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Description	

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Learning Social Relations for Culture Aware Interaction

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***Abstract*—Each person has their private physical and/or psychological area where they do not want to share with others during social interactions. This area gives them comfort about interactions and its size usually depends on various factors such as culture, personal traits, and acquaintanceship. This issue may also arise in case of human-robot interaction, especially when the robot is required to generate a socially competent interaction strategy toward people they are interacting with. Here, we propose a new robot exploration strategy to socially interact with people by considering the social relationship between the robot and each person. To that end, two definitions of interaction area are made: (1) Acceptable area allowed to be shared with other people and robots, and (2) Private area where a human does not want to be interfered by others. Based on these definitions, the robot can optimize the path to maximize the frequency/degree of visiting the acceptable area of each person and to minimize the frequency/degree of trespassing into the private area of them at the same time in an iterative way. In this paper, the social force model (SFM) of each person, based on the potential field concept, is designed by a fuzzy inference system and its parameter is optimized by the reinforcement learning model during interactions. We have shown that the proposed model can generate a suitable SFM of each person, which was quite similar to a ground truth model, allowing to plan a path to simultaneously optimize the two factors of interaction area, respectively.**

1. INTRODUCTION

In the near future, domestic service robot will become essential for assisting humans in daily lives. As they are expected to share an environment with humans, their perceptual and behaviroal abilities in a way conforming to social conventions are the important key challenges for human-robot symbiosis. Developing socially aware robot has been largely studied in robotics research [1] and most of research progresses are in the field of articulated human motion perception and are turned to extend a human interaction data [2]. A Proxemics theory, which describes human social convention, and its correlated concept are frequently used for developing the social robot. However, still it is a challenge to formalize this social theory into the mathematic model for robot-centered social representations. Our ultimate goal is to adhere social convention to design a model of social space of human which enables the robot to predict the human's social area when robot are operated in a shared environment.

For the safe navigation in a human environment, the collision avoidance concerns that humans are important elements for unscathed maneuvers. Moreover, to realize the social exploration of the robot, human comforts feeling should be integrated into path planning. Therefore, the Social Model could be used to describe specific areas around the human in such a way that defines the comfortable area of humans [3]. This concept is also integrated into the various robotic researches, especially safe navigation considering social effects.

Although there are various researches about the social model for the robot navigation, the dynamics of social space of humans have not been paid much attentions yet. It is well known that humans have distinct areas which feel safe and comfort while interacting with others. These areas provide enough space for interaction while considering comfortable feeling for each person. However, these areas are difficult to be predicted by the robot even though a person is well known to it. The reason is that it depends on current human‘s mental states in different situations. Naturally, this process humans can make it automatically by learning from interaction. By mimicking the human being, this can be embedded into the robot to estimate comfort area of humans and avoid the unacceptable area of them. By learning from interacting with humans in the environment, the robot can predict The social area to match with a realistic interacting area. After learning process, the robot can use the prediction result to design efficient path that has proper interaction and not assail comfortable feeling.

Therefore, this paper proposes an extend social model which is designed by potential field concept which relies on the experience of path planning during human-robot interaction in the shared environment. The proposed estimated model adapts Gaussian function parameters by learning from the previously generated path. The result of learning social model improves social model to correctly match with the ground truth social model. This method assists the navigation algorithm and improves efficiency while considering the human's acceptable feeling to interact with the robot.

2. RELATED WORK

The key idea to formalize human-robot interaction is the aspect of human behavior. Therefore, the knowledge of psychology and sociology are used to extend a robot behavior.

