Cooperative Waiting Time Estimation Method
Based on Crowd Behavior Characteristics Using Acceleration and RSSI

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Abstract  Waiting lines are an everyday occurrence in various places. In this paper, we propose a waiting line and waiting time estimation method based on crowd behavior characteristics. The crowd behavior characteristics in a waiting line concern the user actions, where users are either moving or stationary. The proposed method considers the following three types of user movement using the receive signal strength indicator (RSSI) and user action estimated by an acceleration sensor: the user movement of entering the waiting line, the user movement following the crowd behavior characteristic while lining up in the waiting line, and the user movement of leaving the waiting line. Using these movements, the proposed method estimates the waiting line and waiting time. Through experiments, we obtained 95.0% estimation accuracy in the waiting line estimation, so we could mostly distinguish people in a waiting line from those outside. In addition, we obtained a mean estimation error of 2.0 s in the waiting time estimation, so we could obtain the waiting time with high accuracy.

Keywords: waiting line, waiting time, crowd behavior, smartphone

1. Introduction

Waiting lines are an everyday occurrence in various places such as restaurants, event sites, and amusement parks. An unclear waiting time in a waiting line increases the user’s dissatisfaction. To avoid such dissatisfaction, a waiting time estimation method has been proposed [1]. Although there are some methods using cameras or radio frequency identifier (RFID) [2], a camera image or sensing range has a dead angle zone. The main system used for traveling prediction system in road networks is an automatic vehicle identification (AVI) system using two or more closed-circuit television (CCTV) cameras, but the target object of the system is automobiles not humans [3]. Since people generally have a smartphone, we focus on employing users’ smartphones.

Some estimation methods using the receive signal strength indicator (RSSI) have been proposed. One of the estimation methods uses a single monitor to measure the RSSI and distinguishes whether users are near a waiting line using a threshold value for the RSSI [4] or by the detection of a wireless LAN access point [5]. Since these methods are applicable to an area partitioned by a wall, the estimation error of the waiting time may increase in an open space not partitioned by a wall. Next, there is a waiting time estimation method focusing on users’ smartphones and existing wireless LAN access points [6]. The waiting time is measured from the user’s position estimated using the RSSIs of three or more wireless LAN access points. Waiting line areas are preset, and the waiting time is based on the time from when the user enters the waiting line area until when the user leaves. Therefore, this method has a problem that the waiting time of all users in the waiting line area is estimated regardless of whether or not they are in the waiting line.

In this paper, we assume a short-length waiting line and propose an estimation method for the waiting line and waiting time. The advantage of the proposed method compared with the conventional method is that it uses user actions and only one receiver to measure the RSSI from the user. In addition, the proposed method estimates the waiting time in the waiting line rather than in the waiting line area in the conventional method. To improve the estimation accuracy of the waiting time, we distinguish between users inside the waiting line and those outside the waiting line using the crowd behavior characteristics. The waiting line estimation is the judgment of whether a user is in the waiting line. Figure 1 shows a schematic image of waiting line estimation. For the waiting line estimation, we use the RSSI obtained from packets received from smartphones and the crowd behavior characteristics of a waiting line. The crowd behavior in a waiting line has a characteristic concerning whether each user is moving or stationary. The user action is estimated using the acceleration sensor in the user’s smartphone. Smartphones transmit the estimated user action to the server by
Bluetooth low energy (BLE) [7], and the server estimates whether users are in a waiting line using the RSSI and the crowd behavior characteristics. Therefore, the estimated waiting time is the time difference between when the user first enters the waiting line and when he or she exits from the line. In our previous studies, we performed actual experiments that assumed only users in the waiting line [8]. Then, we performed actual experiments including users outside the waiting line [9]. In this study, we perform experiments considering various user behaviors outside the waiting line in addition to the user behaviors in [9]. The effectiveness of the proposed method is shown by comparing the estimated result with a visual observation.

2. Proposed Method

The proposed method employs transmitters that are smartphones owned by users, a receiver receiving BLE advertising packets from smartphones, and a server storing user data for estimation of the waiting line and waiting time.

The user action is used to estimate “MOVE”, representing a moving state, or “STAY”, representing a stationary state, by machine learning using an acceleration sensor mounted on the user’s smartphone. This estimation action is transmitted to the server by an advertising packet. The server stores the user data, which consists of the reception time of the advertising packet from the smartphone, the user action, and the RSSI, and estimates the waiting line and waiting time from the stored user data.

