

AN INTEGRATED NAVIGATION SYSTEM FOR AUTONOMOUS MOBILE ROBOT IN DYNAMIC ENVIROMENTS

Nguyen Lan Anh^{*}, Pham Trung Dung, Truong Xuan Tung

Abstract: *To enable an autonomous mobile robot to navigate safely in a dynamic environment, the mobile robot must address four typical functional blocks of the navigation system including perception, localization, motion planning, and motor control. In this study, we present an integrated navigation system for the autonomous mobile robot in the dynamic environment by incorporating the techniques proposed in our previous studies, including object detection and tracking system, localization system and motion planning system, into a completed navigation system. In addition, we propose an extended timed elastic band (ETEB) technique for online trajectory planning, which allows the mobile robot to proactively avoid obstacles in the surrounding environment. We validate the effectiveness of the proposed model through a series of experiments in both simulated and real-world environments. The experimental 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.*

Keywords: Timed elastic band technique; Autonomous mobile robot; Navigation system; Motion planning system; Proactive collision avoidance.

1. INTRODUCTION

Dynamic social environments are unstructured, clustered, dynamic and uncertain environments with the presence of humans, vehicles, and even other autonomous devices [1] and [2]. Therefore, in order to autonomously and safely navigate in such environments, the most important issue is that the mobile robots must 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 environments [3, 4] and [5].

The existing navigation frameworks can be divided into two groups based on the techniques used to develop the systems: (i) reaction-based methods and (ii) trajectory-based approaches. In the first group, the reactive local planners, e.g., the artificial potential field [6], vector field histogram [7], the dynamic window approach [8], velocity obstacles [9, 10], and social fore model [11, 12], are used to develop the systems. Although these approaches have been evaluated such that the robots are capable of safely avoiding the obstacles in the robot's vicinity, they are often short-sighted in time. To solve that problem, trajectory-based methods, such as elastic band [13], randomized kinodynamic planning [14, 15], timed elastic band (TEB) [16], Rosmann et al. [17, 18], compute plans on longer timescale to produce smoother robot's trajectory. However, most of 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.

The conventional navigation frameworks also can be classified into two categories according to the information used as input of the systems: (i) current states-based approaches and (ii) future states-based techniques. In the former, the methods only take into account the current states position of the surrounding

obstacles. While in the later, both the current and future states of the obstacles are incorporated into the motion planning systems. Several navigation systems have been developed for the mobile robots using the current states of the surrounding obstacle, such as the dynamic window approach [8], 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 suitable for the dynamic environments, because they do not incorporate the future states of the surrounding obstacles, lead to they can only address imminent collision avoidance and fail to offer long-term optimal. Therefore, such developed navigation systems lack robustness in diverse situations in dynamic environments.

To deal with that issue, a few mobile robot navigation systems take into account the future states of obstacles such as HRVO [10], a socially acceptable collision avoidance using a pedestrian model [12], the proactive kinodynamic planning [19] and a proactive social motion model [20]. However, these systems do not directly take into account the motion dynamics of the mobile robots such as the kinodynamic constraints, velocity and acceleration limitations. Hence, it might be difficult to directly utilize the output control command to control the mobile robots in the real-world environments.

In order to overcome the aforementioned shortcomings, in this paper we propose an extended timed elastic band (ETEB) technique and combine with a global path planning algorithm for mobile robot navigation systems. It has been known that the TEB technique only takes into account the velocity and acceleration limitations, kinodynamic and nonholonomic constraints of the mobile robot, and the safety distance of the obstacles and their geometric. While, the motion prediction model utilizes the obstacle's states including position, orientation and velocity, to predict future states of the surrounding obstacles. The ETEB model is proposed by incorporating this motion prediction model into the TEB technique. The mobile robots equipped with our proposed model can proactively avoid obstacles and safely navigate to the given goal. Moreover, our method combines ETEB mode with the A* algorithm to select efficiently an optimal trajectory in global paths.

The rest of the paper is organized as follows. Section 2 presents the proposed mobile robot navigation framework. The experimental results in real-world environments are described in Section 3. We provide the conclusion of the paper in Section 4.

2. PROPOSED NAVIGATION FRAMEWORK

2.1. 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 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 dynamic motion 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 $O = \{\mathbf{o}_1, \mathbf{o}_2, \dots, \mathbf{o}_N\}$, 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.

