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Extraction of Candidate Points for a Destination Estimation Method Based on Behavior Dynamics

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Abstract— **For effective trajectory formation of robots, we propose a method to extract candidate points of the destination of walking people from their walking trajectories. The method is useful for setting the candidate points of the destination automatically which is necessary to estimate the pedestrians' destination. We assume that potential fields influence pedestrians. After estimating parameters of the potential fields and evaluating their minimum points, we extracted candidate points of the respective destinations of pedestrians. To estimate the parameters of the potential fields accurately, we classified data of pedestrian' walking trajectories into groups. Thereby, the trajectories leading to the same destination are gathered in one group. We designed an evaluation function that indicates the conformity between the trajectory and the destination to classify the data correctly. Results obtained from experiments in an actual environment to verify the availability of the proposed method show that appropriate candidate points of the destination are extracted.**

I. INTRODUCTION

Many studies have examined autonomous robots; recent studies have applied them as service robots for sweeping and carrying tasks[1][2][3][4]. Nevertheless, these robots are not yet popular because they are not sufficiently safe to run in human society. Safety must be the priority of service robots because they work in an environment where humans and robots coexist. To ensure safety of autonomous running robots, a function to avoid collision accidents is necessary to safeguard robots' velocity control, avoidance behavior and prediction of pedestrians' behavior based on the walking trajectory. It is certainly important for the robot to stop or take avoidance behavior when it might collide with a person, but if we can confirm the safety of the path at the time of path planning, we can achieve more effective and safer robot operation. However, for conventional methods, the time-span of prediction is too short to confirm the safety at the time of path planning. We need a method with a longer time-span of prediction.

Nishimura et al. proposed a method using a Hidden Markov Model to estimate the destinations of walking people from their walking patterns[5]. Estimation of the destination is effective to forecast a walking person's behavior over a long time span. However, in this method, it is necessary to prepare candidate points manually that might come to be departure or destination points.

Based on the above understanding, we propose a method to extract candidate points of the destination of walking people, which is necessary for estimating the destination automatically according to the trajectories of pedestrians.

II. RELATED WORKS

To avoid collision accidents between pedestrians and robots, the following three approaches are available. Making the robot stop or take avoidance behavior, analyzing pedestrian behavior, and making spaces intelligent.

It is important for the robot to stop or use avoidance behavior when it might crash with a person. Yoda and Shiota developed a distance measuring system with ultrasonic sensors for avoidance motion of a mobile robot[6]. Pacchierotti et al. evaluated the passing distance between robots and pedestrians[7]. However, if we were able to confirm the safety of the path at the time of path planning, we could achieve more effective and safe running of a robot.

To confirm the safety of the path at the time of path planning, it is necessary to analyze pedestrians' behavior and predict it. Umemura et al. investigated a model for the human strategy of path selection behavior in an open space[8]. Brogan and Johnson presented a behavioral model of path planning that fits natural human behavior[9]. However, we can only predict a short time-span of human behavior using these methods. A longer time-span of prediction is needed.

Recently, studies have been undertaken to make the space, not the robot, intelligent to support the robot's task. The Robot Town Project is one approach in intelligent space[10]. Although it might allow the robot to grasp the location of objects in the space, it would not be sufficient to predict human behavior.

According to these related works, we considered that it would be most practical to use the method of Nishimura et al. to predict pedestrians' behavior to avoid collision accidents.

III. THEORY

This section presents a description of the procedure to extract the candidate points of the destination of walking people.

A. Behavior Dynamics

First, we assume that potential fields influence the behavior of pedestrians who are proceeding toward a destination. As described in this paper, we call these potential fields **Behavior Dynamics**, or BD.

Fig. 1 portrays the BD conceptual scheme. Therein, $U(x)$ signifies the potential function, x denotes the position coordinate of the pedestrian, and $\hat{x}$ stands for the coordinate where $U(x)$ takes the minimum. We assumed that BD has the following properties.

1) BD is concave upward.
2) The BD minimum point is the destination.

