HATEB-2: Reactive Planning and Decision making in Human-Robot Co-navigation

Phani Teja S[1] and Rachid Alami[1,2]

Abstract— **We propose a new framework combining decision making and planning in the human-robot co-navigation scenario. This new framework, called HATEB-2, introduces different modalities of planning and shift between them based on the situation at hand. These transitions are controlled by the decision making loop present on top of the planning. We also present the improvements made to human prediction and estimation along with the modifications to a few social constraints from our previous work, that are included in HATEB-2. Finally, several experiments are performed in human-robot co-navigation scenarios and results are presented. One of the modalities of HATEB-2 is used in EU-funded MuMMER [1] project (`http://mummer-project.eu/`).**

I. Introduction

The study of human-aware navigation, sometimes, called social navigation is increasing day by day as assistive robots are being deployed at various places like airports, malls [1], hospitals etc. Various methods of human-aware navigation are proposed, and most of them are based on the theory of proxemics [2] and social force model [3]. Many of the earlier proposed methods, however, do not use human predictions in the planning and hence faced difficulties in complex situations. Consequently, human motion predictions and estimations were introduced into human-aware navigation to have a better planning system. Our previous work, Human Aware Timed Elastic Band (HATEB) based co-navigation planner [4] falls into this category, including human estimations and predictions. HATEB includes human predictions by simultaneously planning for humans and the robot. This allows HATEB to handle intricate situations like narrow corridor crossing and door crossing where human and robot cooperative motion is needed.

With the increasing complexity in environments and the need to navigate robots in such environments, decision making has been introduced into planning [5], [6]. However, these frameworks might make the robot wait in confined spaces instead of proactively planning and hence resulting in larger execution times. Therefore, in this paper, we propose HATEB-2, a new modality based human-robot co-navigation framework, that deals with decision making, to solve crowded as well as intricate scenarios. This is achieved by shifting between different modalities and by simultaneous human-robot planning, similar to HATEB. The main contributions of this paper are three-fold: 1) HATEB-2, a new human-robot co-navigation planner comprising decision making. 2) Improvements and modifications to HATEB. 3) A detailed analysis of human-robot co-navigation in a variety of situations.

This paper is organised as follows. After an overview of the related works in Section II, Section III describes the architecture of the proposed framework along with the modifications in HATEB. It also presents improvements made to human predictions in HATEB-2. Section IV reports the results and analysis based on several experiments. Section V presents the experiments on the real robot, and finally, Section VI talks about the conclusions and future work.

II. Related Work

Human-aware navigation involves navigation planning of a robot around humans. Humans follow certain social norms while navigating in an environment and expect the same from others, who are navigating in the same environment. Therefore, a robot cannot move along the shortest path while navigating around humans. Otherwise, it will create confusion and discomfort to humans. The theory of proxemics [2] provides a set of rules, that can be used to realize more human-like behaviour during robot motion and non-motion tasks [7]. Most state-of-art human-aware navigation planners add proxemics costs around humans in a grid-based map representation of the robot's working environment [8]. There are other approaches like social force models [3] which also make use of proxemics. Nonetheless, proxemics alone may not be sufficient to completely generate a human acceptable trajectory for the robot. In the human-aware navigation planner proposed by Sisbot et al. [9], other social criteria like visibility and hidden zones are considered along with proxemics. Another navigation framework proposed by Kruse et al. [10] introduces the directional cost model, which attempts to solve the spatial conflict by adjusting velocity instead of the path when possible. This model has shown to increase the legibility of the robot motions and hence in HATEB-2, we introduced some new constraints that restrict the path change and adjust the velocity (Eq. (1)) based on the distance between human and the robot. The study conducted by Kruse et al. [11] shows that humans prefer the robot to follow this strategy, especially in path crossing scenarios.