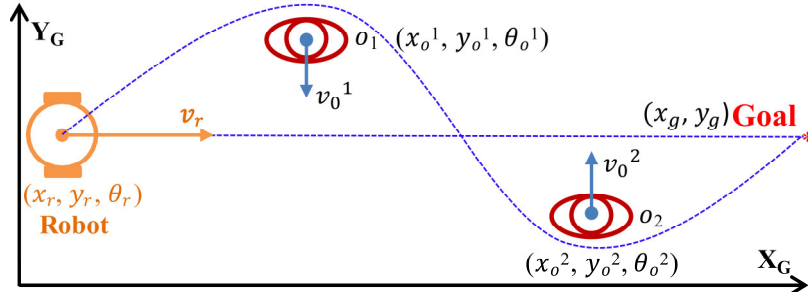


Figure 1. The example scenario of the dynamic environments including a mobile robot and two dynamic obstacles. The robot is requested to navigate to the given goal while avoiding the obstacles o_1 and o_2 . The curved dashed line is the intended optimal trajectory of the mobile robot.

2.2. Mobile Robot Platform

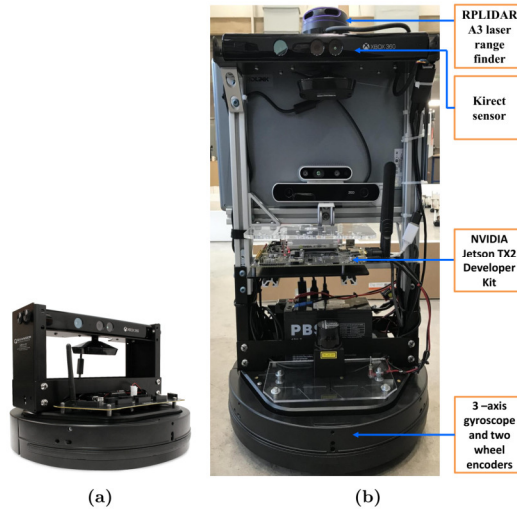


Figure 2. Mobile robot platform: (a) QBot-2e mobile robot platform, and (b) the used mobile robot platform equipped with the laser rangefinder and the NVIDIA Jetson TX2 board.

The QBot-2e mobile robot platform¹ is a two-wheel differential drive mobile robot platform with two additional caster wheels, as shown in fig. 2(a). This platform is equipped with two-wheel encoders and a 3-axis gyroscope. The encoders provide 2578 counts per revolution. In other words, the resolution of the encoders is 0.14° . The 3-axis gyroscope is used to track the angular velocity of the roll, pitch, and yaw of the mobile robot. The two-wheel encoders and 3-axis gyroscope are utilized to estimate the position of the mobile robot.

In this study, we modified the QBot-2e mobile robot platform, and added a RPL- IDAR A3 laser rangefinder and a NVIDIA Jetson TX2 Developer Kit, as shown in fig. 2(b). The laser rangefinder positioned at the height of 0.45[m], provides distance measurements up to 25[m] in the angular field of view 360° , and the resolution 0.33° . The laser rangefinder is used for robot localization and detecting objects in the vicinity of the robot. Whereas, the NVIDIA board is an embedded computer, which is used to install the entire navigation system and other software packages of the mobile robot.

2.3. The Architecture of Navigation Framework

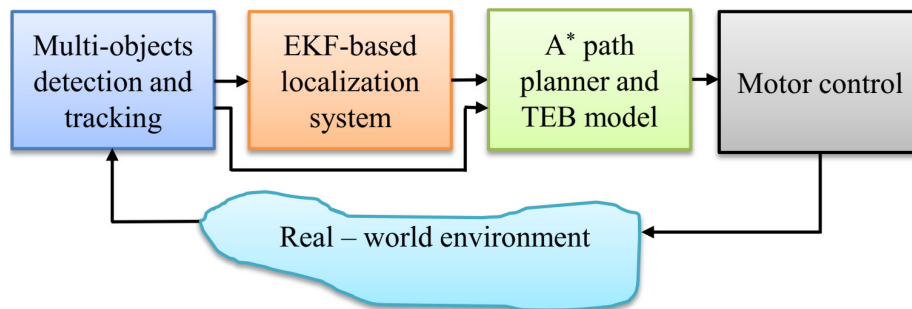


Figure 3. The block diagram of the mobile robot navigation system.

Mobility is the most essential navigation issue of mobile robots. To allow the mobile robots to navigate safely in a real-world environment, the mobile robots must deal with typical functional blocks of the navigation system, including perception, localization, motion planning, and motor control. To accomplish this, in this paper we propose an extended navigation scheme based on the conventional navigation scheme introduced by Siegwart et al. [21], as shown in fig. 3.

Figure 3 illustrates the proposed navigation scheme for autonomous mobile robots in dynamic environments. The navigation system consists of four functional blocks: In the first block, the obstacles in the robot's vicinity are detected and tracked. The output of this block is the position and velocity of the obstacles, which are used as input of the next blocks; In the second block, the extended Kalman filter-based localization system is used to estimate the position of the mobile robot in the environment; In the next block, a A* algorithm-based global path planning algorithm is utilized to find the global path from the starting position to the given goal; Then an extended timed elastic band technique is used to generate the optimal trajectory of the robot from the current position of the robot to

¹<https://www.quanser.com/products/qbot-2e>

the local target. Once the control command of the robot is obtained, it is used as input of the motor control block, which navigate the mobile robot to proactively avoid obstacles and approach the given goal. In the following sections, the proposed navigation system is presented in details.