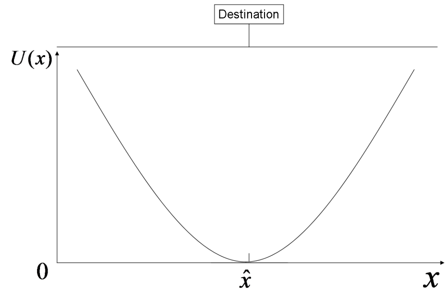

Fig. 1. Conceptual Scheme of Behavior Dynamics

3) The BD gradient is the pedestrians' average velocity.
4) Each BD corresponds to each destination.
5) Pedestrians moving to the same destination are influenced by the same BD.

From the properties presented above, we can derive the BD by describing the connection between the pedestrians' position coordinate and velocity with functions. In addition, by evaluating the BD minimum point coordinates, we can extract the candidate points of the destination.

B. Pedestrians' Walking Trajectories

As the position coordinate of the pedestrians at each time, the pedestrians' walking trajectories are described with $\big(x_i(t), y_i(t)\big) \mid (i = 1, 2, \cdots, N)$, where i denotes a number given to each walking trajectory, t represents time, and N represents the number of data of walking trajectory(Fig. 2).

Furthermore, the x axial velocity and y axial velocity are determined as shown below.

$$\dot{x}_i(t) = x_i(t+1) - x_i(t) \tag{1}$$

$$\dot{y}_i(t) = y_i(t+1) - y_i(t) \tag{2}$$

The expressions above show that the velocity can be determined by the position coordinate at each time. We consider pedestrians walking on a floor using this method. Therefore, we do not consider the z axial direction.

C. Method to Estimate BD Parameters

Two unknown factors exist when the walking trajectory data are present.

1) Parameters of BD
2) Correspondence of each walking trajectory with the BD

Trajectory1

t	$\big(x_1(t), y_1(t)\big)$
1	$\big(x_1(1), y_1(1)\big)$
2	$\big(x_1(2), y_1(2)\big)$
3	$\big(x_1(3), y_1(3)\big)$
4	$\big(x_1(4), y_1(4)\big)$
$\vdots$	$\vdots$

$\cdots$

Trajectory$N$

t	$\big(x_N(t), y_N(t)\big)$
1	$\big(x_N(1), y_N(1)\big)$
2	$\big(x_N(2), y_N(2)\big)$
3	$\big(x_N(3), y_N(3)\big)$
4	$\big(x_N(4), y_N(4)\big)$
$\vdots$	$\vdots$

Fig. 2. Pedestrians' Trajectory Data

The same number of BD exists if multiple destinations exist in an area because, based on the property described above, each BD corresponds to each destination. To determine the parameters of each BD, we must identify the correspondence of each walking trajectory with the BD. On the other hand, to identify the correspondence of each walking trajectory with the BD, we must determine the parameters of each BD. The BD parameters are unknown: we cannot know, initially, the candidate points of the destination. In addition, no information exists about the correspondence with the BD in the walking trajectory data. Therefore, we cannot determine the BD parameters because both factors are unknown at first.

However, if we were able to determine either of the two factors, we would be able to estimate the other. Consequently, we refer to the EM algorithm, which is often used in this case[11]. First, we provisionally determine either of the two factors. Then we estimate the other. Next, we determine the estimated factor as a provisional solution and estimate the other. By repeating these two processes, we can estimate both unknown factors. To determine which BD is most appropriate for each walking trajectory, we classify the data of pedestrians' walking trajectories into groups so that the trajectories that lead to the same destination are gathered in one group. The following is the procedure to group the trajectory data and to determine the BD parameters.

1) Grouping the data randomly
2) Repeating the following sequence until the shifting of groups ends
   a) Carrying out regression analysis using data of each group
   b) Calculating the conformity between the trajectories and the Provisional Destinations
   c) Regrouping the data
3) Determining the BD parameters

The following are details.

1) Grouping the data randomly: The number of the BD is also M if the number of the candidate points of the destination is M. Therefore, we classify the trajectory data into M groups and assume that every set of trajectory data in the same group conforms with the same BD. However, as described above, we cannot identify the BD to which the trajectory data conforms. Therefore, we group the trajectory data randomly and make sure that at least one set of trajectory data exists in each group.