2.1 Advertising packet information

The advertising packet specified in iBeacon [10] consists of a 128-bit universally unique identifier (UUID), 16-bit Major, and 16-bit Minor. The system ID assigned to each system is stored in the UUID, and the user ID assigned to each user is stored in Major. Note that the MAC address of the smartphone may be used as the user ID. In addition, the user action is stored in Minor. The user action is updated at regular time intervals. Therefore, the advertising packet information consists of the system ID, the user ID, and the user action estimated by the acceleration sensor. To transmit the information, a dedicated application is installed on the smartphone.

2.2 User data

The server acquires the RSSI and the advertising packet information after receiving the advertising packet. Here, the proposed method uses only the received packet including the preset UUID. The user data is composed of the user action and the average RSSI for each user for every creation interval. Since the fluctuation of RSSI values is large, the average RSSI in every creation interval is used. In this paper, the creation interval is assumed to be 1.0 s.

2.3 Estimation algorithm

The estimation algorithm performs the waiting line and waiting time estimation based on the user data acquired by the receiver. We use the three judgments shown in Fig.2 [8], IN-judgment, CROWD-judgment, and OUT-judgment, based on the RSSI and the user actions for their estimation. Each judgment is defined as follows:

- **IN-judgment**: For judging the movement of the user from outside the waiting line to inside the waiting line using user actions.

Fig. 2 Example of three judgments [8]

Fig. 3 Circumstances of three judgments

Fig. 4 User wearing transmitter (left) and acceleration sensor axes (right) [8]
- CROWD-judgment: For judging the movement of the user with the progression of the waiting line using user actions.
- OUT-judgment: For judging the movement of the user from near the receiver in the waiting line to outside the waiting line using the RSSI and user actions.

For the waiting line estimation, we use the above three judgments to decide whether the user is in the waiting line. The user who satisfies the three judgments in the order IN-judgment, CROWD-judgment, OUT-judgment is estimated to be in the waiting line. For the waiting time estimation, we use the IN-judgment and OUT-judgment to calculate the waiting time from the difference between the user’s IN-judgment time and OUT-judgment time.

The OUT-judgment of user $i$ is executed when all the following three conditions ($OUT_1$, $OUT_2$, and $OUT_3$) are satisfied. The RSSI threshold value $Thr$ [dBm] is used as the condition $OUT_1$ and the RSSI difference $Diff$ [dB] is used as the condition $OUT_2$. These values are decided by the preliminary experiments shown in Sect. 3.3. Among the candidate times of the OUT-judgments, the latest time is set as the OUT-judgment time ($t_{OUT}$). Hereafter, the unit of time is 1 s. The circumstances of the OUT-judgment are illustrated in Fig.3(a).

- $OUT_1$: When the smartphone is within the sight of the receiver, the RSSI becomes greater than or equal to the threshold value since the receiver receives the direct wave. Thus, this condition is that the average RSSI is greater than or equal to $Thr$ at time $t_{OUT}$.
- $OUT_2$: When the user passes the receiver, the RSSI decreases owing to the metal barrier wall in which the receiver is mounted and the user’s body shield. Thus, this condition is that the average RSSI decreases by $Diff$ or more from time $t_{OUT}$ to $t_{OUT} + 1$.
- $OUT_3$: When the user exits the waiting line, the user moves continuously. Thus, this condition is that the user action becomes MOVE from time $t_{OUT} + 1$ to $t_{OUT} + 5$.

Note that the user is in the waiting line at time $t_{OUT}$. Since the conditions of $OUT_1$ and $OUT_2$ depend on the RSSI, in the case of only $OUT_1$ and $OUT_2$, an incorrect OUT-judgment may be made. To avoid the misjudgment, the condition of $OUT_3$ is useful because this condition depends on the user action not the RSSI.

Among the users in the waiting line, there are crowd behavior characteristics concerning whether the users are moving or stationary. For user $i$, it is the characteristic of changing from stationary to moving within a certain time after other users in the waiting line have moved. The trigger for the CROWD-judgment of user $i$ is the OUT-judgment of some other user $j$ or the CROWD-judgment of some other user $k$. Note that $i$, $j$, and $k$ are all different users. User $j$ is closer to the head of the waiting line than user $i$. User $k$ is in any position within the waiting line in front of or behind user $i$. The CROWD-judgment of user $i$ is executed when the following condition is satisfied. Since the CROWD-judgment is executed whenever the user moves ahead within the waiting line, this judgment is executed several times. The time of the $x$th CROWD-judgment is set as the $x$th CROWD-judgment time ($t_{CROWD,i,x}$). The circumstances of CROWD-judgment are illustrated in Fig.3(b).

