How to Approach Humans?
–Strategies for Social Robots to Initiate Interaction

Satoru Satake, Takayuki Kanda, Dylan F. Glas, Michita Imai, Hiroshi Ishiguro, Norihiro Hagita

ATR Intelligent Robotics and Communication Laboratories
2-2-2 Hikaridai, Seika-cho, Souraku-gun, Kyoto, Japan
{satoru, kanda, dylan, michita, ishiguro, hagita}@atr.jp

ABSTRACT

This paper proposes a model of approach behavior with which a robot can initiate conversation with people who are walking. We developed the model by learning from the failures in a simplistic approach behavior used in a real shopping mall. Sometimes people were unaware of the robot's presence, even when it spoke to them. Sometimes, people were not sure whether the robot was really trying to start a conversation, and they did not start talking with it even though they displayed interest. To prevent such failures, our model includes the following functions: predicting the walking behavior of people, choosing a target person, planning its approaching path, and nonverbally indicating its intention to initiate a conversation. The approach model was implemented and used in a real shopping mall. The field trial demonstrated that our model significantly improves the robot's performance in initiating conversations.

Categories and Subject Descriptors

H.5.2 **[Information Interfaces and Presentation]**: User Interfaces-Interaction styles

General Terms

Algorithms, Performance, Design, Human Factors

Keywords

Approaching behavior, Position-based Interaction, Anticipation

1. INTRODUCTION

Social robots have started to move from laboratories to real environments [11,17,27,28,32,34], where, a robot interacts with ordinary people who spontaneously interact with it. For such a robot, initiating interaction is one of its most fundamental capabilities. In previous studies, many robots were equipped with the capability to encourage people to initiate interaction [14,15,16,22,25]. These robots wait for people to approach them, which is one strategy for robots to initiate interaction.

Alternatively, a "mobile" robot can approach people (Fig. 1) to initiate interaction. This way of providing services is more proactive than waiting, since it enables robots to help people who have potential needs. For instance, imagine a senior citizen who

has gotten lost in a mall. If a robot were placed in the mall for providing route direction, it could wait until the senior citizen approaches it and asks for help; but he might not know what the robot can do, or he might hesitate to ask for help. Instead, it is more appropriate that the robot approaches and offers help.
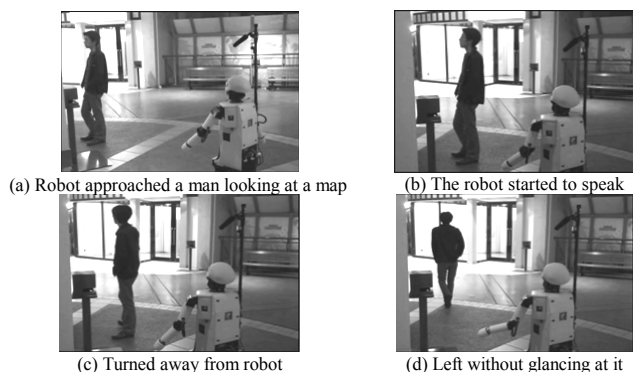

(a) Robot approached a man looking at a map   (b) The robot started to speak

(c) Turned away from robot   (d) Left without glancing at it

Fig. 1 What's wrong? "Unaware" failure in approach

The robot's capability to approach people enables a number of applications. We believe that one promising application is an invitation service: a robot offers shopping information and invites people to visit shops, while giving people the opportunity to interact with the robot since robots are very novel to them.

2. RELATED WORKS

Hall, who classified human interactions based on a concept of distance, coined the following terms. "Public distance" refers to situations in which people give a speech, and "social distance" characterizes situations in which people talk to each other for the first time [10]. Our approach is related to public and social distances. The robot needs to find a person with whom to talk, to start approaching that person at a public distance, and to initiate the conversation at a social distance.

2.1 Finding a Person for Interaction

To find a person for interaction, first, robots need to locate people. In robotics, many traditional studies are related to obstacle avoidance and path planning, and researchers have recently started to study methods for finding and tracking people. Vision as well as distance sensors onboard robots have been used [2,3,4,6,20]. Moreover, researchers have started to use sensors embedded in environments [5,23,29,35] that enable a robot to recognize people from a distance.

After finding people, the robot needs to identify a person with whom to interact. There are previous studies about human behaviors related to this. For example, Yamazaki et al. analyzed how elderly people and caregivers start conversations. They found

that to identify elderly people who require help, a caregiver displays his/her availability non-verbally with body orientation, head direction, and gaze [18]. Fogarty et al. analyzed human interruptibility in an office environment and demonstrated that even simple silence detectors could significantly estimate interruptibility [13].

In HRI, Michalowski et al. classified the space around a robot to distinguish such human levels of engagement as interacting and looking [22]. Bergström et al. classified people's motion toward a robot and categorized people into four categories: interested, indecisive, hesitating, and not interested [25]. Tasaki et al. developed a robot that chooses a target person based on distance [33]. Finke et al. developed a robot that chooses a target person based on motion [20]. Although these studies focused on people's behaviors directed to robots, such information is not available for a robot that approaches people from a distant place. Instead, the robot needs to observe people's behavior, such as their way of walking, to estimate the possibility to talk.

