Understanding Suitable Locations for Waiting

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\textbf{Abstract}—This study addresses the robot that waits for users while they shop. In order to wait, the robot needs to understand which locations are appropriate for waiting. We investigated how people choose locations for waiting, and revealed that they are concerned with “disturbing pedestrians” and “disturbing shop activities”. Using these criteria, we developed a classifier of \textit{waiting} locations. “Disturbing pedestrians” are estimated from statistics of pedestrian trajectories, which is observed with a human-tracking system based on laser range finders. “Disturbing shop activities” are estimated based on shop visibility. We evaluated this autonomous \textit{waiting} behavior in a shopping-assist scenario. The experimental results revealed that users found the autonomous \textit{waiting} robot chose appropriate waiting locations for waiting more than a robot with \textit{random} choice or one controlled manually by the user him or herself.

\textbf{Index Terms}—Understanding environments, model for waiting locations, shopping-assistant robot

\section{I. INTRODUCTION}

Shopping assistance is one of the promising applications for robots. A robot that carries a shopping basket would be useful for assisting the elderly and disabled people [1]. There is currently already a robot that navigates around the shop offering information to visitors [2]. Studies have also shown that elderly people appreciate conversational humanoid robots as a shopping partner because it offers a sense of being together with “someone” [3].

It is indispensable for such robots to have appropriate behavior to \textit{wait} for users while they shop. People often leave the robot while looking around nearby shelves and go to fetch items in a narrow corridor [3]. During the study, we received the following complaint from the head of the shopping mall:

“Yesterday 5pm, there was a robot near a shelf, right? We got a complaint from a customer. She said, the robot was obstructive, which hindered her from grabbing apples. Don’t make it happen again.”

The robot was left near the shelf while the user went to grab items. The robot stayed there not knowing what it should do.

The difficulty in developing \textit{waiting} behavior is that we would need to model people’s common sense about locations. For instance, people are unlikely to stay in front of the entrance gates or the center of corridors while they wait for someone. A robot without such knowledge would disturb others (Fig. 1).

In this study, we investigated people’s choice on \textit{waiting} locations and established a model for finding such locations. Finally, the model is tested in a field experiment.

\section{II. RELATED WORKS}

There are techniques for understanding environments. From the geometrical shapes of locations, pieces of the environment are separated into clusters, topologies are retrieved [4], and categorized into corridors or rooms [5, 6]. From their trajectory, people’s typical behavior in the space has been also modeled [6, 7], and subgoal-networks are retrieved [8]. An interactive approach was taken to retrieve the name of spaces [9-11].

Further, recent advances have endowed human-like understanding of the associated environment on to robots’ actions. For instance, there are studies about interpreting directions given by humans [12, 13], which potentially enables a robot to navigate in a space based on given directions. A model of perception of unknown space enabled a robot to engage in deictic interaction [14]. A model of memory about locations would ease direction giving as a robot could provide destination-description instead of turn-by-turn description [15]. Our study uses a similar approach for modeling human-like understanding for \textit{waiting} behavior, in which people’s perception about suitable location is modeled.

\section{III. COMPUTATIONAL MODEL}

Fig. 2 shows the architecture. We modeled people’s choice of \textit{waiting} locations (section III-B) and identified feasible computational features (section III-C) built upon basic environmental information (section III-A). Finally we build a classifier with SVM (support vector machine) (section III-D).

\subsection{A. Representation of the Environment}

\textbf{1) Statistics on Pedestrian Flow}

We used a human tracking system [16] to observe people’s trajectories, in which 20 Hokuyo UTM laser range sensors were used to cover a 607 m\textsupersquare meter space (Fig. 3(a)). Over 5 hours of
observation, we collected trajectories (time series of positions in x-y coordinates measured every 30 ms) of 3880 persons.

2) List of Shops
For each shop in the shopping mall, we prepared two types of data: the shop region and wall objects. A shop region defines the boundary of the floor of the shop, used to compute whether a person is in a shop, which we manually added from the floor arrangement plan of the shopping mall.

Wall objects are used for computing the shop visibility. If a person stands near wall objects, other persons cannot see him/her from the opposite side. To compute such a type of visibility whether a person can be seen from the other side or not, we manually added every structure higher than 2m as wall objects. Walls and pillars in a shop region (e.g. the ones in Fig. 9) are included in the wall objects.