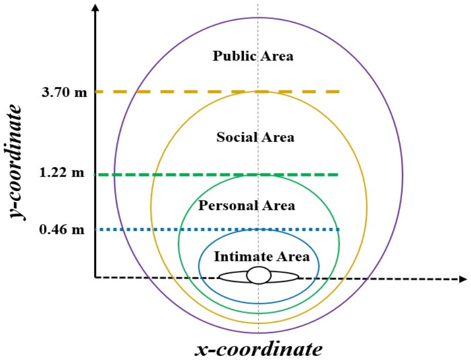

Fig. 1. Human Interaction Area

One famous theory for a social robot is Proxemics theory which describes different interpersonal distances that humans maintain from each other [3]. The theory was proposed by Hall to determine the separated areas depending on types of interaction and relationship between each person. Human interaction areas could be defined by this theory as shown in Fig.1. Among the various types of human interaction areac, *Public area* is the area that often it is used to interact with strangers, *Social area* is to interact with acquaintances, *Personal area* is for interacting with familiar persons, and *Intimate area* is for intimate contacts. Empirical research claims that these spatial distances play an important role to perceive and accept the interaction with a robot, too [4][5][6]. By using this concept, [7] proposed the social space based on geometric models and potential field models.

Social models are described by the geometric models which composed of ellipses or semi-ellipses. This type of models has a clear boundary which suited to represent a sharp transition between different regions of social spaces [8], to represent personal spaces in nearest histograms for local navigation [9][10] and to be applied solely for avoiding human in the environment [11].

Another model is usually used to describe interpersonal space by a potential field which composed of continuous functions. This function assigns the degree of acceptable and/or unacceptable values around each person. The model is usually based on a Gaussian function which centered at the human's position. Avoiding engagement with the human is the most application that uses the potential field concept in social model. For example, [12][13] used the potential field to avoid visitings into comfortable space of human by the robot. [14] proposed a strategy to avoid humans who approach to the robot along a corridor. The robot initiated a right turn to send awareness signal to human and followed avoiding trajectory past the human. Sventrup et al. employed Rapidly Random Tree (RRT) to the social cost map and gained feedback from robot dynamic and human motion prediction [15]. However, the experiment was performed by simplified experimental conditions. Modeling a function of the comfort degree of human field-of-view and posture is used as a cost to guide HAMP planner [16]. Not only avoidance task, but the potential field are also used in approaching the human. [17] proposed three Gaussian functions that blended to find the available area to interact with the robot.

Human social behavior signal and cues are inscribed into a high-level representation. Human's pose, speech, and gesture cues are used to evaluate social space to guide a robot in a socially compliant manner [18]. Adaptive space of human-robot interaction was proposed to dealing with uncertainties of robot perception. Their method based on non-strationay model as skew-normal probability density functions that deals with human space [19]. The social relationship and genders of each person are used as factors to generate social model by fuzzy logic and it is given as input for transition based RRT(T-RRT) algorithm to plan the path that avoids the human collision [20].

To recapitulate, the major weakness of previous works is lack of flexibility of social model because of the fixed spatial functions. On the contrary, our approach enables the robot to adaptively estimate the social model of humans which describe the comfort area that human allows others to work with. From the initialization of the social model, the robot can learn parameters to correctly update the social model of each person during the interaction. This social model can be integrated into a motion planning system to ensure human safety and to give them comfort.

3. Human Social Model

The social characteristics, which describe social cues of humans such as relationships between each person, culture, and emotional states, are important keys to ensure human safeties in robot navigation process. This section will summarize the mathematic model which extends the general social model [3] to the proposed social model that improves the fuzzy social model by learning from human-robot interactions.

