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Automatic configuration of sensor locations by tracking human movement

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Abstract

Different sensing technologies have made way to understand user environment which is a vital task to provide environment-oriented services in an ubiquitous computing scenario. Many sensor devices are expected to be spatially distributed over the user environment. In order to understand the precise status of an user in the space, it is very important to determine the right location of these sensors. Many schemes have been proposed so far to determine sensor locations by means of signal strength in open space. However, these schemes are unable to perform well when obstacle appears in the space like an in-building scenario. In this paper, we propose a location determination scheme based on accumulated data from the sensor devices and show the simulation results.

1 Introduction

The ubiquitous computing environment depends on many kinds of sensors and devices to discern the user's context, a vital piece of information needed to provide environment oriented services. The accuracy with which the positions of the sensor and devices are known is a key determiner of service success. When there are no obstructions, such as outdoors, sensor location can estimated from GPS(Global Positioning System) data.

Unfortunately, GPS is unable to perform well when the sensors do not have a clear line of sight to the satellites. Alternatives to GPS, the use of RFID tags or wireless LANs, have been discussed to detect the location of humans within buildings. A representative research effort is Aware Home[1]. The accuracy of LANDMARC[2] system, which uses RFID tags, is about 3 meters, while that of the ekahau[3] system, which uses a wireless LAN, is about 2 meters. Such levels of accuracy are misleading when we consider that 1 meter can mean the difference between being in a smoking space or being in a smoke-free zone.

We claim that it is not realistic to use wireless devices for detecting human location and the preferred approach is to place many short-range sensors in each room. This raises the practical problem of establishing sensor location. This paper proposes a location determination scheme based on accumulated data from sensors and shows simulation results.

2 Our approach

There are two main approaches to handling location information. The most basic approach is to employ an absolute coordinate system, such as the one employed by GPS. However, since we consider only in-building environments, we use the semantic location model[4] and assume that every room has a sufficient number of sensors. In this paper, "The room" is designated as the unit of position and our goal is to install and group the many sensors in each room. Each sensor has a unique identity number, its detection area is circular and does not extend through internal walls. These sensors return 1 when a human is in the sensing area or else 0. An assumption is that each room has at least one sensor, the key sensor, that holds the identity of the room.

Our goal is to separate the set of all sensors into subsets of sensors. Each subset of sensors corresponds to a room and so includes exactly one key sensor.

The direct approach is to group those sensors whose sensed values are similar. This is because sensors located along a path along which people often walk will be activated in sequence. That is, two sensors belong to the same group, if their values change in a predictable manner.

Our approach basically follows this approach. However, it has a problem with clearly differentiating rooms from each other, because sensor chains can be formed that run from room to room. So, we have to determine which sensors are located on room boundaries. What is a boundary sensor? We assume that the rooms have regular doorways and so the sensors at the door way, the boundary sensors, exhibit greater variation in sensor activation pattern. For example, the doorway may be entered from either side or directly from the front. The first step of our proposed algorithm, described in Section 3, observes the sensor activation patterns from the probability viewpoint, and terminates the group at such points.

The next step of our algorithm, described in Section 4, calculates a rough physical length of the distance between such sensors and the grouped sensor, not in a probabilistic way. In Section 5, we will show simulation results.

3 Grouping sensors algorithm

This algorithm finds the proximity of sensors in the space (refer [5] for details). We introduce a brief outline below. First, we find the sensors activated when a human moves within a room.

Key sensors are defined as $K = \{K_1, K_2, \cdots, K_n\}$, and defined $S = \{S_1, S_2, \cdots, S_m\}$, the group correspond to each key sensors $C = \{C_1, C_2, \cdots, C_n\}$, and defines $C_i = \{K_i\}$, The probability of a human entering sensing area S_i when the human moves from sensing area S_a to sensing area K_b is defined as $P(S_a \rightarrow K_b, S_i)$. The probability of a human entering sensing area C_i when the human moves from sensing area from S_a to C_b is defined as $P(S_a \rightarrow C_b, C_i)$.

We show the algorithm which we find the groups C of the proximity of sensors.

For all b $(1 \leq b \leq n)$, $C_a := C_a \cup \{S_i\}$ if $P(S_a \rightarrow K_b, S_i) > \alpha$.

For all b $(1 \leq b \leq n, i \neq b)$, $C_i := C_i \cup \{S_a\}$ if $P(S_a \rightarrow C_b, C_i) > \alpha$.

This process is continued until C_i stops changing. The result of C is a set of sensor elements.

4 Distance estimation algorithm

This section describes the position estimation algorithm based on the sensor grouping algorithm. The sensor grouping algorithm has a weakness in that sensors that lie on group boundaries are often not grouped. To rectify this omission, we calculate the distance between boundary sensors and non-grouped sensors.

Moving time can be taken as a simple representation of distance, and the naive approach is simply to average the recorded values. However, this is not practical since human movement can be interrupted unexpectedly. Our solution, the distance estimation algorithm, is to calculate the probability of moving from one sensing area to another in a predefined period of time.

