Social constraints-based socially aware navigation framework for mobile service robots

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Abstract— **In this paper, we propose a social timed elastic band (STEB)-based navigation framework which enables a mobile service robot to safely and socially avoid a human in dynamic social environments. The main idea of the proposed framework is to incorporate the socio-spatio-temporal characteristics of the humans including human position, motion related to the robot, and social rules into a conventional online trajectory planing algorithm. We evaluate the developed framework through a series of simulation experiments. The simulation results show that the proposed framework is fully capable of autonomously driving the mobile robot to avoid the individual humans in dynamic social environments, providing the safety and comfort for the humans and the socially acceptable behaviours for the mobile robot.**

I. INTRODUCTION

The ability to navigate autonomously in dynamic social environments such as museums, airports, shopping malls, and urban environments is crucial for mobile service robots. In order to achive that, a number of socially aware robot navigation systems [1], [2] and [3] have been proposed in recent years. The existing socially aware robot navigation frameworks can be roughly divided into two categories based on the method of incorporating human information and social constraints into the navigation systems: (i) social costmap-based approaches and (ii) motion planning system-based techniques. In the former, the navigation systems embed the human information and social rules into the costmap function. While in the later, the social constraints are directly incorporated into the motion planning systems.

Regarding the social costmap-based techniques, a number of mobile robot navigation systems have been proposed in recent years [4], [5], [6] and [7]. In these systems the authors utilize the 2-D Gaussian and linear techniques to model the human information and social rules as social costmap. They then utilize the path planning algorithms [8], [9] and dynamic window approach technique [10] to generate a feasible path and a motion control command for the robots. The robots equipped with these algorithms are capable of safely and socially avoiding the humans in the robot's vicinity, and providing socially acceptable behaviors for the mobile robots, such as avoiding personal space and social interaction space, passing a person on the right side, and overtaking the person on the left side. However, this approach is time consuming, and it is highly computationally difficult to find a feasible path in crowded and dynamic environments [6] and [11].

Regarding the motion planning system-based techniques, several socially aware mobile robot navigation frameworks have been recently proposed [12], [13], [14] and [15]. These frameworks incorporate human information and social rules into the conventional motion planning techniques, such as social fore model [16] and velocity obstacles [17]. Although, these approaches have been successfully applied in real-world environments, the systems do not directly take into account the motion dynamics of the mobile robots. Hence, it might be difficult to directly utilize the output control command to control the mobile robots in the real-world environments, especially for non-holonomic mobile robots. To deal with that problem, recently Khambhaita et al. [18] presents a cooperative trajectory planning system using the robots kinodynamic constraints and social constraints including possible future collision, compatibility of human-robot motion direction, and proxemics.

In this paper, we propose a human-like motion system for socially aware mobile robot navigation framework using kinodynamic constraints and social rules including the personal space, passing a person on the right hand side. In order to accomplish that, we incorporate the social constraints into the conventional timed elastic band (TEB) model [19], which is an online trajectory planing algorithm. The advantage of the TEB technique is that, it takes into account the robot dynamics including the velocity and acceleration limitations, kinodynamic and nonholonomic constraints of the mobile robots, and the safety distance of the obstacles and their geometric. In addition, the TEB model is formulated in a weighted multi-objective optimization framework. Therefore, it is easy to extend by incorporating additional objectives and constraints [20]. Particularly, we incorporate the social rule, which is passing the humans on the right hand side, into the objective function of the conventional TEB model, and propose a social timed elastic band (STEB) model. In addition, instead of using only the human position, the personal space is utilized as the input of the proposed STEB algorithm. The mobile robot equipped with the proposed STEB model is able to socially avoid humans and safely navigate towards the given goal.

The rest of the paper is organized as follows. Section II presents the proposed social timed elastic band technique. The results in a simulation environment are described in Section III. We provide the conclusion of the paper in Section IV.