2.2 Interaction at Public Distance

When people are at a public distance, it is too far for them to talk; but they can recognize each other's presence. At such a distance, interaction is mainly achieved by changing body position and orientation. Sisbot et al. developed a path-planning algorithm that considers people's positions and orientation to avoid disturbances [6,7]. Pacchierotti et al. studied passing behavior and developed a robot that waits to make room for a passing person [9]. Gockley et al. found the merits of a direction-following strategy for a robot when following a person [26].

These robots only use people's current position; however, since human-robot interaction is dynamic and quick, prediction and anticipation are crucial. Hoffman and Breazeal demonstrated the importance of anticipation in a collaborative work context [12]. In contrast, there are few studies about the anticipation of people's positions. Bennewitz et al. utilized such a prediction of position [19], but it was only used for helping a robot avoid people, not for allowing interaction with them. In a previous study, we anticipated people's positions for letting a robot approach them and demonstrated the importance of anticipating positions [31]. But it lacks a path-planning process, which is important for notifying the target person of the robot's presence.

2.3 Initiating Conversation at Social Distances

After entering a social distance, a robot initiates conversation with its target. Humans start conversations with greetings. Goffman suggested that social rules exist for accepting/refusing approaches, including eye-contact, which is a ritual that mutually confirms the start of a conversation [8]. Kendon suggested that friends exchange greetings twice, first nonverbally at a far distance and again at a close distance by smiling [1].

Several previous HRI studies have addressed the greeting process. Dautenhahn et al. studied the comfortable direction of an approach [15] as well as the distance to talk [21]. Greeting behavior initiates human-robot conversation [27,30]. Yamamoto and Watanabe developed a robot that performs a natural greeting behavior by adjusting the timing of its gestures and utterances[24].

These studies assume that the target person intends to talk with the robot; however, in reality people are often indecisive about whether to talk when they see a robot for the first time. A few studies have been conducted on the first-time-meeting situation and making robots nonverbally display a welcoming attitude

[22,25]; but these passive robots only waited for a person to engage in conversation. Although such a passive attitude is fine for some situations, many situations require a robot to engage in an active approach. Our study aims to allow a robot to actively approach a person to initiate conversation.

"An Approach from a robot" is not an easy problem since the robot's approach needs to be acknowledged nonverbally in advance; otherwise, the approached person might not recognize that the robot is approaching him/her or would be surprised by the robot's impolite interruption. Humans do this well with eye gaze [1,8], but in a real environment it is too difficult for a robot to recognize human gazes. Instead, we use the body orientation of the target and the robot for non-verbal interaction.

3. Environment, Hardware, and Task

This study, which focuses on the spontaneous initiation of human-robot interaction, requires a realistic scenario in a real field. We chose a shopping mall for the environment and "advertising about shops" as the robot's task. The robot approaches a person to recommend a shop in the mall to increase interest in visiting it.

3.1 Environment: Shopping Mall

The robot was placed in a shopping mall located between a popular amusement park, Universal Studios Japan, and a train station. The primary visitors of the mall are groups of young people, couples, and families with children. The robot moved within a 20 m section of a corridor (Fig. 1). Clothing and accessories shops are on one side and an open balcony is on the other.

3.2 Hardware

3.2.1 Robot

We used Robovie, a communication robot, who is characterized by its human-like physical expressions. It is 120 cm high and 40 cm in diameter and equipped with basic computation resources as well as WiFi communication. Its locomotion platform is Pioneer3 DX. We set it to move at a velocity of 300 mm/sec (approx. 1.0 km/h) forward and 45 degree/sec for turns. The platform can navigate the robot faster (up to 1600 mm/sec) than these parameters, but we chose a lower velocity for safety.

3.2.2 Sensors

To approach people, the robot needs to robustly recognize their positions and its own position, even in distant places. We decided to use sensors embedded in the environment for tracking human and robot positions. Six SICK LMS-200 laser range finders were positioned around the area's perimeter. Laser range finders were set to a maximum detection range of 80 m with a nominal precision of 1 cm, and each scanned an angular area of 180° at a resolution of 0.5°, providing readings every 26 ms.

For detection and tracking of people and robots, a technique based on the algorithm described by Glas [5] was used. In this algorithm, particle filters are used for estimating people's positions and velocities, and a contour-analysis technique estimates the direction in which a person is facing. This orientation angle helps determine whether the robot should approach a person. This system covers 20 m x 5 m area and concurrently detects over 20 people's locations.

3.3 Task

The robot's task was "advertising shops." It was placed in a corridor of the mall. The robot was designed to approach visitors

and to recommend one of the 24 shops in the mall by providing such shop information as, "It's really hot today, how about an iced coffee at Seattle's Best Coffee?" or "It's really hot today, how about an ice cream shop?" Then the robot pointed at the shop. When the robot was neither approaching nor talking, it roamed on a pre-defined route.

Visitors freely interacted with the robot and could quit anytime. For safety, our staff monitored the robot from a distant place; thus, from the visitors view, it seemed as if the robot moved around and approached them without assistance from human experimenters.

4. Modeling of Approach Behavior

We define the term "approach behavior" as a sequence of the following activities: (1) selecting a target, (2) approaching the target, and (3) initiating conversation from a close distance.