- CROWD: When the waiting line progresses, the user action changes from STAY to MOVE within a certain time of another user’s OUT-judgment or CROWD-judgment. The former condition is $CROWD(1)$ and the latter is $CROWD(2)$. Thus, this condition is that within 2 s from time $t_{OUT}$ or from the CROWD-judgment time of the user in the waiting line, the user action

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changes from STAY at time $t_{\text{CROWD},i,x}$ to MOVE at times $t_{\text{CROWD},i,x} + 1$ and $t_{\text{CROWD},i,x} + 2$.

The IN-judgment of user $i$ is executed when the following condition is satisfied. In the candidate times of the IN-judgments, the time immediately before the first CROWD-judgment time $t_{\text{CROWD},i,x}$ is set as the IN-judgment time ($t_{\text{IN},i}$). The circumstances of IN-judgment are illustrated in Fig.3(c).

- IN: When the user first approaches the waiting line, the user moves continuously. Thus, this condition is that the user action becomes MOVE from time $t_{\text{IN},i} - 5$ to $t_{\text{IN},i} - 1$ and changes from MOVE to STAY at time $t_{\text{IN},i}$.

3. Evaluation Environment

3.1 Transmitter implementation

We implement the transmitter, receiver, server, and estimation algorithm and conduct preliminary experiments. We use iPod touch equipped with an acceleration sensor and a BLE function in the transmitter, and we use Raspberry Pi with a BLE dongle mounted on the receiver. We implement the server in Raspberry Pi, which is also used as the receiver.

We use the application to transmit the estimated user action by advertising packets. In this experiment, the system ID is a fixed value. Each user ID is an arbitrary value that does not overlap with other user IDs. The transmission interval of the advertising packet is found to be about 34.3 ms by actual measurement. Note that the interval cannot be changed on the implementation of the iOS application.

The transmitter, i.e., smartphone, is attached to the user by wearing it around the neck using a strap whose length can be adjusted as shown in Fig.4. We acquire the acceleration data in the X, Y, and Z directions shown in Fig.4 with the sampling interval set to 100 ms. Here, the magnitude of acceleration data, that is, the square root of the sum of the squares of the acceleration in the X, Y, and Z directions, is defined as $\text{ACC}$. The estimation interval of the user action is 1.0 s, and the maximum value $\text{ACC}_{\text{max}}$ and minimum value $\text{ACC}_{\text{min}}$ of $\text{ACC}$ are calculated for each estimation interval. The user action is estimated by the $k$-nearest-neighbor method using the difference between the maximum and minimum values in the estimation interval of the acceleration $\text{ACC}$, $\text{ACC}_{\text{diff}} = \text{ACC}_{\text{max}} - \text{ACC}_{\text{min}}$ as the feature.

In the measurement, we define MOVE as walking and STAY as stopping. We measure the two states of MOVE.
and STAY for three users during each 60 s as training data, and acquire 360 data of \( ACC_{diff} \), which is calculated from about 3,600 acceleration data. As a result of leave-one-out cross-validation, the estimation accuracy for \( k = 1, 2, \) and 3 was 98.33\%, 98.89\%, and 99.17\%, respectively, and the estimation accuracy was 99.17\% for \( k \geq 4 \). In addition, the F-measure was 0.99, indicating extremely high accuracy.

### 3.2 Receiver implementation

The receiver receives the advertising packet and acquires the RSSI. The user data creation interval is 1.0 s, and the user data (user action and average RSSI) is created for each user data creation interval. The created user data is stored in the server. Since the user action estimation interval is 1.0 s, it is the same as the user data creation interval.

### 3.3 Preliminary experiments

Preliminary experiments are conducted to decide the RSSI threshold \( Thr \) [dBm] and the RSSI difference \( Diff \) [dB] of the OUT-judgment time condition in the estimation algorithm. The preliminary experimental environment consists of the starting point (S), receiver point (A), and goal point (G) at 15 m intervals in a passageway of a university campus as schematically shown in Fig. 5. Note that points (m) to (q) are not used in the preliminary experiments and are used in the evaluation experiment shown in Sect. 4. The receiver is set at a height of about 0.9 m, and the BLE dongle faces the direction of point (S). A metal barrier wall is installed between point (A) and point (G) on the receiver side. When the user passes the receiver and moves outside the waiting line, the RSSI significantly decreases since the strength of the direct wave from the transmitter is reduced by the metal barrier wall and the user’s body shield. The heights of the transmitter and receiver are set to be the same by adjusting the length of the user’s strap.