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II. PROPOSED FRAMEWORK

A. Problem Description

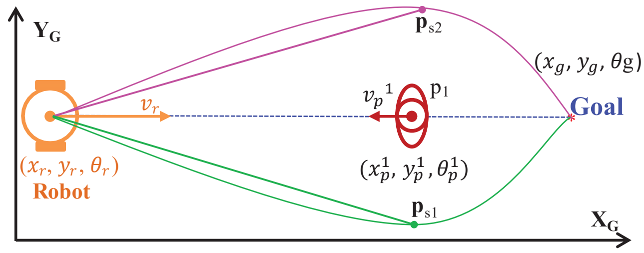

Fig. 1. An example scenario of a dynamic social environment including a mobile robot and a moving human. The robot is requested to navigate to the given goal while avoiding a person p_1 moving towards the robot. The green curved line is the intended social trajectory of the mobile robot.

We consider a dynamic social environment with the presence of a mobile robot and N humans in the robot's vicinity, as shown in Fig. 1. The robot is requested to navigate from the initial pose $\mathbf{s}_s = [x_s, y_s, \theta_s, v_s, \omega_s]^T$ to a given goal $\mathbf{s}_g = [x_g, y_g, \theta_g, v_g, \omega_g]^T$ while safely avoid the humans during its navigation. We assume the robot state $\mathbf{s}_r = [x_r, y_r, \theta_r, v_r, \omega_r]^T$, where $[x_r, y_r]^T$ is the position, θ_r is the orientation, v_r is the linear velocity, and ω_r is the angular velocity. We also assume that, there are N people appearing in the vicinity of the robot $\mathbf{P} = \{\mathbf{p}_1, \mathbf{p}_2, ..., \mathbf{p}_N\}$, where $\mathbf{p}_i$ is the i^{th} person. The state of the person $\mathbf{p}_i$ is represented as $\mathbf{s}_p^i = [x_p^i, y_p^i, \theta_p^i, v_p^i]^T$, where $[x_p^i, y_p^i]^T$ is the position, θ_p^i is the orientation, and v_p^i is the linear velocity. The radius of the robot and human are r_r and r_h, respectively.

B. Timed Elastic Band Technique

Timed elastic band (TEB) is an online trajectory planning algorithm for online collision avoidance, and has been successfully applied in dynamic environments [19], [20] and [21]. In this section, the conventional TEB algorithm are briefly presented. Assume that a discretized trajectory $\mathbf{B}$ is defined in terms of a finite-dimensional parameter vector including of an ordered sequence of mobile robot states $\mathbf{s}_k = [x_r^k, y_r^k, \theta_r^k]^T$, with k = 1, 2, ..., N and time stamps ΔT_k with k = 1, 2, ..., N-1. Thus the set of parameters $\mathbf{B}$ subject to optimization is defined as follows:

$$\mathbf{B} = [\mathbf{s}_1, \Delta T_1, \mathbf{s}_2, \Delta T_2, ..., \mathbf{s}_{N-1}, \Delta T_{N-1}, \mathbf{s}_N]^T \quad (1)$$

where, ΔT_k represents the time interval that the mobile robot has to require to transit between two consecutive poses $\mathbf{s}_k$ and $\mathbf{s}_{k+1}$. The robot's trajectory $\mathbf{B}$ subject to:

$0 \le \Delta T_k \le \Delta T_{max}$,
$\mathbf{h}_k(\mathbf{s}_{k+1}, \mathbf{s}_k) = 0$, (Nonholonomic kinematics)
$\mathbf{o}_k(\mathbf{s}_k) \ge 0$, (Clearance from surrounding obstacles)
$\nu_k(\mathbf{s}_{k+1}, \mathbf{s}_k, \Delta T_k) \ge 0$, (Limitation of robot's velocities)
$\alpha_k(\mathbf{s}_{k+1}, \mathbf{s}_k, \mathbf{s}_{k-1}, \Delta T_k, \Delta T_{k-1}) \ge 0$ (Limitation of robot's accelerations)

The total transition time is approximated by T $\approx \sum_{k=1}^{N-1} \Delta T_k$, ΔT_{max} is an upper limit of ΔT_k in order for the robot moving smoothly in the real time. The aforementioned equality and inequality equations represent the constraint of the environment with the robot, such as nonholonomic kinematics, clearance from obstacles and bounds on velocities and accelerations. All of the constraints are incorporated into the objective function Eq. 2 as additional penalty terms.