3.1. Fuzzy Social Relationship Model

The human states and the social information, e.g. relative positions between the robot and each person, social relationship between them, genders of each person, etc., can be used to design the comfortable areas around humans according to Proxemics theory. These comfortable areas can be formalized by

$$F(x,y) = \sum_{i=1}^{n} f_i(x,y) \tag{1}$$

where n is the number of person, f_i is an interaction force with human i which can be expressed by the bivariate Gaussian distribution function. Let A be an mangnitude of social force signal, and let β_{fr} and β_{si} be the terms of frontal and lateral interaction areas respect to the human. The social force model $f_i(x,y)$ is designed by

$$f_i(x,y) = A * \exp\left(-\left(\beta_{fr} - \beta_{si}\right)\right) \tag{2}$$

which present a discomfort or unacceptable degree of the person i. A maximum degree is set at the human location and it is decreased by considering the distance aparts from the

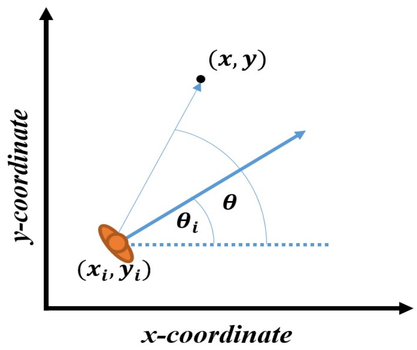

Fig. 2. Human states

human location. β_{fr} and β_{si} terms can be modified by relating with the human's states and the social degree, respectively.

For β_{fr} which defined as the terms of discomfort area of humans, the robot perceives human state which consist of human's states such as his position, velocity and direction. Given the distance d and a direction θ from the human's position and surrounding environment, and human state $(x_i, y_i, \dot{x}_i, \dot{y}_i, \theta_i)$ which can be visualized in Fig. 2. The magnitude of velocity v with its direction θ_i can be computed by

$$v_i = \sqrt{\dot{x}_i^2 + \dot{y}_i^2} \tag{3}$$

To integrate the motion of human by the Eq.(2), β_{fr} can be defined as follows:

$$\beta_{fr} = \begin{cases} \frac{(d*\cos(\theta-\theta_i))^2}{2*\sigma_{f0}^2} & \text{if } \cos(\theta-\theta_i) \leq 0 \\ \frac{(d*\cos(\theta-\theta_i))^2}{2*\left(\sigma_{f0}/\left(1+\gamma_f v_i\right)\right)^2} & \text{otherwise} \end{cases} \tag{4}$$

where σ_{f0} is chosen according to the personal area of the human which is described by Hall. γ_f is the normalization term and The area at the front or the back of the person can be evaluated by the term $\cos(\theta - \theta_i)$. Therefore, the robot pays more attention to aware the area in the front than the back of the human with respect to human velocity and human's field of view.

This paper focuses on using social characteristics between humans and the robot, e.g. genders of humans, the relative distance between humans and robot, and relationship degree of human and robot, to provide the factor of the discomfort area at the side β_{si}. Since these social characteristics are vary depending on the situation, it is difficult to group as a binary function. Therefore, fuzzy logic is a suitable method to define a metric of these factors [20].

The input membership function of human's gender is defined as a binary function subject to male (M) and female (Fe) which is given by:

$$\Gamma_1(g) = \begin{cases} 0, & \text{if } g \text{ is } M \\ 1, & \text{if } g \text{ is } Fe \end{cases} \tag{5}$$

where g is the genders input.

Our next social characteristic is relative distance which is devided into two sets such as near ($Near$) or far (Far). It

TABLE 1
DESIGNING THE SOCIAL CHARACTERISTICS USING FUZZY RULES

Input			Output
Gender (Γ_1)	Social Dist.(Γ_2)	Relative Dist.(Γ_3)	Unacceptable Area $\mathcal{N}(\mu, s^2)$
M	Near	Fam	CPA
M	Near	Acq	NPA
M	Near	Str	SA
M	Far	Fam	CPA
M	Far	Acq	NPA
M	Far	Str	PA
Fe	Near	Fam	NPA
Fe	Near	Acq	SA
Fe	Near	Str	SA
Fe	Far	Fam	NPA
Fe	Far	Acq	PA
Fe	Far	Str	PA

is represented by sigmoidal function. Let r_r be the input of relative distance, a_r is the steepness value of distribution of relative distance and c_s is an inflection point. Then the MFs function of the relative distance is given as follows:

$$\Gamma_2(r_r; a_r, c_r) = 1/\left(1 + exp\left(-a_r * (r_r - c_r)\right)\right) \tag{6}$$