B. Data Collection
1) Method
The data collection was conducted in a shopping mall. 24 Japanese members of our laboratory (9 males and 15 females, 34.8 years old) participated, having no knowledge of our research purpose. We asked each participant to provide preference on nearby waiting locations at 8 viewpoints. We instructed them to imagine a situation where there is a robot that waits for him/her to come back from shopping, and then asked them to choose appropriate and inappropriate locations from a list of candidate locations (shown in Fig. 10(a) in later section). Because our purpose was to establish a model of surely appropriate locations, we only asked them to provide locations that were surely appropriate or inappropriate. Locations not chosen were labeled as undetermined. We also interviewed the reason of their choice.

2) Interview Result
Table 1 shows the categorized response with two or more participants mentioned, classified by two coders. (Their judgments matched well, Cohen’s kappa coefficient was 0.637).

Four major criteria were found. The most frequently mentioned criterion was disturbing pedestrians. One participant said, “If the robot is located at the center of corridor, it really disturbs pedestrians. Especially when a person looks aside, it is easy to collide with the robot.” Another one said, “If the robot stops and waits for the user for a long time, a main street is inappropriate. It completely disturbs pedestrians.”

They were also concerned about disturbing shop activities. One comment was, “If the robot stays in front of the shelf in the shop, it hides shop items or important advertisements.” Another participant said, “a robot does not engage in shopping, thus it just disturbs others entering the shop.”

The robot’s visibility was the matter. One said, “it is problematic if the robot’s waiting location is not visible even nearby.” Thus, we use only visible locations in the planning.

They also commented about the distance from the current location. One said, “Distance is important, but it is not the primary importance. If I find a more appropriate location far from here, I would prefer the robot to wait at that location.” Many others had similar opinions. Thus, in our computation, we compute appropriate location first, and choose the nearest one if there are two or more similarly-appropriate locations.

A few opinions were regarding to safety, concerning the robot to break expensive items and grass window, which we addressed by preparing safety mechanism in robot’s navigation.

### TABLE I. INTERVIEW RESULT ON CRITERIA FOR APPROPRIATE LOCATIONS

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disturbing pedestrians</td>
<td>83.3%</td>
</tr>
<tr>
<td>Disturbing shop activities</td>
<td>75.0%</td>
</tr>
<tr>
<td>Visibility of the robot</td>
<td>70.8%</td>
</tr>
<tr>
<td>Distance from the current location</td>
<td>50.0%</td>
</tr>
<tr>
<td>Safety of the location</td>
<td>12.5%</td>
</tr>
</tbody>
</table>

3) Established Dataset
We observed that there were sometimes disagreements in their choices. For instance, the results were split on a location near a small shelf (Fig. 4 (a)). One person said, “Here is appropriate. The robot can hide behind the small shelf.” In contrast, another one commented that “There are other customers who might look at the shelf in the shop. If the robot stays near the shelf, it disturbs these customers. Therefore, here is inappropriate.” Similarly, the participants disagreed on a location at a center of an intersection (Fig. 4 (b)). One said, “There is a large space here, so pedestrians can avoid the robot easily, so, this is an appropriate location for waiting.” But others said, “Many pedestrians pass by the intersection. If the robot stays here, it simply disturbs the pedestrians,” and “We (humans) never wait at the center of intersections. It is unnatural. Thus, this is an inappropriate location.”

Because we aim to make a robot that chooses a location where everyone can agree on it being appropriate for waiting,
we filtered out locations where participants’ decisions split. We defined the **agreement criteria** \( C(L_i) \) for a location \( L_i \) as:

\[
C(L_i) = \frac{N_{appropriate}(L_i) - N_{inappropriate}(L_i)}{N_{total}(L_i)}
\]  

where \( N_{appropriate}(L_i) \) is the number of the participants who chose this location as appropriate, \( N_{inappropriate}(L_i) \) is the number of the participants who chose this location as inappropriate, and \( N_{total}(L_i) \) is the total number of participants. That is, if all participants chose this location as appropriate for waiting, \( C(L_i) \) is 1.0. If half chose it as inappropriate and others remain undetermined, \( C(L_i) \) is -0.5.

We included locations with \(|C(L_i)| > 0.5\). In total, 116 locations were included in the dataset (20 appropriate and 96 inappropriate locations) out of 170 locations.

C. Retrieving Features

We prepared computational feature that covers the criteria obtained from the interview.

