Toward socially aware trajectory planning system for autonomous mobile robots in complex environments

Van Hung Nguyen, Van Bay Hoang, Chu Anh My, Le Minh Kien and Xuan Tung Truong

***Abstract*— This paper proposes a socio-spatio-temporal human characteristics-based socially aware navigation framework that enables mobile service robots to both approach and avoid humans in dynamic social environments. The proposed framework consists of two major stages. In the first stage, the robots estimate the approaching poses of the robot to the human or human group. In the second stage, the proposed framework will estimate an optimal robot's trajectory using the online trajectory planning technique. The control command extracted from the optimal trajectory is then utilized to drive the mobile robot to approach the individual humans or human groups, while avoiding regular obstacles, humans and human groups during the robot's navigation. The proposed framework is verified in the Gazebo-based simulation environment. The simulation results illustrate that, the mobile robots equipped with our proposed framework are able to safely and socially approach and avoid individual humans and human groups, providing socially acceptable behavior for the robots.**

I. INTRODUCTION

Approaching humans in socially acceptable manners while ensuring the human safety and comfort is necessary for initiating any collaboration and communication activities between social robots and humans. Hence, mobile service robots must approach a human or a human group to interact or collaborate with them, and provide them professional and domestic services. To achieve that, a number of navigation systems, which enable the mobile robots to approach humans, have been recently developed [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. However, a few existing methods were developed for approaching human groups, which is considered more challenging than approaching a single person because the robots have to deal with social rules of both individuals and human groups.

The existing human approaching techniques can be roughly divided into two categories according to the number of humans to be approached: (1) approaching a single person and (2) approaching a group of people. In the former, the developed techniques are capable of driving a mobile robot to approach a standing, moving, or sitting person. In the later, the conventional navigation systems can guide the mobile robot to approach a group of stationary people. The existing human approaching algorithms have been mostly proposed for mobile robots to approach a single person, e.g., a seated person [1], a standing person [2], a sitting and standing person [3], and a moving person [4], [5] and [6]. Some of these human approaching systems have been implemented and verified on mobile platforms to illustrate the viability of generating socially acceptable approaching behaviours of mobile robots. Recently, a few navigation systems have been proposed to allow the robot to safely and socially approach a human group [7], [8], [9], [10]. Nevertheless, most of these methods have only been implemented and validated in static or semi-dynamic environments, and the human groups are only stationary.

To overcome the above-mentioned drawbacks, in this paper, we propose a socially aware navigation framework, which allows the mobile service robot to safely and socially approach and avoid individual humans and human groups in dynamic environments with socially acceptable behaviours. The proposed framework incorporates the socio-spatio-temporal characteristics of the human and human groups to estimate the approaching pose of the mobile robot to the human groups. These characteristics and estimated approaching poses are then utilized as inputs of the timed elastic band (TEB) technique, which takes into account the robot dynamics. The motion control commands generated by the proposed model can drive the mobile robot to reach the estimated approaching pose while avoiding other people during the robot's navigation.

The remainder of this paper is organized as follows. Section II presents the proposed socially aware navigation framework for mobile service robots in dynamic social environments. Section III shows comprehensive simulation results developed on the Robot Operating System and Gazebo simulator. We draw conclusions in Section IV.

II. PROPOSED FRAMEWORK

A. Architecture of Socially Aware Navigation Framework

The primary objective of the paper is to develop a socially aware navigation framework, which enables the mobile robots to navigate safely and socially in the dynamic social environments, providing the safety and comfort for the humans, and the socially acceptable behaviors for the robots in two essential tasks: (i) avoiding humans, and (i) approaching humans. To achieve that, in this paper we develop a socially aware navigation framework based on the conventional robot navigation scheme presented in [11], as shown in Fig. 1.