2.4. Perception System

In this study, we use humans as dynamic obstacles in the vicinity of the mobile robot. Thus, we utilize the human detection and tracking algorithm developed in [22] to estimate the position and velocity of the surrounding humans. The basic idea of this approach is to fuse the human information detected by laser data as presented in [23] and Kinect sensor data as explained in [24] using a particle filter. A detailed description of the technique can be found in [22]. As a result, the output of the perception system are the obstacle states $\mathbf{s}_o^i = [x_o^i, y_o^i, \theta_o^i, v_o^i]^T$. This information is then used as the input of the motion planning system, as shown in fig. 3. Fig. 4 shows an example of the human detection and tracking system, in which the green dot is the human position in the navigation plane of the mobile robot.

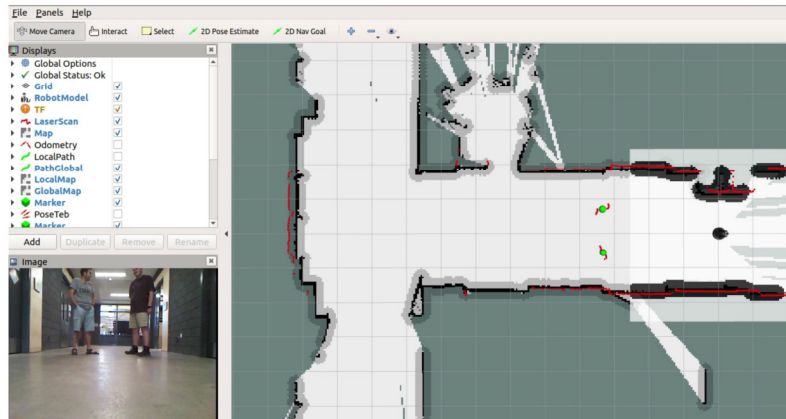


Figure 4. The example of the human detection and tracking algorithm.

2.5. Localization system

In order to navigate autonomously in a dynamic environment, a mobile robot must maintain an accurate knowledge of its position and orientation related to such environment. Therefore, in this study we utilize the localization system presented in [25]. In their paper, the authors utilized the extended Kalman filter presented in [26] to fuse the data from different data sources including wheel encoders, the global positioning system sensor and the inertial measurement unit sensor, to enhance the localization system of the autonomous mobile robots in the dynamic environments. In this study, we aim at estimating the robot states in the indoor environment. Thus, the data from the global positioning system sensor is missed. Figure 5 shows an example of the comparison between the proposed localization system and the conventional system. In which, the red curve illustrates the estimated robot's position using the proposed localization system, while the magenta curve depicts the robot's position using only odometry information. As a

result, the proposed localization system outperforms the conventional algorithm in term of accuracy.

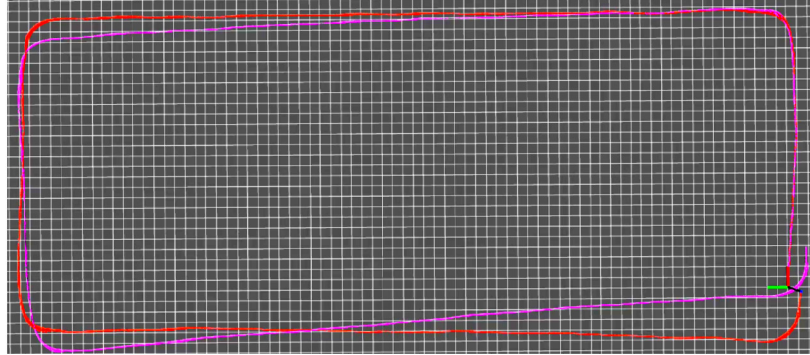


Figure 5. The comparison result of localization systems. The red curve illustrates the result of the proposed EKF-based localization algorithm while the magenta curve depicts the result of the conventional localization system.

2.6. Motion Planning System

2.6.1. Path Planning System

In this study, the A* path planning algorithm [27] is used for finding the global path from the initial position to the final position of the mobile robot. It is the one of the most popular choices for path planning, because it's fairly simple and flexible. This algorithm considers the map as a two-dimensional grid with each tile being a node or a vertex. And it is based on graph search methods and works by visiting vertices (nodes) in a graph starting with the current position of the robot all the way to the goal. The key to the algorithm is identifying the appropriate successor node at each step.

