons and a standard consumer mobile device.

The total deployment is of 50 beacons over a store area of around 6000m^2. However, our experimental data was collected over a subsection of around 800m^2, containing 25 beacons. The mountain is laid out as a grid, with series of aisles containing typical retail products and connecting aisles running perpendicular. Each aisle comprises a series of tall metal shelving units,The objective of our system is to determine which aisle the user is in, and, as accurately as possible, their position along the aisle. This provides enough information to determine which milestone are adjacent to the user.

A. Related work

A. Position detection of the signal source

There are some methods to detect the position of the signal source by multiple observations at different positions. The methods are divided into mainly two groups [2]. One is called Range-Based method, in which we use the information of the distance between the receiver and the signal source or the direction of the signal arrival. The other is called Range-Free method, in which we detect the position without explicit calculation of the distance. Generally speaking, Range-Based method is more accurate than Range-Free method but it is more costly. On the other hand Range-Free method is less costly and more robust than the Range-Based method. In both methods, the position of the sensor at each time step is assumed to be known. We show some representative examples of each method.

1) *RSSI(Received Signal Strength Indicator):* The position detection using RSSI is classified as Range-Based method. We estimate the distance between the receiver and the signal source based on the following formula of the signal propaga-tion.

$$P^{(i)} = P_0 - 10\kappa \log_{10}\left(\frac{d^{(i)}}{d_0}\right) + {}^{(i)} \qquad (1)$$

In this eq. (1) the left-hand $P^{(i)}$ is the signal strength received by the *i*th sensor. The right-hand P_0 is the signal strength at unit distance, d_0 is the unit distance, $d^{(i)}$ is the distance between the *i*th sensor and the signal source, κ is the atten-uation coefficient, and ${}^{(i)}$ is the observation noise at the *i*th sensor. We can estimate the distance between the signal source and the *i*th sensor by solving this equation. We denote the position of the *i*th sensor as $[x_s^{(i)}, y_s^{(i)}]^T$. The signal needs to be observed by three or more sensors in this method. When we draw circles each of which is centered at the *i*th sensor position and has radius of d_i, the intersection point of the circles is expected to be the target position (see Figure 1). However the circles do not intersect at one point actually because the received signal contains observation noise. Furthermore the signal is attenuated in proportion to the squared distance and the attenuation coefficient κ is equal to 2 in theory but in fact changes depending on the environment. P_0 also depends on the environment. Therefore we have to estimate κ and P_0 as well. Assuming that the observation noise follows a zero-mean normal distribution, we define the negative log likelihood function $L(\theta)$(eq. (2)) [3], [4], [5]. Then we can estimate $[x_{tar}, y_{tar}, P_0, \kappa]^T$ by minimizing $L(\theta)$.

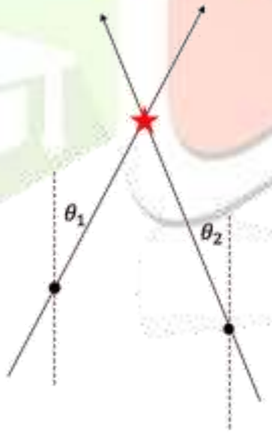

Figure 2. Position detection by using AOA

$$N_{i\,(i)} = d_{(i)}\,(P - P_0 + 10\kappa \log_{10} d_0) \qquad (2)$$

3) Centroid method: Centroid method is classified as Range-Free method, which does not explicitly calculate the distance or use the angle. Assume that we observe the signal

$$L(\theta) = d_{(i)}\,(x_{tar} - x_s^{(i)})^2 + (y_{tar} - y_s^{(i)})^2 \qquad (3)$$

at many points and divide the points into two groups, one is the group which receive the signal and the other is which do not. Then the centroid of the former group is the estimated target position (see Figure 3). For example, in Figure 3 the black points represent the sensors which receive the signal, the white points represent the ones which do not and the red star represents the centroid. As we just have to calculate the

In this eq. (2),

$\theta = x_{tar}, y_{tar}, P_0, \kappa]^T$, $\theta = [\, \hat{x}_{tar}, \hat{y}_{tar}, P_0, \hat{\kappa}]$

[denotes the set of unknown parameters. We obtain the parameter estimates which gives the minimum value of centroid of the sensors so, the computational cost is very low. However many sensors are needed in order to ncrease the accuracy.

$L(\theta)$ from the N data samples.

