Estimating Person's Awareness of an Obstacle using HCRF for an Attendant Robot

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ABSTRACT
This paper describes an estimation method of a person's awareness of an obstacle. We assume that the person's awareness influences the person's motion, and construct a model of the relationship between the awareness and the motion using HCRF. We extract a sequence of motion features from the person trajectory, and then classify whether the person is aware of the obstacle or not using the model. Awareness estimation experiments are conducted in order to validate the method and evaluate its performance. Since the method uses only the position and the velocity of the person, it can be applicable to mobile robots.

ACM Classification Keywords
H.1.2. MODELS AND PRINCIPLES: User/Machine Systems

Author Keywords
awareness estimation; sequence estimation; attendant robot

INTRODUCTION
Falls are the second leading cause of accidental deaths, worldwide and over 400 thousand persons die by falling every year [11]. In particular for the elderly, falling is one of the most common and often fatal accidents since their attentiveness tends to decrease and they are often unable to react to a falling situation. Our motivation is to develop a service robot which attends to an elderly person and protects them from such accidents.

If a person is not aware of an obstacle or a step, there is a high probability that he/she stumbles on it and falls. If we can estimate the person's awareness, we could assess the risk of falling, and an attendant robot could prevent such accidents by making the person have an awareness of an obstacle or a step. We consider that estimating a person's awareness is important for attendant robots.

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Our goal is to realize an attendant robot (see Fig.1). The robot estimates a person's awareness of surrounding environments while following her. If she is not aware of an obstacle, the robot takes an action, such as warning her or interposing itself between her and the obstacle, so that the obstacle attracts her attention. On the other hand, if the person is aware of it, the robot just continues to follow the person without hindering her motion.

Awareness estimation has been dealt with in several research domains. In driver assistance, in order to prevent accidents, the person's awareness of pedestrians is estimated from the driver's gaze and driving actions, such as accelerating, braking, and steering [1, 6]. In human-computer interaction, the person's awareness of other persons is estimated from the gaze and the head orientation of the person to realize a comfortable human assistance system [10, 2]. Those works show that gaze and head orientation reflect the person's awareness well. In the case of mobile robots, however, such information is not available or is difficult to obtain reliably. We can use only limited person information, such as the position and the velocity of a person.

Toward realizing an attendant robot, we propose a method of estimating the person's awareness of an obstacle. The purpose of this paper is to show that a person's awareness of an obstacle can be estimated by only observing his/her motion.

If a person is not aware of an obstacle, the person moves as if the obstacle were not there, and if the person is aware of it, the person changes his/her trajectory to avoid it. We, thus, consider that the person's motion is affected by the person's awareness of the obstacle and that the person's awareness can be estimated from their movement with respect to the obsta-

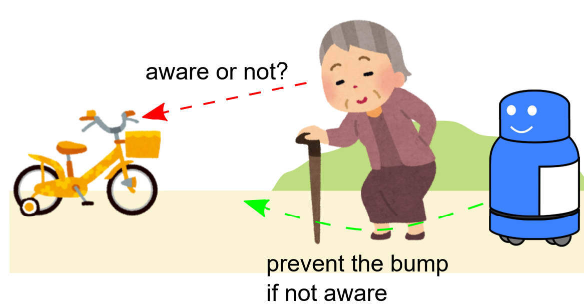


Figure 1. Attendant robot.

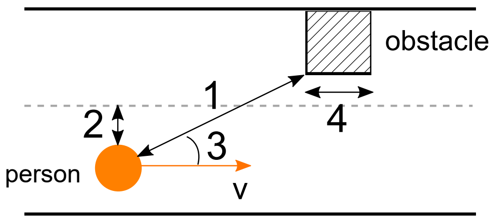


Figure 2. Person's motion features.

cle. We first extract motion features from the person trajectory and model the relationship between the awareness and the motion using HCRF (Hidden Conditional Random Fields) [3]. We then estimate the person's awareness of the obstacle from the observed motion using the model. As a first step, we deal with a case where a person walks in a hallway and focus on estimating that person's awareness of an obstacle. We expect that the proposed framework can be extended to awareness of other things, such as a step, and more complicated environments.

The rest of the paper is organized as follows. The next section describes the estimation method for person's awareness of an obstacle. This is followed by an evaluation of the proposed method. Finally, conclusions are drawn, and future work is discussed.