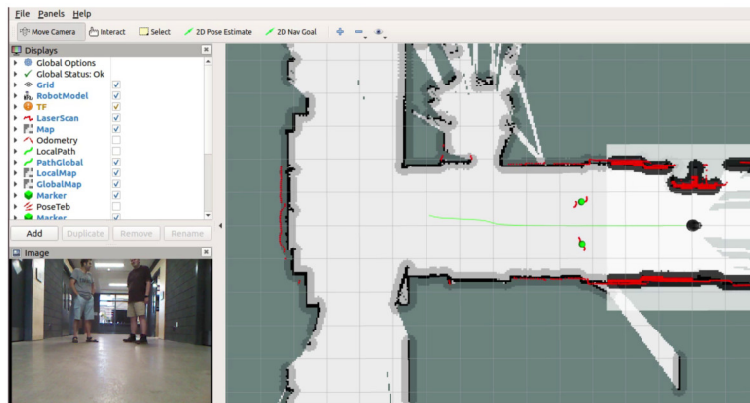


Figure 6. The example result of the A*-based path planing algorithm (the green curve).

Given the information regarding the goal node, the current node, and the obstacle nodes, we can make an educated guess to find the best next node and add it to the list. A* algorithm uses a heuristic algorithm to guide the search while ensuring that it will compute a path with minimum cost. It calculates the distance (also called the cost) between the current location in the workspace, or the current

node, and the target location. It then evaluates all the adjacent nodes that are open (i.e., not an obstacle nor already visited) for the expected distance or the heuristic estimated cost from them to the target, also called the heuristic cost $h(n)$. It also determines the cost to move from the current node to the next node, called the path cost $g(n)$. Thus, the total cost to get to the target node $f(n) = h(n) + g(n)$ is computed for each successor node and the node with the smallest cost is chosen as the next point. Figure 6 depicts an example of the path planning system using A* algorithm. The green curve is the found path from the initial position to the final position of the mobile robot.

2.6.2. Timed Elastic Band Technique

The elastic band [13] 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. However, 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 robot's 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 $k = 1, 2, \dots, N$ and time stamps ΔT_k with $k = 2, \dots, N-1$. Thus the robot's trajectory \mathbf{B} is presented as follows:

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

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:

$$V(\mathbf{B}) = \sum_{k=1}^{N-1} \left[\Delta T_k^2 + \delta_h \|\mathbf{h}_k\|_2^2 + \delta_v \|\min\{\mathbf{0}, \mathbf{v}_k\}\|_2^2 + \delta_o \|\min\{\mathbf{0}, \mathbf{o}_k\}\|_2^2 + \delta_a \|\min\{\mathbf{0}, \mathbf{a}_k\}\|_2^2 \right] \quad (2)$$

$$V(\mathbf{B}) = \mathbf{w}^T f(\mathbf{B}) \quad (3)$$

subject to:

$$0 \leq \Delta T_k \leq \Delta T_{\max},$$

$$\mathbf{h}_k(\mathbf{s}_{k+1}, \mathbf{s}_k) = 0, \text{ (Nonholonomic kinematics)}$$

$$\mathbf{o}_k(\mathbf{s}_k) \geq 0, \text{ (Clearance from surrounding obstacles)}$$

$$\mathbf{v}_k(\mathbf{s}_{k+1}, \mathbf{s}_k, \Delta T_k) \geq 0, \text{ (Limitation of robot's velocities)}$$

$$\alpha_k(\mathbf{s}_{k+1}, \mathbf{s}_k, \mathbf{s}_{k-1}, \Delta T_k, \Delta T_{k-1}) \geq 0 \text{ (Limitation of robot's accelerations)}$$

Where $\|\cdot\|$ denotes the Euclidean distance. 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 $T \approx \sum_{k=1}^{n-1} \Delta T_k$ 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:

$$\mathbf{B}^* = \arg_{\mathbf{B} \setminus \{s_1, s_2\}} \min V(\mathbf{B}) \quad (4)$$

where, the notation $\mathbf{B} \setminus \{s_1, s_2\}$ 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 control sequence \mathbf{B}^* . The detail information of the TEB algorithm is referred to [17].

The TEB technique has been applied in real-world environment and has achieved considerable success. However, in dynamic 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 enable the robot to switch to the current globally optimal trajectory among the candidate trajectories of distinctive topologies. Thus 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 present the extension TEB technique [17] and [18]. In this scenario, the mobile robot is requested to navigate 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 obstacles. The extension TEB technique consists of three main steps: (i) exploration, (ii) optimization and (iii) selection, as shown in fig. 7(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. 7(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; finally a set of M topological alternatives are identified using H-signature

technique [28]. As a result, the exploration graph is obtained, as shown in fig. 7(a). In the second step, 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 $p = 1, 2, \dots, M$. In the final step, the least-cost trajectory is selected \mathbf{B}_p^* 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 equations:

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

$$\hat{\mathbf{B}}^* = \arg_{\mathbf{B}_p^* \in \{\mathbf{B}_1^*, \mathbf{B}_2^*, \dots, \mathbf{B}_M^*\}} \min V_c(\mathbf{B}_p^*) \quad (6)$$

