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A Proactive Trajectory Planning Algorithm for Autonomous Mobile Robots in Dynamic Social Environments

Lan Anh Nguyen, Trung Dung Pham, Trung Dung Ngo and Xuan Tung Truong

Abstract— **This paper proposes a proactive trajectory planning algorithm for autonomous mobile robots in dynamic social environments. The main idea of the proposed proactive timed elastic band (PTEB) system is to combine the advantages of the timed elastic band (TEB) technique and the hybrid reciprocal velocity obstacle (HRVO) model by incorporating the potential collision generated by the HRVO model into the objective function of the TEB technique. The output of the proposed PTEB system is the optimal trajectory, which enables the mobile robots to navigate safely in the dynamic social environments. We validate the effectiveness of the proposed model through a series of experiments in simulation environments. The simulation results show that, our proposed motion model is capable of driving the mobile robots to proactively avoid dynamic obstacles, providing the safe navigation for the robots.**

I. INTRODUCTION

Dynamic social environments are unstructured, clustered, uncertain and dynamic environments with the presence of humans, vehicles, and even other autonomous devices [1] and [2]. Therefore, in order to autonomously navigate in such environments, the most important issue is that mobile robots must safely avoid both static and dynamic obstacles during its navigation. To this end, several navigation frameworks have been developed for the autonomous mobile robots in the dynamic social environments [3], [4] and [5].

The navigation frameworks can be divided into two categories based on the robot dynamics used to develop the motion planning systems: (i) none robot dynamics-based approaches and (ii) robot dynamics-based techniques. In the former, the methods do not directly take into account the dynamic constraints of the mobile robots. While in the later, the robot dynamics such as the kynodynamic constraints, velocity and acceleration limitations, are directly incorporated into the motion planning system.

Regarding to the none robot dynamics-based techniques, a number of obstacle avoidance and motion control algorithms such as the artificial potential field [6], vector field histogram [7], elastic band [8], velocity obstacles [9], [10], and social fore model [11], [12] techniques have been proposed for the autonomous mobile robots. These approaches have been evaluated such that the robots are capable of safely avoiding the obstacles in the robot's vicinity, and navigating towards to the given goal. However, 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 address that issue, several robot dynamics-based approaches have been proposed in the recent years, such as the dynamic window approach [13], randomized kinodynamic planning [14], [15] and timed elastic band (TEB) [16] methods. Although, these approaches have been successfully applied in real-world environments, they might not be suitable with the dynamic environments, because the robots equipped with these techniques are unable to transit across obstacles in the dynamic environments. To deal with that problem, recently Rosmann et al. [17], [18] proposed extensions of the TEB technique by using parallel trajectory planning in spatially distinctive topologies. Using this technique, the mobile robots can switch to the current globally optimal trajectory among the candidate trajectories of distinctive topologies, which are maintained and optimized in parallel. However, these approaches only take into account the position of the obstacle and do not incorporate the potential collisions between the robots and the surrounding obstacles. Therefore, such developed navigation systems lack robustness in diverse situations in the dynamic social environments.

In order to overcome the aforementioned shortcomings, in this paper, we propose a proactive timed elastic band (PTEB) technique for autonomous mobile robot navigation systems in dynamic social environments using the conventional TEB method and the hybrid reciprocal velocity obstacle [10] (HRVO) model. Because, the TEB technique takes into account the velocity and acceleration limitations, kinodynamic and nonholonomic constraints of the mobile robots, and the safety distance of the obstacles and their geometric. And the HRVO model utilizes the obstacle's states including position, orientation and velocity, to model the potential collision of the mobile robots with the surrounding obstacles. The main idea of the proposed technique is to combine the advantages of the conventional TEB technique and the HRVO model. Particularly, we incorporate the orientation of the velocity vector generated by the HRVO model into the objective function of the TEB model. By incorporating the potential collision between the robots and the obstacles into the TEB technique, the mobile robots equipped with our proposed PTEB model can proactively avoid obstacles and safely navigate towards the given goal.