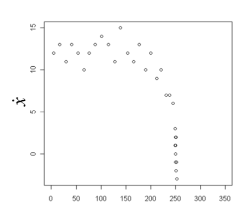

Fig. 3. Relation between x and $\dot{x}$

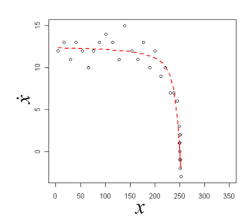

Fig. 4. Nonlinear regression analysis

2) Regression analysis: Fig. 3 presents the relation between the position coordinate x and the velocity $\dot{x}$ of a certain trajectory of a pedestrian. The data's destination is $x = 250$. Considering a function related to the velocity corresponding with the position coordinate of the pedestrian, the function represents the BD potential function. Therefore, by regression analysis, configuring x as the explanatory variable and $\dot{x}$ as the explained variable, the parameters of the model can be determined. Fig. 4 presents an example. According to this, a nonlinear model might be appropriate to represent the relation between the position coordinate and the velocity of pedestrians.

However, nonlinear regression analysis is not practical because its initial value problem is quite difficult. On the other hand, nonlinear functions can be approximated locally to linear functions. Therefore, we use linear approximated data near the destination (as in Fig. 5) and carry out regression analysis of it (as in Fig. 6). It can be inferred that pedestrians' velocity might decrease as they approach the destination, and might be 0 at the destination. Therefore, the requirement of exclusion for the linear approximation is the following.

$$|\dot{x}_i(t)| > \frac{1}{T}\sum_{\tau=1}^{T}|\dot{x}_i(\tau)| \quad (3)$$

This results from the idea that pedestrians' velocity is higher when they are far from the destination and lower when they are near. We also use the linear approximated y element data just as we did with the x element data to extract the candidate points of the destination.

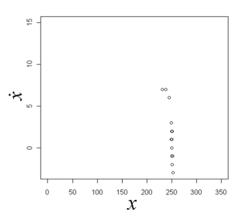

Fig. 5. Relation between x and $\dot{x}$

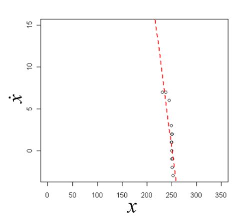

Fig. 6. Nonlinear regression analysis

The values N of the trajectory data were classified into M groups by the final sequence. We integrate all trajectories in each group together. Then we carry out regression analysis to the integrated data of each group. Each regression line would be as follows.

$$\begin{cases} \dot{x} = a_j x + b_j \\ \dot{y} = c_j y + d_j \end{cases} \quad (j = 1, 2, \cdots, M) \quad (4)$$

These regression lines are expected to be the BD gradient of each group. The BD is expected to be determined using the parameters of these regression lines. However, no assurance exists that all the trajectories in the same group conform with the same BD. Therefore, we cannot extract the correct candidate points of the destination with these regression lines. Next we regroup the trajectory data so that the trajectories that conform with the same BD are gathered into the same group.

3) Calculating conformity: To regroup the trajectory data, we must evaluate the conformity between the trajectory data and the regression lines. To do so, first we configure M Provisional Destinations from the M pairs of regression lines. Then we design an evaluation function that represents conformity between the trajectories and the Provisional Destinations.

The following is the method to configure the Provisional Destinations. The Provisional Destination's coordinate of group j is the (x, y) of $\dot{x} = a_j x + b_j, \dot{y} = c_j y + d_j$ at $\dot{x} = 0, \dot{y} = 0$. Because the BD gradient is the regression line, the position coordinate at $\dot{x} = 0, \dot{y} = 0$ is the minimum point. It is the candidate point of the destination, of the BD. It is merely provisional because no assurance exists that all the trajectories in the same group conform with the same BD.

It is possible to determine the evaluation function indicating the conformity between the trajectories and the Provisional Destinations. To determine the evaluation function, we devote attention to three aspects as follows.