In the beginning, we implemented a "simple" approach behavior, where (1) the robot selects the closest person, (2) takes the shortest path to that person, and (3) greets him/her when it arrives within the social distance (3 m); however, such a simplistic approach behavior was too simple because it often failed to initiate conversation. In this section, we describe the lessons learned from failures and introduce our model for more efficient and polite "approach behavior."

4.1 Lessons Learned

Many people ignored the robot. These failures, which reflected many problems in the "simple" approach behavior, were analyzed and categorized into four categories: *unreachable*, *unaware*, *unsure*, and *rejected*. Table 1 summarizes the failure categories, which we introduce in this subsection and discuss how the robot can avoid them. We classified failures by watching videos and position data.

Table 1 Classification of failures

Category	What happened
unreachable	- The robot did not get close to target person.
unaware	- The person did not look at robot. - The person did not listen to it.
unsure	- The person recognized its presence and reacted (e.g., checked its reactions); but the robot did not respond correctly in time.
rejected	- The person recognized its presence and its greeting behavior, but did not start a conversation.

Unreachable

One typical failure is a case where the robot failed to get close enough to a target person. This failure happened because (a) the robot was slower than the target person, and/or (b) the robot chose a person who was leaving.

Unaware

When unaware of the robot, a person does not recognize its action as initiating conversation, even when the robot speaks to him/her.

Figure 1 shows one such failure. In this case, a man was looking at a map on a wall when the robot spoke to him (Fig. 1(b)), but he wasn't listening (Fig. 1(c)) and left without even glancing at the robot (Fig. 1(d)). He probably did not hear the robot because the mall was quite noisy; perhaps he heard but he did not recognize

that it was directed at him; he might have recognized it but simply ignored it.

Figure 2 shows another example where two women were walking together (Fig. 2(a)). The robot started approaching one of them from the front and seemed to be within her sight (Fig. 2(b)). When the robot reached the distance to talk, it approached her right side (Fig. 2(c)). Unfortunately, since she wasn't looking at the robot but at a shop, she ignored the robot as if nothing happened and walked on.

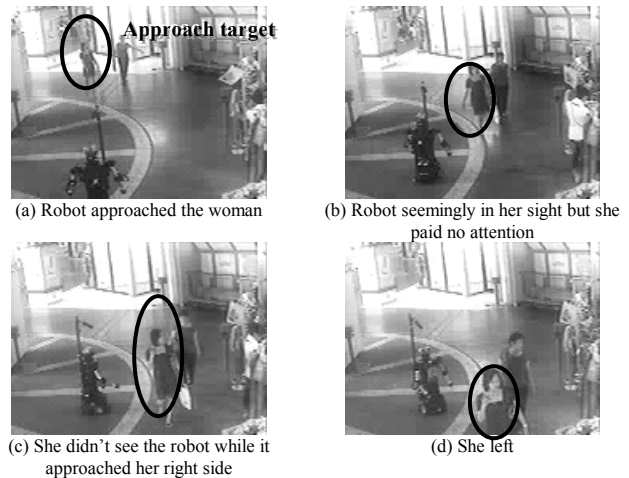To avoid this type of failure, the robot needs to improve its notifying behavior.

(a) Robot approached the woman

(b) Robot seemingly in her sight but she paid no attention

(c) She didn't see the robot while it approached her right side

(d) She left

Fig. 2 "Unaware" failure: a person is walking and talking to another person

Unsure

We labeled another type of failure as "unsure." Sometimes, although people were aware of the robot, it failed to initiate conversation. They observed the robot's behavior and recognized its utterances. However, they did not stop since they seemed unsure whether the robot intended to talk to them. Some people even "tested" the robot's reaction after its greeting, but since the robot was not prepared to react to such "testing" behaviors, it failed to provide an appropriate reaction. Thus, the robot failed to initiate conversation.

Figure 3 shows one such failure. A woman and a man entered the environment (Fig. 3(a)). The robot approached and greeted her. She stopped walking and performed a kind of "test" by reaching her hand to the robot's face (cp. Fig. 3(c)). The robot, however, did not respond, so the woman left a few seconds later.

To avoid this type of failure, the robot must establish mutual understanding with the target with whom they are going to engage in a conversation. In addition, it should quickly establish contingency with the person (e.g., facing the person, re-orienting its body to the person, etc.) when it is going to initiate a conversation.

Rejected

Some people are not interested in conversation with the robot, presumably because they are too busy. These people avoided the robot at a glance and rejected to talk to it, although they were aware of it and knew that the robot was trying to talk to them. We called this failure "rejected." These people should simply not be approached.

(a) Robot approached a person

(b) She stopped when robot started to speak

(c) She observed robot's reaction

(d) She left when robot did not immediately react

Fig. 3 "Unsure" failure: woman unsure whether robot intended to speak to her

4.2 Modeling

By summarizing the lessons learned from the failures in the "simple" approach behavior, we developed a model for a more efficient and polite "approach behavior," as shown in Table 2. It consists of three phases.