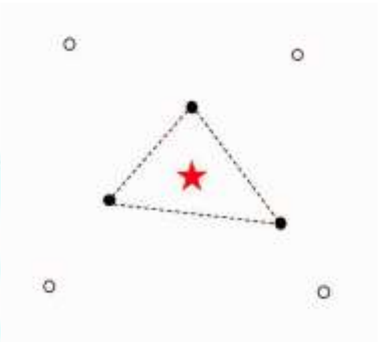

Figure 3. Position detection by Centroid method

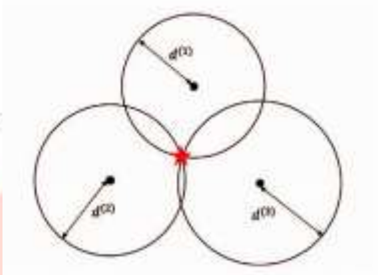

Figure 1. Position detection by using RSSI

III. PROPOSED METHOD

In the conventional methods of position estimation usingRSSI described in the previous section, the positions of the *AOA(Angle of Arrival):* The position detection using receivers are arranged in a lattice or fixed beforehand. They AOA is classified as Range-Based method. We estimate the assume that the signal is observed by multiple sensors all position of the signal source with the angle that the signal at once and the position of the signal source is estimated arrives from (see Figure 2). We need to observe at two or more from the observation data. In contrast, this paper considers points in this method and we can draw the straight lines toward an advanced problem where a UAV equipped with a receiver those directions by calculating the angles at those points. The dynamically or sequentially estimates the target (beacon) intersection point (red star in Figure 2) of these lines is the position by alternately observing the signal at the current estimated target position. We need less sensors in this method position and choosing the next observation position.

In this than in the RSSI position detection, whereas the sensors should method, we use the particle filter or sequential Monte Carlo to have sharp directivity. estimate the unknown parameters including the target position and environment-dependent radio wave characteristics. The estimated distribution on the parameters is updated every time a new observation is obtained. Another important problem is how to choose an appropriate observation point for the next time step so that the UAV can find the target as quickly as possible. In order to resolve this problem in this paper we apply a method inspired by the concept of active learning, which is one field of the machine learning. Active learning is the learning strategy for the problem in which obtaining label information is expensive or time-consuming. In this paper we propose the method that combines the particle filter and an active learning-like observation point selection and show the method can realize the accurate and efficient estimation. Furthermore, it is noteworthy that the proposed method combined with the Range-Based method can estimate P_0 and κ as well which change depending on the environment and the system.

A. Structure of the proposed method

In this proposed method, the basic cycle consists of three steps - 1) observation of the signal from the target, 2) update of the distribution, and 3) determination of the next observation position, as illustrated in Figure 4. By repeating this process, the estimation becomes gradually more accurate. The distribution of the target is thought to be non-Gaussian in general, because we often have to keep track of multiple hypotheses in practice and thus a Kalman filter is not suitable. In this paper we use a particle filter to update and estimate the target's distribution and use an active learning-like method to determine the next observation position.

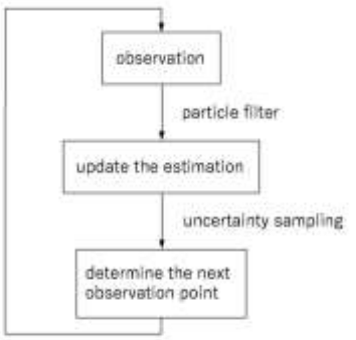

Figure 4. Structure of the proposed method

B. Particle Filter

We use the Sampling Importance Resampling algorithm [6]. We calculate the likelihood for each particles every time the observation is done and update the distribution by resampling the particles according the likelihood.

C. Active Learning

Active learning is a field of machine learning in which the learner is assumed to query the data labels interactively, when the label information is expensive or time-consuming and we can reduce the amount of learning data by using an appropriate active learning algorithm.

There are several approaches to determine which data samples should be labeled [7], [8]. In this paper we need to determine the next observation position in order to estimate the target's position quickly and accurately therefore we refer to the method in an active learning-like or active learning inspired method. In the next section and on we explain how these two methods are combined and applied to the beacon-based target search problems.

D. Proposed method based on the Range-Based method

First, we combine the Range-based position estimation method with RSSI with the proposed method. We update the particles by calculating the likelihood for each particles based on the difference between the predicted and actual observations and resampling particles. And then we determine the next observation point. We proceed the estimation by repeating these two steps. In the next two sections, we show the specific method of updating and the method of determining the next observation point. We set the value of d_0 (unit distance) to 1 in equation(1), i.e., d_0 = 1, hereafter.