1) Pedestrian velocity
2) Distance between the pedestrian and the Provisional Destination
3) Direction of the pedestrian toward the Provisional Destination

Let $v_i(t)$ be the pedestrian velocity in Trajectory i and let $r_{ij}(t)$ represent the distance between the pedestrian in trajectory i and the Provisional Destination j at t. Then the relation between the conformity, $v_i(t)$ and $r_{ij}(t)$ should be as presented in Table I. This results from the assumptions related to pedestrians walking toward a destination. If they are near the destination, their velocity decreases. If they are far from the destination, their velocity increases. On the other hand, if the pedestrian's velocity is high, even if near a certain point, or if the pedestrian's velocity is low even if far from a certain point, then it is certain that the certain point is not the pedestrian's destination. Therefore, as presented in Table I, if the values of $v_i(t)$ and $r_{ij}(t)$ are both large or both small, the trajectory conforms with the Provisional Destination. If either is large, but the other is small, the trajectory does not conform with the Provisional Destination.

Let $\theta_{ij}(t)$ be the direction of the pedestrian in Trajectory i toward the Provisional Destination j at t, the angle between the pedestrian's velocity vector and the line from the Provisional Destination to the position coordinate of the pedestrian. When pedestrians walk toward the destination, the direction of the velocity vector is expected to be toward

TABLE I

RELATION BETWEEN THE CONFORMITY, $v_i(t)$ AND $r_{ij}(t)$

$v_i(t)$ \ $r_{ij}(t)$	Small	Large
Small	High Conformity	Low Conformity
Large	Low Conformity	High Conformity

the destination. That is to say, the conformity is high if the velocity vector is directed toward the Provisional Destination. The conformity is low if it is not directed toward the Provisional Destination, as presented in Fig. 7.

Based on the understanding above, we design an evaluation function that describes the conformity of the trajectory data with the Provisional Destination.

The evaluation function must have the following properties.

1) It indicates the maximum value at $v_i(t) = r_{ij}(t)$.
2) Its value decreases if the value of either $v_i(t)$ or $r_{ij}(t)$ is large, whereas the other is small.

The following $s(i, j, t)$ would be determined from the properties.

$$s(i, j, t) = \cos\big(v_i(t) - r_{ij}(t)\big) + 1 \tag{5}$$

The graph of $s(i, j, t)$ is presented in Fig. 8. According to this graph, it is readily apparent that (5) satisfies the properties of the evaluation function. However, the domains of this evaluation function are $0 \le v_i(t) \le \pi$ and $0 \le r_{ij}(t) \le \pi$. Therefore, to correspond the data with these domains, we normalize the data so that the maximum value would be π. To be specific, when we devote attention to Trajectory i and Provisional Destination j, let v_{imax} be the maximum value of $v_i(t)$ and r_{ijmax} be the maximum of $r_{ij}(t)$. Then we determine $v'_i(t)$ and $r'_{ij}(t)$ for every t as follows.

$$v'_i(t) = \frac{v_i(t)}{v_{imax}}\pi \tag{6}$$

$$r'_{ij}(t) = \frac{r_{ij}(t)}{r_{ijmax}}\pi \tag{7}$$

We interchange these $v'_i(t)$ and $r'_{ij}(t)$ as new $v_i(t)$ and $r_{ij}(t)$ and determine (5).

Next, as presented in Fig. 7, the value of the evaluation function related to $\theta_{ij}(t)$ must be large when the angle between the pedestrian's direction and the Provisional Destination is small, and be small when the angle is large. Therefore,

$$\cos\theta_{ij}(t) \tag{8}$$

satisfies the requirement.

The evaluation function is expected to be the summation of the product of (5) and (8).

$$S(i, j) = \sum_{t=1}^{T} s(i, j, t)\cos\theta_{ij}(t) \tag{9}$$

4) Regrouping the data: We regroup the trajectory data using the evaluation function $S(i, j)$. Because the value of $S(i, j)$ increases when the conformity is high, we regroup Trajectory i to the group for which the value of $S(i, j)$ is the largest of $S(i, 1), S(i, 2), \cdots, S(i, M)$. We carry out this regrouping for every i.