1) **Locations related to “Disturbing Pedestrians”**

About the **disturbing pedestrian** criteria, we found that many pedestrians pass through inappropriate locations, such as in front of automatic doors and elevators (Fig. 5 (a)). Further, some **appropriate** locations were locations near pillars (Fig. 5 (b)) and near walls, where we observed a relatively small amount of pedestrian flow. Note that people might infer the amount of pedestrian flow without actual observation. For instance, one would infer that “people frequently go through a door", without actually seeing a significant number of people pass through. Nevertheless, a robot system can observe a lot of pedestrian trajectories.

![Fig. 5. Locations relevant to disturbing pedestrian criteria](image)

We used a grid-based representation with a 33 cm x 33 cm grid size, which is small enough for a person/robot who would occupy the space (i.e for waiting). For each grid cell \( g_i \), we counted the number of people that passed per hour (denoted as \( num(g_i) \)). Fig. 6 shows the statistics on people per hour observed from the collected trajectories for each grid cell. The dark red color represents a large amount, and light red represents a small amount. While many pedestrians passed through the main corridor (Fig. 6 (a)) and hallway (Fig. 6 (b)), only a small number of people passed around the pillar and around benches (Fig. 6 (c)).

We then normalized \( num(g_i) \) for use as a computational feature (subtracted by average, and then divided by standard deviation), which is described as:

\[
\text{pedestrianPassed}(g_i) = \frac{\text{num}(g_i) - \text{average}(\text{num}(g_j))}{\text{sd}(\text{num}(g_j))}
\]  

2) **Locations related to “Disturbing Shop Activity”**

The locations far from shops are apparently safe from disturbing shop activity. Moreover, even near the shops, there are some locations which people consider to be safe from disturbing shop activity. For example, while locations nearby shop entrances and shop shelves are chosen as inappropriate (Fig. 7 (a)), locations in front of a shop pillars and shop walls (Fig. 7 (b)) are chosen as appropriate.

![Fig. 7. Locations relevant to disturbing shop activity criteria](image)

We consider reproducing this notion of disturbing shop activity based on the shop visibility as an approximation (Fig. 8 (a)). The idea is that people would either consider a line of sight from possible locations of a shopkeeper to him/her (considering shopkeepers would walk around, visibility from any locations in the shop is computed) or a line of sight from him/her to the inside of shops (that is, any location from which the shop can be seen) (Fig. 8 (b)), and avoid locations where such line of sight can be established. As some people consider that staying at the side of low shelves would be disturbing, we computed that shop visibility is only blocked by structures with enough height (called wall object, defined as structures with 2m or higher). Note that people would only concern the disturbance when he/she is in a nearby distance from the shop.

![Fig. 8. Shop visibility concept](image)

Based on the above consideration, a feature corresponding to the disturbing shop activity criteria is computed from the
shop visibility. In concrete, the computation is done using the grid-based representation, in which we computed the size of the grids that satisfy shop visibility from the robot. We introduce the visibility function \( \text{visible}(g_k, g_l) \) where \( g_k \) and \( g_l \) represent grid cells: it returns 1 if \( |g_k - g_l| < d_{th} \) and the line from \( g_k \) to \( g_l \) is not blocked by a wall object; otherwise it returns 0. The shop visibility at a grid cell \( g_l \) is defined as:

\[
\text{shopVisibility}(g_l) = \sum_{g_k \in G_{\text{shop}}} \text{visible}(g_l, g_k) \cdot s
\]

where \( G_{\text{shop}} \) is a set of grid cells included in a shop region, and \( s \) is a size of a grid cell. We calibrated \( d_{th} \) to be 2.5 m, which yields the best performance in recognition of waiting location (result is reported in Sec. III. D).

\[
\text{Inappropriate} = \text{inappropriate location} \text{ (4, 5)}
\]

\[ \text{Appropriate} = \text{appropriate location} \] (3)

Fig. 9 shows the results of the shop visibility computation. The dark red represents the locations with higher visibility, and light red represents the locations with lower visibility. The areas around entrances and in front of shelves are computed as locations with high visibility, while locations in front of pillars and high walls are computed as locations with low visibility.

D. Classification of locations

1) SVM configuration

We used SVM (Support Vector Machine) [17] for classifying each candidate location (represented as grid cell \( g_l \)) into either appropriate or inappropriate location for waiting. The input vector consists of two variables \( \text{pedestrianPassed}(g_l) \) and \( \text{shopVisibility}(g_l) \), as defined in the section III-C. We used the radial basis function (RBF) kernel, and calibrated basic parameters with a grid search. We tested the SVM with 10-fold cross validation with the dataset obtained in the section III. The recognition performance is computed from the average of the 10-fold test, where the performance for each fold is computed as the correct recognition ratio for each class, appropriate and inappropriate.

