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A Method to Estimate Destination of a Walking Person with Hidden Markov Model for Safety of Human Friendly Robots

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Abstract —In this paper, we proposed a method to estimate the destination of walking persons from their walking patterns, for avoidance of collision accidents between pedestrians and robots in a Human-Robot Coexistence Environment. We adopted the Hidden Markov Model (HMM) as a model to represent walking patterns. We constructed a model for each movement pattern. A movement pattern was defined with a departure point and destination point of a person. Comparing the likelihood with the achieved model, we discriminated walking patterns for which the destination is unknown. We did some experiments in an actual environment to verify the availability of the proposed method. Results show that the discrimination ratio approached 80% within 2 s of observation.

Keywords: *Human Friendly robots, Behavior analysis, Estimation of destination, Hidden Markov Model*

I. Introduction

For development of human friendly robots that move around in public spaces, avoidance of collision accidents involving pedestrians and robots is very important. It is necessary to take evasive action while forecasting the pedestrian's behavior because emergency shut down is rather dangerous.

Many studies have been performed for tracking people using computer vision [1], [2], [3] . For such studies, various methods have been adopted for prediction of positions of pedestrians using the person's trajectory, e.g., Kalman filter, Particle filter, and Bayesian filter. However, for all of these methods, the time-span of prediction is too short to adapt them to trajectory generation of robots.

Estimation of the destination is efficient to forecast the walking person's behavior over a long time span. Tanaka et al. acquired location information by reading the RF tag spread over the floor with an RFID reader on the user's shoes[4]. However, targets are limited to a person who has an RFID reader. A method using information obtained with fixed cameras is available to relax this limitation. Makanae et al. assume that the person selects the shortest route to the destination, and proposes route search processing using the Dijkstra method[5]. Moreover, Ogai et al. model the wandering behavior of a person in an urban area in which the pedestrian's behavioral traits are given attention[6]. These are approaches based on the defined person's walking model, which is based on certain assumptions about human behavior. In short, these models do not exactly reflect an actual pedestrian's behavior. It is expected that the accuracy will be improved with modeling using an actually observed movement trajectory according to the environment.

Based on the above understanding, we take the trajectory of an object person using a fixed camera, and construct a learning model of the walking pattern described using the Hidden Markov Model (HMM). Then, we define movement patterns that describe pairs of departure points and destination points, and determine the parameters of models corresponding to each movement pattern with walking patterns for which the destination is known. Calculating the likelihood of walking patterns for each HMM using these parameters, a person's destination is inferred.

II. Theory

This section presents a description of the procedure that applies the hidden Markov model (HMM) to the destination estimation problem from the walking person's trajectory.

A. Representation of Trajectory

First, points which might come to be departure or destination points are prepared as *picked points*. For example, doorways are typical in a chamber. Guide plates will be also picked in the station yard, and so on.

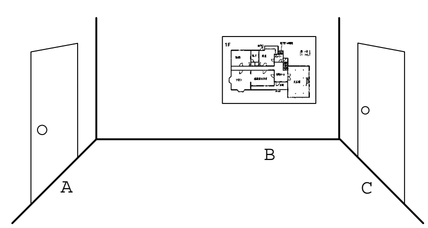

Fig. 1. An example of picked points. (A, B, and C)

Next, pairs of picked points are defined as *movement patterns* based on the assumption that a person's movement is classified according to migration between picked points. Additionally, we represent the trajectory achieved by the elapsed time T from the beginning of observation using time-series data of position coordinate values. We designate it as the *walking pattern*, expressed as

$$P = (p_0, p_1, \cdots, p_T),$$

where p_t is the position coordinate value of the object person at time t. The object person is at the departure point when $t = 0$.

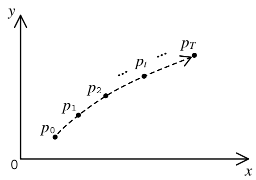

Fig. 2. Example of a walking pattern.