Table 2 Model of approach behavior

Phase	Robot's behavior	Failures to be moderated
Finding an interaction target	Selecting a likely interaction target	Unreachable/ Rejected
Interaction at public distance	Announcing its presence and intention to talk	Unaware
Initiating conversation at social distance	Nonverbally showing intention to interact	Unsure

Finding an interaction target

The first phase is "finding an interaction target." The robot needs to predict how people walk and estimate who can be reached with its locomotion capability. It also needs to anticipate those who might be willing to interact with it; this requirement is really difficult, but at least it can avoid choosing busy people who are probably unwilling to talk with it.

Interaction at public distance

The second phase is "interaction at a public distance," where the robot notifies its presence to the target at a public distance by approaching from his/her front. The difficulty here is that the robot must predict the target's walking course to position itself within his/her sight before starting the conversation.

Initiating conversation at a social distance

The last phase is "initiating conversation at a social distance." One might argue that this can be done simply by such greetings as "hello;" however, greeting strangers is not easy. People are sometimes unaware of the robot's utterance. People sometimes do not recognize that its greeting is directed to them. Instead, we focused on using nonverbal behavior to indicate the robot's intention to initiate a conversation. When the target is about to change her course, the robot faces her so that she can clearly recognize that the robot is trying to interact with her. We assume

that, if she stops, she is accepting interaction with the robot. After receiving such an acknowledgement, the robot starts a conversation.

5. Implementation

We implemented approach behavior with 4 functions: (1) tracking people, as described in section 3.2.2, (2) anticipating people's behavior, (3) planning path to approach, and (4) initializing conversation. These functions were executed in this order.

5.1 Anticipating people's behavior

In a shopping mall, most of the people have rather simple intentions, such as passing to a destination or walking for window shopping. Consequently people's walking behavior (trajectories and speed) are similar to each other. A busy passenger tries to follow the shortest path with high velocity while a window shopper prefers to pass a side of a shop with slow velocity. In our previous study [31], we anticipate people's future behavior by gathering and clustering a tens thousand of people's trajectories.

To anticipate people's future behavior, we applied a SVM (support vector machine) to classify 2-seconds of each trajectory into four behavior classes: fast-walking, idle-walking, wandering, and stopping. This classification is based on features of shapes of trajectory and velocity.
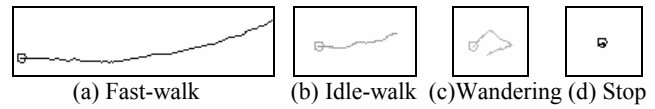

(a) Fast-walk   (b) Idle-walk   (c)Wandering (d) Stop

Fig. 4 Classification of trajectories to behaviors

A clustering algorithm with a DP matching method was applied to a whole length of gathered trajectories. As the result of the clustering, we got 300 clusters, some clusters represented "busy person" patterns (Fig.5 (a)), and some cluster represented "window shopper" patterns (Fig. 5 (b)). In Fig. 5, blue color represents a location where trajectories in a cluster were usulaly classfied as fast-walking behavior. Green represents a location where trajectories were ussually classifed as idle-walk behavior

Gathered trajectories in a cluster enable to anticipate people's future location and behavior. From the trajectories, we derived likelihood values of each behavior at each grid in a cluster at any time *after* a person whose trajectory belongs to the cluster appears. We manage these likelihood values as an "expectation map".
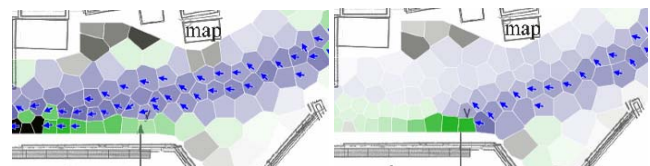
(a) A "busy person" pattern   (b) A "window shopper" pattern

Fig. 5 Extraction of typical behaviors

A predicted position of a person is the expectation value of the position. If a trajectory of a person is observed from tracking people function, we search the nearest 5 clusters to the trajectory and merge likelihood of each exception map to anticipate the person. Fig. 6 shows expectation maps for various time increments of a person. The red circles represent the positions of the person walking through the space. The expected behaviors can be seen tracing a path through the corridor, heading toward the upper right. In fact, this course was correctly predicted, and the person followed that general path.
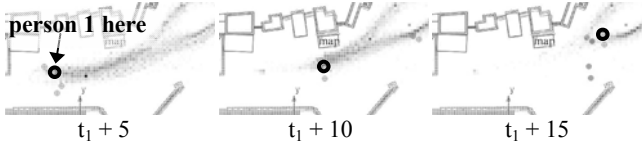
person 1 here

| $t_1 + 5$ | $t_1 + 10$ | $t_1 + 15$ |

Fig. 6 Example of anticipation

The robot

t_0
The person

t_{arrive}

$Pos(i,t_2)$

t_{margin}

Turning point
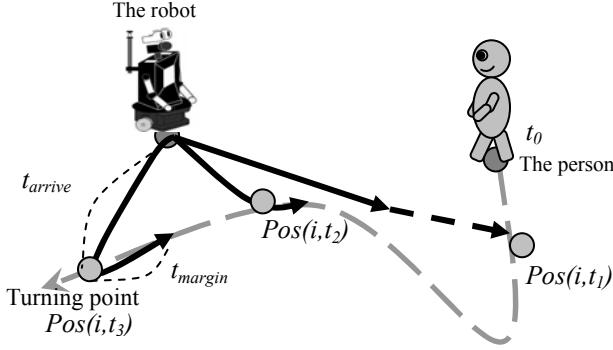$Pos(i,t_3)$

$Pos(i,t_1)$

Fig. 7 Approach from frontal direction

5.2 Planning path to approach

Fig. 7 shows overview of our path planning strategy. The robot predicts the trajectory of its target person (the dashed line from the person in Fig. 7) and finds the turning point where the robot has enough time to correct its orientation in order to approach from frontal direction after the robot arrives. In the figure, three possible *approach paths* are described. A robot plans to arrive to a point named *turning point*, and orient its body direction to approach to the person from the frontal direction.

