# Social interactive intention prediction and categorization

Xuan Tung Truong, Qiang Ye, and Trung Dung Ngo

***Abstract*— In this study, we propose a method of social interactive human intention prediction and categorization for socially aware robot navigation in dynamic social environments. The proposed method is composed of two functional blocks: (1) social interactive intention prediction using human states and social cues, (2) categorizing and modeling the social interactive intentions. To evaluate the proposed method, we incorporated it into our developed framework of socially aware robot navigation system. The simulation results show that the social interactive intention prediction enables the mobile robot to not only approach but also avoid humans in a socially acceptable manner, guaranteeing human comfort and safety in their surrounding environment.**

## I. INTRODUCTION

Socially aware mobile robot navigation systems have been well studied in recent years [1], [2]. The main objective of these systems is to guarantee the socially acceptable manner (human safety and comfort) during the robot navigation. In general, these robot navigation systems can be divided into two groups: (1) avoiding human, (2) approach human.

In the former, a mobile robot must distinguish humans from regular obstacles, then extract human features such as human states (human position, orientation, motion, field of view) relative to the mobile robot and social interaction features of the human–object and human group interactions from the socio-spatio-temporal characteristics of the humans and human groups. The human and social interaction features are modelled and incorporated into the robot navigation system [3], [4] and [5]. In the later, an approaching pose of the mobile robot to an individual or groups of people is estimated and predicted, then incorporated into the motion planning system to generate motion control commands enabling the mobile robot to approach individuals, human groups, and human-object interactions [6], [7] and [8]. Although these conventional robot navigation systems are capable of driving the mobile robot to avoid and approach humans in a socially acceptable manner, and providing respectful and polite behaviors akin to the humans, they still surfer the following drawbacks if we wish to deploy the robots into our daily life settings: (1) a robot should react according to social cues and signals of humans (facial expression, voice pitch and tone, body language, human gestures), and (2) a robot should predict future action of the human.

Xuan Tung Truong and Trung Dung Ngo are with The More-Than-One Robotics Laboratory, University of Prince Edward Island, Canada `xuantung.truong@gmail.com, tngo@upei.ca`

Qiang Ye is with the Faculty of Computer Science, Dalhousie University, Canada

We acknowledge the support of the NSERC-DG (2017-05446) and MITACS (IT11073)

Human intention information has been studied and incorporated into robotic systems. Human intention essentially means the goal of his/her current and/or upcoming action as well as motion towards the goal. The human intention was successfully applied to trajectory planning of robot manipulation [9], [10], [11], mobile robot navigation [12], [13], [14], [15], [16], and autonomous driving [17], [18]. However, these motion planning systems only predict and incorporate the human motion intention for human avoidance, not human approaching which is essential for applications of mobile service robots.

Unlike the aforementioned human intention prediction and estimation, we propose a new method of social interactive intention prediction and categorization for socially aware robot navigation systems. Incorporating the social interactive intention information in a robot navigation system, we equip the mobile robot with the capacity of adapting to various social situations and interacting with people in dynamic social environments. Because human intention information will be mental states that represent commitments of carrying out on-going actions and human social interactive intention indicates how a human wishes to interact with a robot, other humans or interesting object. We categorize the social interactive intention in three groups: (1) human–robot interactive intention (a human intends to interact with a robot), (2) human group interactive intention (a human intends to interact with another human in a group), and (3) human–object interactive intention (a human intends to interact with an interesting object).

The rest of this paper is organized as follows. The social interactive intention prediction and categorization for a socially aware robot navigation system is presented in section II. Section III describes the system integration of the proposed method into a differentially driven wheeled mobile robot. Section IV shows the simulation results. We conclude our paper in section V.

## II. THE PROPOSED FRAMEWORK

### *A. Social Interactive Intention Prediction*

To ensure the human safety and comfort and generate the socially acceptable behaviours of a mobile robot in a human–robot social interaction, the robot should predict on-going and upcoming actions of humans and behave accordingly. In this paper, we propose a social interactive intention prediction method of extracting externally observable information of humans using the robot perception system.

In a social interaction, human intention can be predicted by key social cues, e.g. facial expression, body language, voice pitch and tone, personal space, human states [19].

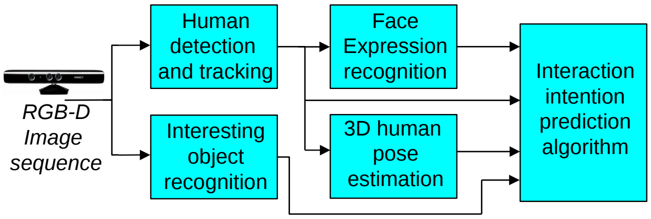



Fig. 1: The block digram of the social interactive intention prediction system.