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

Lan Anh Nguyen, Trung Dung Pham and Xuan Tung Truong are with Faculty of Control Engineering, Le Quy Don Technical University, Hanoi, Vietnam. Trung Dung Ngo is with The More-Than-One Robotics Laboratory, University of Prince Edward Island, Canada. xuantung.truong@gmail.com

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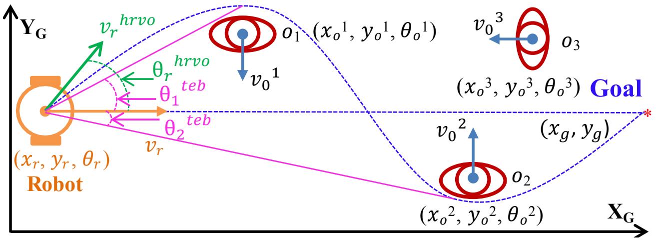

Fig. 1. The example scenario of the dynamic social environments including a mobile robot and three dynamic obstacles. The robot is requested to navigate to the given goal while avoiding two crossing obstacles o_1 and o_2, and a moving forward obstacle o_3. The curved dashed line is the intended optimal trajectory of the mobile robot.

II. PROPOSED FRAMEWORK

A. Problem Description

In this study, we consider a dynamic social environment with the presence of an autonomous mobile robot and O obstacles in the robot's vicinity, as shown in Fig 1. The robot is requested to navigate from the initial position to a goal while safely avoid the obstacles during its navigation.

We assume the robot state $\mathbf{s}_r = [x_r, y_r, \theta_r, v_r, \omega_r]^T$, where $\mathbf{p}_r = [x_r, y_r]^T$ is the position, θ_r is the orientation, v_r is the linear velocity, and ω_r is the angular velocity. The motion dynamics of the mobile robot is $(v_{min}, v_{max}, \omega_{min}, \omega_{max}, \dot{v}_{max}, \dot{\omega}_{max})$, where, v_{min}, ω_{min} are the minimum linear and angular velocities, respectively, v_{max}, ω_{max} are maximum linear and angular velocities, and $\dot{v}_{max}, \dot{\omega}_{max}$ are maximum linear and angular accelerations, respectively. The goal position of the robot is $\mathbf{p}_g = [x_g, y_g]^T$. We also assume there are N obstacles appearing in the vicinity of the robot $O = \{\mathbf{o}_1, \mathbf{o}_2, ..., \mathbf{o}_N\}$, where $\mathbf{o}_i$ is the i^{th} obstacle. The state of the obstacle $\mathbf{o}_i$ is represented as $\mathbf{s}_o^i = [x_o^i, y_o^i, \theta_o^i, v_o^i]^T$, where $\mathbf{p}_o^i = [x_o^i, y_o^i]^T$ is the position, θ_o^i is the orientation, and v_o^i is the linear velocity. The radius of the robot and obstacle are r_o and r_r, respectively.

B. Timed Elastic Band Technique

The elastic band [8] is a well-known motion planning technique, which deforms a path to the goal by applying an *internal contraction force* resulting in the shortest path and *external repulsive forces* radiating from the obstacles to receive a collision-free path. Nevertheless, this approach does not take into account time information. In other words, the robot's kinodynamic constraints are not considered explicitly, and hence a dedicated path following controller is required. In order to solve that issue, Rosmann et al. [16] presented an online trajectory planning algorithm for online collision avoidance, called timed elastic band (TEB) approach, which locally optimizes the robots trajectory by minimizing the trajectory execution time, separation from obstacles and compliance with kinodynamic constraints such as satisfying limitations of velocities and accelerations. In this study, we briefly present the TEB algorithm described in [16].

We assume a discretized trajectory $\mathbf{B}$ is defined by an ordered sequence of mobile robot poses $\mathbf{s}_k = [x_r^k, y_r^k, \theta_r^k]^T$, with k = 1, 2, ..., N and time stamps ΔT_k with k = 1, 2, ..., N-1. Thus the robot's trajectory $\mathbf{B}$ is presented 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 have to requires to transit between two consecutive poses $\mathbf{s}_k$ and $\mathbf{s}_{k+1}$. The main purpose of TEB method is to find control commands in order to drive the robot from an initial pose $\mathbf{s}_1$ to a final pose $\mathbf{s}_N$ with a minimal time interval, while guaranteeing kinodynamic constraints and separating from obstacles with a safe distance. Therefore, the objective function $V(\mathbf{B})$ is defined as follows:

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

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

For the remainder of Eq. 2, the cost function $V(\mathbf{B})$ is expressed in terms of the dot product, in which $\mathbf{w}$ captures individual weights and $f(\mathbf{B})$ contains individual cost terms. 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. In addition, the number of robot's pose N is alternative by comparing current time intervals ΔT_k with a desired ΔT_{ref}. 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.