Algorithm 1: Timed elastic band algorithm

input : robot state $\mathbf{s}_r$, start pose $\mathbf{s}_s$, goal pose $\mathbf{s}_g$, set of obstacles $\mathbf{O}$
output: Control command $\mathbf{u}_r$

1 **begin**
2 $\quad$ $\mathbf{G} \leftarrow$ createGraph($\mathbf{s}_r$, $\mathbf{s}_s$, $\mathbf{s}_g$, $\mathbf{O}$);
3 $\quad$ $\mathbf{D} \leftarrow$ depthFirstSearch($\mathbf{G}$);
4 $\quad$ $\mathbf{H} \leftarrow$ computeH-Signature($\mathbf{D}$, $\mathbf{G}$);
5 $\quad$ $\mathbf{R} \leftarrow$ removeRedundantPath($\mathbf{D}$, $\mathbf{H}$, $\mathbf{G}$);
6 $\quad$ $\mathbf{T} \leftarrow$ initializeTrajectories($\mathbf{R}$, $\mathbf{G}$);
7 $\quad$ **for** each trajectory $\mathbf{B}_p \in \mathbf{T}$ **do**
8 $\quad\quad$ $\mathbf{V} \leftarrow$ objectiveFunction(); $\triangleright$ using Eq. 2
9 $\quad\quad$ $\mathbf{B}_p^* \leftarrow$ Optimizer($\mathbf{B}_p, \mathbf{O}, \mathbf{V}$); $\triangleright$ Solve Eq. 3
10 $\quad\quad$ $\mathbf{B}^* \leftarrow$ storeLocalOptimalTrajectory($\mathbf{B}_p^*$);
11 $\quad$ **end for**
12 $\quad$ $\mathbf{V}_c \leftarrow$ newObjectiveFunction(); $\triangleright$ using Eq. 5
13 $\quad$ $\hat{\mathbf{B}}^* \leftarrow$ Optimizer($\mathbf{B}^*, \mathbf{O}, \mathbf{V}_c$); $\triangleright$ Solve Eq. 4
14 $\quad$ Return $\mathbf{u}_r = [\upsilon_r, \omega_r]^T$;

$$V(\mathbf{B}) = \sum_{k=1}^{N-1} [\ \Delta T_k^2 + \delta_h \|\mathbf{h}_k\|_2^2 + \delta_v \|min\{\mathbf{0}, \nu_k\}\|_2^2 + \delta_o \|min\{\mathbf{0}, \mathbf{o}_k\}\|_2^2 + \delta_\alpha \|min\{\mathbf{0}, \alpha_k\}\|_2^2\ ] = \mathbf{w}^T f(\mathbf{B}) \quad (2)$$

where, the remainder of Eq. 2 is expressed in terms of the dot product, in which $\mathbf{w}$ captures individual weights and $f(\mathbf{B})$ contains individual cost terms. With objective function $V(\mathbf{B})$ the overall optimization problem is defined by:

$$\mathbf{B}^* = arg \min_{\mathbf{B}} V(\mathbf{B}) \quad (3)$$

The TEB approach utilized the Levenberg-Marquardt algorithm [22] to solve Eq. 3, and obtained the optimal robot trajectory $\mathbf{B}^*$. Finally, the desired control commands are directly extracted from the optimal trajectory $\mathbf{B}^*$. The classical TEB technique [20] has been applied in real-world environment and has achieved considerable success. However, it still has a drawback of only optimizing a single trajectory leading to stuck to a locally optimal trajectory somewhere, especially in dynamic environments. To tackle this problem, recently the TEB approach was extended to parallel trajectory planning in spatially distinctive topologies [19] and [21], which enable the robot to switch to the current globally optimal trajectory among the candidate trajectories of distinctive topologies.

Algorithm 1 presents the extension TEB technique [19] and [21], which consists of three major steps: (i) exploration (Lines 2-6 of the Algorithm 1), (ii) optimization (Lines 7-11 of the Algorithm 1) and (iii) selection (Lines 12-13 of the Algorithm 1). The input of the Algorithm 1 includes the robot state $\mathbf{s}_r$, start pose $\mathbf{s}_s$, goal pose $\mathbf{s}_g$ and set of obstacles

Algorithm 2: Proposed social timed elastic band

input : robot state $\mathbf{s}_r$, start pose $\mathbf{s}_s$, goal pose $\mathbf{s}_g$, set of obstacles $\mathbf{O}$, set of humans $\mathbf{P}$
output: Control command $\mathbf{u}_r$