At the point where the pedestrian reaches a selected point, it is considered that the destination has been reached. In such a situation, it is readily apparent that the movement pattern corresponds to the observed walking pattern, because the movement pattern is determined with a departure and destination point. We designate such a walking pattern as *the walking pattern of which the movement pattern is given.* Incidentally, when a walking pattern passes through a picked point, it is assumed that two movement patterns are separated by the picked point.

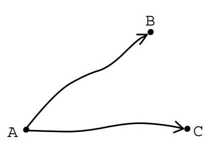

Fig. 3. Examples of a walking pattern of which the movement pattern is given.

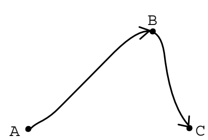

Fig. 4. Example of a separated walking pattern.

A walking pattern where the object person has not arrived at any selected point yet can be considered as halfway of the walking pattern of which the movement pattern is given. Because we cannot determine the movement pattern of the walking pattern, we designate such a walking pattern as *a walking pattern of which the movement pattern is unknown.* As presented in Fig. 5, even if a walking pattern is the same as another one, it is plausible that these corresponding movement patterns mutually differ. For this reason, it is probable that the movement pattern corresponds to a walking pattern of which the movement pattern is unknown.

We consider the model which represents walking patterns corresponding to each walking pattern to determine the movement pattern of a walking pattern of which the movement

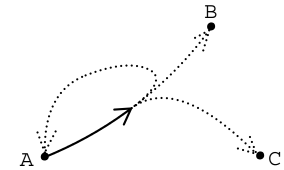

Fig. 5. Example of a walking pattern of which the movement pattern is unknown.

pattern is unknown. We can decide the movement pattern by computing likelihood using models when the parameters of these models are achieved.

As depicted in Fig. 6, it can be considered that multiple walking patterns correspond to a movement pattern. Therefore, walking patterns corresponding to a movement pattern are expected to be explained using a probabilistic model. Moreover, the coordinate value p_t of a certain walking pattern in the lead up to time t depends on the values $p_{t'}$ $(0 \leq t' < t)$. For the reasons presented above, it is just as well to express walking patterns corresponding to a movement pattern with Markov model. However, we cannot observe the state transition of the Markov model directly. Therefore, we assume a hidden Markov model (HMM) for parameter estimation of the model. Next, the model construction procedure is described in detail.

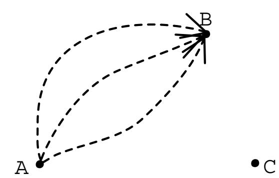

Fig. 6. Examples of walking patterns corresponding to the same movement pattern.

B. Hidden Markov Model (HMM)

A HMM is a finite-state automaton that has probabilistic state transition and probabilistic symbol output. This property of HMM is fit to express walking patterns such as those described above.

When the number of states is N, and the number of output symbols is M, an HMM is defined by five terms as

- $Q = \{q_1, \cdots, q_N\}$: finite set of states.
- $\Omega = \{\omega_1, \cdots, \omega_M\}$: finite set of output symbols.
- $A = \{a_{ij}\}$: transition matrix.
  where a_{ij} means the transition probability from state q_i to state q_j, and it meets conditions $\sum_{j=1}^{N} a_{ij} = 1$.
- $B = \{b_i(\omega_k)\}$: symbol output probability matrix.
  where $b_i(o_k)$ means the probability of which outputs symbol ω_k on state q_i; it meets conditions $\sum_{k=1}^{M} b_i(\omega_k) = 1$.
- $\Pi = \{\pi_i\}$: initial state probability matrix

Figure 7 shows an example of an HMM of which the number of states is $N = 3$.

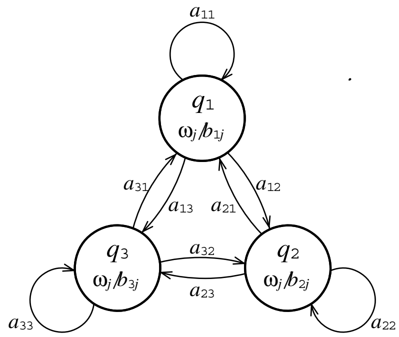

Fig. 7. An example of HMM.