Employing social constraints alone may not be sufficient to develop a socially acceptable navigation planner, and this arises the need for including human motion predictions into the framework [12]. Many methods based on social force model [3] predict homotopically distinct trajectories for humans and design planners that learn the navigation policies for the robot based on human demonstrations [12]. Although

[1]Authors are with LAAS-CNRS, Universite de Toulouse, CNRS, Toulouse, France, {ptsingaman, rachid.alami}@laas.fr

[2]Author is with Artificial and Natural Intelligence Toulouse Institute (ANITI)

these methods involving independent human predictions work fine in large open spaces, they might require re-learning of parameters to handle situations such as long corridor crossing or passage through a door, where a cooperative behaviour is needed between human and the robot. Hence planning for humans along with the robot is required in such situations. The approach presented by Ferrer et al. [13], uses the social force model for both to predict human paths and to control the robot motion. In this approach, the human predictions based on the previously planned path are used. Other approaches [14], [15] try to predict the possible human goals based on some type of reasoning and generate locally optimal motion for the robot. One of the recent approaches [16] suggests the use of probabilistic human predictions to handle various uncertainties and plan robot motion on top of these probabilistic predictions. This approach is particularly useful in systems with unreliable sensors. All these approaches are effective in densely crowded environments as a virtue of remaining purely reactive but could lead to needless detours in intricate situations. Our previous work [4] is specifically developed to handle such intricate situations in semi-crowded environments. Such planning for humans along with the robot is usually required in robot-human handover scenarios, to know where to perform a task, and who performs a task [17], [18]. Similarly, in HATEB, the tightness of the elastic band can be adjusted to make either robot or the human take more load.

The concept of modality shifting in human-aware navigation is discussed in works by Mehta et al. [6] and Qian et al.[5], where Partially Observable Markov Decision Process (POMDP) is used for decision making. In both of the works, different modalities necessary for human-aware navigation are proposed, assuming that the robot takes all the load of the navigation process. Hence these methods may also suffer problems like purely reactive planners in complex situations leading to unnecessary detours or long halts. HATEB-2 includes HATEB as one of the modalities and hence can handle both intricate situations as well as crowded scenarios, by switching between different modalities when needed. In this work, however, we focus mainly on different intricate situations involving cooperative motion between the human and the robot.

III. HATEB 2: Architecture and Methodology

The proposed framework, HATEB-2 combines decision making and planning into a single framework and opens up new frontiers for reactive planning. This new framework can encompass a large variety of problems by allowing the transition between different modalities based on context. In this work, however, we study only the human-robot co-navigation problem. HATEB-2 introduces decision making on the top of planning, and this makes the planner to adapt better to the situations at hand. These situations might be very different from each other and need to be handled differently. Hence, having only a single way of planning may not be sufficient. Therefore, we introduce different modalities into planning, and the transition between these modes is handled by the decision making loop. The decision making loop of HATEB-2 can be seen in Fig. 1. In this work, we use three different modalities, and all these modalities are based on Timed Elastic Band (TEB) [19] approach.

TEB is one of the well-known approaches for robot navigation around dynamic obstacles, which allows us to include several kinodynamic and custom constraints (like holonomic, non-holonomic, human-aware constraints) into the local reactive planning. TEB is modelled as a non-linear least squares optimization problem using hypergraphs [20] which makes it possible to introduce new constraints by adding new edges (and sometimes vertices) to this hypergraph. In our previous work [4], we extended the Timed Elastic Band approach by introducing prediction and optimization of human trajectories along with social constraints into it, thereby making it Human Aware Timed Elastic Band (HATEB). HATEB addresses the human-robot co-navigation problem by adding elastic bands to both humans and robot, optimizing the human-plans and the robot-plans together taking into consideration the human-aware constraints. More details about the implementation and the social constraints can be found in [4].

In HATEB-2, HATEB is used as one of the modalities and encompasses a large part of human-robot co-navigation planning. We have also made few modifications to HATEB to remove its drawbacks before using it in the new framework. The other two modalities possess the same social constraints as HATEB, but they differ significantly in their behaviour. Different modes of HATEB-2 and its architecture along with modifications of HATEB are discussed below. We start with explanation of different modalities and the decision making process.