In this paper, we assume the following three types of action of user’ waiting in the waiting line.

1. Moving to waiting line
2. Alternately stationary and moving in waiting line
3. Leaving waiting line

Users start to transmit the advertising packet at the starting point (S). Users perform the above actions (1) to (3), and stop transmitting the advertising packet at the goal point (G). Users wait at 1 m intervals from the receiver point (A) to the starting point (S). We assume that the user at the head of the waiting line waits 30 s before the receiver and then moves to the goal point (G).
Five users line up twice, so the number of users is ten. In the second lap, the user IDs are changed and the users are counted as new users. Specifically, in the first lap, the user IDs of the five users are set from 1 to 5, and the users start from point (S). In the second lap, the user IDs are changed to 6 to 10 and each user begins to line up after reaching the goal point (G) in the first lap. This preliminary experiment is carried out twice. In the first experiment, users start every 10 s from point (S), and the second experiment, they start every 15 s.

Fig.6 shows the number of users with the OUT-judgment for each Diff as a result of combining the first and second preliminary experiments [8]. The maximum number of users with the OUT-judgment is 20. Diff and Thr, which decide the number of users with the OUT-judgment, are decided. Here, when Diff and Thr are small, there is a possibility of incorrect OUT-judgment when RSSI fluctuation occurs in positions other than the receiver point (A). To prevent OUT-judgment errors and to ensure that the OUT-judgment occurs at only the receiver point (A), it is necessary to set large values of Diff and Thr.

According to Fig.6, when Diff is 11 dB, since the maximum number of judged users is 19, it is necessary that Diff is 10 dB or less. If Thr is greater than or equal to -57 dBm, since the number of judged users is 19 or less when Diff is 7 to 10 dB, Thr must be -58 dBm or less. In this paper, we set Diff to 8 dB and Thr to -60 dBm considering the fluctuation of the RSSI.

4. Experimental Evaluation

The experimental environment is the same as in the preliminary experiments as shown in Fig.6. A photograph taken during the experiment is shown in Fig.7. In addition to the targets of the preliminary experiments, we determine the movements of users outside the waiting line and users in the waiting line and clarify that the proposed method can distinguish between them. We confirm the accuracy of the waiting time obtained in the proposed method by comparison with a visual observation. The waiting time in the visual observation is measured by one person, with a stopwatch.

Twelve users are in the waiting line, the waiting time of the user at the head of line is 30 s, and the first five users start every 15 s. We do not assume that all the waiting users pass the side of the receiver at the same time because the user at the head of the waiting line has to wait. In addition, there are three users outside the waiting line (Users 13, 14, and 15), and the time they stay near the waiting line is 90 s. Users 13, 14, and 15 do not exist simultaneously. Users outside the waiting line move to points (m), (n), (o), (p), and (q) shown in Fig.5 at every movement interval time, where the distance between adjacent points is 3 m and the distance between points (o) and (A) is 1 m. Here, the movement interval time is the time from starting to move from the current point to arriving at the next point. This time consists of the staying time and the traveling time. Whenever the movement interval time has elapsed, Users 13 to 15 start to move from the current point to the next point. For example, User 13 moves from point (m) to point (o) then from point (o) to point (q) every movement interval time as shown in Fig.8.

We conduct the experiment four times. In first two times, the movement interval time is set to 15 s, and in last two times, it is set to 25 s. These movement interval times are related to the waiting time of the user at the head of the line. In particular, the movement interval time of 15 s is half of the waiting time of the user at the head of the line. Thus, the movement of Users 13 to 15 in first two times more closely resembles the movement of Users 1 to 12 in comparison with the case of a movement in last two times. The movements of Users 13, 14, and 15 are shown in Fig.8. Users 13, 14, and 15 start to transmit the advertising packet from point (m) and start to move one by one at the time when Users 1, 5, and 9 reach point (A), respectively. User 13 moves by two-point intervals, User 14 moves by one-point intervals, and User 15 alternately moves by two-and one-point intervals. After 90 s from their start time, Users 13, 14, and 15 stop transmitting the advertising packet then and there. We show the results of the four evaluation experiments at every movement interval time.