1 **begin**
2 $\quad$ $\mathbf{G} \leftarrow$ createGraph($\mathbf{s}_r$, $\mathbf{s}_s$, $\mathbf{s}_g$, $\mathbf{O}, \mathbf{P}$);
3 $\quad$ $\mathbf{D} \leftarrow$ depthFirstSearch($\mathbf{G}$);
4 $\quad$ $\mathbf{H} \leftarrow$ computeH-Signature($\mathbf{D}$, $\mathbf{G}$);
5 $\quad$ $\mathbf{R} \leftarrow$ removeRedundantPath($\mathbf{D}$, $\mathbf{H}$, $\mathbf{G}$);
6 $\quad$ $\mathbf{T} \leftarrow$ initializeTrajectories($\mathbf{R}$, $\mathbf{G}$);
7 $\quad$ **for** each trajectory $\mathbf{B}_p \in \mathbf{T}$ **do**
8 $\quad\quad$ $\mathbf{V} \leftarrow$ objectiveFunction(); $\triangleright$ using Eq. 2
9 $\quad\quad$ $\mathbf{B}_p^* \leftarrow$ Optimizer($\mathbf{B}_p, \mathbf{O}, \mathbf{P}, \mathbf{V}$); $\triangleright$ Solve Eq. 3
10 $\quad\quad$ $\mathbf{B}^* \leftarrow$ storeLocalOptimalTrajectory($\mathbf{B}_p^*$);
11 $\quad$ **end for**
12 $\quad$ $\mathbf{V}_c \leftarrow$ newObjectiveFunction(); $\triangleright$ using Eq. 5
13 $\quad$ $\tilde{\mathbf{V}}_c = \mathbf{V}_c + \Delta\mathbf{V}$; $\triangleright$ using Eq. 6
14 $\quad$ $\hat{\mathbf{B}}^* \leftarrow$ Optimizer($\mathbf{B}^*, \mathbf{O}, \mathbf{P}, \tilde{\mathbf{V}}_c$); $\triangleright$ Solve Eq. 4
15 $\quad$ Return $\mathbf{u}_r = [\upsilon_r, \omega_r]^T$;

$\mathbf{O}$, and the output is the control command $\mathbf{u}_r = [\upsilon_r, \omega_r]^T$ of the mobile robot. *In the exploration step*, a graph $\mathbf{G}$ is generated to connect from $\mathbf{s}_s$ to $\mathbf{s}_g$ by forward directed edges. The graph is then filtered using depths-first search algorithm to keep only the acyclic graph. Finally, the H-Signature [23] technique is utilized to filter redundant paths that have the same H-Signature; as a result, a set of M primitive candidate paths that belong to alternative distinctive topologies are obtained. *In the second step*, locally optimal trajectories for all M alternative topologies are planned in parallel by using the TEB optimization with respect to the objective function Eq. 2, which generates M locally optimal trajectories respectively $\mathbf{B}_p^*$, with p = 1, 2, ..., M. *In the final step*, the best TEB $\hat{\mathbf{B}}^*$ or the least-cost trajectory is selected from the set of alternatives $\mathbf{B}_p^*$ obtained by solving the following equation, which reveals the global minimizer.

$$\hat{\mathbf{B}}^* = arg \min_{\mathbf{B}_p^* \in \{\mathbf{B}_1^*, \mathbf{B}_1^*, \ldots, \mathbf{B}_M^*\}} V_c(\mathbf{B}_p^*) \tag{4}$$

where, the objective function $V_c(\mathbf{B}_p^*)$ is presented as follows:

$$V_c(\mathbf{B}_p^*) = \mathbf{w}_c^T f_c(\mathbf{B}_p^*) \tag{5}$$

C. Proposed Social Timed Elastic Band Algorithm

The extension TEB technique has been successfully applied in real-world environment, and achieved considerable success [19] and [21]. However, in the TEB planner the humans are treated like regular obstacles, which results in an unintelligent robot's behavior. Figure 1 shows a scenario, in which the mobile robot equipped with the TEB technique might generate an optimal trajectory, presented as the magenta curve, which may not be social and comfortable. The main idea is to take the advantages of the TEB technique, and incorporate the socio-spatial characteristics of the humans, thus a social timed elastic band (STEB) model is proposed, as