ESTIMATING THE AWARENESS OF AN OBSTACLE

Using biometric information, such as gaze, is direct and the most common way to estimate a person's awareness [1, 2, 10]. Since such information is usually hard to obtain by mobile robots, we propose a method of estimating a person's awareness of an obstacle solely from a person's movement.

Person's Motion Features

In order to describe a person's motion with respect to an obstacle, we define the following four features (see Fig. 2).

1. Distance to the obstacle: When the person is close to the obstacle, the person's motion is affected strongly by the obstacle.
2. Distance to the skeleton of the hallway: This feature is designed to describe how the person's trajectory is affected by the obstacle. Since the person will move along the hallway if there is no obstacle, this feature will be changed by the existence of an obstacle.
3. Angle between the velocity vector and the vector from the person to the obstacle: This feature represents whether the person moves toward the obstacle or not. If the person is avoiding the obstacle, this feature will be large.
4. Size of the obstacle: The person's motion may be affected by several characteristics of the obstacle. We simply use its size to model the obstacle.

Person's awareness model using HCRF

We represent the motion of a person as $\mathbf{x} = \{x_1, x_2, \cdots, x_t\}$ which is a sequence of motion features with length t. Let y be

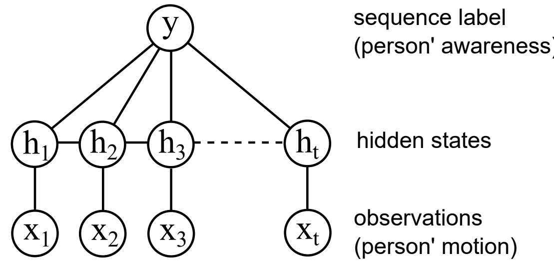


Figure 3. Person's awareness model.

a binary label of a sequence denoting whether the person is aware of the obstacle or not. We assume that the person's motion is influenced by the condition of the person's awareness. This relationship can naturally be modeled using a sequence classifier, such as CRF (Conditional Random Fields) [9] and HCRF (Hidden Conditional Random Fields) [3]. In this work, we use HCRF to construct the model. We also use CRF as a baseline.

By introducing HCRF, we can model the relationship between the person's awareness and the person's motion as shown in Fig. 3. Following the work of [7], the relationship is modeled as:

$$P(y|\mathbf{x},\theta) = \sum_{\mathbf{h}} P(y,\mathbf{h}|\mathbf{x},\theta) = \frac{\sum_{\mathbf{h}} \exp^{\psi(y,\mathbf{h},\mathbf{x};\theta)}}{\sum_{y',\mathbf{h}} \exp^{\psi(y',\mathbf{h},\mathbf{x};\theta)}} \quad (1)$$

where θ is the parameter of the model, ψ is a potential function parameterized by θ. A sequence of hidden states $\mathbf{h} = \{h_1, h_2, \cdots, h_t\}$ is introduced as the possible hidden labels inside the model. In our model, the number of possible values of each hidden state is set to three.

The parameter θ is optimized using a stochastic descent method [3], and then, we estimate the label of the sequence as follows:

$$\arg\max_{y} P(y|\mathbf{x},\theta) \quad (2)$$

We obtain observations every 0.5 [s] and use six consecutive observations as one sequence. The duration of a sequence is 3 [s]. We assume that the duration is long enough to describe the person's obstacle avoiding motion.

EXPERIMENTS

Person's motion measurement system

In order to measure a person's motion, we developed a measurement system using 3D LIDAR (Velodyne HDL-32e). The system first detects candidate objects of a human using a Euclidean clustering method, and then classify whether an object is an actual human or not using Kidono's shape descriptive features [4] and Adaboost classifier [8]. The detected people are tracked by a Kalman filter with a constant velocity model and global nearest neighbor data association [5]. Since the LIDAR provides very accurate range data, the system can reliably detect and track persons.

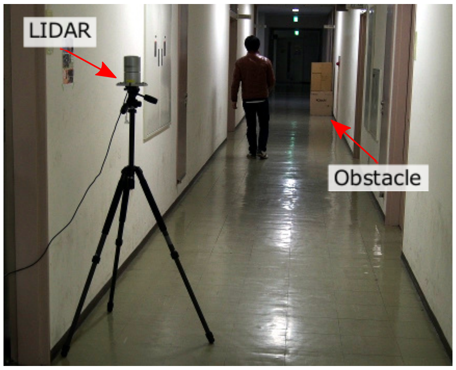


Figure 4. Experimental environment.