1) update the particles *of the distribution:*

Let N_p be the number of $(i-1)$ $(i-1)$ $(i-1)$ and θ_1 , θ_2 ,· · · , θ_{N_p} be the particles resampled after the (i − 1)th observation is obtained. The index j (j = 1, 2, · · · N_p) represents the particle number then each $\theta_j^{(i-1)}$ contains the parameters of the target position, the signal strength at unit distance and the attenuation coefficient,

$\theta_j^{(i-1)} = [x_{p_j}^{(i-1)}, y_{p_j}^{(i-1)}, P_{0_j}^{(i-1)}, \kappa_j^{(i-1)}]^T$.

We denote the ith observation position and observed value by $[x_o^{(i)}, y_o^{(i)}]^T$ and $P^{(i)}$, respectively. When we get the ith observed value $P^{(i)}$, and assuming that the mean and variance of the observation noise are equal to 0 and σ^2 espectively, we can calculate thelikelihood $w_j^{(i)}$ for each particle as follows.

$$w(i)= \tilde{w}_j^{(i)} \quad (4)$$

$$^{N}pj(i)_{j=1}\ \tilde{w}_j(i) \exp(-(P(i) - R_j(i))2 \quad (5)$$

$$\tilde{w}_j=)\sigma^2\ R_j^{(i)}=P_{0_j}^{(i-1)} - 10\kappa_j^{(i-1)} \log_{10} d_j^{(i)} \quad (6)$$

$$d_j^{(i)}=(x_o^{(i)}-x_{p_j}^{(i-1)})2 + (y_o^{(i)}-y_{p_j}^{(i-1)})2 \quad (7)$$

Once the set of likelihoods $\{w_j^{(i)}\}$ is obtained, the next particles $\theta_1^{(i)}$, $\theta_2^{(i)}$, · · · , $\theta_N^{(i)}$ are resampled according this like-plihood.

2) determination of the next observation position: After the distribution is updated, we decide which position should be the next observation point. For example if we choose a point $[x_o, y_o]^T$, the set of N_p observations R predicted by the particles depends on $[x_o, y_o]^T$ as below.

E. Proposed method based on the Range-Free method

3) As described previously, the centroid method uses only the information of whether the sensors (receivers) catch the signal from the beacon or not. In this paper, on the other hand, we propose a novel range-free method based on the relative strength of signals received by sensors. In this method, every time a new observation is obtained, the likelihood of each particle is computed based on the relative signal strength of sensors, and the particles are resampled. In the rest of this section, we will explain in detail how we update the estimates and determine the next observation point.

1) update of the distribution: We assume that the number of particles and the parameters contained in each particle are the same as in the case of Range-Based method described in the previous section. What is unique in our method based on the range-free approach is that it compares the strength of signals received by multiple sensors at one time and computes the likelihood of each particle based on the relative signal strength to update the distribution and resample the particles. Let N_s be the number of sensors and we denote the ith observation points as below.

$$R= [R_1, R_2, \cdots , R_{Np}]^T \quad (8)$$

$$R_j= P_{0_j}^{(i-1)} - 10\kappa_j^{(i-1)} \log_{10} d_j \quad (9)$$

$$d_j =(x_o - x_{p_j}^{(i-1)})2 + (y_o-y_{p_j}^{(i-1)})2 \quad (10)$$

If the N_p predicted values R_j (j = 1, 2, · · · , N_p) are near to each other, the distribution does not change greatly before and after the next observation. On the other hand, if the N_p

$O_{(i)(i)(i)} \cdot\cdot\cdot {}_{(i]}{}^{T}$(12) =[$o_1, o_2, o_{N_s}$

IV. Result of the simulation

$o_k^{(i)}$=[$x_{o}{}^{(i}{}_{,k}{}^{)}$, $y_{o}{}^{(i}{}_{,k}{}^{)}$]^T ($k$ = 1, 2, · · · , N_S) (13)

In this section we show the result of the simulation. First We assume that we obtain N_s measurements of signal trength at each observation time step and denote them by $P_k^{(i)}$ (k = we show the result of Range-Based method and then we show (i) the result of Range-Free method. We can confirm that the1, 2, · · · , N_s). Here, we introduce an ordinal variable a_k (k = estimation can be done correctly by using the particle filter 2· · , N_s) that indicates the ranking of the signal strength and we can choose the adequate observation points by using^{1,}(i)P_k in descending order among the N_s measurements. For uncertainty sampling. The procedure and assumptions in this example, if P