A. Architecture and different Modes of planning

HATEB-2 operates mainly in three modes of planning: 1) Single Band, 2) Dual Band and 3) VelObs, however, an intermediate mode is present before the occurrence of Dual Band $\rightarrow$ VelObs[1] transition. The intermediate mode refers to the trajectory planning in the close vicinity of the human (for distances $\leq 2.5m$), where large velocity changes are restricted, and the elastic band is made tighter. More details about these changes are presented in the next sub-section. We briefly explain different modes of this framework below.

1) Single Band Mode: Here, the elastic band is added only to the robot to avoid the obstacles in the environment. This mode is computationally less expensive as it does not deal with human estimates and trajectory predictions. This mode can be seen as a purely reactive mode with social constraints. In this work, this mode is used when the humans are far from the robot or there are no humans. However, this can be extended to the crowded situations when needed.

2) Dual Band Mode: This mode is same as the standard HATEB where elastic bands are added to humans and robot and trajectories are optimized simultaneously. However, few modifications are made before using it in HATEB-2 and

[1] $\rightarrow$ represents one sided transition

these are explained in the next sub-section. This mode adapts trajectory planning according to the motion of the humans and the predicted goals. The main advantage of this mode is that it always proposes a possible solution from the current scenario besides being more proactive. The main drawback is the entanglement problem which is discussed below.

The entanglement Problem: HATEB assumes that humans keep moving and try to adapt its path according to their motion. Therefore, the planner continuously plans assuming that both human and the robot will be moving at each instant of time. This assumption could result in an entanglement of trajectories when the human no longer moves, and the robot keeps waiting for the human to move, neglecting the other possible solutions. These situations can commonly occur in corridors. Two such situations are shown in Fig. 2. This problem is addressed by HATEB-2 by shifting to VelObs mode and partially removing the human plan prediction.

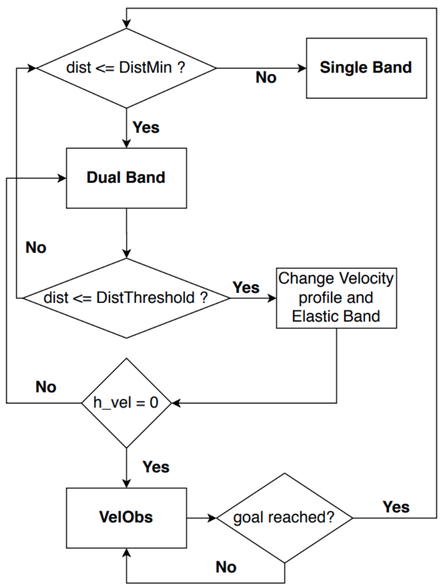

Fig. 1. Mode transition procedure. *dist* is the current distance between the closest human and the robot, *DistMin* is the minimum value of *dist* to add a double band and *DistThreshold* is the minimum cutoff *dist* to initiate transition between Dual Band and VelObs. *h_vel* is the velocity of human. Note that, under *DistThreshold*, the elastic band and velocity profile are changed irrespective of the mode of planning.

3) VelObs Mode: In this mode, the elastic bands are added to the humans, and trajectories are predicted, only if they are moving (have velocity). The trajectory is predicted assuming that human follows the same velocity for the duration of the prediction window, and the prediction is updated after each time step. In our work we have chosen a prediction window of $5s$. This mode makes the robot less proactive, but the entanglement problem does not exist and allows for an active re-planning when human stops moving.