Table 1. Estimation Results.

Method	Precision	Recall	F1
CRF	0.743	0.745	0.744
HCRF	0.921	0.941	0.931

Awareness estimation experiments

Ideally, the HCRF model should be constructed from a person's motion data which contains both the situations where a person is aware and unaware of an obstacle. However, it is difficult to intentionally make situations where a person is unaware of an obstacle. Also, in the viewpoint of research ethics, it is illegal to conduct experiments in such situations since there is risk that the person will fall and sustain injury. We thus assume that there is no significant difference between the person's motions under situations where the person is unaware of an obstacle and where there is no obstacle. Therefore, we train the HCRF model from a person's motion data with and without obstacles.

We first collected a set of person trajectories with and without obstacles. Fig. 4 shows the experimental setting. The experiments were conducted in two kinds of settings; in the first one, an obstacle was placed in the hallway, and in the second, no obstacle was placed. Five persons walked in the hallway and avoided the obstacle if there was an obstacle. We measured the person's trajectory 30 times for each person with and without obstacles, respectively.

Fig. 5 shows the heatmap created from the measured trajectories. Red indicates where the persons passed on frequently, and blue indicates where the persons did not pass. The white circles indicate the size and the position of the obstacles. As we can see in Fig. 5, the person's motion is affected by the obstacles. If there is no obstacle, persons move straight along the hallway. On the other hand, if there is an obstacle, persons change their trajectories to avoid the obstacle.

In situations where a person is unaware of an obstacle, the person's motion is independent of the obstacle. To simulate the situation using the situations without obstacles, we randomly choose obstacle data from the situations with obstacles and extract the person's motion features as if there was a chosen obstacle. We train the HCRF model using the extracted features.

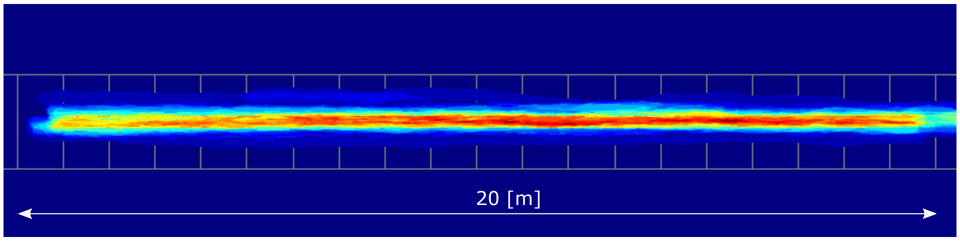
The set of the trajectories is divided into five parts, and one of them is used as a test set and the rest are used as a training set. The number of the motion sequences in the test set is 785, and the number of the sequences in the training set is 3146. Table 1 shows the estimation results. HCRF shows a better estimation performance than CRF, and in the case of HCRF, we achieve an estimation accuracy of 92.1%. Fig. 6 shows the relationship between the distance to the obstacle and the estimation accuracy. As a person get closer to an obstacle, the person's motion is influenced by the obstacle strongly, and the motion becomes distinguishable from when the case without the obstacle. As a result, the estimation accuracy increases. When the distance between the person and the obstacle is less than 4 [m], the method can estimate the person's awareness with an estimation accuracy of over 90%.

Online awareness estimation experiments

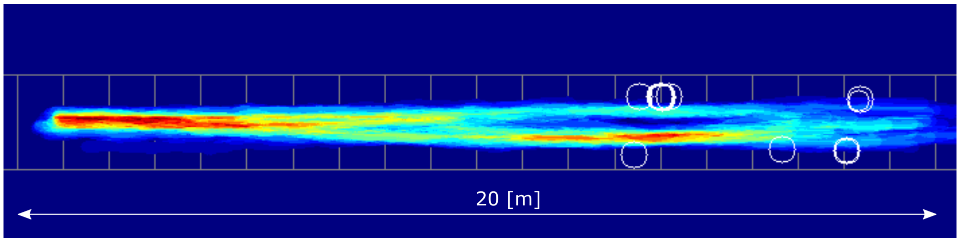
We measure three person's trajectories without obstacles and nine trajectories with obstacles for an online test. In order to validate the applicability of the proposed method to real attendant robots, we examine the point where the method judged that the person was aware of the obstacle.