Three states are q_1, q_2 and q_3. The initial state is distributed probabilistic as represented with $\Pi = \{\pi_1, \pi_2, \pi_3\}$, and the transition from state i to state j occurs with probability a_{ij}. Moreover, at each transition from state i to state j, it outputs the symbol ω_j with probability b_j.

C. Transformation of the Walking pattern

We regard a walking pattern as a series of output symbols of an HMM to apply HMM to construct a model of walking patterns. To simplify the problem, we divided the area in which walking persons existed into some proper segments, and transformed a walking pattern to series of output symbols. Consequently, the number of patterns is reduced. Figure 8 shows an example of correspondence between the walking pattern and output symbols.

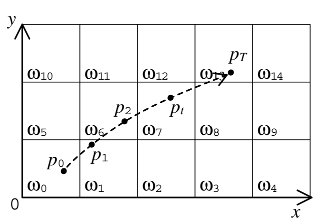

Fig. 8. An example of correspondence between the walking pattern and output symbols

For this example, a walking pattern $P = (p_0, p_1, p_2, \cdots, p_t, \cdots, p_T)$ is transformed into a series of output symbols as

$$O = (o_0, o_1, o_2, \cdots, o_t, \cdots, o_T) \quad (1)$$

$$= (\omega_0, \omega_1, \omega_6, \cdots, \omega_7, \cdots, \omega_{13}), \quad (2)$$

where O is a series of output symbols that represents a walking pattern.

D. Estimation of Model Parameters

Then, we assumed that an HMM corresponding to a certain movement pattern outputs a series of symbols corresponding to that one pattern.

Parameters of the HMM must be determined using *walking patterns of which the movement pattern is given.* For this purpose, we adopted the Baum-Welch algorithm[7], which is a kind of expectation-maximization (EM) algorithm that is expected to estimate the HMM's parameters when a set of parameters $\lambda = \{Q, \Omega, O\}$ is given.

The procedure of estimation using the Baum-Welch algorithm is the following.

1) Initialize
2) Calculate forward probability and backward probability
3) Updating of parameters.

E. Discussion of Model Topology

The Baum-Welch algorithm presents the problem that it will converge to a local maximum depending on the initial state probability or its model topology.

According to its model topology, an HMM is called an ergodic model or a left-to-right model, and so on. In an ergodic model, each state has the probability of transition to all other states. In other words, all a_{ij} are not equal to 0. On the other hand, in a left-to-right model, the transition of state is directional. Figure 9 presents an example of the model topology of a left-to-right model. No path exists from a right state to a left state. Namely, the values of a_{ij} $(i > j)$ are equal to 0.

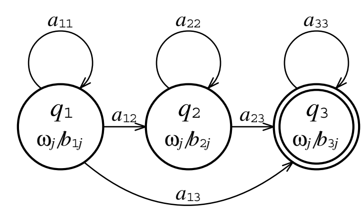

Fig. 9. An example of model topology of a left-to-right model.

Additionally, dependence on the initial state probability is said to be larger in an ergodic model than in a left-to-right model because of the difference of their restraint condition. At the same time, it can be considered that a person walking toward a destination has three states: the state in the neighborhood of the departure point, in the halfway area, and in the neighborhood of the destination point. Furthermore, the transition of state is directional. For this reason, we adopt a left-to-right model as the model representing walking patterns.

F. Evaluation of Fitness

For each movement pattern, the model which outputs corresponding walking patterns is constructed using the procedure described above. Fitness of the walking pattern for each model is evaluated to decide the movement pattern corresponding to a walking pattern of which the movement pattern is unknown.