The optimal trajectory $\mathbf{B}^*$ of the mobile robot is obtained by solving the following nonlinear program:

$$\mathbf{B}^* = arg \min_{\mathbf{B} \setminus \{\mathbf{s}_1, \mathbf{s}_N\}} V(\mathbf{B}) \quad (3)$$

where, the notation $\mathbf{B} \setminus \{s_1, s_N\}$ implies that neither the start pose $\mathbf{s}_1$ nor the goal pose $\mathbf{s}_N$ are subject to optimization. It is noted that, during optimization the trajectory is clipped at the current robot pose $\mathbf{s}_k$ and the desired goal pose $\mathbf{s}_N$. Finally, the desired control commands are directly extracted from the optimal trajectory $\mathbf{B}^*$. The detail information of the TEB algorithm is referred to [16].

C. Hybrid Reciprocal Velocity Obstacle Model

The hybrid reciprocal velocity obstacle (HRVO) technique introduced by Snape et al. [10] is an extension of the reciprocal velocity obstacles method [19]. This technique is a velocity obstacles-based approach [9] taking the motion of other agents into account for collision avoidance in multi-agent systems. The HRVO model has successfully been applied to multi-robot collision avoidance [20]. Thus, the HRVO technique can be also understood as a control

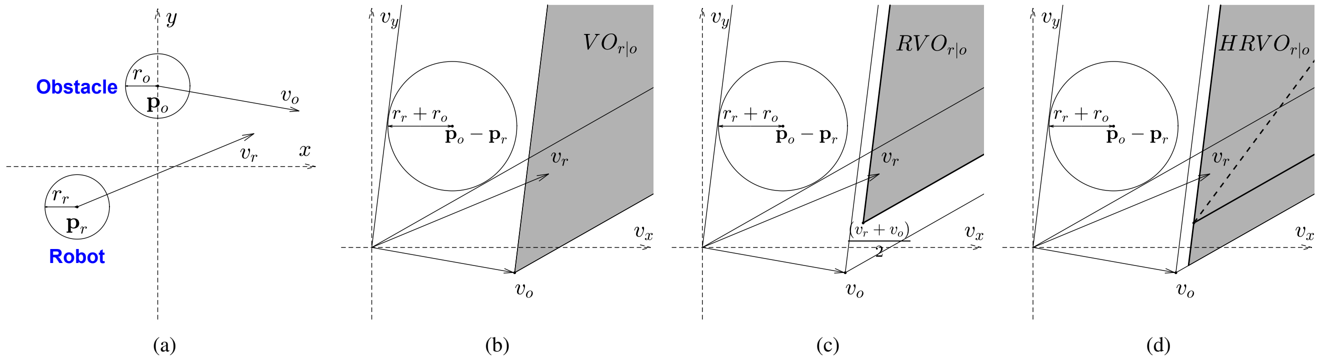

Fig. 2. Procedure of the hybrid reciprocal velocity obstacle of a robot and an obstacle: (a) A configuration of a disc-shaped robot and a obstacle in the $xy-plane$ with radii r_r and r_o, positions $\mathbf{p}_r$ and $\mathbf{p}_o$, and velocities v_r and v_o, respectively; (b) The velocity obstacle (VO) [9] for the robot induced by the obstacle; (c) The reciprocal velocity obstacle (RVO) [19] for the robot induced by the obstacle; (d) The hybrid reciprocal velocity obstacle (HRVO) [10] for the robot induced by the obstacle.

policy where each agent selects a collision-free velocity from the two-dimensional velocity space in the $xy-plane$. A construction of the HRVO model of a robot and an obstacle is illustrated in Fig. 2.