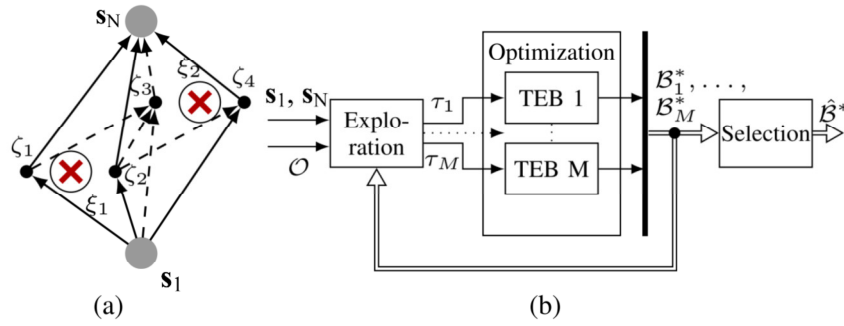


Figure 7. The example of exploration graph (a). The block diagram of parallel trajectory planning of time elastic bands (b) [18].

2.6.3. Proposed Extended Timed Elastic Band

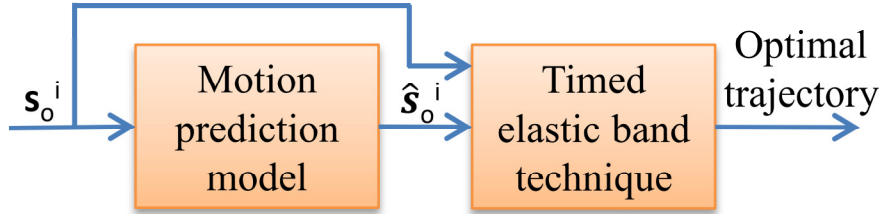


Figure 8. The proposed extended timed elastic band algorithm.

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 manner in the dynamic environments. Figure 1 shows a crossing scenario, in this case the TEB technique might generate an optimal trajectory in front of the obstacles, which may not be feasible. In order to address that issue, in this study we propose an extended timed elastic band (ETEB) model, as presented in fig 8. To accomplish that, we first predict the future states of the surrounding obstacles using the extended Kalman filter algorithm [26] and the data association technique [29]. The output of the motion prediction model is the future states of the obstacles \hat{s}_o^i . We then incorporate both the current states s_o^i and the future states \hat{s}_o^i of the obstacle o_i into

the conventional timed elastic band algorithm, as shown in fig.8. In other words, in stead of using only current states of the surrounding obstacles, the proposed extended timed elastic band model take both the current and future states into account. Assume that, there are R obstacles O_i , $i=1, 2, \dots, R$ in robot's vicinity. The robot will predict the future states of the obstacles. Thus, the total number of obstacles becomes \hat{O}_l , $l= R+R$. As results, the inequality constraint $\mathbf{o}_k(\mathbf{s}_k)$ that maintaining a minimum distance between all obstacles and the robot pose \mathbf{s}_k would be changed.

In this study, we first examine the proposed ETEB model in a simulation environment, and visualize the results in RViz environment². Simultaneously, the results of ETEB model are compared with the conventional TEB model. The simulation results are shown in fig.9. In this scenario, the mobile robot is requested to navigate from left to right, while avoiding two crossing people.

Obviously, at the time stamps T1 and T4, the simulation results of the conventional TEB algorithm and the proposed ETEB model are similar. Because, at the time stamp T1 the humans are approaching the straight line between the starting position and the goal position but they are far from the straight line, as shown in figs.9(a) and 9(e), or at the time stamp T4 the humans are close to the straight line but they are moving away the straight line, as shown in figs.9(d) and 9(h).

However, at the time stamps T2 and T3, the optimal trajectory is generated in front of two people, as shown in figs. 9(b) and 9(c), in these cases, the mobile robot can safely avoid people but its behavior might not smoothly. In contrast, the optimal trajectory is generated behind the left person, it illustrates that the robot is able to proactively avoid people, as shown in figs. 9(f) and 9(g). Because, the proposed ETEB model takes into account the potential collision of the robot with the surrounding humans.