The system searches for the most promising *approach path* based on the algorithm shown in the Table 3. In the table, i represents the person's id, t_0 represents the current time, and t represents the future time. In Fig. 7, t_1, t_2, and t_3 also represent future time ($t_0 < t_1 < t_2 < t_3$). $Pos(i, t)$ represents the expected position of the person i at time t, provided by an expectation map described in section 5.1. The estimation of the success of the approach is given by $P_{approach}(i,t)$, which is computed from 4 probabilities: $P_{ack}(i,t)$, $P_{front}(i,t)$, $P_{gaze}(i,t)$, and $Uncertanty(t)$ (Fig. 8). Each of these probabilities is estimated as follows:

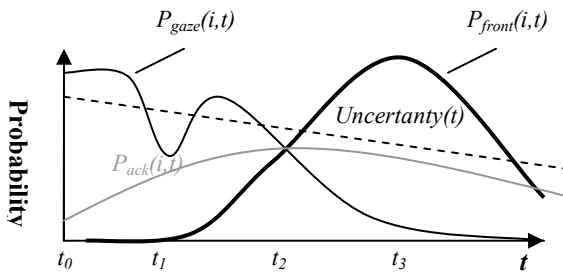**Table 3 The algorithm to choose the target person and point**

Fig. 8 Probability functions for the person at Fig. 7

$P_{ack}(i,t)$
It represents a probability whether target person might be willing to interact. It is difficult to accurately estimate this; instead, as we discussed in 4.2, our strategy is to choose a person whose future behavior class is *idle-walking* rather than *busy-walking*. Thus,

likelihood value of "*idle-walking*" of $Pos(i,t)$ at the future time t is used as $P_{ack}(i,t)$.

$P_{front}(i,t)$
It represents a probability that the robot approach the target person from frontal direction. To approach from frontal direction, the robot needs to appear in advance to the place where the person will come. We calculated this based on the largeness of margin time to change robot's orientation. The following algorithm is applied. To notify the robot's presence at public distance, we must choose an approach plan that has high $P_{front}(I,t)$.

1. Calculate t_{arrive}, the time the robot arrives at the $Pos(i,t)$
2. Calculate t_{margin}, that is, $t - t_{arrive}$. If $t_{margin} < 0$, $P_{front}(i,t)=0$
3. $P_{front}(i,t)= t_{margin} / threshold$. If $t_{margin} > threshold$, $P_{front}(i,t)=1$

In Fig. 7 t_{margin} at t_2 is less than t_{margin} at t_3, therefore $P_{front}(i,t_2)$ is less than $P_{front}(i,t_3)$ (Fig. 8). In Fig. 7, t_{margin} is less than 0 and $P_{front}(i,t_1)$ equals 0 (Fig. 8).

$P_{gaze}(i,t)$
It represents a probability that the robot orient its head to the target person during its approach so that the target person could find the robot looking at him/her. To notify the robot's intention at public distance, this gazing behavior is needed. $P_{gaze}(i,t)$ is calculated based on the angular difference between the robot's head orientation and the direction of locomotion. The robot has mechanical constraint on the head direction, thus it can only look at the direction within a certain range. Moreover, it is uncertainty in the prediction of the target motion. If the angular difference is small, it is highly possible for the robot to orient its head to the target person continuously.

$Uncertanty(t)$
There is a large uncertainty in the prediction of target person's trajectory in the future, although the robot plans *approach path* based on the prediction. If the system tries to plan *approach path* in the far future, the likelihood of error of the prediction is larger. Thus, $Uncertanty(t)$ is bigger when t is larger.

5.3 Initializing conversation

Initializing conversation has two purposes: (1) nonverbally showing the robot's intention to interact, and (2) recognizing an acknowledgment to start interaction from its target. It decides the

1	For each person i, for each t ($t_0 < t < t_0+20$), calculate $P_{approach}(i,t) = P_{ack}(i,t) \cdot P_{front}(i,t) \cdot P_{gaze}(i,t) \cdot Uncertatinty(t)$
2	Find i' and t' which satisfy $P_{approach}(i',t') = max(P_{approach}(i, t))$
3	Approach path is set to $Pos(i', t')$

robot's behavior based on human behavior within the social distance.

Table 4 shows the strategy of this function. It classifies human behavior into 4 categories: *approaching*, *stopping*, *avoiding*, and *leaving*. When a person changes his/her course, his/her behavior is categorized as "avoiding" and the robot faces its body orientation to him/her to show its intention to talk to him/her. When a person stops, the robot starts a conversation. When a person leaves the robot, the robot gives up starting a conversation.