Suppose that a set of dynamic and static obstacles O appear in the robot's vicinity. The combined $HRVO$ for the mobile robot given in the existence of several obstacles is the union of all the $HRVOs$ induced by all the obstacles:

$$HRVO_r = \bigcup_{o \in O} HRVO_{r|o} \tag{4}$$

According to [10], to avoid collisions with obstacles, the velocity $\mathbf{v}_r^{hrvo}$ of the mobile robot should be selected outside the $HRVO_r$ and close to the preferred velocity vector of the robot $\mathbf{v}_r^{pref}$. In other words, $\mathbf{v}_r^{hrvo}$ is calculated as follows:

$$\mathbf{v}_r^{hrvo} = arg \min_{\mathbf{v} \notin HRVO_r} \|\mathbf{v} - \mathbf{v}_r^{pref}\|_2 \tag{5}$$

where, $\mathbf{v}_r^{pref}$ is computed as follows:

$$\mathbf{v}_r^{pref} = v_r^{pref} \frac{\mathbf{p}_r - \mathbf{p}_g}{\|\mathbf{p}_r - \mathbf{p}_g\|_2} \tag{6}$$

where, $\mathbf{p}_r$ is the current position of the robot, $\mathbf{p}_g$ is the goal position, and v_r^{pref} is the preferred speed of the mobile robot.

D. Proposed Proactive Trajectory Planning Algorithm

The TEB technique has been applied in real-world environment and has achieved considerable success. However, in dynamic social environments, the mobile robot equipped with TEB technique is unable to transit across obstacles. Thus, the TEB approach was recently extended to parallel trajectory planning in spatially distinctive topologies [17] and [18], which enables the robot to switch to the current globally optimal trajectory among the candidate trajectories of distinctive topologies. Therefore TEB model is efficiently integrated with state feedback to repeatedly refine the trajectory w.r.t. disturbances and changing environments.

In this paper, we utilize the scenario presented in Fig. 1 to briefly describe the extension TEB technique [17] and [18]. In this scenario, the mobile robot is requested to navigate

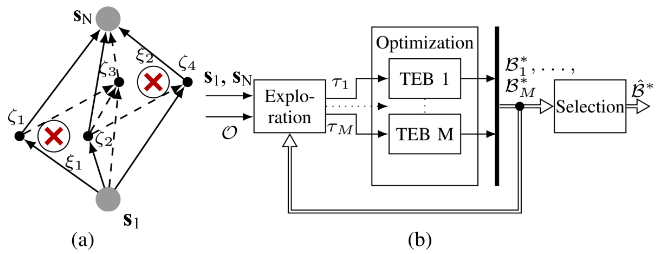

Fig. 3. The example of exploration graph (a). The block diagram of parallel trajectory planning of time elastic bands (b) [18].

from the starting pose $\mathbf{s}_1 = [x_r^1, y_r^1, \theta_r^1]^T$ to the goal pose $\mathbf{s}_N = [x_r^N, y_r^N, \theta_r^N]^T$, while avoiding two crossing obstacles. The extension TEB technique consists of three main steps: (i) exploration, (ii) optimization and (3) selection, as shown in Fig. 3(b). In the exploration step, for each obstacle we first add a pair of nodes to the left and right sides to the graph (there are two pairs of nodes ζ_1, ζ_2 and ζ_3, ζ_4 in Fig. 3(a)); next, we connect nodes from $\mathbf{s}_1$ to $\mathbf{s}_N$ by forward directed edges; we then utilize the depths-first search algorithm for resulting acyclic graph, as shown in Fig. 3(a); finally, a set of M topological alternatives are identified using using H-signature technique [21], as illustrated by solid arrows in Fig. 3(a). As a result, the exploration graph is obtained. Finally, the locally optimal trajectories for all M alternative topologies are planned in parallel by using the TEB optimization, which generates M locally optimal trajectories $\mathbf{B}_p^*$, with p = 1, 2, ..., M. In the final step, the least-cost trajectory is selected from the set of alternatives $\mathbf{B}_p^*$, to reveal the global minimizer. The best TEB $\hat{\mathbf{B}}^*$ is obtained by solving the following equation:

$$\hat{\mathbf{B}}^* = arg \min_{\mathbf{B}_p^* \in \{\mathbf{B}_1^*, \mathbf{B}_1^*, \ldots, \mathbf{B}_M^*\}} V_c(\mathbf{B}_p^*) \tag{7}$$

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

$$V_c(\mathbf{B}_p^*) = \mathbf{w}_c^T f_c(\mathbf{B}_p^*) \tag{8}$$

The extension TEB technique has been successfully applied in dynamic environments [17] and [18]. Nevertheless, the TEB planner only incorporates the position of the obstacles and does not take into account potential collision of the robot with the obstacles, which results in an unintelligent behavior in the dynamic environments. Figure 1 shows an example of crossing scenario, in this case the TEB technique might generate an optimal trajectory, presented as the straight dashed line, which may not be feasible.