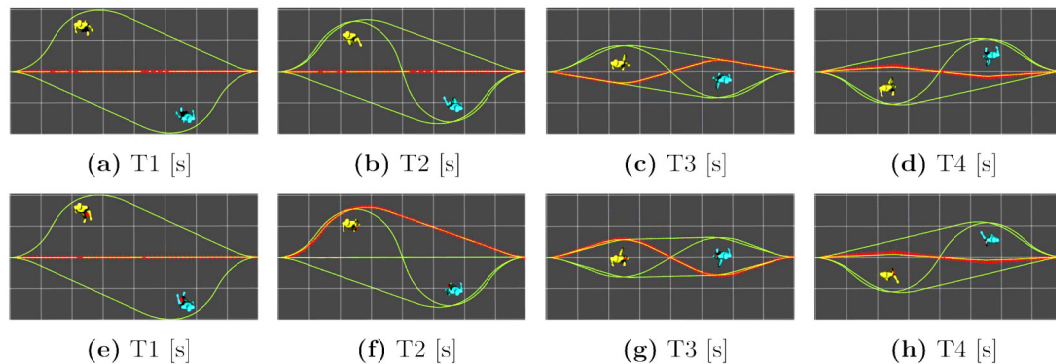


Figure 9. Four snapshots at four timestamps of the two experiments in the simulation environment. The first row shows the results of the conventional TEB algorithm, whereas the second row presents the results of the proposed ETEB model. The green curves illustrate the distinctive candidate trajectories, while the green curve with red arrows depicts the optimal selected trajectory of the mobile robot.

² <http://wiki.ros.org/rviz>

2.7. Motor Control

Once the optimal trajectory is generated by the proposed ETEB algorithm, the motion control command $\mathbf{u}_r = [v_r, \omega_r]^T$ 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:

$$\begin{bmatrix} x_r^{k+1} \\ y_r^{k+1} \\ \theta_r^{k+1} \end{bmatrix} = \begin{bmatrix} x_r^k \\ y_r^k \\ \theta_r^k \end{bmatrix} + \begin{bmatrix} v_r^k \Delta T_k \cos(\theta_k) \\ v_r^k \Delta T_k \sin(\theta_k) \\ L \omega_r^k \Delta T_k \end{bmatrix} \quad (7)$$

where L denotes the wheelbase of the robot.

3. EXPERIMENTS

We have implemented and installed the entire navigation system on our mobile robot platform to validate its feasibility and effectiveness. We then conducted experiments in a corridor-like environment to examine whether our robot equipped with the proposed ETEB model could safely and proactively avoid obstacles. In this study, we made use of humans as moving obstacles in all experiments.

3.1. Experimental Setup

In this paper, we used a QBot-2e mobile robot platform³ equipped with a RPL-IDAR A3 laser rangefinder and a NVIDIA Jetson TX2 Developer Kit, as shown in fig. 2(b). The laser rangefinder is used for robot localization and detecting humans in the vicinity of the mobile robot.

The software of the proposed framework is implemented using the C/C++ programming language. The entire navigation framework are developed based on the Robot Operating System (ROS) [30] and run on Jetson TX2 board. The conventional TEB package⁴ and HRVO library⁵ were inherited and modified for developing the proposed extended TEB algorithm. The human detection and tracking algorithm presented in Section 2.4 is utilized to estimate the human states \mathbf{s}_p including the position and motion of the humans in the robot's vicinity.

3.2. Experimental Results

We conducted an experiment in a corridor to examine whether our mobile robot could avoid humans, obstacles while navigating safely in the real-world environment. The robot is requested to navigate from the initial position to the final goal, while avoiding the obstacles during its navigation. The experimental results are shown in fig. 10. Videos with our experimental results can be found at the hyperlink⁶. The experimental results illustrate that, the proposed ETEB model is feasibility and effectiveness in real-world environments. It enables the mobile

³<https://www.quanser.com/products/qbot-2e>

⁴http://wiki.ros.org/teb_local_planner

⁵<http://gamma.cs.unc.edu/software/>

robot to safely avoid dynamic humans in the vicinity of the robot. In other words, the proposed extended timed elastic band model is able to apply to the real-world environments.

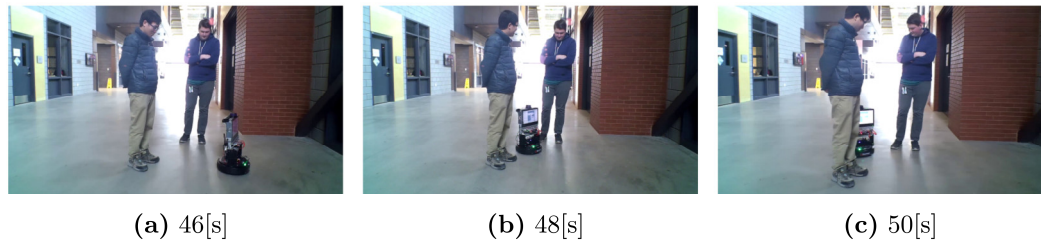


Figure 10. Three snapshots at four timestamps of the experiment in the sparse environment.

The experimental results illustrate that, the proposed ETEB model is feasibility and effectiveness in real-world environments. It enables the mobile robot to safely avoid dynamic humans in the vicinity of the robot. In other words, the proposed extended timed elastic band model is able to apply to the real-world environments.