Table 4 The strategy of initializing conversation

Human behavior	Robot behavior
approaching	Approach
stopping	Start conversation
avoiding	Show intention to talk strongly
leaving	Give up having a conversation

We transform human trajectory to robot coordinate system and apply SVM. SVM classified 1-second of each transformed person's trajectory (Fig. 9). This classification used features of shapes of trajectory, velocity, and direction. We used 45 trajectories for learning and its recognition rate was 88.9 % tested with leave-one-one method.
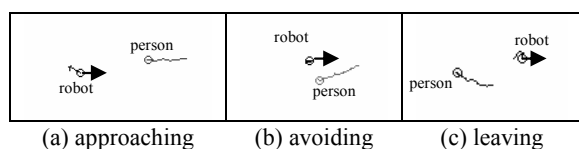

(a) approaching   (b) avoiding   (c) leaving

Fig. 9 Classification of trajectories at initializing conversation phase to behaviors

6. Field Trial

We conducted a field trial at a shopping mall[1] to evaluate the effectiveness of the "proposed" approach behavior. The robot's task was to approach visitors to provide shopping information. The details of the environment and task are described in Section 3.

6.1 Procedure

We compared the proposed method with the "simple" approach behavior to evaluate the effectiveness of the "proposed" method. The "simple" approach behavior is described in Section 4. In the "proposed" approach behavior, the robot follows the model reported in Section 4.2 and uses all the implemented techniques reported in Section 5.

For comparisons, we ran the trials for several sessions to eliminate environmental effects, such as the time of the trial. Each session lasted about 30 minutes. The two conditions, "simple" and "proposed," were assigned into sessions whose order was counterbalanced. In total, we ran the experiment for two hours for each condition, and about the same number of approach behaviors were conducted in both conditions.

6.2 Improvement of Success Rate

Fig. 10 shows the comparison results. The approach behavior was defined as successful when the robot's approach target stopped and listened to the robot's utterance at least by the end of its greeting. In this section, we defined the term "trials" to mean actual approaches toward people, and not simply the number of people passing through the area.

With the proposed method, the robot was successful in 33 approaches out of 59 trials (252 people passed through). On the other hand, with the simple method the robot was only successful 20 times out of 57 trials (221 people passed through). A chi-square test revealed significant differences among conditions ($\chi^2(1)$ =5.076, p<.05). Residual analysis revealed that in the proposed method, "successful approach" is significantly high (p<.05) and "failed approach" is significantly low (p<.05). Thus, the experimental result indicates that the proposed method contributed to better success in approach behavior.
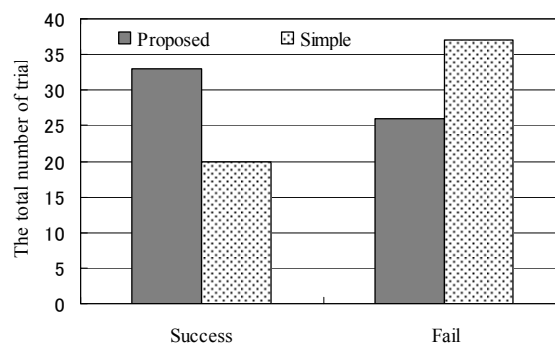

Fig. 10 Comparing results of field trial

6.3 Detailed Analysis of Failures

To reveal why failures decreased in the "proposed" approach, we classified the failures based on the criteria of Table 1. This analysis was conducted by a third person, who didn't know the purpose of the research. He classified failures by watching videos and position data during the field trial.
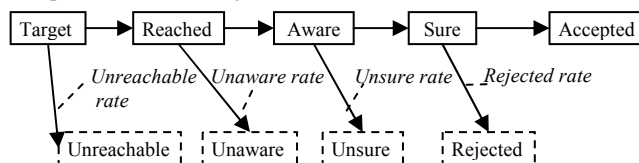

Fig. 11 Calculating failure rate at each step

These failures are consequentially related: "unaware" failure only happened when the robot "reached" the person, and "unsure" failure only happened when the person was "aware" of the robot. Only a "sure" person would "reject" the approach. Thus, we can model these processes as a probabilistic state transition. Fig. 11 summarizes the calculations at each failure category.

Table 5 shows the failure rate at each step in each condition. In table 5, the denominators used for calculating each failure are different; "unreachable" used number of approach trials, but "unaware" used number of "reached" people. Overall, we believe that the proposed method affects each step of the approach behavior. It shows a trend where the proposed approach behavior less often failed than the simple approach behavior at any of the steps. Unreachable and unaware failures were largely decreased.

Table 5 Failure rate at each step

	proposed	simple
unreachable	3%	25%
unaware	4%	14%
unsure	18%	24%
rejected	27%	29%

7. Discussion

7.1 Applications

A couple of possible applications are enabled by a robot with better approach capabilities. As demonstrated in this paper, providing advertisement information is one possible application. During the field trial, we noted revealing observations about the robot's effect on advertisement. For example, the robot approached a young couple and said, "There's a nice restaurant named Restraint Bay in this mall. You can see Osaka Bay from it. The view is beautiful!" The women said to the man, "He says the restaurant has a good view. How about visiting it?" A similar interaction happened with a child who hoped to get some ice cream from his mother. These examples show that a robot can help people by providing information.