Fig. 7 shows examples of the estimation results. Thick lines indicate the trajectory of a person and estimation results. Blue color indicates that the system is accumulating motion data and is not classifying the motion due to an insufficient amount of data. Green and red colors indicate that the person is unaware of the obstacle, and that the person is aware of the obstacle, respectively. In the case of Fig. 7(a), the system started to accumulate the person's motion data when the person entered into the environment. After a sufficient amount of motion data is accumulated, the system successfully classified the person's motion as being unaware of the obstacle. In the case of Fig. 7(b), after the accumulation of data was finished, the system classified the person's motion as being unaware of the obstacle. However, as the person got closer to the obstacle, within about 10 [m], the system judged that he was aware of the obstacle. When a person is close to an obstacle, the system reliably estimates the person's awareness since the identification accuracy increases as a person gets closer to an obstacle as shown in Fig. 6.

In all of the cases without obstacles, the classifier did not judge that the person was aware of the obstacle, and in all of the cases with obstacles, the classifier successfully judged that the person was aware of the obstacle before the person reached to the obstacle. Table 2 shows the statistics of the point where the classifier judged. The classifier can realize that a person is aware of an obstacle at a point about 8.5 [m] from the obstacle on average, and about 6.1 [m] at least. If the person is walking at 1.2 [m/s], the time to bump into the obstacle is about 5.1 [s]. If the robot takes preventative action within this time, it can avoid the collision. We consider that the robot can interact with the person within this duration if the robot approaches the person in advance. At least the robot can call the person to make the obstacle attract their attention within this duration.



(a) Without obstacles.



(b) With obstacles.

Figure 5. Heatmap of persons' trajectories. Red indicates where the persons passed on frequently, and blue indicates where the persons did not pass. The white circles indicate the size and the position of the obstacles.

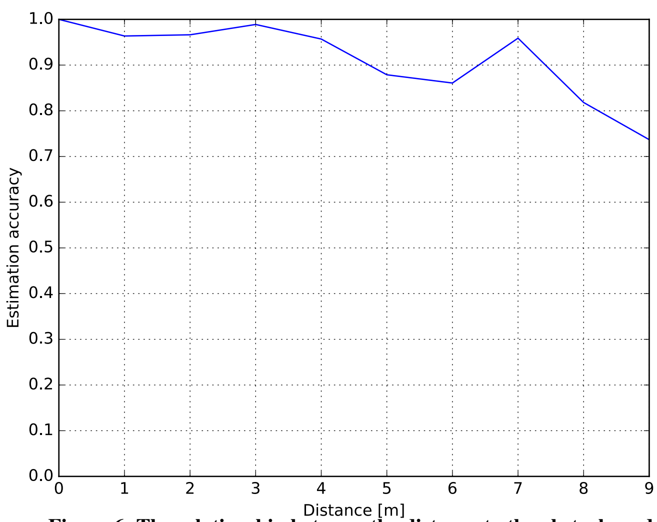


Figure 6. The relationship between the distance to the obstacle and estimation accuracy.

Table 2. Statistics of the point where the classifier judged that the person is aware of the obstacle.

	mean	std. dev.	min	max
distance [m]	8.53	1.88	6.09	11.41

CONCLUSION AND FUTURE WORK

This paper has described a method of estimating a person's awareness of an obstacle using only the person's motion. The method extracts motion features from their trajectory, and then classifies whether the person is aware of the obstacle or not using HCRF. We validated the method through real experiments and confirmed that the estimation is accurate enough.

Currently, we have developed only an estimation method of a person's awareness of an obstacle. Since the person may bump into not only just obstacles but also other persons, we have to extend the method to be able to estimate person's awareness of other persons and work in more complicated environments. Also, motion planning with consideration of estimated awareness has also to be developed in order to realize socially acceptable attendant behavior.

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REFERENCES

1. Tobias Bar, Denys Linke, Dennis Nienhuser, and J. Marius Zollner. 2013. Seen and missed traffic objects: A traffic object-specific awareness estimation. In *Proceedings of the 2013 IEEE Intelligent Vehicles Symposium (IV)*. IEEE.