Algorithm 3: Compute $\Delta V(\mathbf{B})$

input : Robot position $\mathbf{p}_r = [x_r, y_r]^T$, goal position $\mathbf{p}_g = [x_g, y_g]^T$, position and orientation of i^{th} person $\mathbf{p}^i = [x_p^i, y_p^i]^T$ and θ_p^i, $d_{min}, \delta_1, \delta_2$
output: $\Delta V(\mathbf{B})$

1 **begin**
2 $\quad$ $\mathbf{v} = d_{min} \frac{[-(y_g - y_r), (x_g - x_r)]}{\sqrt{(x_g - x_r)^2 + (y_g - y_r)^2}}$;
3 $\quad$ $\mathbf{p}_{s1} = \mathbf{p}^i - \mathbf{v}$;
4 $\quad$ $\mathbf{p}_{s2} = \mathbf{p}^i + \mathbf{v}$;
5 $\quad$ $\theta_1 = atan2(y_g - y_r, x_g - x_r)$;
6 $\quad$ $\Delta\theta = \theta_1 - \theta_p^i$;
7 $\quad$ **if** $\cos(\Delta\theta) < -\frac{\sqrt{3}}{2}$ **then**
8 $\quad\quad$ $\mathbf{p}_s = SelectLeftPoint(\mathbf{p}_{s1}, \mathbf{p}_{s2}, \mathbf{p}^i, \mathbf{p}_g)$;
9 $\quad$ **else**
10 $\quad\quad$ $\mathbf{p}_s = \mathbf{p}^i$;
11 $\quad$ $d_{pteb} = distanceTEB(\mathbf{p}_s, \mathbf{B}_p^*)$;
12 $\quad$ $d_{prg} = distanceRG(\mathbf{p}^i, \mathbf{p}_r, \mathbf{p}_g)$;
13 $\quad$ $\Delta V(\mathbf{B}) = \delta_1 \tanh(d_{pteb})(1 - \tanh(\delta_2 d_{prg}))$;
14 $\quad$ Return $\Delta V(\mathbf{B})$;

presented in Algorithm 2. To accomplish that, in the objective function presented in Eq. 5, an additional factor using social constraints is added, as illustrated in Eq. 6.

$$\tilde{V}_c(\mathbf{B}_p^*) = V_c(\mathbf{B}_p^*) + \Delta V(\mathbf{B}) \tag{6}$$

where, $\Delta V(\mathbf{B})$ is computed using Algorithm 3. The input of the Algorithm 3 consists of the states of robot and humans, the robot's goal, and the minimum distance from the robot to the humans d_{min}, and two predefined factors δ_1 and δ_2. We first determine a pair of points for each person including one left point and one right point (Lines 2-4 of the Algorithm 3). Then the algorithm determines whether the robot's action is passing on the right hand side or not (Lines 5-10 of the Algorithm 3). If the robot's action is passing the person on the right we select the left point of the person (Lines 7-8 of the Algorithm 3), and else the robot's action is normal (Line 9-10 of the Algorithm 3). We then compute the minimum distance from the selected point $\mathbf{p}_s$ to the all candidate robot's trajectories $\mathbf{B}_p^*$ (Line 11 of the Algorithm 3), and compute the distance from the person position to the line going through the robot and goal positions (Line 12 of the Algorithm 3). Finally $\Delta V(\mathbf{B})$ is computed using the equation in Line 13 of the Algorithm 3. It is noted that, the difference between Algorithms 1 and 2 is lines 13 and 14 of the Algorithm 2.

D. System Integration

Once the social robots trajectory is generated by the proposed STEB algorithm, the motion control command $\mathbf{u}_r$=[υ_r, ω_r]^T is extracted and used to drive the mobile robot to safely and socially avoid the humans in the robot's vicinity. In this study, we utilize a two-wheel differential drive mobile robot platform, with the state of the robot at the time k is $\mathbf{s}_r^k$ = $[x_r^k, y_r^k, \theta_r^k]^T$. Therefore, the state of the mobile robot at the time $(k+1)$ is governed by the following equation:

$$\begin{bmatrix} x_r^{k+1} \\ y_r^{k+1} \\ \theta_r^{k+1} \end{bmatrix} = \begin{bmatrix} x_r^{k} \\ y_r^{k} \\ \theta_r^{k} \end{bmatrix} + \begin{bmatrix} \frac{v_r^r + v_r^l}{2} \cos(\theta_k) dt \\ \frac{v_r^r + v_r^l}{2} \sin(\theta_k) dt \\ \frac{v_r^r - v_r^l}{L} dt \end{bmatrix} \tag{7}$$