4. CONCLUSION

We have presented a extended timed elastic band algorithm for autonomous mobile robots in dynamic environments. The main idea of the paper is to integrate the techniques proposed in our previous studies into a completed navigation system. In addition, we propose an extended timed elastic band technique for online trajectory planning, which allows the mobile robot to proactively avoid obstacles in the surrounding environment. We validate the effectiveness of the proposed model through a series of experiments in both simulated and real-world environments. The experimental 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.

In the future, we will apply powerful deep learning techniques [31] and [32] for predicting the motion and trajectory of the obstacles in the robot's vicinity and incorporate these information into the motion planning system of the autonomous mobile robots.

REFERENCES

- [1]. T. Kanda, M. Shiomi, Z. Miyashita, H. Ishiguro, and N. Hagita, "An affective guide robot in a shopping mall," in Proceedings of the 4th ACM/IEEE International Conference on Human Robot Interaction, 2009, pp. 173-180.
- [2]. G. Ferrer, A. Garrell, and A. Sanfeliu, "Social-aware robot navigation in urban environments," in European Conference on Mobile Robots (ECMR), September 2013, pp. 331-336.
- [3]. T. Kruse, A. K. Pandey, R. Alami, and A. Kirsch, "Human-aware robot navigation: A survey," *Robotics and Autonomous Systems*, vol. 61, pp. 1726-1743, 2013.
- [4]. J. Rios-Martinez, A. Spalanzani, and C. Laugier, "From proxemics theory to socially-aware navigation: A survey," *International Journal of Social*

- Robotics, September 2014.
- [5]. J. Cheng, H. Cheng, M. Q. . Meng, and H. Zhang, “*Autonomous navigation by mobile robots in human environments: A survey*,” in 2018 IEEE International Conference on Robotics and Biomimetics, December 2018, pp. 1981-1986.
 - [6]. O. Khatib, “*Real-time obstacle avoidance for manipulators and mobile robots*,” in Proceedings of the IEEE International Conference on Robotics and Automation, **vol. 2**, March 1985, pp. 500-505.
 - [7]. J. Borenstein and Y. Koren, “*The vector field histogram-fast obstacle avoidance for mobile robots*,” IEEE Transactions on Robotics and Automation, **vol. 7**, no. 3, pp. 278-288, June 1991.
 - [8]. D. Fox, W. Burgard, and S. Thrun, “*The dynamic window approach to collision avoidance*,” IEEE Transactions on Robotics and Automation, **vol. 4**, no. 1, pp. 23-33, Mar. 1997.
 - [9]. P. Fiorini and Z. Shillert, “*Motion planning in dynamic environments using velocity obstacles*,” International Journal of Robotics Research, **vol. 17**, pp. 760-772, 1998.
 - [10]. J. Snape, J. Van den Berg, S. Guy, and D. Manocha, “*The hybrid reciprocal velocity obstacle*,” IEEE Transactions on Robotics, **vol. 27**, no. 4, pp. 696-706, August 2011.
 - [11]. D. Helbing and P. Molnár, “*Social force model for pedestrian dynamics*,” Physical Review E, pp. 4282-4286, 1995.
 - [12]. M. Shiomi, F. Zanlungo, K. Hayashi, and T. Kanda, “*Towards a socially acceptable collision avoidance for a mobile robot navigating among pedestrians using a pedestrian model*,” International Journal of Social Robotics, **vol. 6**, no. 3, pp. 443-455, 2014.
 - [13]. S. Quinlan and O. Khatib, “*Elastic bands: connecting path planning and control*,” in Proceedings IEEE International Conference on Robotics and Automation, **vol. 2**, May 1993, pp. 802-807.
 - [14]. S. M. LaValle and J. J. Kuffner, Jr., “*Randomized kinodynamic planning*,” The International Journal of Robotics Research, **vol. 20**, no. 5, pp. 378-400, 2001.
 - [15]. D. Hsu, R. Kindel, J. C. Latombe, and S. Rock, “*Randomized kinodynamic motion planning with moving obstacles*,” The International Journal of Robotics Research, **vol. 21**, no. 3, pp. 233-255, 2002.
 - [16]. C. Rosmann, W. Feiten, T. Wosch, F. Hoffmann, and T. Bertram, “*Trajectory modification considering dynamic constraints of autonomous robots*,” in 7th German Conference on Robotics, May 2012, pp. 1-6.
 - [17]. C. Rosmann, F. Hoffmann, and T. Bertram, “*Integrated online trajectory planning and optimization in distinctive topologies*,” Robotics and Autonomous Systems, **vol. 88**, pp. 142-153, 2017.
 - [18]. C. Rosmann, M. Oeljeklaus, F. Hoffmann, and T. Bertram, “*Online trajectory prediction and planning for social robot navigation*,” in IEEE International Conference on Advanced Intelligent Mechatronics (AIM), 2017, pp. 1255-1260.