Moreover, approach capability enables a robot to proactively serve people who are not aware of its presence or of its capabilities, e.g., a robot can provide route direction for a person who is lost. Since people sometimes hesitate to ask for help, a proactive way of serving is also helpful for such reluctant people. In our study, people could nonverbally reject these services if they wanted; we believe that this functionality is also useful to politely provide such a proactive service. The proposed approach model, however, is not limited to information-providing tasks; it can also be applied to such functions as porter, shop salesperson, receptionist, and security guard.

7.2 Generalizability and Future Works

To apply our model to such different applications, the approach model must be improved. The "finding an interaction target" phase especially needs to be adjusted for each of the applications. For example, a route-guide robot needs to find a person who got lost, which might affect observations of a person's trajectory to find certain patterns. A porter robot might need to be able to observe a piece of baggage to find a person who potentially needs such a service. We also attack cultural difference of our model.

The "interaction at a public distance" phase might depend on the robot's speed. In our case, we assume that robots move slower than people. We believe that this option is safe for using robots in a crowded city environment; but around fewer people, robots could move faster than people. If this is the case, our path-planning algorithm needs to be refined.

The "initiating conversation at a social distance" is currently limited by its sensing capability. The robot failed to recognize people's gazes and other behaviors such as hand movements. However, gaze has an important role in the phase[1,8]. Our implementation was limited by the current technology; if gaze-recognition is developed to work robustly in a real environment, this phase could be greatly improved because the robot could engage in eye contact to decide whether to initiate interaction.

8. Conclusion

The research aim of this paper might seem simple: "how to let a robot approach a person." One might argue that approaching is easy, "just send the robot to the person and let it speak!" This was in fact what we thought. However, it was not successful at all. People walked so much faster than the robot. We were surprised that people were sometimes unaware of the robot; sometimes they failed to start conversations because they were not sure whether the robot intended to do so. Studying these failures, we developed a model of approach behavior. The robot selects a target person who seems approachable and willing to interact. The robot starts to approach on its path planned for notifying its presence. When it reaches the social distance to the person, it nonverbally shows its intention to interact.

The results of the field trial demonstrated the effectiveness of the proposed model. The success rate of approaches significantly increased. The proposed model was successful in 33 out of 59 approaches; the simplistic approach was only successful 20 out of 57 approaches. Moreover, during the field trial, we observed that people enjoyed receiving information from the robot, suggesting the usefulness of a proactive approach in initiating services from a robot. The applications of approach behavior will be various. They are not limited to simple advertisement services where a robot just recommends shops, but will be connected to other services for helping people with both physical services (e.g., transporting baggage) and information-providing services. Our interesting future work will connect other services with the proposed model of approach behavior.

10. REFERENCES

[1] A. Kendon, Features of the structural analysis of human communicational behavior. *In Walburga von Raffler Engel, ed., Aspects of Nonverbal Communication.* 1980.

[2] A. Scheidig, S. Mueller, C. Martin, and H.-M. Gross, Generating Persons Movement Trajectories on a Mobile Robot, *IEEE Int. Workshop on Robot and Human Interactive Communication (Ro–Man 2006)*, pp. 747–752, 2006.

[3] B. Fransen et al., Using Vision, Acoustics, and Natural Language for Disambiguation, *In Proc. Int. Conf. on Human-robot interaction (HRI2007)*, pp. 73-80, 2007.

[4] B. Jensen et al., The interactive autonomous mobile system RoboX, *In Proc. Int. Conf. Intelligent Robots and Systems (IROS2002)*, 2002.

[5] D. Glas et al., Laser Tracking of Human Body Motion Using Adaptive Shape Modeling, *In Proc. Int. Conf. Intelligent Robots and Systems (IROS2007)*, pp. 602-608, 2007.

[6] E. A. Sisbot et al., Implementing a Human-Aware Robot System, *IEEE Int. Workshop on Robot and Human Interactive Communication*, pp. 727-732, 2006.

[7] E. A. Sisbot et al., "Navigation in the Presence of Humans," *IEEE-RAS International Conference on Humanoid Robots,* 2005

[8] E. Goffman, Behavior in public place: Notes on the Social Organization of Gatherings, 1963.

[9] E. Pacchierotti, H. I. Christensen, and P. Jensfelt, Design of an office guide robot for social interaction studies, *In Proc. Int. Conf. Intelligent Robots and Syste ,* pp. 4965-4970, 2006.

[10] E. T. Hall, The Hidden Dimension, 1966.

[11] F. Tanaka et al., Socialization between toddlers and robots at an early childhood education center, *Proceedings of the*

National Academy of Sciences of the USA, 104(46), pp. 17954-17958, 2007.

[12] G. Hoffman and C. Breazeal, Effects of Anticipatory Action on Human-Robot Teamwork, *In Proc. Int. Conf. on Human-Robot Interaction (HRI2007),* pp. 1-8, 2007.

[13] J. Fogarty, S. E. Hudson, C. G. Atkeson, D. Avrahami, J. Forlizzi, S. Kiesler, J. C. Lee, and J. Yang, Predicting Human Interruptibility with Sensors, *ACM Trans. on Computer-Human Interaction,* 12(1), pp. 119-146, 2005.