Now we move on to the decision making process involved in transitioning between these modalities. In this work, we have the following mode transitions: 1) Single Band $\leftrightarrow$ Dual Band[2] and 2) Dual Band $\rightarrow$ VelObs. The transition procedure and decision making loop is shown in Fig. 1. The transition between Dual Band to VelObs is one-sided, and it does not happen the other way around. As this transition occurs mostly at the robot-human crossing, it is intuitive to assume that human would be behind the robot and no longer interferes with the robot trajectory after the transition. This assumption also reduces the cost of computation as we no longer plan for stationary human. Note that, this transition occurs only when human and robot are under a specified distance, called the *DistThreshold*. Under this *DistThreshold*, the robot's maximum velocity is reduced and the homotopy class change is constrained to make the robot more legible for the human. The weight of the proxemics constraint is also reduced under this distance to allow the planner to find a solution in very narrow corridors. *DistThreshold* is taken as $2.5m$ in this work. The decision concerning the transition between Single Band and Dual Band is based on cutoff distance, *DistMin*. *DistMin* is the distance between human and robot, above which the influence of human on the robot's trajectory is negligible. If the current distance of robot from any human is less than *DistMin*, the planning shifts from Single to Dual Band and vice versa. *DistMin* is taken as $10m$ in this work. All these modalities are implemented using the same hypergraph based optimization used in HATEB and the details of this implementation can be found in [4]. HATEB-2 is implemented in ROS and integrated as a local planner in Move Base package. HATEB-2 follows the same software architecture as HATEB and is integrated with a global planner. A human navigation package is also implemented using ROS that allows the direct execution of trajectory planned by HATEB-2 as well as manual control using a Joystick. Human is shown as a green cylinder with an arrow throughout this work, where the direction of the arrow corresponds to the front direction. We now proceed to

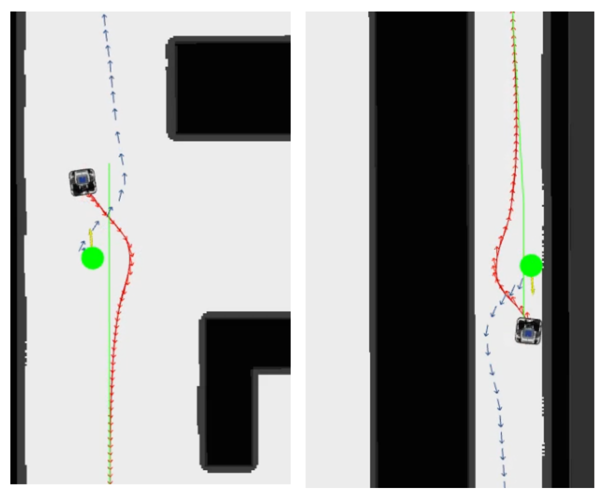

Fig. 2. Robot getting stuck due to entanglement of trajectories. The blue trajectories correspond to human trajectories, and the red ones correspond to robot trajectories. In both situations shown, there exists an alternate solution for the robot to solve the problem. However, the assumption that human is always moving and the constraint of proxemics makes the robot wait in the same entanglement, speculating the motion of human. The picture on left is of open space, whereas the one on the right is of a narrow corridor.

[2] $\leftrightarrow$ represents two side transition

discuss about the modifications made in HATEB.

B. Modifications in HATEB

The following constraints are modified to increase the legibility and acceptability of the robot motion, particularly in the close vicinity to human.

1) Modified Elastic Band: The default settings of the elastic band allow it to rapidly change the homotopy class. This change is good when the robot is at a large distance from humans. In the closer distances, it may lead to the loss of legibility as the study in [11] says. Hence, we address this issue by restricting the changing of homotopy class under a threshold distance, *DistThreshold*, from a human. This restriction is implemented, by decreasing the time interval between consecutive poses, which tightens the elastic band and decreases the possibility of homotopy class change, as shown in Fig. 3.

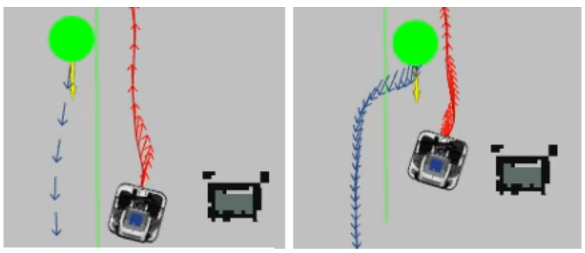

Fig. 3. Modified Elastic band. The blue trajectory is of human, and the red one is of the robot. Tightening of the elastic band results in very close pose predictions in the trajectories and slow velocities.

2) Modified Robot Velocity constraint: In the place of a constant velocity, we assigned a non-linear profile for the velocity of the robot which slows down the robot up to 75% in the close vicinity of the human. This change is made in order to avoid rapid changes in velocity and increase the legibility of motion. The velocity function used in this constraint is given as follows:

$$v(d) = min(1.0, max(10^{d-2}, 0.25)) \tag{1}$$

where d is the distance between the human and the robot and v is velocity of the robot.