Figure 1 depicts the extended navigation scheme for mobile service robots in dynamic social environments. The proposed social navigation framework is composed of two essential components: (1) the conventional navigation system, and (2) the socially aware navigation framework (in the dash line box). In the first part, the conventional navigation

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2020 7th NAFOSTED Conference on Information and Computer Science (NICS) | 978-0-7381-0553-6/20/$31.00 ©2020 IEEE | DOI: 10.1109/NICS51282.2020.9335845

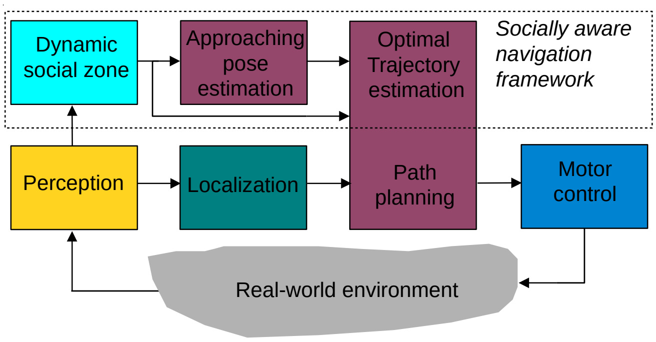


Fig. 1. The block diagram of the mobile robot navigation system.

system consists of four typical modules, including the perception, localization, motion planning, and motor control. In the extended part of the proposed framework, the dynamic social zone (DSZ) block is utilized to model the space around the human and human groups using the socio-spatio-temporal human characteristics including human's position, orientation and motion, and the social interactions including human groups and human–object interactions. Once the DSZ have been modeled, the approaching pose estimation block is made use of to estimate the approaching pose of the robot to the individual humans or human groups. The outputs of the DSZ block and the estimated approaching poses are then fed into the optimal trajectory estimation block, which enables the mobile robot to estimate optimal robot's trajectory. The control command generated from the robot's trajectory allows the mobile robot to safely and socially approach humans and human groups while avoiding the other humans and obstacles in socially acceptable manners.

B. Robot and Human States

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. In dynamic social environments, 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 the estimated approaching pose $\mathbf{s}_g = [x_g, y_g, \theta_g, v_g, \omega_g]^T$ while safely avoiding the individual humans and human groups during its navigation.

C. Dynamic Social Zone

To safely and socially approach and avoid a human or a human group in socially acceptable manners, a mobile robot must be capable of modelling the human and human group infomation. In this study, we adopted the dynamic social zone technique proposed by Truong et al. [12]. Therefore, in this section we will briefly present the DSZ model. The DSZ algorithm is integrated of six functional blocks, including: (1) human detection and tracking, (2) human states extraction, (3) social interaction detection, (4) extended personal space, (5) social interaction space, and (6) dynamic social zone. Specifically, a human detection and tracking function is used to detect and track humans in the real-world environment. Once the human states including position, orientation and motion are extracted and the social interactions including human groups and human-object interactions are detected, an extended personal space and a social interaction space are built. As a result, a dynamic social zone is consequently generated around the humans and human groups. The DSZ is then used for estimating the approaching pose of the robot to the humans, and avoiding humans in the next section. Technical details of such functional blocks can be found in Truong et al. [12] and [13].

D. Approaching Pose Estimation Algorithm

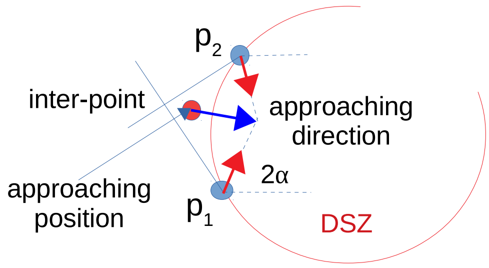


Fig. 2. An example of approaching pose estimation algorithm.

