Measuring the Effects of Autonomous Mobile Robot on Pedestrian Behavior

Carolina Minami Oguchi¹, Ryo Nishida^{1,2}, Shusuke Shigenaka^{1,3} and Masaki Onishi¹

¹National Institute of Advanced Industrial Science and Technology (AIST)

²Tohoku University

³University of Tsukuba

carolinaminami-oguchi@aist.go.jp, ryo.nishida.t4@dc.tohoku.ac.jp, shusuke-shigenaka@aist.go.jp, onishi@ni.aist.go.jp

Abstract

Autonomous mobile robots are recently used in public facilities like airports or hotels and moves around in a crowd environment. These robots may psychologically affect surrounding pedestrians and change their behavior. Some may take extra distance or change walking velocity. In order to improve the control design of robots, the effect is required to be measured. In this paper, we propose a method based on Social Force Model in order to measure how a robot affects pedestrian movement. Each pedestrian trajectory is modeled based on actual data by estimating the parameters of Social Force Model using CMA-ES (Covariance Matrix Adaptation Evolution Strategy). The distributions of the parameters of each person's trajectory data are compared between a robot present and absent. Under the effect of robot presence, the pedestrians become more considerate of the nearby moving people and robot, and less conscious of the stationary architectural structures such as the borders.

1 Introduction

Innovative environmental structures have been built into every corner of our society owing to the recent developments in AI and studies on human crowd dynamics. A social mobile robot is an example. How do people interact and cope with it when they happen to share space and time together in a casual environment? A conventional research shows that people are psychologically affected by a nearby robot [Kanda *et al.*, 2001]. These effects were measured with a stationary robot [Butail, 2015]. In our paper, we propose a method to explain the influence on pedestrian movements induced by a mobile robot, using Social Force Model [Helbing and Molnar, 1995]. The parameters are estimated for modeling the trajectories of pedestrian movements by using CMA-ES (Covariance Matrix Adaptation Evolution Strategy) [Hansen, 2016].

2 Measuring Effects on Pedestrian Trajectory

We propose a method to measure effects on pedestrians by a mobile robot based on parameters of Social Force Model.

2.1 Social Force Model

Social Force Model explains how pedestrians move towards a destination. It assumes that pedestrians decide their movement as if physical forces are applied to their body. The model consists of 4 forces: attractive force from destination, repulsive force from other pedestrians, repulsive force from borders, and attractive force by other pedestrians or objects.

Attractive force on pedestrian i from destination d at time t is calculated as below.

$$\boldsymbol{F}_{i,d}(t) = \left(v_i^0 \boldsymbol{e}_i(t) - \boldsymbol{v}_i(t) \right) / \tau_i \tag{1}$$

 $v_i^0 e_i(t)$ represents desired velocity, $v_i(t)$ is actual velocity, $\tau_i (0 < \tau \le 1)$ is relaxation time, and $e_i(t)$ is a unit vector of the pedestrian direction. Repulsive force on a pedestrian *i* from another pedestrian *j* or a border *k* follows the formula below.

$$\boldsymbol{F}_{i,Z} = A_X \exp\left(\frac{-b_{i,Z}}{B_X}\right) \boldsymbol{n}_{i,Z}$$
(2)

Z is j and X is 1 for another pedestrian, and Z is k and X is 2 for a border. $b_{i,Z}$ is the distance from other pedestrian or a border, $n_{i,Z}$ is a unit vector from other pedestrians or borders. $A_X (A_X \ge 0)$ and $B_X (0 < B_X \le 1)$ are parameters that controls magnitude of the force and sensitivity to surrounding objects respectively. A parameter $c (0 \le c \le 1)$ is multiplied on $F_{i,j}$ as an consideration weight for pedestrians behind. The last force is attractive force from attractors such as other pedestrians or objects l, denoted as $F_{i,l}$. All the forces together, Social Force Model is defined as below.

$$\boldsymbol{F}(t) = \boldsymbol{F}_{i,d} + \sum_{j \neq i} c \cdot \boldsymbol{F}_{i,j} + \sum_{k} \boldsymbol{F}_{i,k} + \sum_{l} \boldsymbol{F}_{i,l} \qquad (3)$$



Figure 1: Actual Trajectory of Pedestrians and Robot. Left: Experimental Setting. Right: Trajectory record of a set of experiment.