2) Classification result

Table II shows the confusion matrix. The overall result is 87.5%, which we consider to be reasonably good. Both the appropriate and inappropriate classes were recognized well. It is particularly notable that there are no false-positives for appropriate locations (i.e. an inappropriate location recognized as appropriate). We need a robot system that can choose an appropriate location when requested. Here, the choice of the appropriate location should not be mistaken; otherwise the robot would occasionally wait at an inappropriate location.

![Table II. Confusion Matrix](image)

<table>
<thead>
<tr>
<th></th>
<th>Prediction</th>
<th>Success ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>actual</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Appropriate</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Inappropriate</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>5</td>
<td>75.0%</td>
</tr>
<tr>
<td>0</td>
<td>96</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Fig. 10 (b) shows the classification result of appropriate locations (shown as grids painted with red) detected from all the grids in the map (ones in dataset as well as other grids that were not included in the dataset), for which we built SVM using all the data points included in the dataset. The classification result seems to provide reasonable locations. For instance, the location (1) in the figure is the side of an automatic door, which is detected as appropriate. We sometimes see people stop and talk there. The location (2) is the location people use for waiting around the restaurant. The dataset includes some inappropriate locations, such as in front of doors,
in the center of corridors, and in front of shops. Similar locations were classified as inappropriate (thus painted with white).

IV. ROBOT SYSTEM

A. Overview
We developed a shopping companion robot system. The robot autonomously follows a user while carrying shopping basket and moves to a waiting location when requested. We followed a semi-autonomous approach [18] in which a human operator can help the robot recover from errors in autonomy, and interprets the user’s spoken command for the robot such as requests to stop or to resume from waiting, as speech recognition in noisy environment is specifically difficult.

![Software Architecture](image)

Fig. 11. Software Architecture

Fig. 11 illustrates our software architecture. It consists of three modules: planner, localization, and people tracking (section V.B). The planner executes waiting behavior (section V.D) when the system receives a request to wait. When the user comes back and provides the resume command, it starts the following behavior (section V.C).

B. Hardware, Localization, and People Tracking

We used Robovie-II, which has a maximum speed of 750 mm/sec. It has one range laser sensors (Hokuyo UTM-30LX) attached at a height of 8 cm. Localization is done with a particle filter with the ray tracing approach with a grid map [19]. People-tracking was based on detection and segmentation of human legs with laser sensors. See [15] for further details. When this module fails to track the target person, it requests a human operator for help.

C. Following Behavior

The system performs a line-following algorithm to form a line from its current position to the followed user. In addition, we prepared a simple safety mechanism to prevent collisions with dynamic obstacles [20] that limits the forward velocity to be safe enough to stop before colliding with the nearest object.

D. Waiting Behavior

In the waiting behavior, the system first computes the waiting location. The waiting location is selected based on the developed model of waiting location (section III-D). Among all locations $L_i$ that are visible from the robot’s current location, it chooses the nearest location that satisfies eqn. 3:

$$\text{appropriateness}(L_i, \text{size}) > th$$

where appropriateness$(L_i, \text{size})$ is an average of appropriateness$(L_i)$ the average of nearby grids $L_j$ that satisfy $|L_j - L_i| < r$ ($r$ is the radius of the robot), and appropriateness$(L_i)$ is the probability output from the SVM, which takes a value ranging [0,1] where value larger than 0.5 represents the appropriate class and smaller than 0.5 represents the inappropriate class. We start this computation with initial threshold value $th = 0.9$, and gradually reduce $th$ by 0.1 per step until $th = 0.5$ if no location is found before then. Then, the robot plans a path to move to the selected location while avoiding static obstacles. Finally, after arriving, in order to express its intention of waiting for the user, the robot orientates its body toward the point where the user asked the robot to wait.

V. EVALUATION EXPERIMENT

We evaluated the model in a shopping-assistance scenario. A robot followed elderly users by carrying their shopping basket, and waited for them when requested.

A. Hypothesis and Predictions

Since there are no other comparative models for finding the waiting location, we compared the proposed model as described in section IV with the robot that randomly chooses a location to wait at. If the choice of waiting location by the proposed model is appropriate and if it matters to the users, then users would find the difference in waiting location. Based on this hypothesis, we made the following predictions:

Prediction 1: The robot with the proposed model is rated higher in perceived appropriateness of the waiting location than that of the random condition.