$^{(i)}$ is the largest and $P^{(i)}$ is the smallest among k $l$simulation study are described as below. the N_s measurements, $a_k^{(i)}$ and $a_l^{(i)}$ are 1 and N_s, respectively. Set the number of particles of Particle Filter to 1,000. Next, we predict the signal strength for N_s sensors for each • particle $\theta_j^{(i)}$ (j = 1, 2, · · · , N_p). Let $R_{j,k}^{(i)}$ (k = 1, 2, · · ·, N_s) • Set the initial values $x_{p}{}^{(0)}{}_j$, $y_{p}{}^{(0)}{}_j$, $P_0{}^{(0)}{}_j$, $\kappa_j^{(0)}$ randomly in denote the signal strength for the k-th sensor predicted by the range below.

(i) – 500 ≤ (0) ≤ 500

xp_j the j-th particle. We define another ordinal variable $b_{j,k}$ that (0) (i) −500 ≤ yp_j ≤ 500 indicates the ranking of $R_{j,k}$ for each particle. Finally we (0)

compute the likelihood of the j-th particle by the following 50 ≤ P_{0j} ≤ 80 equations, where σ is a certain constant value.

1.8 ≤ $\kappa_j^{(0)}$ ≤ 2.4 (i) $\tilde{w}_j{}^{(i)}$ (14)• Set the initial values of the signal source x_{tar}, y_{tar} wj = randomly in the range below.

N_p I $_{j=1}$ $\tilde{w}_j$ ((i)(i) || 2 −500 ≤ x_{tar} ≤ 500 (i) ||A− B_j (15) −500 ≤ y_{tar} ≤ 500 $\tilde{w}_j$ = exp(−)•

Set the P_0 to 60.0 and κ to 2.2 i.e., P_0 = 60.0 and σ^2 $_A$(i)(i)(i)(i)]^T (16)

κ = 2.2.=[a_1, a_2, · · · , a_{Ns}•]

Assume the observation noise is white Gaussian noise,

$B_j^{(i)}$=[$b_{j,}{}^{(i}{}_1{}^{)}$, $b_{j,}{}^{(i}{}_2{}^{)}$, · · · , $b_{j,N}{}^{(i)}{}_s$]^T(17) the mean and variance is equal to 0 and 1 respectively.

- The sensor can not receive the signal that is weaker than 0dB and we set the value of P (received signal strength) to −30 on calculation in such a situation, i.e., P = −30.

A. Result of the simulation based on the Range-Based method

First, we show the result of the simulation based on the Range-Based method in Table I, II. δ_x, δ_y , δ_{P0} , δ_κ in these ta-ble represent the estimation error of each unknown parameter. Here, we describe the mean of 100 simulations in each table. We can confirm that the estimation is done more accurately with less observations by using uncertainty sampling than by determining the observation points randomly. We also show the state that the observation points are determined properly by using uncertainty sampling in the following Figure (5). In this figure, the red star represents the true position of the target, the blue point represents the position of the sensor(observation position), and the green points represent the particles. The top of the Figure (5) is the state at certain time t = T , the middle is the state which is resampled after the random observation, and the bottom is the state which is resampled after the uncertainty sampling observation.

confirm that the parameters P_0 and κ are not estimated because we do not consider RSSI but only the relative signal strength in this method. We also show the state that the observation points are determined properly by using uncertainty sampling in the following Figure 6. In this figure, the red star represents the true position of the target, the blue points represent the positions of the sensors, and the green points represent the particles. The top of the Figure 6 is the state at certain time $t = T$, the middle is the state which is resampled after the random observation, and the bottom is the state which is resampled after the uncertainty sampling observation.

A. CONCLUSION

In this paper, we show that we can proceed the estimation gradually by using particle filter. We also show that we can estimate the parameters efficiently with the small observations by determining the observation point based on uncertainty sampling which is used in active Learning. However the most important thing while searching for the missing person is not to reduce the number of observations but to reduce the time to take to estimate the position. Reducing the number of observations is actually important but it does not necessarily result in the reduction of time. It is because if the observation points are far from each other, the number of the observations itself is small but the time to move from one point to another becomes long. Thus it is the future task to consider the model containing the effect of the movement time.

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