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 wheel speeds v_r^r and v_r^l are computed using the velocity control command $\mathbf{u}_r$ as follows:

$$v_r^r = \upsilon_r + \frac{L\omega_r}{2} dt \tag{8}$$

$$v_r^l = \upsilon_r - \frac{L\omega_r}{2} dt \tag{9}$$

III. Experiments

To verify the effectiveness of the proposed social timed elastic band technique, we have implemented and tested it in a simulation environment. The software of the proposed framework is implemented using the C/C++ programming language. The entire navivation framework is developed based on the Robot Operating System (ROS) [24]. The conventional TEB package[1] was inherited and modified for developing the proposed STEB model.

A. Simulation Setup

In this study, we examine the proposed STEB model in a simulation environment. To accomplish that, we create scenarios, as shown in the first and fourth rows in Fig. 2. The initial pose of the robot is $\mathbf{s}_s = [-5, 0, 0]^T$, and the goal pose is $\mathbf{s}_g = [5, 0, 0]^T$. The mobile robot is requested to navigate from the initial pose to the goal pose while socially avoiding a person moving towards the robot.

In order to demonstrate the performance of the proposed STEB model, we compare it with the conventional online trajectory planning algorithm TEB [19]. In addition, to validate the proposed socially aware navigation framework, we adopted the *social individual index (SII)* proposed by Truong et al. [25]. The SII value is utilized to measure the physical safety and psychological safety of each individual human. The robot behavior is considered as comfort if the SII value is smaller than 0.14. Whereas, it is physical safety if the SII value is between 0.14 and 0.54. The mobile robot crashes into the person if the SII value is greater than 0.54.

B. Simulation Results

A video clip of our simulation results can be found at this link[2].

The simulation results are shown in Fig. 2, in which the first and fourth rows show the snapshots of the scenarios. The trajectory of the mobile robot generated by the conventional TEB model is red curve, whereas the social robot's trajectory is blue curve when the robot equipped with the proposed STEB model; the second and fifth rows depict the trajectory of the robot and the person; and the third and last rows illustrate the SII value along the robot's trajectory.

As can be seen in the first, second, fourth and fifth rows in Fig. 2, the mobile robot equipped with the proposed STEB technique successfully pass the moving person on the right hand side. In contrast, the mobile robot selects the optimal trajectory (red curve) if it is installed the conventional TEB model. Therefore, it will pass the moving person on the left hand side.

In addition to the social rule of passing the humans on the right hand side, we also incorporate the personal space into the proposed STEB model to demonstrate the effective of the propose method. The first, second and third rows in Fig. 2 show the simulation results of the proposed STEB model with the personal space, while the STEB model without the personal space is illustrated in the fourth, fifth and sixth rows. As can be seen in the third row in Fig. 2, the mobile robot often maintains a comfort distance to the humans. On the contrary, although the mobile robot equipped with the propose STEB technique successfully pass the moving person on the right hand side, its trajectory is very close to the person, as shown in the sixth row in Fig. 2.

In summary, the simulation results illustrate that, the robot equipped with the proposed STEB model is capable of socially avoiding dynamic humans in the robot's vicinity, and safely navigate to the given target.

IV. Conclusions

We have presented a social timed elastic band-based navigation framework which enables a mobile robot to safely and socially avoid humans in dynamic social environments. The main idea of the proposed framework is to incorporate the socio-spatio-temporal characteristics of the human and social social constraints into the conventional online trajectory planing algorithm. We evaluate the developed framework through a series of simulation experiments. The simulation results show that the proposed framework is fully capable of autonomously driving the mobile robot to avoid the humans in dynamic social environments, providing the safety and comfort for the humans and the socially acceptable behaviours for the mobile robot.

In the future, we will implement and install the proposed framework on our mobile robot platform and evaluate it based on a variety of scenarios, particularly those with different social situations and dynamic environments.