In this paper, we omit the voice pitch and tone and only utilize the social cues based on visual information as major cues used determine the social interactive intention. Using a robot vision system, we can extract facial expression, 3D human pose, human states (position, orientation, motion), and interesting objects as social interactive information, as shown in Fig. 1.

We adopt the multiple objects detection and tracking system proposed by Thang et al. [20] to detect humans and recognize interesting objects in the robot's vicinity. The face detection is based on Single-Shot-Multibox detection method [21], and using 10-layer residual networks architecture as the backbone [22]. We utilize the deep neural network presented in [23] for human facial expression recognition with the face database [24].

Conventionally, the human intention prediction took advantages of the hidden Markov model [12] or partially observable Markov decision process [17]. However, inspired by the potentials of the deep learning methods in robotics [25], in this study we adopted the Long short-term memory (LSTM) networks [26] for predicting the social interactive intention. Because the LSTM networks have been successfully used to learn and generalize the properties of data sequences like hand writing recognition [27] and time series like speech recognition [28]

### B. *Social Interactive Intention Categorization and Modelling*

*1) Social Interactive Intention Categorization:* The social interactive intention information predicted by the robot vision system in section II-A can be incorporated into the mobile robot navigation system for avoiding and approaching behaviours, and divided into three group as follow:

**Human–robot interactive intention:** If a robot intends to interact with a human and the robot predicts that a human intents to interact with it, the robot should estimate the approaching pose, and plan to approach the human. In contract, if the human does not intend to interact with the robot, the robot should plan to avoid the human in a socially acceptive manner.

**Human–human interactive intention:** When a robot predicts that humans intend to interact with other humans in the robot's vicinity, the robot should plan to avoid or approach the human group with respect to the rules of social interactive group.

**Human–object interactive intention:** In this case, when the mobile robot predicts that humans intend to interact with an interesting object. The robot should plan to avoid and approach with respect to the rules of the human-object interaction.

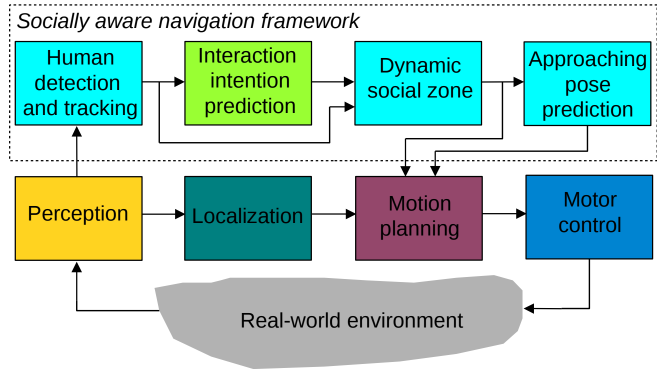
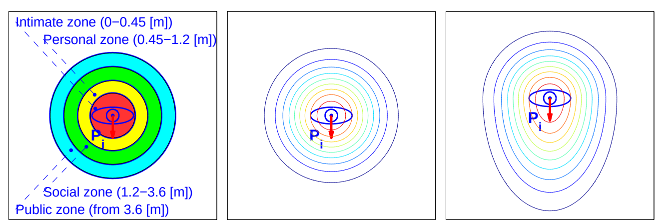



Fig. 2: The social interactive intention prediction embedded into the dynamic social zone of the socially aware mobile robot navigation framework.

*2) Social Interactive Intention Modeling:* In this paper, in order to demonstrate the usefulness of the social interactive intention information, we incorporate it into the dynamic social zone proposed by Truong et al. [29] and [7]. As seen in Fig. 2, the social interactive intention information is used as an input of the dynamic social zone. Particularly, the social interactive intention will be the additional factors in modelling of the space around the human, human group, and human–object interaction.




(a) (b) (c)

Fig. 3: Hall model and extended personal space: (a) Hall model [30], (b) basic personal space, and (c) extended personal space with the velocity information.