The relationship degree describes the relationship between humans and robot which can be set by three Gaussian functions, familiar(Fam), acquaintance(Acq), and stranger(Str). Let r_i is the relationship degree that the robot perceives from humans. Therefore, the relationship degree MFs are given as follows:

$$\Gamma_3(r_i) = \begin{cases} \mathcal{N}\left(\mu_{Fam}, s_{Fam}^2\right) & \text{if } Fam \\ \mathcal{N}\left(\mu_{Acq}, s_{Acq}^2\right) & \text{if } Acq \\ \mathcal{N}\left(\mu_{Str}, s_{Str}^2\right) & \text{if } Str \end{cases} \tag{7}$$

For the output of fuzzy logic, there are several distances in the human's interaction areas which give the different standard deviations σ_{si}. Therefore, four Gaussian functions are used to represent a change of standard deviation(σ_{si}) in each interaction area which is defined as:

$$\sigma_{si} = \mathcal{N}\left(\mu, s^2\right) = \begin{cases} \mathcal{N}\left(\mu_{PA}, s_{PA}^2\right) & \text{if } PA \\ \mathcal{N}\left(\mu_{SA}, s_{SA}^2\right) & \text{if } SA \\ \mathcal{N}\left(\mu_{NPA}, s_{NPA}^2\right) & \text{if } NPA \\ \mathcal{N}\left(\mu_{CPA}, s_{CPA}^2\right) & \text{if } CPA \end{cases} \tag{8}$$

To combine the social characteristics by Eq.(2), β_{si} can be defined as follows:

$$\beta_{si} = \frac{(d * \sin(\theta - \theta_i))^2}{2 * \mathcal{N}(\mu, s^2)^2} \tag{9}$$

This means that, to avoid humans's discomfort area, the robot aims to estimate this area based on these social characteristics factors. Thus, the fuzzy rules are as shown in Table 1.

3.2. Learning Fuzzy Social Model

In this paper, we proposed learning membership function to social model estimation. The Reinforcement Learning(RL) method is used to be a learner that learns from robot's experience to the human in the environment. In our paper, we integrate reinforcement learning into fuzzy membership

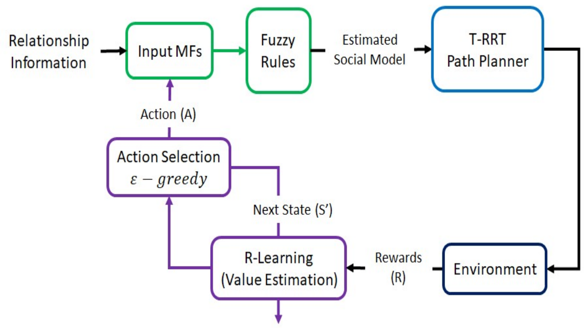

Fig. 3. Learning Membership Functions Process

Algorithm 1 R-Learning

Input: Reward R
Output: action a
Initialisation :
$\bar{R}$ and Q(S,a);
LOOP Process
$S \leftarrow$ current state;
Choose action a in S using behavior policy (e.g. ε-greedy)
Take action a, observe R, next state S'
$\delta \leftarrow R + \bar{R} + max_a Q(S',a) - Q(S,a)$
$Q(S,a) \leftarrow Q(S,a) + \alpha\delta$
if $Q(S,a) = max_a Q(S',b)$ **then**
  $\bar{R} \leftarrow \bar{R} + \beta\delta$
end if

function, as shown in Fig 3. The membership function, as the agent, learns to improve the social model in the sense of learning how to increase the total amount of reward from human-robot interactions. After that, the action is selected by behavior policy and this action adjusts the membership functions to effectively generate the social map to make a path through the environment. This process will be occurred to provide a maximum reward in an iterative way.