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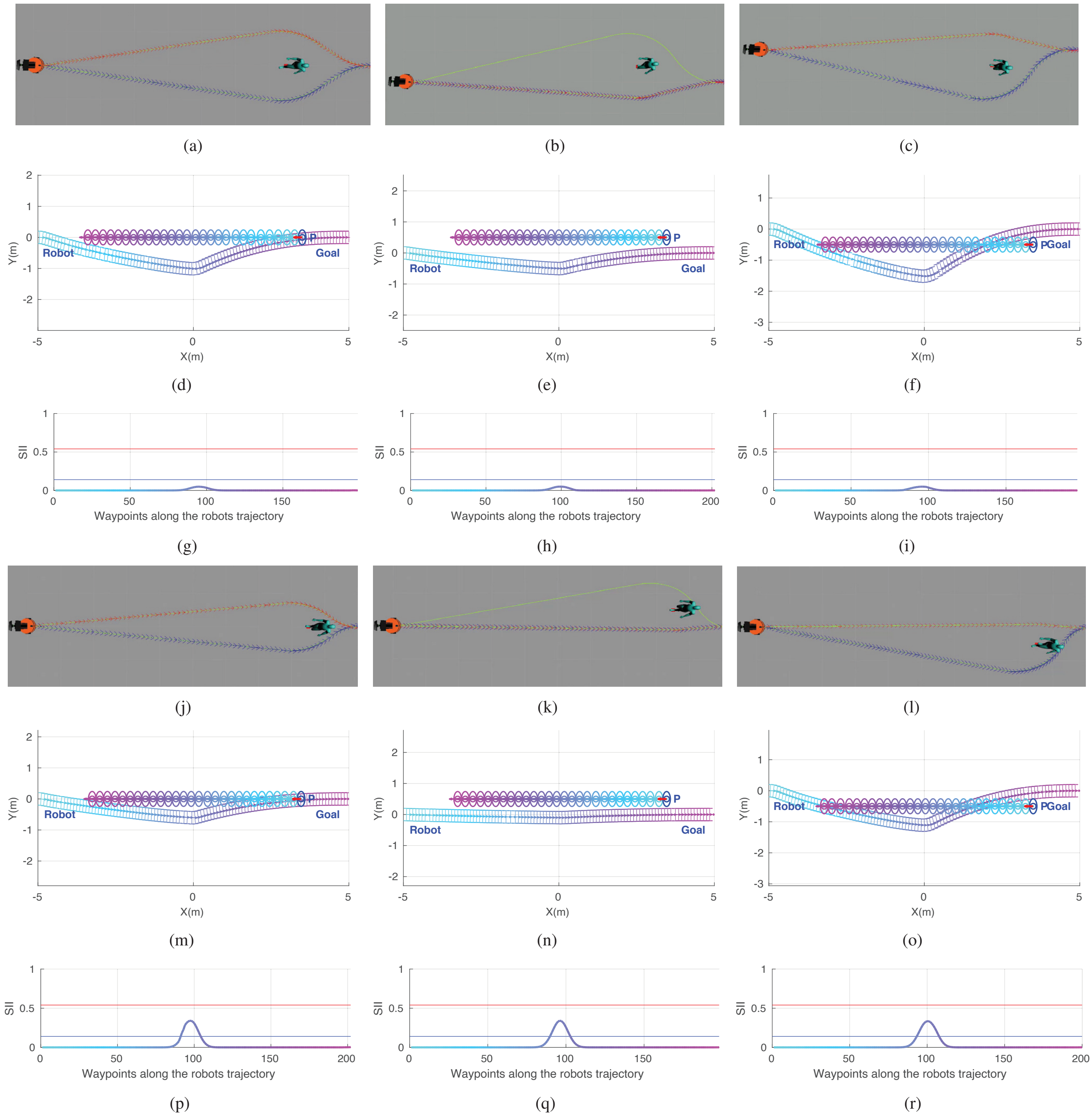

Fig. 2. The simulation results of avoiding a person moving towards the mobile robot. The first and fourth rows show the scenarios of the experiments. The optimal robot's trajectory of the conventional TEB algorithm is red curve, while the social robot's trajectory of the proposed STEB model is blue curve. The second and fifth rows illustrates the trajectory of the robot equipped with the proposed STEB model, and the human trajectories. The third and sixth rows depicts the social individual index (SII). The blue line is equal to 0.14 whereas the red line is equal to 0.54.

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