2. Anup Doshi and Mohan M. Trivedi. 2010. Attention estimation by simultaneous observation of viewer and view. In *Proceedings of the 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*. IEEE.

3. Asela Gunawardana, Milind Mahajan, Alex Acero, and John C. Platt. 2005. Hidden Conditional Random Fields for Phone Classification. In *Proceedings of the International Conference on Speech Communication and Technology*. International Speech Communication Association.

4. Kiyosumi Kidono, Takeo Miyasaka, Akihiro Watanabe, Takashi Naito, and Jun Miura. 2011. Pedestrian recognition using high-definition LIDAR. In *Proceedings of the 2011 IEEE Intelligent Vehicles Symposium (IV)*. IEEE.

5. Pavlina Konstantinova, Alexander Udvarev, and Tzvetan Semerdjiev. 2003. A study of a target tracking algorithm

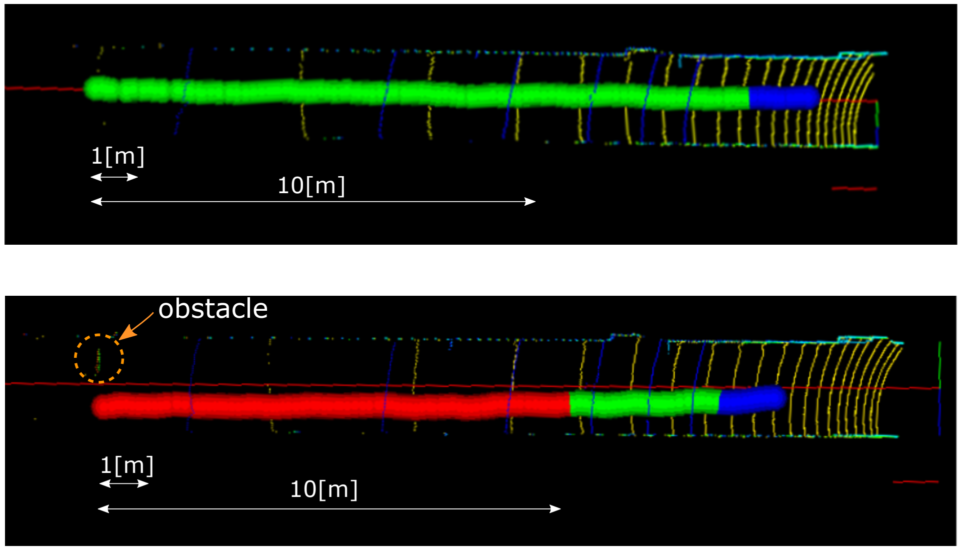

Figure 7. Examples of estimation results. Thick lines indicate the trajectory of a person and the estimation results. Blue color indicates that the system is accumulating motion data and is not classifying the motion due to an insufficient amount of data. Green and red colors indicate that the person is unaware of the obstacle, and that the person is aware of the obstacle, respectively.

using global nearest neighbor approach. In *Proceedings of the International Conference on Computer Systems and Technologies (CompSysTec' 03)*. 290–295.

6. Minh Tien Phan, Vincent Fremont, Indira Thouvenin, Mohamed Sallak, and Veronique Cherfaoui. 2014. Recognizing Driver Awareness of Pedestrian. In *Proceedings of the 17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*. IEEE.
7. Ariadna Quattoni, Michael Collins, and Trevor Darrell. 2004. Conditional random fields for object recognition. In *Advances in neural information processing systems*. 1097–1104.
8. Robert E. Schapire and Yoram Singer. 1998. Improved boosting algorithms using confidence-rated predictions. In *Proceedings of the Annual conference on Computational learning theory - COLT 98*, Vol. 37. ACM, 297–336.
9. Fei Sha and Fernando Pereira. 2003. Shallow parsing with conditional random fields. In *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology - NAACL03*. ACL.
10. Rainer Stiefelhagen and Jie Zhu. 2002. Head orientation and gaze direction in meetings. In *Proceedings of the Extended Abstracts on Human Factors in Computing Systems - CHI02*. ACM.
11. WHO Media centre. 2012. Fact sheet 344: Falls. (oct 2012). `http://www.who.int/mediacentre/factsheets/fs344/en/`