In order to approach a human or a human group in socially acceptable manners, a mobile service robot should be capable of estimating an approaching pose, and then safely and socially navigate towards this pose. Therefore, an approaching pose estimation algorithm plays an important role in our proposed socially aware navigation framework. Truong et al. [12] and [13] figured out that, the suitable approaching position of the robot to a human or a human group should be located in the field of view of the humans and outside the DSZ area. In this study, we proposed new approaching pose estimation algorithms, as presented in Algorithms 1 and 2. The main idea of the algorithms is that, we first find the suitable inter-areas of the field of view of all humans in the group. We then reduce the inter-areas by the DSZ. Finally, we find the center points of the inter-areas, and those points are the candidate approaching positions. The direction of the robot is the direction of the vector from the approaching positions to the person's position or to the center of the human group. Figure 2 illustrates an example result of the approaching pose estimation algorithm. In this example the robot wants to estimate the approaching pose to a group of two people. The input of the approaching pose estimation algorithms is the DSZ, set of people $\mathbf{P}$, and humans field of view 2α. Whereas, the output of the algorithms is a set of candidate approaching poses $\mathbf{S}_g = \{\mathbf{s}_g^1, \mathbf{s}_g^2, ..., \mathbf{s}_g^L\}$. We then select an approaching pose based on the distance from the robot to the candidate approaching poses. In the next section, we will present an algorithm for estimating an optimal

Algorithm 1: Approaching pose estimation algorithm of a group of people

input : Dynamic social zone DSZ, set of people $\mathbf{P} = \{\mathbf{p}_1, \mathbf{p}_2, ..., \mathbf{p}_N\}$, human field of view $\mathbf{2}\alpha$
output: Set of approaching poses $\mathbf{S}_g = \{\mathbf{s}_g^1, \mathbf{s}_g^2, ..., \mathbf{s}_g^L\}$

begin
  $c\_point \leftarrow \emptyset$; $app\_point \leftarrow \emptyset$;
  $\mathbf{S}_g \leftarrow \emptyset$; $delta\_\alpha \leftarrow \emptyset$; $step\_\alpha \leftarrow 2.5$;
  while True **do**
    $c\_point \leftarrow$ computeGroupCenter($\mathbf{P}$);
    for i =1, N **do**
      tmpl1 $\leftarrow$ Line($\mathbf{p}_i$,c_point);
      line1 $\leftarrow$ rotateRight(tmpl1,$\mathbf{p}_i$,α+$delta\_\alpha$);
      if (i==N) **then**
        tmpl2 $\leftarrow$ Line($\mathbf{p}_1$,c_point);
        line2 $\leftarrow$ rotateLeft(tmpl2,$\mathbf{p}_1$,α+$delta\_\alpha$);
      else
        tmpl2 $\leftarrow$ Line($\mathbf{p}_{i+1}$,c_point);
        line2 $\leftarrow$ rotateLeft(tmpl2,$\mathbf{p}_{i+1}$,α+$delta\_\alpha$);
      end if
      $i\_point \leftarrow$ line1 $\cap$ line2;
      $visual\_area \leftarrow$ polygon(i_point,$\mathbf{p}_i$,$\mathbf{p}_{i+1}$);
      $app_area \leftarrow visual_area \backslash$DSZ;
      $app\_point \leftarrow$ computeCenterPoint(app_area);
      $\theta \leftarrow$ atan2(app_point,c_point);
      $\mathbf{S}_g$.append(app_point,θ);
    end for
    if($\mathbf{S}_g$==$\emptyset$) **then**
      $delta\_\alpha$ += $step\_\alpha$;
    else
      break;
    end if
  end while
  Return $\mathbf{S}_g$;

Algorithm 2: Approaching pose estimation algorithm of a human–object interaction

input : Dynamic social zone DSZ, a person $\mathbf{p}$, an object $\mathbf{o}$, human field of view $\mathbf{2}\alpha$, r_{step}
output: Set of approaching poses $\mathbf{S}_g = \{\mathbf{s}_g^1, \mathbf{s}_g^2, ..., \mathbf{s}_g^L\}$

begin
  Initialize rs_circle;
  $c\_line \leftarrow$ Line($\mathbf{p}$,$\mathbf{o}$);
  $l\_line \leftarrow$ rotateLeft(c_line,$\mathbf{p}$,α);
  $r\_line \leftarrow$ rotateRight(c_line,$\mathbf{p}$,α);
  while True **do**
    $s\_circle \leftarrow$ circle($\mathbf{p}$,rs_circle);
    $lv\_area \leftarrow$ polygon($\mathbf{p}$,c_line,l_line,s_circle);
    app_area.append($lv_area \backslash$DSZ);
    $lr\_area \leftarrow$ polygon($\mathbf{p}$,c_line,r_line,s_circle);
    app_area.append($rv_area \backslash$DSZ);
    for i=1, length(app_area) **do**
      $app\_point \leftarrow$ computeCenterPoint(app_area);
      $\theta \leftarrow$ atan2(app_point,$\mathbf{p}$);
      $\mathbf{S}_g$.append(app_point,θ);
    end for
    if($\mathbf{S}_g$==$\emptyset$)
      rs_circle += r_{step};
    else
      break;
    end if
  end while
  Return $\mathbf{S}_g$;

robot's trajectory from the current robots pose to the selected approaching pose.