3) Modified Time to Collision (TTCplus) constraint: Time to collision constraint, as per its name calculates the time the robot takes to collide with the human from the current position and velocity. The original implementation in [4] computes the error all the time and adds it to the optimization. This implementation results in many false negatives which affects the quality of the trajectory. To decrease the number of false alarms and also to maintain the advantages of the constraint, we have to regulate the addition of the error to the optimization. The regulation is implemented in HATEB-2 as follows:

$$error = \begin{cases} ttc_{error} & \text{if } t_a > t_d \text{ and } t_m < 5t_d \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where t_d is the threshold time, t_a is the cumulative time with positive ttc_{error} and t_m is the cumulative time with zero ttc_{error}. t_a is reset whenever $t_m \geq 5t_d$ and t_m is reset when a positive error is observed. This new implementation shown in Eq. (2), called *TTCplus* decreases the number of false negatives, avoiding the unnecessary oscillations and improving the quality of trajectory as well as the acceptability. The main advantage of including *TTC* constraint is better trajectory planning and earlier intention show by making the robot move in the intended direction early. This can be seen in the Fig. 4. Although, the difference seems small in the image, it is more than half a meter in the real world. *TTCplus* preserves these properties eliminating the drawbacks of *TTC*.

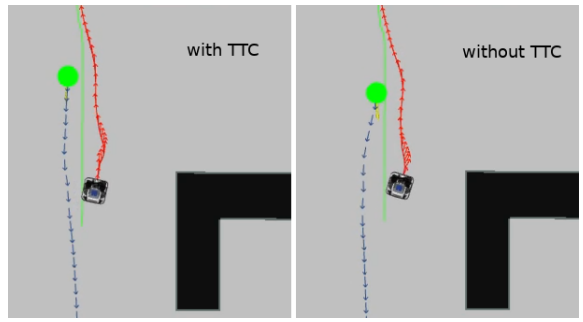

Fig. 4. Intention show of the robot with and without *TTC*. Inclusion of *TTC* or *TTCplus* constraint results in an early intention show as can be seen from the picture on left. Even though the difference seems small from the pictures, this corresponds to more than half a meter in the real world. Red: Robot Trajectory, Blue: Human Trajectory

C. Improved Human Predictions in HATEB-2

The better the estimates of humans, the better the reactive planning can plan the joint trajectories. Therefore, we have made the following improvements in HATEB-2 to have better estimates and predictions for humans.

1) Human Velocity Estimate: The nominal velocity of a human was assumed to be constant in our previous work. However, this assumption leads to a trajectory plan that does not necessarily comply with the current human trajectory. Although, HATEB-2 being a reactive planner quickly re-plans and adapts, this wrong estimate can sometimes lead to unexpected behaviours of the robot. Therefore, a moving average filter based estimate of velocity is added to the human prediction to avoid this and thus providing an adaptive and better nominal velocity estimate to the optimization.

2) Human Goal Prediction: We include human goal prediction into the system to address the changes in the human goal during the planning process. We adopt the method proposed in [21] with a predefined set of the goals for the human. HATEB-2 quickly adapts to the changes in the human goal and re-plans, as shown in Fig. 5, making it more adaptable to real-world scenarios.

IV. Results and Analysis

Various experiments are conducted using simulated PR2[3] robot and Humans in MORSE[4] [22] to demonstrate the ca-

[3]`http://wiki.ros.org/Robots/PR2`
[4]`https://www.openrobots.org/wiki/morse`

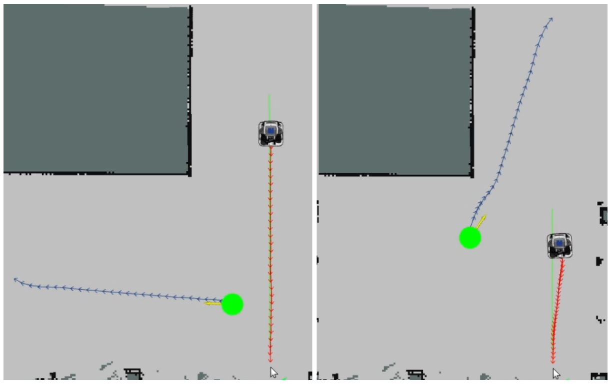

Fig. 5. Human goal prediction in HATEB-2. On the left side, the initial predicted goal, and the calculated trajectory by HATEB-2 are shown. On the right, human decides to move in a different direction, and HATEB-2 predicts a new possible goal and calculates path. Red: Robot Trajectory, Blue: Human Trajectory.