5) Determining the BD: As described above, we repeat the following sequence until the shifting of groups ends.

1) Carrying out regression analysis to the data of each group
2) Calculating the conformity between the trajectories and the Provisional Destinations
3) Regrouping the data

Although not every trajectory data in the same group conforms with same BD at first, trajectory data that conform with the same BD gather to the same group as the sequence repeats. The BD parameters are determined by the regression line when the regrouping ends. Because the velocity represents the BD gradient,

$$U_j(x, y) = \iint \sqrt{(a_j x + b_j)^2 + (c_j y + d_j)^2}\mathrm{d}x\mathrm{d}y \tag{10}$$

represents the BD.

D. Extraction of candidate points of the destination

Finally, we extract candidate points of the destination, which is our main purpose. The position coordinate of the BD minimum points represents the candidate points $(\hat{x_j}, \hat{y_j})$ as follows.

$$(\hat{x}_j, \hat{y}_j) = \left(-\frac{b_j}{a_j}, -\frac{d_j}{c_j}\right) \tag{11}$$

IV. EXPERIMENT

We performed a destination extraction experiment using actually observed movement trajectories to verify the proposed method. We used Morishita's method to detect the coordinate points of the pedestrians[12].

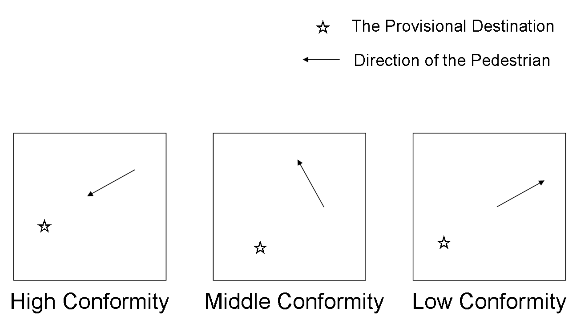

Fig. 7. Relation between the conformity and the pedestrian direction

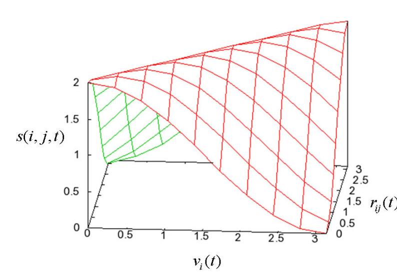

Fig. 8. Evaluation function that describes the conformity

We performed experiments in two conditions: an experiment in which we gave instructions to the subjects and an experiment for which we gave no instructions to the subjects. We can find the correct location of the candidate points in the experiment for which we gave instructions to the subjects. By comparing that location with the result, we can verify the availability of the model. The experiment for which we gave no explanation to the subjects was performed to verify the availability of the method when the correct location of the candidate points is unknown.

A. Experiment giving instructions to the subjects

We gave instructions to the subjects and observed them with a fixed camera. Using the barycentric coordinates as trajectory data, we verified the availability of the proposed model.

The experiment was performed at the Shared Meeting Room of RACE Research Centers, the University of Tokyo Kashiwa Campus. We set two placards as presented in Fig. 9(a).

We gave instructions to three male subjects to move in front of the placards and read the contents written there. We treated the movements of going toward a placard and stopping in front of it as one trajectory. We finally acquired 15 trajectories. We verified the availability of the proposed model by setting the number of candidate points as $M = 2$.

B. Experiment giving no instructions to the subjects

We gave **no** instructions to the subjects and observed them with a fixed camera. Using the barycentric coordinates as trajectory data, we verified the availability of the proposed method.

The experiment was performed in the open campus held at the University of Tokyo Kashiwa Campus, at the same place described above. We set placards in the three places presented in Fig. 9(b).

We observed the visitors using a fixed camera. Although we described the visitors that we were observing them with a camera, we did not describe the purpose of extracting the candidate points of the destination. We treated the movement of going toward a placard and stopping in front of it as one trajectory. We finally acquired eight trajectories. We verified the availability of the proposed method by setting the number of candidate points $M = 3$.