4.1 Movement interval time of 15 s

Tables 1 and 2 respectively show the estimation errors of the waiting time between the visual observation and the proposed method in the first and second experiments with the movement interval time of 15 s. Here, the first user (User 1), who started in the waiting line, was not estimated. Figs.9 and 10 show each judgment of users who satisfy the OUT-judgment. Note that the users are in ascending order of OUT-judgment time, and the earliest time among the judgments is set to 0 s.

In the waiting line estimation with the movement interval time of 15 s, 28 out of 30 users were correctly estimated, so the estimation accuracy was 93.3%. As shown in Figs.9 and 10, since Users 2 to 12 satisfy the IN-judgment, the CROWD-judgment, and the OUT-judgment in this order, they are assumed to be in the waiting line, in agreement with the visual observation.

User 13 in the first and second experiments was not in the waiting line according to the visual observation but was judged to be in the waiting line by the proposed method. This was because each judgment was made for the following reasons. The OUT-judgment was made because of motion from point (o) near the receiver point (A) to point (q). The CROWD-judgment was made because the user’s movement interval of 15 s was half of the waiting time of 30 s at each point. The IN-judgment was made because the movement by two points caused MOVE of five or more. Since Users 14 and 15 did not satisfy the three types of judgment, they were assumed to be outside the waiting line, in agreement with the visual observation.

In the waiting time estimation with the movement interval time of 15 s, the average estimation error was 1.9 s.
4.2 Movement interval time of 25 s

Tables 3 and 4 respectively show the estimation errors of the waiting time in the first and second experiments with the movement interval time of 25 s. Here, the first user (User 1), who started in the waiting line, was not estimated. Figs 11 and 12 show each judgment of users who satisfy the OUT-judgment. Note that the users are in ascending order of OUT-judgment time, and the earliest time among the judgments is set to 0 s.

In the waiting line estimation with the movement interval time of 25 s, 29 out of 30 users were correctly estimated, so the estimation accuracy was 96.7%. As shown in Figs.11 and 12, since Users 2 to 12 excluding User 8 in the second experiment satisfy the IN-judgment, the CROWD-judgment, and the OUT-judgment in this order, they are assumed to be in the waiting line, in agreement with the visual observation.

User 8 in the second experiment was in the waiting line according to the visual observation but was judged to be outside the waiting line by the proposed method. This was because the OUT-judgment, especially OUT₂, was not satisfied for the following reason. To satisfy the condition of OUT₂, the RSSI difference must exceed 8 dB, but the RSSI difference was about 6 dB.

User 13 in the first experiment satisfied the OUT-judgment, but did not satisfy the IN-judgment and CROWD-judgment, so User 13 was assumed to be outside of the waiting line, similarly to in the visual observation. Users 13 and 15 in the second experiment satisfied the IN-judgment, the CROWD-judgment, and the OUT-judgment, but because the order of the three judgments was not occur, they were assumed to be outside the waiting line, consistent with the visual observation. User 14 in the first and second experiments and User 15 in the first experiment did not satisfy the three types of judgment and were assumed to be outside the waiting line, as in the visual observation. In the waiting time estimation, the average estimation error was 2.2 s.

5. Conclusion

In this paper, we proposed a waiting line and waiting time estimation method using the crowd behavior characteristics in a waiting line. Through actual experiments, we obtained an estimation accuracy of 95.0% in the waiting line estimation and a mean error of 2.0 s in the waiting time estimation. We achieved high estimation accuracy of the waiting time by distinguishing between users inside and outside the waiting line.

If the length of the waiting line is long compared with our experimental environment, we need to set the receiver to receive the user action within the waiting line because the receiver of the user at head of the line cannot receive the user action from distant users. In addition, although the proposed method uses the RSSI, we assume that the number of users around the head of a line where the receiver is set is small, so the interference between iBeacon and the receiver is small and there is no problem in measuring the RSSI. A future work is to confirm the effectiveness of the proposed method in waiting lines with various shapes including non-straight lines where a camera image cannot measure the waiting time. Finally, we aim to increase the improvement of the system by performing waiting time estimation in real time.

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Appendix

A list of abbreviations and a list of terms defined in the paper are given in Tables A.1 and A.2, respectively.

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