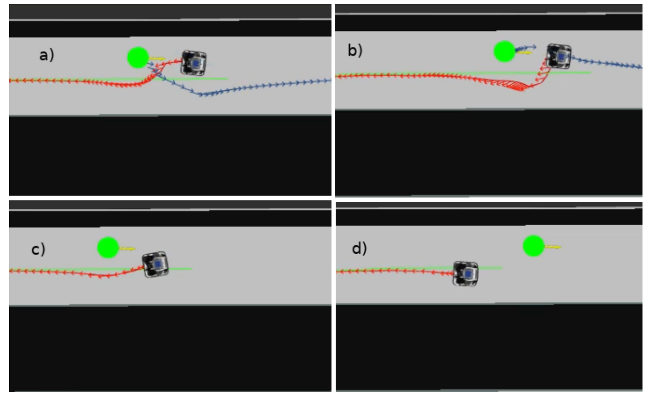

Fig. 6. HATEB-2 solving the entanglement. The various stages of entanglement resolution are as shown: a) Detection of Entanglement: The entanglement is detected based on the human velocity and the current distance between human and robot. b) Re-planning: HATEB-2 tries to re-plans the trajectory before changing the mode c) Mode Transition: Mode transition occurs as human is still and no longer moves. d) Execution of new plan: Finally the robot executes the planned trajectory reaching the expected goal. Red: Robot Trajectory, Blue: Human Trajectory

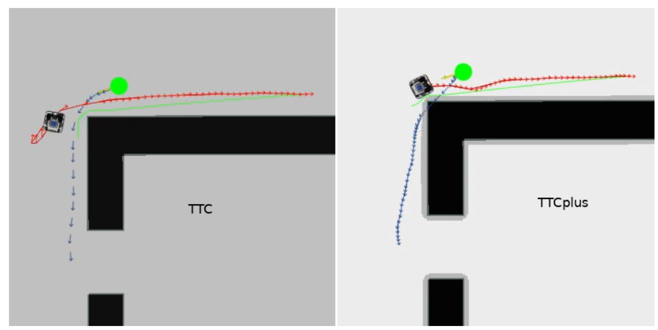

Fig. 7. The original *TTC* constraint-based trajectory shown on the left results in unnecessary oscillations due to exaggerated constraint. However, *TTCplus* constraint regulates this exaggeration and results in a smooth trajectory as shown on the right. Note that the trajectory on the left is making the robot move backwards even when there is no necessity. Red: Robot Trajectory, Blue: Human Trajectory.

pabilities of HATEB-2. Two different environments are used to test several scenarios and the results are presented in this section. Both *Qualitative* as well as the *Quantitative* analysis are performed and the corresponding results are presented. We start with the *Qualitative* analysis and demonstrate the improvements in HATEB-2[5].

A. *Qualitative Analysis*

Here, three different analyses on HATEB-2 are presented, contrasting and comparing the improvements made and situation handling. We also present an analysis discussing the importance of double band in human-robot co-navigation planning. During all these experiments, we manually control the human using a Joystick.

1) Entanglement Resolution: One of the main drawbacks of HATEB is the entanglement issue presented in the previous section. With the introduction of decision making and mode transition in HATEB-2, this entanglement is resolved and the robot finally reaches the goal without getting stuck. When the human stops moving and blocks the robot, a new trajectory is planned and the transition from Dual Band mode to VelObs mode occurs. Since, the human's velocity is zero, the VelObs mode does not plan any trajectory for the human until he starts moving again. During this time, the robot escapes from the entanglement and starts following its trajectory to the goal. The various stages of this entanglement resolution are illustrated in Fig. 6.