To exploit the advantages of both TEB and HRVO models, we propose a proactive timed elastic band model for autonomous mobile robots in dynamic social environments by taking into account both the dynamic constraints of the mobile robot and the its potential collision of the robot with the surrounding obstacles. To accomplish this, in the objective function in Eq. 8, we add one more factor using the orientation of the velocity vector generated by the HRVO model. More specifically, the orientation θ_r^{hrvo} of the velocity vector $\mathbf{v}_r^{hrvo} = [\upsilon_x, \upsilon_y]^T$ generated by the HRVO model in Eq. 5 is used to compute the difference between it and the angles θ_p^{teb} of the M locally optimal trajectories, with p = 1, 2, ..., M.

$$\theta_r^{hrvo} = atan2(\upsilon_y, \upsilon_x) \quad (9)$$

$$\theta_p^{teb} = atan2(y_p^{teb} - y_r, x_p^{teb} - x_r) \quad (10)$$

$$\Delta\theta_p^{teb} = |\theta_r^{hrvo} - \theta_p^{teb}| \quad (11)$$

where, (x_r, y_r) is the current position of the mobile robot, (x_p^{teb}, y_p^{teb}) is the coordinates of the node ζ_p, which is added beside the obstacles, as shown in Fig. 3(a). It is noted that, the value of $\Delta\theta_p^{teb}$ ranges from 0 to π, and the numbers of $\Delta\theta_p^{teb}$ are equal to the numbers of locally optimal trajectories generated by individual TEB models. Finally, we obtain the objective function of the proposed PTEB model as follows:

$$\tilde{V}_c(\mathbf{B}_p^*) = V_c(\mathbf{B}_p^*) + \delta_{hrvo}\Delta\theta_p^{teb} \quad (12)$$

where, δ_{hrvo} is a normalization factor and are predefined value. Using the objective function presented in Eq. 12, the result of solving Eq. 7 provides us a globally optimal trajectory, which will enable the mobile robot to avoid the potential collision with the obstacles. Figure 1 shows an example result of the proposed PTEB model. In this case, the curved dashed line is the intended globally optimal trajectory of the mobile robot. Because the difference between the θ_r^{hrvo} and the θ_1^{teb} is smallest.

E. System Integration

In order to conduct experiments, we integrate the proposed PTEB model into the conventional navigation scheme introduced by Siegwart et al. [22], as shown in Fig. 4. Thus, the navigation system consists of two major parts: (i) the conventional navigation scheme, and (ii) the extended part (in the dashed rectangular). The conventional navigation scheme is typically based on the composition of four functional blocks: perception, localization, motion planning, and motor control. In the extended part, the multi-objects detection and tracking block is used to detect and track objects in the vicinity of the robot. Then the HRVO model utilizes the object state including position, orientation and velocity, to model the potential collision of the robot with the surrounding objects. This information and the object state are then used as the inputs of the proposed PTEB algorithm.

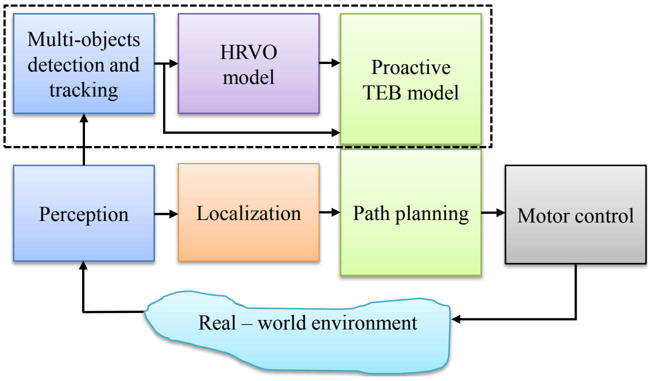

Fig. 4. The block diagram of the mobile robot navigation system.