Specifically, we incorporated the social interactive intention into the extended personal space developed in our previous work [7], as shown in Fig. 3. The pair of parameters $\sigma_i^{px}$ and $\sigma_i^{py}$ of person $p_i$ is re-calculated as stated in Algorithm 1. The output of the Algorithm 1 is a new pair of parameters $\sigma_{i_{new}}^{px}$ and $\sigma_{i_{new}}^{py}$, used to build the extended personal space around human $p_i$. Algorithm 1 can be roughly divided into four cases according to the social interactive intention prediction, as explained in Section II-A:

**Case 1 - Human–robot interactive intention:** If human $p_i$ intends to interact with the mobile robot, the extended personal space around human $p_i$ is the basic personal space (line 5 in Algorithm 1), as shown in Fig. 3b. In contract, if human $p_i$ does not want to interact with the robot, e.g. being angry, the extended personal space of human $p_i$ is expanded using the $f_{int}$ factor (line 8 in Algorithm 1). If human $p_i$ is in natural emotion, the extended personal space remains unchanged.

**Case 2 - Human–human interactive intention:** If the robot predicts that human $p_i$ intends to interact with human $p_j$, the extended personal space of the human $p_i$ will be expanded towards the direction of human $p_j$ and vice versa. That is, the social interactive group between human $p_i$ and $p_j$ is changed accordingly.

**Case 3 - Human–object interactive intention:** If human $p_i$ intends to interact with an interesting object $obj_j$, the extended personal space of human $p_i$ will be extended towards the direction of object $obj_j$.

**Case 4 - Otherwise:** The extended personal space of human $p_i$ will remain unchanged like the extended personal space calculated in Algorithm 1 in [7]. That is, the pair $\sigma_i^{px}$ and $\sigma_i^{py}$ is used in the role of $\sigma_{i_{new}}^{px}$ and $\sigma_{i_{new}}^{py}$ to model the space around the human.

**Algorithm 1:** Compute $\sigma_{i_{new}}^{px}, \sigma_{i_{new}}^{py}$

**input :** *Social interactive intention*, $\sigma_0^{px}, \sigma_0^{py}$, $\sigma_i^{px}, \sigma_i^{py}$, $p_i = (x_i^p, y_i^p)$, $p_j = (x_j^p, y_j^p)$, $ob_j = (x_j^{ob}, y_j^{ob})$

**output:** $\sigma_{i_{new}}^{px}, \sigma_{i_{new}}^{py}$

1 **begin**
2   **switch** *social interactive intention* **do**
3     **case** *human–robot interactive intention* **do**
4       **if** *a human intends to interact with a robot* **then**
5         $\sigma_{i_{new}}^{px} \leftarrow \sigma_0^{px}, \sigma_{i_{new}}^{py} \leftarrow \sigma_0^{py}$;
6       **else**
7         **if** *human does not intend to interact with a robot* **then**
8           $\sigma_i^{px} \leftarrow (1+f_{int})\sigma_0^{px}$; $\sigma_i^{py} \leftarrow (1+f_{int})\sigma_0^{py}$;
9         **else** `/* human is in natural emotion */`
10           $\sigma_{i_{new}}^{px} \leftarrow \sigma_i^{px}, \sigma_{i_{new}}^{py} \leftarrow \sigma_i^{py}$;
11     **case** *human–human interactive intention* **do**
12       $\sigma_{i_{new}}^{py} \leftarrow \frac{\sqrt{(x_i^p - x_j^p)^2 + (y_i^p - y_j^p)^2}}{2}$
13     **case** *human–object interactive intention* **do**
14       $\sigma_{i_{new}}^{py} \leftarrow \frac{\sqrt{(x_i^p - x_j^{ob})^2 + (y_i^p - y_j^{ob})^2}}{2}$
15     **otherwise do**
16       $\sigma_{i_{new}}^{px} \leftarrow \sigma_i^{px}$, $\sigma_{i_{new}}^{py} \leftarrow \sigma_i^{py}$;
17   **return** $\sigma_{i_{new}}^{px}, \sigma_{i_{new}}^{py}$;

## III. System Integration

In this study, in order to demonstrate the usefulness of the social interactive intention information, we incorporate this information into our previous framework of socially aware robot navigation system in [29] and [7]. Truong et al. [29] and [7] presented a socially aware navigation framework, which was based on the conventional robot navigation system [31], for mobile robot in dynamic social environment. In those papers, we proposed the dynamic social zone representing the space around individuals, human groups, human–object interaction using human states (human position, motion, orientation, field of view, and hand poses) and the basic rules of social interaction. Once the dynamic social zone has been generated around humans and social interactions, and the approaching pose of the mobile robot to a human has been calculated using the approaching pose prediction, as seen in Fig. 2, the motion planning system automatically generates the control command $u = [u_v, u_\omega]$ to drive the robot to approach the human while socially maintaining a certain distance with other humans, social interactions, and regular obstacles. In this study, we examined the D-star path planning algorithm [32] to generating a feasible path and the dynamic window approach algorithm [33] to generating the velocity commands of the differentially driven mobile robot platform. We define the state of the robot $r(t) = (x_r(t), y_r(t), \theta_r(t))$ at time $t$, where the position is $(x_r(t), y_r(t))$, and the orientation is $\theta_r(t)$. The state of the robot at time $(t+1)$ is governed by the following equations:

$$\begin{bmatrix} x_r(t+1) \\ y_r(t+1) \\ \theta_r(t+1) \end{bmatrix} = \begin{bmatrix} x_r(t) \\ y_r(t) \\ \theta_r(t) \end{bmatrix} + \begin{bmatrix} \frac{v_r^r + v_r^l}{2} \cos(\theta_r(t))dt \\ \frac{v_r^r + v_r^l}{2} \sin(\theta_r(t))dt \\ \frac{v_r^r - v_r^l}{L} dt \end{bmatrix} \quad (1)$$

where $v_r^r$ and $v_r^l$ are the linear velocity commands of the right and left wheels of the robot, respectively, and $L$ denotes the wheelbase of the robot. The linear velocity commands of the right and left wheels of the robot $v_r^r$ and $v_l^r$ are computed as follows:

$$\begin{bmatrix} v_r^r \\ v_l^r \end{bmatrix} = \begin{bmatrix} 1 & \frac{L}{2} \\ 1 & -\frac{L}{2} \end{bmatrix} \begin{bmatrix} u_v \\ u_\omega \end{bmatrix} \quad (2)$$

where the linear velocity command $u_v$ and the angular velocity command $u_\omega$ are generated by the dynamic window approach technique.

## IV. Experiments

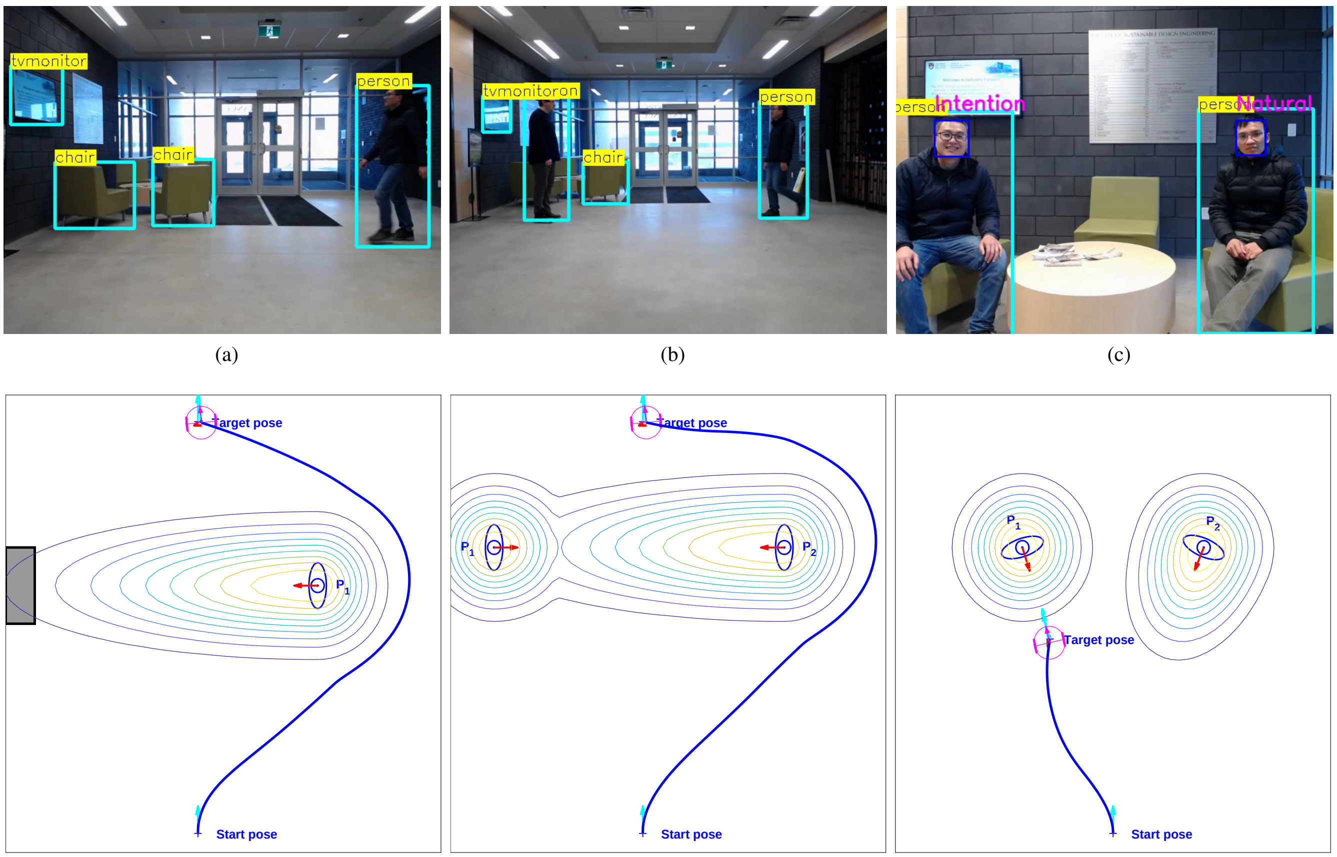
To verify the feasibility of the proposed social interactive intention prediction and categorization for socially aware mobile robot navigation systems, we conduct experiments in the simulation. The social interactive intention prediction algorithm was implemented using Python and transferred to the MATLAB for modelling the dynamic social zone and the approaching pose prediction. Using input of the dynamic social zone and approaching pose prediction, the motion planing system of the mobile robot then generated a feasible trajectory of the robot. In this paper, we used an empirical set $\sigma_0^{px} = \sigma_0^{py} = 0.45$ and $f_{int} = 3\sigma_0^{py}$.