2) TTC vs TTCplus: TTC constraint in HATEB makes the robot very reactive and leads to unnecessary oscillations as discussed previously. Fig. 7 shows the trajectory of the robot in the same scenario using *TTC* and *TTCplus* constraints respectively. As can be seen from the trajectory on the left, plan using *TTC* constraint is making the robot back off further when it is already at sufficient distance from the human. This exaggerated reaction results in long execution times apart from the oscillations. The trajectory planned using *TTCplus* in HATEB-2 is shown on the right and it can be clearly seen from the Fig. 7 that this trajectory results in faster execution as it removes the problem of oscillations. Clear differences in the followed trajectory can be seen in the video [6].

3) Single band vs Double band: Single band refers to the addition of elastic band only to robot along with the human-aware constraints, where as double band includes an addition of elastic band to human as well. We test the following hypothesis to see if double band has any advantage over the single band:

"The presence of an elastic band for human and co-planning allows the robot to predict the human motion better and adapt its trajectory accordingly."

To test the hypothesis we controlled the human manually and tried to block the robots trajectory and observed the reactivity of the robot. We conducted two different experiments (wide space and narrow passage (Fig. 9)) and in both the experiments, the robot reacted slowly while using a single band. However, while using a double band, the robot proactively backs off as human moves towards it. Therefore,

[5]Source code for the HATEB-2 is available at `https://github.com/sphanit/hateb_local_planner/tree/hateb_new`

we can say that our hypothesis is correct and inclusion of an elastic band for human is advantageous in human-aware navigation planning. These experiments can be seen in the video[6].

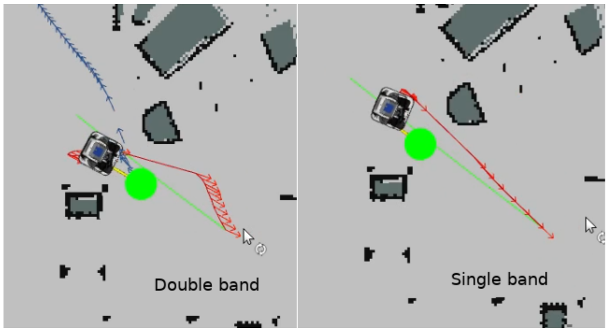

Fig. 8. Double band and Single band trajectories while passing through a narrow passage. As the red trajectory corresponds to the robot, it can be observed from the picture on the left that double band based planning is making the robot back off and provide a way to the human. Whereas, Single band based planning shown on the right provides a way by backing off a little and then moving sideways.

4) Pass through narrow opening: This experiment can be thought of as passing through a door where only a single person can fit. Suppose two persons arrive at the narrow opening at the same time, one has to back off and give way for the other to pass through. We tried to simulate this scenario [6] in the human-robot co-navigation, and we want the robot to back off, and give way to the human. To increase the complexity of this problem further, human crosses the opening and stops close to this opening. Enough space is present for the robot to pass through, but the trajectory might need re-planning. This scenario is shown in Fig. 9. We tested all the three planners (HATEB, HATEB-2 and Single Band) in this scenario and snap shots of the trajectories at this crossing are shown in Fig. 8 for both double band (HATEB, HATEB-2) and single band planning. Both HATEB and HATEB-2 reacted in the same way to back off and provide way to human, which is shown in the left picture of Fig. 8. Although they reacted similarly at this instant, HATEB gets stuck in entanglement when the human stops moving after crossing the opening. HATEB-2 breaks the entanglement and re-plans to reach the given goal. Coming to the case of single band, the human has to stop in front of the robot and wait for the robot to back off and re-plan. Single band also solves this case as it does not suffer from entanglement, but with lesser reactive speeds. Also, note that the robot backs off in a double band scenario, whereas it tries to move aside in single band case.