E. Timed Elastic Band Technique

To socially navigate from the current position of the robot to the selected approaching pose, in this study we adopt the timed elastic band (TEB) technique. Because it is an online trajectory planning algorithm for online collision avoidance, and has been successfully applied in dynamic environments [14], [15] and [16]. 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:

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

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:

$0 \leq \Delta T_k \leq \Delta T_{max}$,
$\mathbf{h}_k(\mathbf{s}_{k+1}, \mathbf{s}_k) = 0$, (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)

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.

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

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:

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

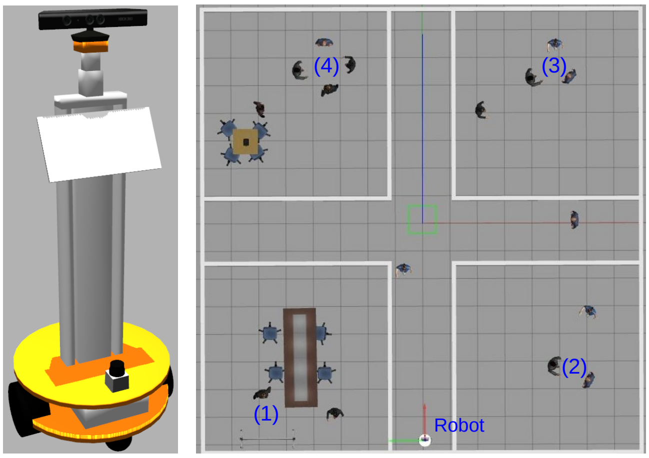
Algorithm 3: Timed elastic band algorithm

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 $\mathbf{u}_r = [\upsilon_r, \omega_r]^T$;

The TEB approach utilized the Levenberg-Marquardt algorithm [17] 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 [15] 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 [14] and [16], which enable the robot to switch to the current globally optimal trajectory among the candidate trajectories of distinctive topologies.

Algorithm 3 presents the extension TEB technique [14] and [16], which consists of three major steps: (i) exploration (Lines 2-6 of the Algorithm 3), (ii) optimization (Lines 7-11 of the Algorithm 3) and (iii) selection (Lines 12-13 of the Algorithm 3). The input of the Algorithm 3 includes the robot state $\mathbf{s}_r$, start pose $\mathbf{s}_s$, goal pose $\mathbf{s}_g$ and set of obstacles $\mathbf{O}$, 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 [18] 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.



(a) (b)

Fig. 3. The robot model and simulation scenario: (a) The 3D model of the robot using the Gazebo simulator with a simulated Kinect sensor and a laser rangefinder; (b) A simulated office-like scenario with rooms, doors, corridors, walls, objects, interesting objects, and humans. A mobile robot, six moving people, and ten standing people are distributed in the scenario. The robot has to sequentially navigate to approach individual humans, and human groups in various social situations: (1) a human–object interaction; (2) a group of two standing people; (3) a group of three standing people; and (4) a group of four standing people.

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

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

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

F. System Integration

Once the optimal trajectory is generated by the TEB algorithm, the motion control command $\mathbf{u}_r$=[υ_r, ω_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 $\mathbf{s}^k_r = [x^k_r, y^k_r, \theta^k_r]^T$. Therefore, the state of the robot at the time $(k+1)$ is governed by the following equation:

$$\begin{bmatrix} x_r^{k+1} \\ y_r^{k+1} \\ \theta_r^{k+1} \end{bmatrix} = \begin{bmatrix} x_r^{k} \\ y_r^{k} \\ \theta_r^{k} \end{bmatrix} + \begin{bmatrix} \frac{v^r_r + v^l_r}{2}\cos(\theta_k)dt \\ \frac{v^r_r + v^l_r}{2}\sin(\theta_k)dt \\ \frac{v^r_r - v^l_r}{L}dt \end{bmatrix} \tag{6}$$