The sensor reaction sequence A_t is given as $A_t = \{s_{t1}, s_{t2}, \cdots, s_{tn}\}$ in time t. Each s_{ti} is 1 if a human is in sensing area s_{ti} at time t, but s_{ti} is 0 otherwise. We define the sequence B_i $(0 \leq i \leq m)$ when interval time is T $(T \geq 1)$.

$$B_i = (\max(s_{(iT)1}, s_{(iT+1)1}, \cdots, s_{(iT+T-1)1}), \cdots, (\max(s_{(iT)n}, \cdots, s_{(iT+T-1)n})$$

B_i is the sensing status sequence discerned from time iT to $(i+1)T-1$, and we define B_{ik} as the nth element of B_i. Next we define f as follows.

$$f(i,j,k) = \max(B_{ij}, B_{ik})$$

We define probability $P'(j,k,T)$ which means that a human moves from sensing area S_j to sensing area S_i at time t

$$P'(j,k,T) = \frac{\sum_{l=0}^{m-1} f(l,j,k)}{m}$$

We calculate the minimum T $(P(j,k,T) > \beta)$ and we define the distance $d(j,k) = T$, and calculate the average distance M_i between non-grouping sensor S_x and grouped sensor $C_i = \{S_{i1}, S_{i2}, \cdots, S_{ik}\}$.

$$M_i = \frac{\sum_{k=1}^{|C_i|} d(ik, x)}{|C_i|}$$

$|C_i|$ is the number of elements C_i.

We find the minimum M_i, and determine the group of S_x. Group C_i is the group of S_x.

5 Simulation results

We simulated the following environment using the algorithms introduced in Sections 3 and 4. First, we set 6 rooms in a virtual space as shown in Figure 1. We set one key sensor at the center of each room; the other sensors were set randomly throughout the space. We set a human movement pattern as follows.

- The human sets destination randomly in this space and walks straight to the destination.
- The human waits for a definite period of time at the destination.
- Next, the human sets another destination randomly and walks straight to that destination.
- Walking speed is a constant velocity with a random variation of up to 10% .

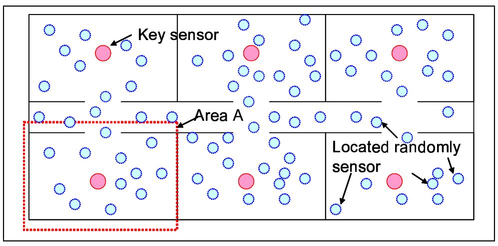

Figure 1: Simulation space

Only one human was present in this simulation space, and we simulated the grouping of sensors based on the proposed algorithms. In this simulation, threshold value alpha was set at 0.5.

We define below the correct answer percentage C for evaluating our algorithm.

$$C = 1 - \frac{(\text{Erroneous group count}) + (\text{non-grouped count})}{\text{count of sensors in area A}}$$

Erroneous group count is grouped sensors not in area A. Non-grouped count is non-grouped sensors in area A. Count of sensors in area A is total number of sensors in area A. We ran the simulation 100 times, and sensor location was changed randomly in each trial.

C was 78% if only the algorithm of Section 3 was used. We show one of the simulation results in Figure 2. Black circles are non-grouped sensors, and white circles are grouped sensors.

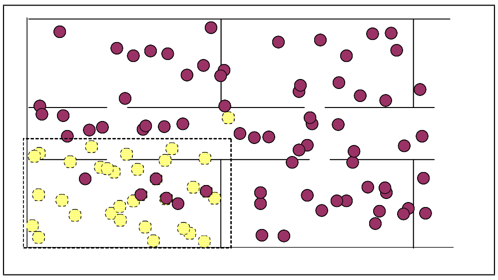

Figure 2: Simulation result (only Section 3 algorithm used)

Section 3 algorithm was unable to achieve full grouping due the random behavior of the simulated human. In Figure 3, the paucity of human presence meant that some sensors were not grouped successfully.

Next, we applied the algorithms of Sections 3 and 4, and reran the simulations. Threshold value beta was set at 0.5. The result is C=92%, which indicates the benefit of applying both algorithms.

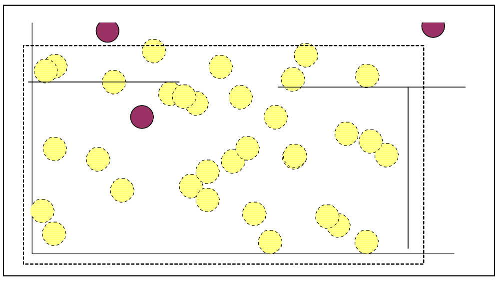

Figure 3: Simulation result (Both proposed algorithms used)

This paper describes the simulation of just one room pattern, but we have checked many other room patterns and found similar levels of grouping performance.

6 Conclusion

To automatically group large numbers of sensors spread throughout buildings, we focused on the patterns of sensor activation created by humans as they walked around the rooms containing the sensors.

We have proposed an algorithm which groups such sensors according to the room configuration. Our algorithm consists of two steps, rough grouping using probabilistic calculation and distance estimation for detail grouping.

The simulation results show that our algorithm can group sensors at 92% accuracy.

References

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