The Viterbi algorithm[8] is commonly used in the context of HMM. It decides the most likely sequence of state transition with the following procedure. First, the probability of optimum state to state i for a walking pattern O at time t is defined as the following.

$$\delta_t(i) = \max_{s_1, s_2, \cdots, s_{t-1}} P(s_1, s_2, \cdots, s_t = io_1, o_2, \cdots, o_t|\lambda)$$

Then, $\delta_{t+1}(j)$ is calculated as follows:

$$\delta_{t+1}(j) = [\max_{i} \delta_t(i) a_{ij}] \cdot b_{ij}(o_{t+1}).$$

In addition, $\delta_0(i) = \pi_i$. Next, let $\psi_t(j)$ be the optimum state transition in state j at time t, calculated as

$$\psi_t(j) = \underset{i}{\operatorname{argmax}}[\delta_{t-1}(i) a_{ij} b_{ij}(o_t)].$$

In addition, $\psi_0(j) = \pi_j$. Third, let s_t^* be the optimum state at time t. The most likely sequence of states for O is achieved as

$$s_T^* = \underset{i}{\operatorname{argmax}}[\delta_T(i)] \quad (3)$$

$$s_t^* = \psi_{t+1}(s_{t+1}^*) \quad (0 \leq t < T). \quad (4)$$

It noteworthy that s_t^* $(0 \leq t < T)$ decides from s_T^* in descending order.

Finally, the production probability of S^* is calculated as follows.

$$P^* = \max_{i}[\delta_T(i)]$$

Consequently, this is regarded as the fitness of the walking pattern O to the model.

Figure 10 presents an example of application of the Viterbi algorithm.

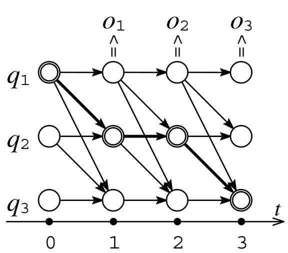

Fig. 10. Example of a Viterbi algorithm application

The optimum states s_t^* are indicated by a double circle. For this example, the most likely sequence of states S^* for the walking pattern $O = (o_1, o_2, o_3)$ is decided as follows:

$$S^* = (s_0^*, s_1^*, s_2^*, s_3^*) \quad (5)$$

$$= (q_1, q_2, q_2, q_3). \quad (6)$$

G. Decision of the Corresponding Movement Pattern

Calculating the production probability of S^* for each model and comparing them, the movement pattern corresponding to a walking pattern is decided. Namely, let $f(m)$ be P^* of the movement pattern m for O. The corresponding movement pattern $\hat{m}$ is defined as

$$\hat{m} = \underset{m}{\operatorname{argmax}} f(m).$$

H. Calculation of the Discrimination Ratio

For this study, we calculated the discrimination ratio with walking patterns for which the movement pattern is given. The discrimination ratio at time t is defined as the ratio of walking patterns of which correct answer is estimated. However, if a wrong answer is estimated later than that time, we do not regard it as a correct answer. We illustrate that point using the example in Table I.

TABLE I
EXAMPLE OF DECIDING A DISCRIMINATION RATIO

Time t	1	2	3	4	5	Correct ans.
Answer 1	B	**A**	**A**	**A**	**A**	A
Answer 2	A	B	A	**B**	**B**	B
Discrimination Ratio	0.0	0.5	0.5	1.0	1.0	

Two walking patterns of length five exist. The corresponding movement pattern A or B is estimated each time t and represented as answers. At time $t = 1$, both answers are wrong. Therefore, the discrimination ratio is 0.0. At time $t = 2$, although both answers are correct, Answer 2 does not contribute to the discrimination ratio. The reason is that wrong answers exist at time $t = 3$. In short, because a wrong answer is estimated as later than at time $t = 2$, it is conceivably a mere coincidence. After the time $t = 4$, both answers become correct again and it remains until the end. Therefore, the discrimination ratio becomes greater than 1.0. The discrimination ratio is achieved as above; it is monotone increasing.

III. EXPERIMENT

We performed a destination estimation experiment using actually observed movement trajectories to verify the availability of the proposed method for description in the preceding paragraph.