(a) Experiment giving instructions

(b) Experiment giving no instructions

Fig. 9. Experiment Conditions

V. RESULTS AND DISCUSSION

A. Experiment giving instructions to the subjects

Evaluated values of the parameters are presented in Table II. Fig. 10 presents the extracted candidate points of the experiment of giving instructions to the subjects. The point of the circle represents the candidate points. It might be readily apparent from these figures that the extracted candidate points are in the region of a person who is standing in front of the placards. According to this, we can understand that the proposed model is available.

B. Experiment giving no instructions to the subjects

The evaluated values of the parameters are presented in Table III.

Fig. 11 presents the extracted candidate points of the experiment of giving no instructions to the subjects. The point of the circle represents the candidate points. It might be readily apparent from these figures that two of the extracted candidate points are in front of the placards. The other one may be influenced by the trajectories toward the entrance. In addition, it is quite certain that the candidate points are also extracted appropriately in this experiment because we were able to extract the correct candidate points in the previous experiment. Accordingly, we can understand that the proposed method is available for extracting the candidate points of the destination.

VI. CONCLUSIONS AND FUTURE WORK

A. Conclusions

We proposed a method to extract candidate points of the destination of walking people, which are necessary for use in the method of estimating the destination automatically by taking the trajectories of pedestrians. We assumed that potential fields influence pedestrians. By estimating the parameters of the potential fields and evaluating their minimum points, we were able to extract the candidate points of the destination of pedestrians. We determined the parameters of the potential fields using regression analysis. To estimate the parameters of the potential fields accurately, we classified data of pedestrians' walking trajectories into groups so that the trajectories that lead to the same destination are gathered into a single group. We designed an evaluation function showing the conformity between the trajectory and the destination to group the data correctly. We performed

TABLE II
PARAMETERS OF THE EXPERIMENT GIVING INSTRUCTIONS

	a_j	b_j	c_j	d_j
$j = 1$	-1.56×10^{-2}	0.853	-1.63×10^{-2}	2.07
$j = 2$	-1.79×10^{-2}	3.79	-1.52×10^{-2}	2.45

(a) Candidate Point 1 (b) Candidate Point 2

Fig. 10. Results of the experiment giving instructions

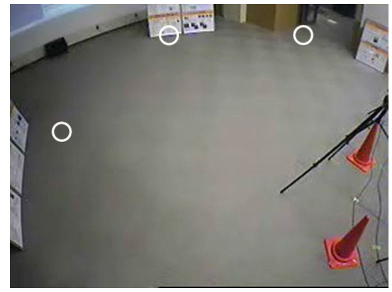

Fig. 11. Candidate Point of the experiment giving no instructions

TABLE III

PARAMETERS OF THE EXPERIMENT GIVING NO INSTRUCTIONS

	a_j	b_j	c_j	d_j
$j = 1$	-8.49×10^{-3}	1.62	-1.44×10^{-2}	3.09
$j = 2$	-6.59×10^{-3}	0.407	-2.28×10^{-2}	3.05
$j = 3$	-1.09×10^{-2}	3.03	-4.67×10^{-3}	0.601

some experiments in an actual environment to verify the availability of the proposed method. Results show that we can extract the appropriate candidate points of the destination using the proposed method.

B. Future Works

Two subjects of future work occurred to us as we completed this study.

The first is to accommodate the BD transition. In this method, we treated movement toward and stopping at the destination as one trajectory. This treatment arose from the assumption that when a pedestrian reached the certain destination and changed direction toward another destination, the BD that influences them was also shifted. However, we must determine the transition by viewing at present. By determining the transition, we could apply the model to more various pedestrian movements such as turns. Therefore, a method to determine the transition automatically is needed.

The second is to accommodate data that do not conform to the proposed model. In this experiment, to confirm that pedestrians who walk toward destinations are influenced by BD, we used data that appear to accommodate the proposed model. However, some data do not conform to the proposed model by definition. For example, data of pedestrians who are not toward any destination and are just walking aimlessly or wondering. Therefore, a method to discriminate whether data conform to the model or not is needed.

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