The other comparative condition is without autonomous waiting. Before leaving the robot, a user finds a location for the robot to wait. However, there is a certain amount of labor involved to let it wait at an appropriate location, which the user might not want to perform, and thus might leave the robot at a less appropriate location. Therefore, we consider that if the autonomous waiting behavior of the robot is appropriate, it would result in better waiting locations with the autonomous waiting. We made the following prediction:

Prediction 2: The robot with the proposed model is rated higher in perceived appropriateness of the waiting location than that of the manual condition.

B. Method

1) Participants
Eighteen elderly Japanese people (7 males and 11 females, average 70.7 years old) participated, for which they were paid.

2) Conditions
The experiment was a within-subject design having one factor, method of waiting. Three conditions were prepared:

- Autonomous-waiting with the proposed model (Proposed condition): The system used the proposed model. When requested to wait, the robot selects the waiting location with the model and autonomously moves to the selected location.
- Autonomous-waiting with random location choice (Random condition): Instead of the proposed model, the system selects the waiting locations randomly from
nearby visible locations. The distance of the location is limited to be within 5m (roughly the width of a corridor) from the location requested.

**Without autonomous waiting behavior (Manual condition):** The robot waits for the user at the location where s/he asks the robot to wait. In this manual condition, we told participants that when they want to enter the shop they need to walk to the location appropriate for the robot to wait, and let the robot follow them as usual (i.e. with its autonomous following behavior); and then, ask the robot to wait at the location so that the robot simply stays there.

3) **Procedure**

The experiment was conducted in an area of the mall where 10 shops are included. Participants were instructed to go shopping. The robot was introduced as a shopping companion robot that follows them and carries their shopping basket. For each session, we instructed them to enter three shops, in which they looked around at items. They were allowed to walk freely and visit shops of their choice. They participated in all three conditions. The orders of conditions were counterbalanced.

We informed them that a robot needs to wait for them outside of the shop when they enter a shop, because the robot cannot go through the narrow spaces in the shop. In the case of the autonomous conditions (proposed and random condition), we instructed them to ask the robot to wait when they enter the shop. We did not inform them how the robot computes the waiting location; instead, we told them that the robot will do its own computation for the waiting location, which could be good or bad, thus they need to evaluate the robot’s capability as a test user. After they come back from shopping, they will ask the robot to continue following them.

4) **Measurement**

**Perceived Appropriateness of Location:** After each session, we asked this with 1-to-7 point Likert scales where 7 is the highest.

**C. Scene of interaction**

The robot followed participants while they walked around (Fig. 12(a)). When they entered a shop, they asked the robot to wait. Fig. 12(b) is a scene where the robot waits for the user (in the proposed condition) while looking back at the sport where the user requested it to wait. We observed that there were a few participants who started to notice the robot’s waiting behavior when they requested it to wait (Fig. 12(c)), after they found the robot waited at unusual locations.

All participants visited three shops per condition as instructed. On average, they shopped for approximately 5 minutes. There were some participants who were absorbed in shopping and spent more than 10 minutes in a shop. About half of participants bought items, and majority of them put the bought items in the shopping basket the robot carried. Some participants also put their own bags in the basket (Fig. 12(d)).

Overall, it seemed that this was a very enjoyable experience for the participants. At the end, almost all participants voluntarily commented that it was a good experience for them and they enjoyed it.

D. **Verification of hypothesis**

Fig. 13 shows the result. Error bars represents standard error. A one-way repeated-measure analysis of variance (ANOVA) was conducted with the Huynh-Feldt ε correction. A significant main effect was revealed (F(2.0, 34)=9.789, p<.001, 2p_K=.365). Multiple comparison with the Bonferroni method revealed that the location score in the proposed condition is significantly higher than the score in the manual condition (p<.001) and in the random condition (p=.004). No significant difference was found between manual and random condition (p=1.0).

Thus, as predicted, the participants certainly found the difference between proposed and random conditions, and rated the location ratings higher for proposed condition than other conditions. Thus, predictions 1 and 2 are supported.

E. “Random” and “Manual” conditions

The perceived appropriateness of location rating was not significantly different between random and manual conditions. It is interesting that the manual condition was rated so low.
We observed that *random* was not necessarily bad all the time, while the location in *manual* was sometimes not very good at all. Fig. 14 shows some examples seen in *random* condition. By chance, the robot sometimes went to appropriate locations (e.g. Fig. 14 (a)), and sometimes went to inappropriate locations (e.g. Fig. 14 (b)). Because the robot only waited 3 times of per condition, not all the participants suffered from such bad choices.