### A. Experiment 1: Social interactive intention prediction

In this experiment, the people were standing in front of the mobile robot. The robot utilized the proposed social


(a) (b) (c) (d)

Fig. 4: The example results of the social interactive intention prediction system: (a) a person intends to interact with the robot; (b) a person is in natural state; (c) a person does not intend to interact with the robot; and (d) a person intends and the other does not intend to interact with the robot.




(a) (b) (c)

(d) (e) (f)

Fig. 5: The example results of the socially aware mobile robot navigation framework. The first row shows the experiment scenarios. The second row illustrates the extended personal space of the human and the trajectory of the mobile robot corresponding to each social interactive intention categories: (a) and (d) the human–object interactive intention, (b) and (e) human–human interactive intention, and (c) and (f) human–robot interactive intention.

interactive intention prediction to predict whether the human did or did not intend to interact with the robot. As seen in Fig. 4, the proposed system were capable of detecting the human body and face, and predicting the the social interactive intention of every person in the robot's vicinity.

### *B. Experiment 2: Human–object interactive intention*

In this experiment we aim to examine whether a human intends to interact with a interesting object. Figure 5a shows that the robot vision system successfully detected a moving person and recognized the interesting objects (screen). Moreover, it indicated that a person intends to interact with the objects. Figure 5d shows a trajectory of the mobile robot. It indicates that the robot must navigate behind the human in respect to the human–object interactive space, which is considered as a socially acceptable behaviour.

### C. Experiment 3: Human–human interactive intention

The objective of this experiment is to examine the response of the socially aware robot navigation system when a person intends to interact with the other. As seen in Fig. 5b, the robot detected two people within its field of view and predicted that such people intend to interact with each other. Figure. 5e illustrates that the mobile robot was capable of avoiding a social interactive group in a socially acceptable manner.

### D. Experiment 4: Approaching a person

In this experiment, we verify the role of the social interactive intention prediction for human approaching behaviour. As seen in Fig. 5c, the robot detected two people in its field of view but only the person over the left was willing to interact with the mobile robot while the person on the right was in natural status. Therefore, the mobile robot decided to approach the person on the left and avoid the person on the right, as shown in Fig. 5f.

Overall, the experimental results shown in Figs. 4 and 5 highlight that the mobile robot equipped with the proposed social interactive intention prediction and categorization is capable of not only avoiding but also approaching humans in socially acceptable manners while still guaranteeing the human safety and comfort dynamic social environments.

## V. Conclusions

We have presented a social interactive intention prediction and categorization for socially aware robot navigation systems in dynamic social environments. The proposed framework was composed of two major functional blocks including (1) social interactive intention prediction based on human sates and social cues, (2) modelling and categorization of social interactive intention. We integrated our social interactive intention prediction and categorization into our previously developed framework of socially aware robot navigation system for experiment and evaluation. Our experiment results showed that the social interactive intention prediction and categorization enabled a mobile robot to not only approach but also avoid humans in socially acceptable manners, providing the comfort and safety for the human in the surrounding environment.

In the future, we will implement the method on our mobile robot platform and evaluate its performance in several social situations. In addition, various kinds of social cues and signals presented in [34] and [35] will be incorporated into the social interactive intention prediction system so that the robot is capable of dealing with more complicated social situations and contexts.

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