Figure 3: Histogram of Data Set D_A . Shows each parameter distribution when the robot is absent.

2.2 Measurement Based on Social Force Model

Based on the above mentioned Social Force Model, we propose a method to measure the effects on pedestrians by a robot. The method includes three steps as follows. First, obtain two-dimensional trajectory data of two groups of pedestrian traffic: a group G_P with a robot and a group G_A without it. Second, model the trajectory using Social Force Model by estimating each pedestrian parameter. The parameters are τ , A_1, B_1, c, A_2 , and B_2 . The other parameters are constant. (Note that the attractive force from other pedestrians and object $F_{i,l}$, as mentioned in Section 2.1, is ignored in our experiment because it is out of our interest). Third, compare the distribution difference of the six parameters between two groups G_P and G_A using Mann Whitney U Test to investigate the influence of a robot. The test assumes that the two groups for comparison are independent, variables are continuous, and not normally distributed.

3 Experimental Results

3.1 Experiment

The experiment was conducted in a cross-shaped area of approximately 100 square meters where 15 people were moving around as actual data visualized in Figure 1. In the all 20 sets of experiments, each person is assigned to repeatedly leave an arbitrary side end for an end of any other three sides in the cross-shaped area until the experiment is over. In the experiment that a robot is present, the robot passes across the people. The wheeled robot is about one meter tall. The movement is autonomous based on deep learning. Trajectory data of pedestrians and a robot are measured using LiDAR (Light Detection and Ranging), a sensor whose laser light source measures a distance from surrounding objects.

After obtaining the data, we name the trajectory data set from experiment of G_P (with a robot present) as D_P and data set from G_A (with robot absent) as D_A . Then, we pre-process the trajectory data to reduce noise by taking weighted average of the walking steps of trajectory. Then, the observed trajectory is modeled. The parameters are estimated using CMA-ES. The objective function is set to minimize the difference of actual observed trajectory and model based trajectory. Finally, optimized parameter values are ready for a comparison between the two groups.

3.2 Results and Discussion

Figures 2 and 3 show each parameter distribution to compare it between the data sets D_P and D_A . Frequency is normalized in the figures. According to Mann Whitney U Test, distribution of parameters τ , B_1 , c, B_2 of data set D_P and data set D_A rejected the null hypothesis that the two populations are equal. The rest of the pairs accepted the hypothesis. In other words, the pairs that had non-equal distributions were parameters τ , B_1 , c, B_2 .

To verify the distribution difference stated in the last paragraph, we tested groups of two other pairs. The pairs are: a half of the data set G_P and the other half, and a half of the data set G_A and the other half. As a result of testing, no parameters rejected the null hypothesis: the two populations are equal. Therefore, the differences in distribution were only found between data set G_P and G_A .

The result shows that a mobile robot explicitly affects its surrounding pedestrians. From the histograms, we know that when a robot is present, τ is larger, B_1 is smaller, c is larger, and B_2 is larger. This means that the pedestrian tends to slow down while paying more attention to the mobile robot and the other pedestrians walking behind them. Due to the change of their attention to their nearby conditions, they become less conscious of the stationary architectural structures such as the borders (walls) in our experiment.

4 Conclusion

We proposed a method to measure effects on pedestrians by an autonomous mobile robot. Testing the difference in distribution of parameters of Social Force Model estimated for each pedestrian made the difference clear. The results have shown that using parameters of Social Force Model is effective. The proposed method is useful as a guidance for improving the control of robots because each parameters has its own role in the model and explains the kind of effect on pedestrians. Also, the proposed method only requires trajectory data of a pedestrian flow. This simplicity has saved us a labor of collecting feedback from examinees. For future work, we would like to validate the method with diverse settings of robot movements and improve the method by introducing new parameters that are not within Social Force Model.

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