Once the optimal trajectory is generated by the proposed PTEB algorithm, the motion control command $\mathbf{u}_r$=$[\upsilon_r, \omega_r]^T$ is extracted and used to drive the mobile robot to proactively avoid the obstacles in the robot's vicinity and approach a given goal. 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 robot at the time $(k+1)$ is governed by the following equation:

$$\begin{bmatrix} x_r^{k+1} \\ y_r^{k+1} \\ \theta_r^{k+1} \end{bmatrix} = \begin{bmatrix} x_r^{k} \\ y_r^{k} \\ \theta_r^{k} \end{bmatrix} + \begin{bmatrix} \frac{v_r^r + v_r^l}{2}\cos(\theta_k)dt \\ \frac{v_r^r + v_r^l}{2}\sin(\theta_k)dt \\ \frac{v_r^r - v_r^l}{L}dt \end{bmatrix} \quad (13)$$

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:

$$v_r^r = \upsilon_r + \frac{L\omega_r}{2}dt \quad (14)$$

$$v_r^l = \upsilon_r - \frac{L\omega_r}{2}dt \quad (15)$$

III. Experiments

To verify the effectiveness of the proposed PTEB algorithm, we have implemented and tested it in simulation environments. The software of the proposed framework is implemented using the C/C++ programming language. The entire navivation framework are developed based on the Robot Operating System (ROS) [23]. The conventional TEB package[1] and HRVO library[2] were inherited and modified for developing the proposed PTEB model.

A. Simulation Experiment in RViz Environment

In this study, we first examine the proposed PTEB model in a simple simulation environment, and visualize the results in RViz environment[3]. The mobile robot is requested to

[1]http://wiki.ros.org/teb_local_planner
[2]http://gamma.cs.unc.edu/software/
[3]http://wiki.ros.org/rviz

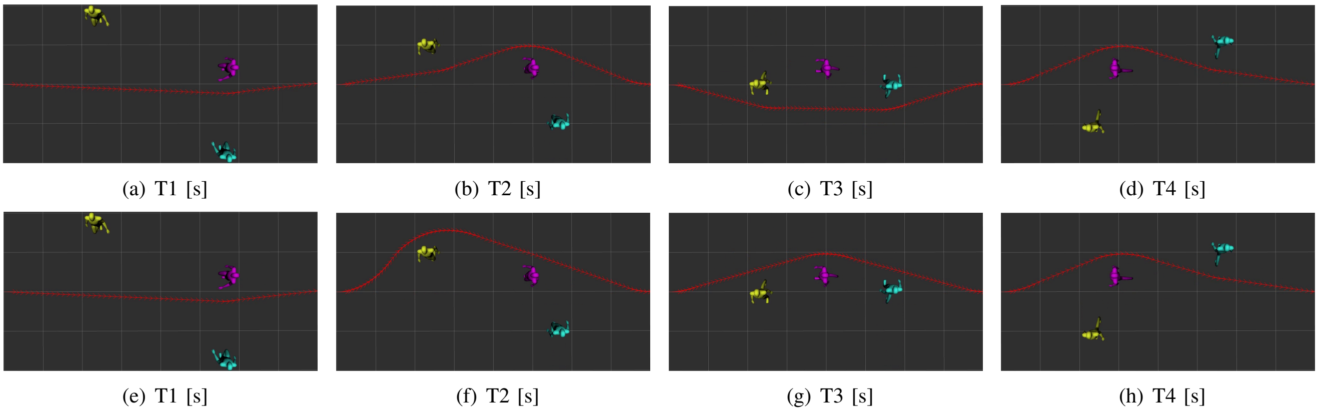

Fig. 5. Four snapshots at four timestamps of the two experiments in the simulation environment. The first row shows the results of the conventional TEB algorithm, whereas the second row presents the results of the proposed PTEB model. The curve with red arrows depicts the optimal trajectory of the mobile robot.