A. Setting of Picked Points

The walking person's trajectories were measured at the entrance hall of Kashiwa Library, The University of Tokyo. We installed a fixed camera on the top of the entrance, as portrayed in Fig. 11, and notified users with signs during the experimental period.

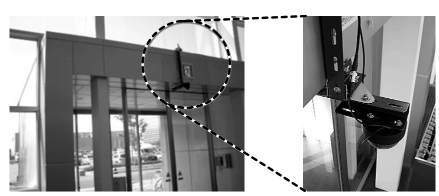

Fig. 11. An installed fixed camera

Figure 12 shows an image taken by the fixed camera. Points selected as picked points are indicated with dots.

Four picked points exist. They are *Entrance*, *Right hand*, *Stairs*, and *Left corridor*. According to these picked points, we defined three movement patterns as presented in Table II.

Fig. 12. An Image Taken by the Fixed Camera and Picked Points

TABLE II
DEFINITION OF MOVEMENT PATTERNS

Pattern	From	To
A		*Right hand*
B	*Entrance*	*Stairs*
C		*Left corridor*

B. Achievement of walking pattern

First, to achieve the trajectory of a target person, we adopted a background subtraction method with adaptive background estimation[9] as a simple method for extraction of a moving object. We extracted the area of a moving object, and assumed the barycenter of this area as the position coordinate of the target person. Incidentally, it was distinguished manually whether each scene had one or more people.

Next, to define output symbols, we divided the area into 20 parts in a reticular pattern, as shown in Fig. 13. Then, we transformed the achieved walking patterns to series of output symbols according to this definition.

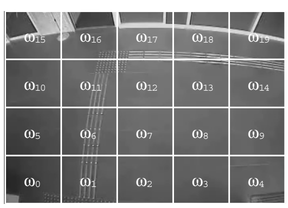

Fig. 13. Area segmentation.

The number of walking patterns for each behavior pattern is shown in Table III.

TABLE III
THE NUMBER OF WALKING PATTERNS FOR EACH BEHAVIOR PATTERN

Pattern	From	To	Number
A		*Right hand*	30
B	*Entrance*	*Stairs*	34
C		*Left corridor*	18

C. Setting of an HMM and a Baum-Welch Algorithm

For the reason described above, we adopted a left-to-right model for HMM model topology. In other words, we set initial values of the transition probability a_{ij} $(i > j)$ equal to 0. The states N are 3, and the output symbols M are 20, as presented in Fig. 13.

Initial values of a_{ij} are set randomly, except under the condition $i > j$. The values of a_{ij} are set at 0 when $i > j$. Moreover, initial values of $b_j(k)$ are set randomly, too. On the other hand, initial values of π_i are set as follows:

$$(\pi_1, \pi_2, \pi_3) = (0.9, 0.1, 0.1).$$

IV. Results and Discussion

Figure 14 shows the transition of the discriminate ratio corresponding to each movement pattern respectively. The horizontal axis shows the elapsed time of the observation for a person, and the vertical axis shows the discrimination ratio. The discrimination ratio increases when observations are carried out; the discrimination ratio approaches 80% in about two seconds. In other words, after 2 s from the start time of observation, the discrimination ratio approaches 80%.

Nevertheless, the span of 2 s might be too long to estimate the destination of a target person. The result of estimation is not available at all if the mean time to reach it is about 2 s. Therefore, the ratio of completion must be considered to confirm the availability of our method.

Figure 15 shows the transition of the discrimination ratio according to the ratio of completion. As shown in Fig. 14, the vertical axis shows the discrimination ratio, but the horizontal axis is the normalized elapsed time, which shows the ratio of completion. The increase of the discrimination ratio tends to slow when it reaches a certain value. The time at which the increase of discrimination ratio becomes more gradual is represented as a dashed line. For a person walking to the *Right hand* or *Upstairs*, observation of 30–40% of the whole walking time is sufficient for discrimination. On the other hand, for the person walking to the *Left Corridor*, it is 60–70% of the entire walking time. Nevertheless, pedestrians walking to the *Left Corridor* are faster than in the other case to walk out from the frame of camera. It is plausible that this is the reason why the result for the person walking to the *Left Corridor* is not good relative to the others.