The R-Learning is used as the learner. In many learners in reinforcement learning problem have to abandon the discounted reward setting. To maximize the average reward per time, the average-reward setting is replaced in R-learning method. Therefore, R-Learning neither discounts nor divides experience into distinct episodes with a finite return. This is suited to learn the social map from the environment that should be learnt by experience until gaining the maximum reward.

The transition matrix depends on the action by an agent. In this paper, the state S consists of value of each membeship function. We focus only mean values $\boldsymbol{\mu}$ of MFs to be learnt, therefore, the state will consist of three *means* of *Familiar*, *Acquaintance* and *Stranger* functions, $\boldsymbol{\mu} = [\mu_{Fam}, \mu_{Acq}, \mu_{Str}]$. The action, $a \subset A$, is how each membership function can be adjusted. To select the action a, the ε-greedy method is used to select the action that has maximum estimated state-action value Q. Therefore, the value of state S with the action a can be defined as:

$$Q(S,a) = Q(S,a) + \alpha[R + \bar{R} + max_a Q(S',a) - Q(S,a)] \quad (10)$$

where S' is the next state, α is a constant learning rate, $\bar{R}$ is the average reward value and R is the reward signal that gained from the environment. In the real robot experiments, the robot can receive this reward from interaction degree and unacceptable degree from each person. Interaction degree(ID) presents the degree of human's comfort to interact with the robot. Unacceptable degree(UD) is the degree that human feels discomfort during human-robot interactions. Both degrees depend on the distance between human and robot according to Proxemics Theory [3]. Therefore the reward can be defined as:

$$R = \frac{k_1 * ID}{k_2 * UD + c} \quad (11)$$

where $k_1 and k_2$ are the weights of each degree, and constant c is used to prevent zero division. ID and UD are collected by the predefined ground truth social map. Therefore, interaction degree and unacceptable degree can be determined as:

$$ID = \begin{cases} \sum_p \sum_{i=1}^{n} -f_i(p) + 1, & p \text{ is in social area} \\ 0, & otherwise \end{cases} \quad (12)$$

$$UD = \begin{cases} \sum_p \sum_{i=1}^{n} f_i(p), & p \text{ is in social area} \\ 0, & otherwise \end{cases} \quad (13)$$

where F_{ID} and F_{UD} are the interaction degree and unacceptable degree that collected from generated path p which is a set of coordination (x_p, y_p) starts from an intinial position to a final destination in the predefined social map. Therefore, this membership function can be learnt by the $\boldsymbol{\mu}$ to maximize the reward that includes maximum ID while minimize UD. The complete R-Learning algorithm is given as Algorithm 1.

4. Simulation and Result

This section shows the influence of our proposed learning social model to the T-RRT navigation which integrated with the genetic algorithm to solve traveling sales man problem. The robot tries to plan a path to visit all humans in the environment without colliding into humans unacceptable area but in the range that humans could be able to interact. To validate the propsoed model, we need to receive the reward from humans as the ground truth, therefore, we use the concept of social relationship model in [20] and set the ground truth relationship degree MFs as three triangular functions as folows:$a_{Fam} = -0.2$, $b_{Fam} = 0.0$ and $c_{Fam} = 0.3$ to *Fam* set, $a_{Fam} = 0.0$, $b_{Fam} = 0.2$ and $c_{Fam} = 0.6$ to *Acq* set, and $a_{Str} = 0.4$, $b_{Str} = 0.7$ and $c_{Str} = 1.1$ to *Str* set. The ground truth MFs is shown in Fig.5 (Top).