where, v^r_r and v^l_r 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^l_r are computed using the velocity control command $\mathbf{u}_r$ as follows:

$$v^r_r = \upsilon_r + \frac{L\omega_r}{2}dt \tag{7}$$

$$v^l_r = \upsilon_r - \frac{L\omega_r}{2}dt \tag{8}$$

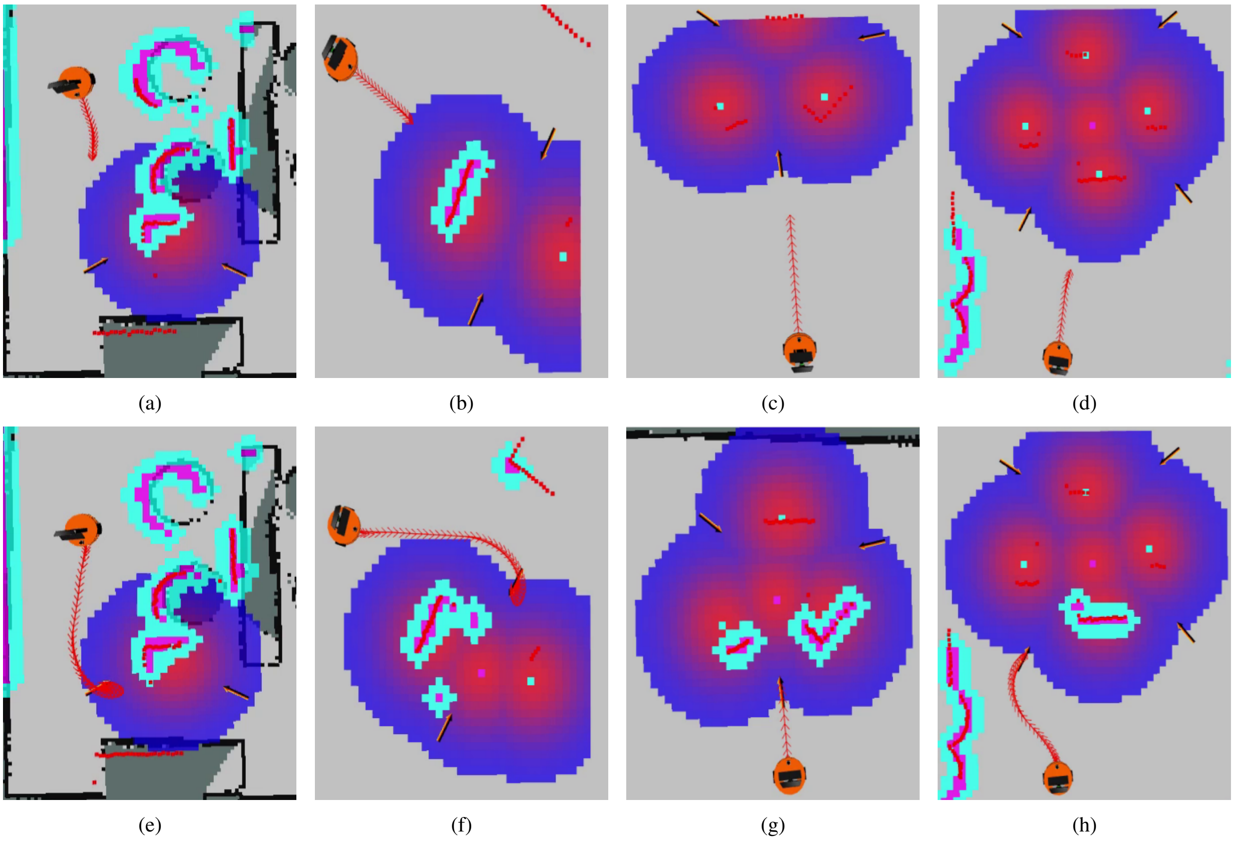


Fig. 4. Four snapshots of the results of four scenarios in the simulation environment. The first row illustrates the results of the approaching pose estimation algorithm. The second row presents the results of the optimal robot's trajectory, which is the curve with red arrows.