V. Conclusion

In this paper, a method for pedestrian destination estimation using a Hidden Markov Model was proposed. The model parameters are determined using actually observed movement trajectories according to the environment.

We performed destination estimation experiments using actually observed movement trajectories to verify the availability of the proposed method. We made a comparative study of the presumption results using two indices of the discrimination ratio evaluation according to the elapsed time and its relation to the ratio of completion. As the result, we achieved an 80% discrimination ratio in 2 s of elapsed time. Considering that the ratio of completion is less than 0.4 in most cases, this result is satisfactory. In short, the result means that a discrimination ratio that is not too low is achieved in a sufficiently short elapsed time.

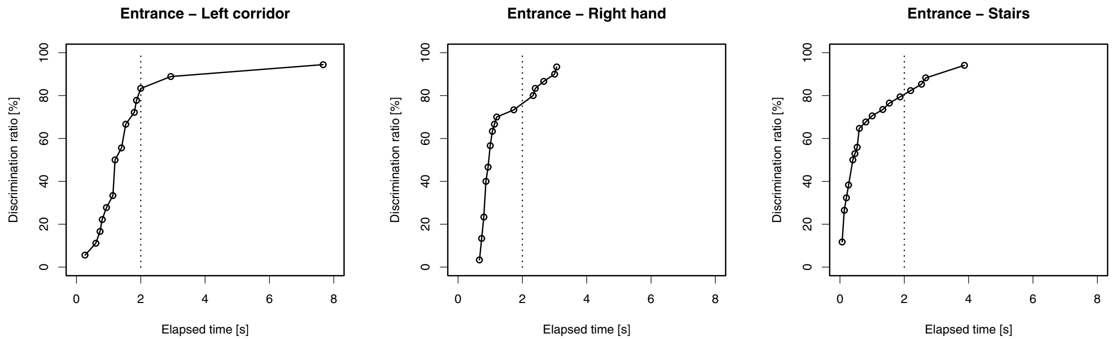

Fig. 14. Discrimination ratio for elapsed time

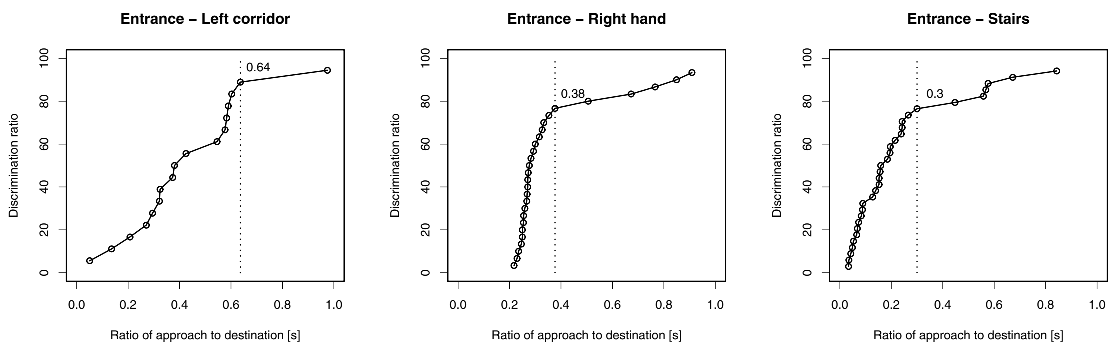

Fig. 15. Discrimination ratio for the ratio of approach to the destination

Our method can estimate final destination of a pedestrian differently from other related works. Using this information, human-friendly robots will be able to avoid collision accidents with pedestrians. Because, the robots can do trajectory planning with a long-term vision. Moreover, it is obvious that the positions of pedestrians are not need to be observed precisely if paying attention to the resolution of images for generation of walking patterns.

Future work will implement a method for determination of the time to break observation and decide the results of estimation.

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