To estimate social model, the initial parameters of the **RelationshipDegree** MFs in Eq.(7) are designed as follows: s_{Fam} = 0.15, μ_{Fam} = 0 to *Fam* set, s_{Fam} = 0.15, μ_{Acq} = 0.5 to *Acq* and s_{Str} = 0.15, μ_{Str} = 1 to *Fam* set, as shown in Fig.5 (Middle). These parameters can be learnt from our proposed method. For the **RelativeDistance** MFs, a_{Near} = -0.35, c_{Near} = 300 to *Near* set and a_{Far} = 0.35, c_{Far} = 300 to *Far* set. For the output function, the **SocialRelationArea**

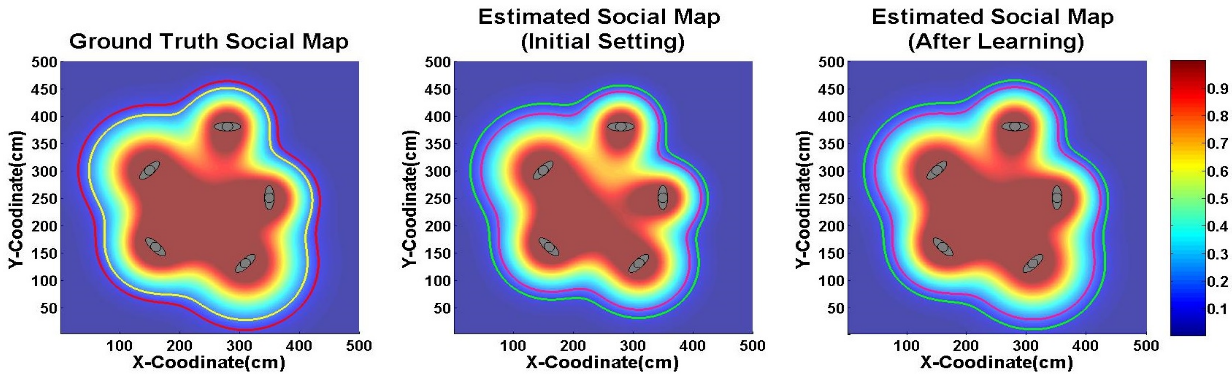

Fig. 4. **Social Map:** Comparison of the social maps at different time. Ground truth social map (*Left*), initial social map (*Middle*), and estimated social map by learning process (*Right*)

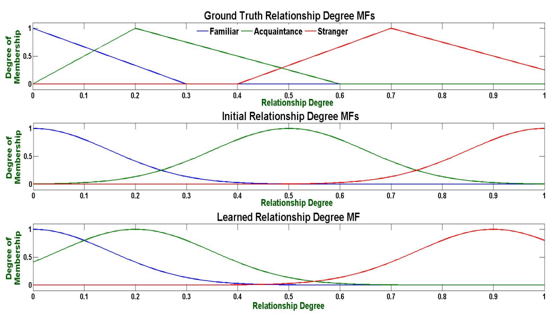

Fig. 5. Comparison of parameters of social relationship model (fuzzy membership functions). Ground truth values (*Top*), Initial parameters of membership functions (*Middle*), and Trained parameters of membership functions (*Bottom*)

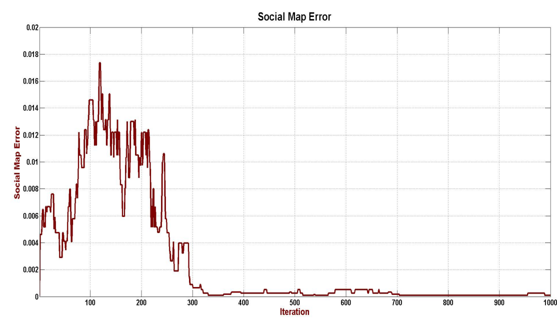

Fig. 6. **Social Map Error:** The error of social map shows the difference between the estimated social map and ground truth. The error was decreased and got closer to zero during the learning iteration