In the *manual* condition, some participants exerted little effort to find a suitable waiting place for the robot. Fig. 15 is an example of such a scene. When she found the shop interesting, she did not look around for waiting locations but entered to the shop directly (Fig. 15 (a)). At the entrance she asked the robot to wait (Fig. 15 (b)), and entered the shop (Fig. 15 (c)). For such participants, it was probably not as important to find a suitable waiting location for the robot, as their primary purpose was to go shopping. Nine participants said “It is bothersome to park the robot. I prefer to use the robot that waits autonomously.” Three participants also commented that “It was difficult for me to find appropriate waiting locations”, though they might not have spent the time to seriously try and find location for the robot.

In the *manual* condition who did not look for waiting location, but simply left the robot at the entrance

**VI. DISCUSSION**

**A. Other required capabilities**

This study addressed a specific capability, waiting, in a shopping assistant robot. Other capabilities could be developed as well. For instance, one would be concerned with whether a robot can keep a shopping basket or other baggage in a secure way. The robot should be perhaps equipped with a capability to recognize such incidents as stealing, and should also be able to deal with it, e.g. record the event and/or call security staff. An alternative is to implement a safe container inside a robot’s body. In fact, a similar mechanism is already implemented [21].

One would argue that a robot should try to go inside the shop and keep being along with the user. It would certainly be a useful capability. However, this is very difficult with the robot’s present perception and actuation. It cannot go into narrow corridors of shops because there is a risk of colliding with shop items. We agree that this would be a future possibility. Yet, such robots would find it difficult to pass each other in narrow corridor, which would be a much harder problem to solve.

**B. Implication**

Humans share an intuitive knowledge in the perception of environments. An example that appeared in this study was that we rarely wait for our friends or stand and talk to our friends for a long time in locations like shop entrances or in front of doors. Our study revealed a way for a robot to acquire such sense. Specifically, we took an approach to gain such knowledge by observing the environment. We observed the flow of pedestrians and the structural shape (pillar, walls and shop regions) of the environment; and used them to understand the possible disturbances a robot could cause.

While this study only addresses waiting behavior, this method can easily be extended to other type of behaviors, such as talking (while standing) and meeting locations, in which the robot would need to compute disturbances to others activities when it decides its standing location in the space.

**C. Brief test in other environments**

To confirm the generalizability, we briefly tested the model in three different environments. We tested at a corridor (Fig. 16 (a): people’s density is 4050 persons/hour/m$^2$ at the center of the way) and atrium (Fig. 16 (b): density peak in the atrium was 2656 persons/hour/m$^2$) in a shopping mall in the Osaka bay area where there are many weekend visitors, and an underground corridor in Osaka connecting train stations and malls where there are many daily commuters (Fig. 16 (c): at the center of the corridor, 1170 persons/hour/m$^2$). We recorded pedestrians’ trajectories each of there for one day. With these observed trajectories and map with shop regions and walls manually prepared, the same SVM reported in section III-D was used without any additional calibration.

Fig. 16 shows the results. The red color represents appropriate places to wait (the result on the grid map was manually transferred to the photo to assist the readers’ comprehension). The result seems to fit with our common sense. In the corridor (Fig. 16 (a)), there are shops on the right side of the photo, though in the left side, there are extra spaces in which less pedestrians pass through; such spaces are chosen as appropriate waiting locations. In fact, we sometimes saw people waiting there as well. Similarly, the chosen locations seem to be appropriate in the other two scenarios. In the atrium (Fig. 16 (b)), the areas around the red and gray column are chosen which are beside the main passage. In Fig. 16 (c), the sides of the corridor (particularly between columns) were chosen which pedestrians rarely pass through.

Fig. 16. *Appropriate* waiting locations from different environments
D. Limitations and future work

The developed model is prepared for a human-sized robot, and parameters are obtained in a Japanese culture. When the model is used in other countries, or on other types of robots (e.g., big robots that occupy a larger space) we would need to extend the model or adjust the parameters. In the study, we manually drew the shop areas, and added wall objects. We believe that this process can be automated soon. For instance, there are techniques to classify locations [5, 6] which we could extend to classify shop areas.

VII. Conclusion

We addressed the waiting behavior of the robot. We modeled how humans choose waiting locations, and developed a computational model in which two features are computed, disturbing other pedestrians and disturbing shop activities. A classification system was made using support vector machines. The model was used in a shopping assistance scenario, in which users compared it to a robot with random location choice and a robot with manual control. The results reveal that the proposed model is successful enough in finding appropriate waiting locations in a real environment so that users perceived the model to appropriately select waiting locations.

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References