III. Simulation

To verify the effectiveness of the proposed algorithm and narrow the gap between the simulated and real-world environments, we implemented and tested the proposed human approaching framework using the Gazebo simulator [19] and Robot Operating System (ROS) [20]. We created an office-like scenario with rooms, walls, doors, objects, interesting objects and humans, as shown in Fig. 3(b). The conventional TEB package[1] were inherited.

A. Simulation Setup

In the Gazebo simulator, we built up a 3D model of the simulated mobile platform, and added a simulated Kinect sensor and a laser rangefinder on it, as shown in Fig. 3(a). Thanks to the physical properties available in the Gazebo simulator, we have the advantage of being able to implement and test our method, which was developed in ROS, in the simulation before verifying it on the real mobile platform. The standard Kinect sensor composed of an infrared light projector, a depth sensor, a RGB camera, and a multi-array microphone was positioned at a 1.35 m height from the ground. The depth sensor range is from 0.8 m to 6.0 m with a vertical viewing angle of 43^o and a horizontal viewing angle of 57^o. This low-cost hardware can provide RGB-D data with 640 x 480 pixels resolution at a maximal frame rate of 30 frames per second. The laser range finder, the Hokuyo UTM-30LX-EW laser positioned at the height of 0.4 m, provides distance measurements up to 25.0 m in the angular field of view 270^o, and is utilized for robot localization system.

We have created an office-like environment based on Gazebo simulator. The 3D models of the humans and objects downloaded from 3D Warehouse[2] were placed to create social situations. The complete simulated office-like environment is shown in Fig. 3(b). In this scenario, we deployed 16 3D-human models, $\mathbf{P} = \{\mathbf{p}_1, \mathbf{p}_2, ..., \mathbf{p}_{16}\}$, regular objects, and interesting objects. The scenario is generated with four crucial situations to demonstrate the typical interaction situations between humans and the robot in social contexts. The mobile robot is guided to sequentially navigate to approach the humans and human groups in these social situations, as shown in Figure 3(b). The humans are detected if they are within the field of view of the Kinect sensor and are not occluded by the other humans, walls, or objects.

B. Simulation Results

The simulation results are shown in Fig. 4. A video of our experiments can be found at the link[3].

As can be seen in Fig. 4(a), 4(b), 4(c) and 4(d). The mobile robot equipped our proposed socially aware navigation framework has ability to model the space around the

[1] http://wiki.ros.org/teb_local_planner

[2] https://3dwarehouse.sketchup.com

[3] https://youtu.be/qWjfSsiREWk

individual humans and human group, and estimate suitable approach poses of the robot to the humans and the group of people. In addition, the mobile robot is capable of generating socially optimal trajectory, which allows the mobile robot to navigate safely and socially to the selected approaching pose, as presented in Fig. 4(e), 4(f), 4(g) and 4(h).

In summary, the simulation results illustrate that, the mobile robot equipped with the proposed framework is able to estimate the approaching poses and socially robot's trajectory, and safely and socially drive the mobile robot to the selected pose, providing the comfortable safety for the mobile robot in two essential task approaching and avoiding the humans and human groups.

IV. CONCLUSIONS

We have presented a socio-spatio-temporal human characteristics-based socially aware navigation framework that enables mobile service robots to both approach and avoid humans in dynamic social environments. The proposed framework consists of two major stages. In the first stage, the robots estimate the approaching poses of the robot to the human or human group. In the second stage, the proposed framework will estimate an optimal robot's trajectory. The proposed framework is verified in the Gazebo-based simulation environment. The simulation results illustrates that, the mobile robots equipped with our proposed framework are able to safely and socially approach and avoid individual humans and human groups, providing socially acceptable behavior for the mobile robots.

In the future, we will install the proposed socially aware navigation framework on our mobile robot platform and conduct experiments in real-world environments to verify its feasibility and effectiveness.

ACKNOWLEDGMENT

This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 102.01-2018.10.

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