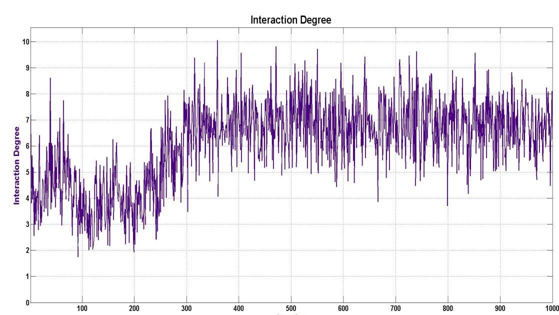

Fig. 7. **Interaction Degree:** Interaction degree presents the acceptable degree that the robot can receive it from human along generated path. The robot should plan the path to receive high interaction degree which means the path get close enough to possible interact with humans.

splits into four Gaussian sets. The parameters of Eq. (8) are as follows: $\mu_{PA} = 0.035$, $s_{PA} = 0.005$, $\mu_{SA} = 0.045$, $s_{SA} = 0.005$, $\mu_{NPA} = 0.0035$, $s_{NPA} = 0.06$, $\mu_{CP} = 0.0035$, $s_{CP} = 0.065$. These parameters are assigned by considering the human interaction area concept[4].

For reinforcement learning process, we set the discrete states which consists of three mean vales of each relationship function i.e., $[\mu_{Fam}, \mu_{Acq}, \mu_{Str}]$. The action set for each function is simply defined as stay, move right and move left i.e., [0 +0.1 -0.1]. The membership functions can be adjusted by learning iteration until gaining the high reward signal.

The results of social map of ground truth and estimation parameters can be seen in Fig.4. The ground truth social map has bigger size compare to initial estimated social map. However, after learning process, the estimated social map has similar size compare to the ground truth. The estimated MFs has been changed compare to initial setting Fig.5 (Bottom).

Fig.6 shows the error of estimated compare to ground truth social map. At the beginning, the initial social map has error around 0.006 but after learning over 100s iteration, the error decreasing until close to zero at over 300 iterations. Interaction degree and unacceptable degree can be shown in Fig.7 and Fig. 8 respectively. The results show that after 200 iterations, the interaction degree is increasing and get higher value which is compared with the initial condition. In case of the unacceptable degree, it is decreased during the learning process and got lower value comparing with the initial setting.

5. Conclusion

In this paper, new social model is proposed to realize the socially competent exploration strategy by integrating between fuzzy inference systems and the reinforcement learn-

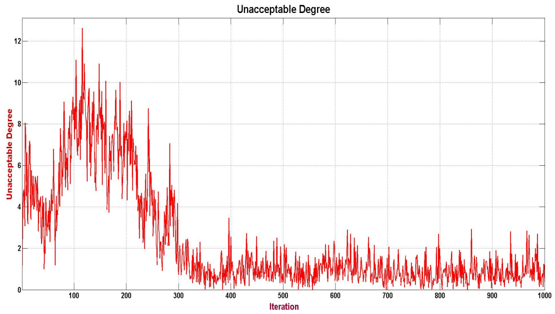

Fig. 8. **Unacceptable Degree:** Unacceptable degree presents the total discomfort feeling that robot can receive it from humans along generated path. The robot should plan the path avoid to enter the human's private area.

ing method. The proposed method uses social characteristics as the factors to determine the social model of humans in shared environment; however, the prior knowledge setting may produce an incorrect social maps. This problem may effect to the robot generated the path that may intrude into human's discomfort area or far away from possible interaction area. The proposed method uses concept of learning from the experience to update the social map of humans relate to human feedback. This concept improves the accruacy of social map generation and to correct robot path planning decision to avoid the human discomfort area while maintaining the path in the possible interaction area. Simulation results show that our proposed method provides correct social map during learning process which can increase the interaction degree and reduce the unacceptable degree. However, this learning method requires long iteration to learn which not suit to realistic and is not used in the real experiment. Therefore, In the future, we will invstigate the improvement of social model with the real robot experiments.

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