[14] J. Schulte, C. Rosenberg, and S. Thrun, Spontaneous, short-term interaction with mobile robots, *IEEE Int. Conf. on Robotics and Automation* (ICRA'99), pp. 658-663, 1999.

[15] K. Dautenhahn et al., How may I serve you?: a robot companion approaching a seated person in a helping context, *In Proc. Int. Conf. on Human-robot interaction (HRI2006),* pp. 172–179, 2006.

[16] K. Hayashi, D. Sakamoto, T. Kanda, M. Shiomi, S. Koizumi H. Ishiguro, T. Ogasawara, and N. Hagita, Humanoid robots as a passive-social medium - a field experiment at a train station -, *ACM/IEEE 2nd Annual Conference on Human-Robot Interaction (HRI2007),* pp. 137-144, 2007.

[17] K. Wada, T. Shibata, T. Saito, and K. Tanie, Analysis of Factors that Bring Mental Effects to Elderly People in Robot Assisted Activity, *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems,* 2002.

[18] K. Yamazaki et al., Prior-to-request and request behaviors within elderly day care: Implications for developing service robots for use in multiparty settings, *Proceedings of the Tenth European Conference on Computer Supported Cooperative Work,* pp. 61-78, 2007.

[19] M. Bennewitz, W. Burgard, G. Cielniak, and S. Thrun, Learning Motion Patterns of People for Compliant Robot Motion, *Int. J. of Robotics Research,* 24(1), pp. 31-48, 2005.

[20] M. Finke, Kheng Lee Koay, and Kerstin Dautenhahn, Hey, I'm over here – How can a robot attract people's attention, *IEEE Int. Workshop on Robot and Human Interactive Communication (Ro-Man 2005),* pp. 7 – 12, 2005.

[21] M. L. Walters, D. S. Syrdal, K. L. Koay, K. Dautenhahn, R. te Boekhorst, Human Approach Distances to a Mechanical-Looking Robot with Different Robot Voice Styles, *IEEE Int. Symposium on Robot and Human Interactive Communication (Ro-Man 2008),* pp. 707-712, 2008.

[22] M. P. Michalowski, S. Sabanovic, and R. Simmons, A Spatial Model of Engagement for a Social Robot, *IEEE International Workshop on Advanced Motion Control (AMC'06),* pp. 762-767, 2006.

[23] M. Shiomi, T. Kanda, H. Ishiguro, and N. Hagita, Interactive Humanoid Robots for a Science Museum, *IEEE Intelligent Systems*, vol. 22, no. 2, pp. 25-32, 2007.

[24] M. Yamamoto and T. Watanabe, Timing Control Effects of Utterance to Communicative Actions on Embodied Interaction with a Robot, *IEEE Int. Workshop on Robot and Human Interactive Communication,* pp. 467-472, 2004.

[25] N. Bergström, T. Kanda, T. Miyashita, H. Ishiguro, and N. Hagita, Modeling of Natural Human-Robot Encounters, *Int. Conf. Intelligent Robots and Systems (IROS2008),* 2008.

[26] R. Gockley, J. Forlizzi, and R. Simmons, Natural person-following behavior for social robots, *In Proc. Int. Conf. on Human-robot interaction (HRI2007),* pp. 17-24, 2007.

[27] R. Gockley et al., Designing robots for long-term social interaction, *In Proc. Int. Conf. Intelligent Robots and Systems (IROS2006),* pp. 1338- 1343, 2006.

[28] R. Siegwart et al., Robox at expo.02: A Large Scale Installation of Personal Robots, *Robotics and Autonomous Systems*, 42(3), pp. 203-222, 2003.

[29] S. Kagami, S. Thompson, Y. Nishida, T. Enomoto, and T. Matsui. Home robot service by ceiling ultrasonic locator and microphone array, *IEEE International Conference on Robotics and Automation (ICRA2006),* pp. 3171-3176, 2006.

[30] S. Li, B. Wrede, and G. Sagerer, A dialog system for comparative user studies on robot verbal behavior, *IEEE Int. Symposium on Robot and Human Interactive Communication (Ro-Man 2006),* pp.129-134, 2006.

[31] T. Kanda, D. F. Glas, M. Shiomi, H. Ishiguro, and N. Hagita, Who will be the customer?: A social robot that anticipates people's behavior from their trajectories, *Int. Conference on Ubiquitous Computing (UbiComp 2008)*, 2008.

[32] T. Kanda et al., Interactive Robots as Social Partners and Peer Tutors for Children: A Field Trial, *Human Computer Interaction,* 19(1-2), pp. 61-84, 2004.

[33] T. Tasaki, S. Matsumoto, H. Ohba, M. Toda, K. Komatani, T. Ogata, and H. G. Okuno, Dynamic Communication of Humanoid Robot with multiple People Based on Interaction Distance, *IEEE Int. Workshop on Robot and Human Interactive Communication (Ro-Man 2004),* pp.71-76, 2004.

[34] W. Burgard et al., The interactive museum tour-guide robot, *Proc. of National Conference on Artificial Intelligence,* pp. 11-18, 1998.

[35] X. Shao et al., Detection and tracking of multiple pedestrians by using laser range scanners, *Int. Conf. on Intelligent Robots and Systems (IROS 2007)*, pp. 2174-2179, 2007.