- [19]. G. Ferrer and A. Sanfeliu, "Proactive kinodynamic planning using the extended social force model and human motion prediction in urban environments," in IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2014), September 2014, pp. 1730-1735.
- [20]. X. T. Truong and T. D. Ngo, "Toward socially aware robot navigation in dynamic and crowded environments: A proactive social motion model," IEEE Transactions on Automation Science and Engineering, **vol. 14**, no. 4, pp. 1743-1760, October 2017.
- [21]. R. Siegwart, I. R. Nourbakhsh, and D. Scaramuzza, "Introduction to Autonomous Mobile Robots". The MIT Press, February 2011.
- [22]. X. T. Truong, N. Y. Voo, and T. D. Ngo, "RGB-D and laser data fusion-based human detection and tracking for socially aware robot navigation framework," in Proceedings of the 2015 IEEE Conference on Robotics and Biomimetics, December 2015, pp. 608-613.
- [23]. K. O. Arras, O. M. Mozos, and W. Burgard, "Using boosted features for the detection of people in 2d range data," in IEEE International Conference on Robotics and Automation, April 2007, pp. 3402-3407.
- [24]. M. Munaro, F. Basso, and E. Menegatti, "Tracking people within groups with rgb-d data," in IEEE/RSJ International Conference on Intelligent Robots and Systems, October 2012, pp. 2101-2107.
- [25]. L. A. Nguyen, P. T. Dung, T. D. Ngo, and X. T. Truong, "Improving the accuracy of the autonomous mobile robot localization systems based on the multiple sensor fusion methods," in International Conference on Recent Advances in Signal Processing, Telecommunications Computing, 2019, pp. 33-37.
- [26]. G. Welch and G. Bishop, "An Introduction to the Kalman Filter". Chapel Hill, NC, USA: Tech. Rep. TR-95-041, University of North Carolina at Chapel Hill, 2006.
- [27]. P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," IEEE Transactions on Systems Science and Cybernetics, **vol. 4**, no. 2, pp. 100-107, July 1968.
- [28]. S. Bhattacharya, "Topological and geometric techniques in graph-search based robot planning". Ph.D. dissertation, University of Pennsylvania, 2012.
- [29]. H. W. Kuhn, "The Hungarian Method for the Assignment Problem". Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 29-47.
- [30]. R. Wheeler, and A. Ng, "ROS: An open-source Robot Operating System," in ICRA Workshop on Open Source Software, **vol. 32**, 2009, pp. 151-170.
- [31]. A. Alahi, K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei, and S. Savarese, "Social LSTM: Human trajectory prediction in crowded spaces," in IEEE Conference on Computer Vision and Pattern Recognition, June 2016, pp. 961-971.
- [32]. A. Rudenko, L. Palmieri, M. Herman, K. M. Kitani, D. M. Gavrila, and K. O. Arras, "Human motion trajectory prediction: A survey," <https://arxiv.org/abs/1905.06113v3>, 2019.

TÓM TẮT

MỘT HỆ THỐNG ĐIỀU HƯỚNG ĐƯỢC TÍCH HỢP CHO ROBOT DI ĐỘNG TRONG MÔI TRƯỜNG ĐỘNG

Để robot di động có khả năng điều hướng an toàn trong môi trường động, robot phải thực hiện đầy đủ bốn khối chức năng cơ bản trong hệ thống điều hướng bao gồm: nhận thức, xác định vị trí, lập kế hoạch chuyển động và điều khiển động cơ. Trong nghiên cứu này, chúng tôi trình bày một hệ thống điều hướng tích hợp cho robot di động tự trị trong môi trường năng động bằng cách kết hợp các kỹ thuật được đề xuất trong các nghiên cứu trước đây của chúng tôi, bao gồm hệ thống phát hiện và theo dõi đối tượng, hệ thống định vị và hệ thống lập kế hoạch chuyển động, vào một hệ thống điều hướng hoàn chỉnh. Ngoài ra, chúng tôi còn đề xuất một kỹ thuật ETEB để lập kế hoạch quỹ đạo trực tuyến cho phép robot tránh được một cách chủ động vật cản xung quanh. Sau đó, chúng tôi xác nhận tính hiệu quả của mô hình đề xuất thông qua một loạt các thử nghiệm trong cả môi trường mô phỏng và thực tế. Kết quả thử nghiệm cho thấy, mô hình điều hướng được đề xuất của chúng tôi có khả năng điều khiển các robot di động để chủ động tránh các chướng ngại vật động, cung cấp điều hướng an toàn cho các robot.

Từ khóa: Kỹ thuật TEB; Robot di động tự động; Hệ thống điều hướng; Hệ thống lập kế hoạch chuyển động; Tránh va chạm chủ động.

Received 19th March 2020

Revised 21th April 2020

Published 06th May 2020

Author affiliations:

The Faculty of Control Engineering, Le Quy Don Technical University, Hanoi, Vietnam.

*Corresponding author: lananh.bk@gmail.com.