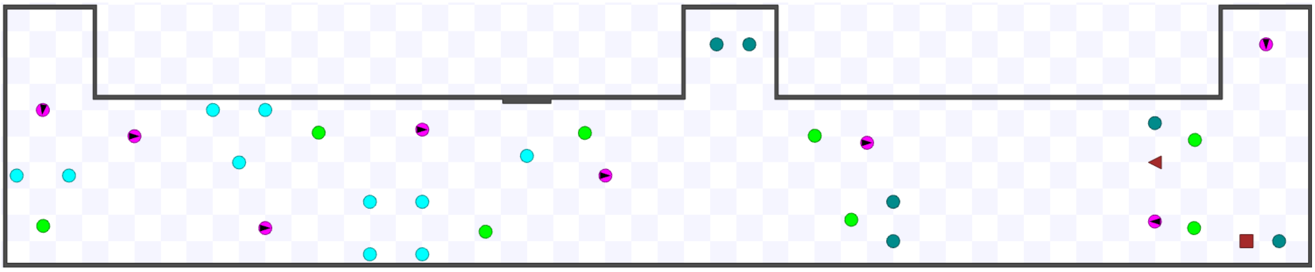

Fig. 6. A hallway-like scenario with walls, objects, humans, and goals. The mobile robots (magenta dots), 10 stationary people (cyan dots), 6 moving people (dark blue dots), and two moving object (brown triangle and square), and 8 goals (green dots) are distributed in the scenario. The robot is assigned a task to navigate to approach goals while avoiding humans and objects.

navigate from left to right, while avoiding three dynamic people. The simulation results are shown in Fig. 5. At the time stamps T1 and T4, the simulation results of the conventional TEB algorithm and the proposed PTEB model are similar. Because, at the time stamp T1 the two crossing humans are approaching the straight line between the starting position and the goal position but they are far from straight line, as shown in Figs. 5(a) and 5(e), or at the time stamp T4 the two crossing humans are close to the straight line but they are moving away the straight line, as shown in Figs. 5(d) and 5(h). At the time stamps T2 and T3, the globally optimal trajectory is generated in front of the left person, as shown in Figs. 5(b) and 5(c), in these cases, the mobile robot can safely avoid people but its behavior might not be smooth. In contrast, the globally optimal trajectory is generated behind the left crossing person, it illustrates that, the robot is able to proactively avoid people, as shown in Figs. 5(f) and 5(g). Because, the proposed PTEB model takes into account the potential collision of the robot with the surrounding humans.

B. Simulation Experiment in Stage Environment

In order to narrow the gap between simulation and real-world experiments, we have created a hallway-like scenario with walls, objects, humans and goals based on the Stage robot simulator [24], as depicted in Fig. 6. The moving humans and objects are controled using social force model proposed by Helbing et al. [11] and the available software platform[4].

We have installed the proposed PTEB algorithm on the mobile robot to validate its effectiveness. We then conducted experiments to examine whether our robot equipped with the proposed PTED model could safely and proactively avoid dynamic obstacles.

1) Experimental Setup: In this paper, we create a simulated differential drive robot, which equips with a laser rangefinder positioned at the height of 0.45[m]. The laser provides distance measurements up to 8[m] in the angular field of view 270^o, and the resolution 0.25^o. The laser rangefinder is used for robot localization and detecting obstacles in the vicinity of the mobile robot.

2) Simulation Results: We conducted two experiments in the simulated environment to examine whether our mobile robot could avoid dynamic obstacles while navigating safely in the environments. In first experiment, the mobile robot is requested to navigate from each starting position (magenta dot) to a corresponding goal (green dot), while avoiding the static and moving objects in the scenario. In the second experiment, a mobile robot is requested to navigate to approach each goal respectively in the scenario while avoiding dynamic objects during its navigation.

The simulation results illustrate that, the mobile robot equipped with the proposed PTEB model is able to proac-

[4] http://pedsim.silmaril.org

tively avoid static and dynamic objects in the vicinity of the robot, and safely navigate to the given goal.

IV. CONCLUSIONS

We have presented a proactive timed elastic band algorithm for autonomous mobile robots in dynamic social environments. The main idea of the proposed PTEB model is to incorporate the potential collision generated by the HRVO model into the objective function of the conventional TEB technique. The output of the proposed PTEB algorithm is the optimal trajectory, which is utilized to control the mobile robots. We validate the effectiveness of the proposed model through a series of experiments in simulation environments. The simulation results show that, our proposed motion planing model is able to drive the mobile robots to proactively avoid dynamic obstacles, providing the safe navigation for the robots.

In the future, we will predict the future position and the trajectory of the obstacles in the robot's vicinity and incorporate these information into the motion planning system of the autonomous mobile robots.

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