B. Quantitative Analysis

To perform the *Quantitative* analysis, five different experiments were conducted, and each experiment is repeated 10 times using HATEB and HATEB-2. The list of the performed experiments is given in table I. The experiment *Narrow opening 1* is same scenario presented in Fig. 9, where as *Narrow opening 2* corresponds to similar case with opening that can be seen in Fig. 7. *L-crossing* is the same experiment that is shown in Fig. 7 and finally *Narrow corridor and Wide space* represents the scenarios presented in Fig. 2. In all these experiments the goal of the human is assumed to be behind the robot and the human executes the trajectory planned by the corresponding local planner. A set of five metrics are defined to analyse the results: 1) Initial plan length, ipl, 2) Total time for completion, ct, 3) Traversed path length, tpl 4) Minimum distance from human, d_{min} and 5) Length deviation factor, α. The minimum distance from human metric, d_{min}, refers to the closest distance between human and the robot while executing a planned trajectory. Length deviation factor, α, is defined as follows:

$$\alpha = \frac{|tpl - ipl|}{ipl} \quad (3)$$

where $|\ \ |$ denotes the absolute value. After determining ipl and tpl from the experiments, α is calculated using Eq. (3).

All these metrics are calculated for each experiment and mean value over 10 experiments are presented in the table I. The values highlighted in each row corresponds to the best values in the given experiment. The evaluation of best values for the metrics is done in the following manner. For ipl, the value closest to the tpl is taken as the best value, as it suggests that the initial plan is very close to the traversed path. In case of tpl and ct, smaller value represents the best value. The greater the distance of the robot from human, the more the safety factor for the human and hence the larger distance is the best value. Finally, the lower value of α represents the lesser deviation from the initial plan and hence showing better performance of the planner. By observing the values of α from the table, it can be inferred that HATEB-2 performs better than HATEB in all the cases, except *Narrow opening 1*. In all these scenarios it can also be seen that ipl has the best value, and hence we can say that HATEB-2 predicts better plan than HATEB. The cause of this result can be directly associated with the improvements in human prediction and the new $TTCplus$ constraint, thereby demonstrating the importance of human prediction in human-aware navigation. As the maximum allowed velocity decreases below *DistThreshold* in HATEB-2, an increase in ct is expected and it is true in 3 out of the 5 cases. In *Narrow opening 2* and *L-crossing* cases, HATEB-2 has lesser ct than HATEB and this is because of the improved *TTC* constraint, *TTCplus*. Since HATEB uses the original *TTC*, the robot suffers from unnecessary oscillations and results in a longer path length, tpl as well as ct. It can be observed that HATEB-2 completely out performs HATEB in these two scenarios. Although, HATEB has better tpl values in the other three scenarios, the tpl values of HATEB-2 are very close to those HATEB. Finally it can observed that overall performance of HATEB-2 is better than HATEB.

V. Experiments

In this section, we present the experiments we have conducted using the proposed framework. We have ported the

[6]Link to the video: `https://youtu.be/xEG4e-Y9z8g`

Fig. 9. Narrow passage passing scenario. In this scenario, human and robot arrive at the common passage at the same time, and one should back off to provide way to another. Otherwise, there exists no solution. This is one of the intricate situations addressed in this work, and the picture on the left shows the simulation of this scenario in MORSE [22]. Right side picture shows the trajectories for the human (blue) and the robot (red), generated using the proposed framework, HATEB-2. It can be seen from the picture that the robot's trajectory (red) is making the robot to move backwards and hence providing way to the human.

	HATEB					HATEB-2				
Experiment	$ipl(m)$	$tpl(m)$	$ct(s)$	$d_{min}(m)$	α	$ipl(m)$	$tpl(m)$	$ct(s)$	d_{min}(m)	α
Narrow opening 1	**5.2589**	**5.9372**	**13.635**	**0.7222**	**0.1290**	5.3597	6.3423	17.6350	0.539	0.1903
Narrow opening 2	8.7117	11.0897	24.2917	0.1455	0.2730	**9.0233**	**9.1606**	**21.9319**	**0.1505**	**0.0152**
L-crossing	10.6641	15.2904	32.5567	0.1455	0.4338	**13.4602**	**13.0613**	**29.8967**	**0.3430**	**0.0296**
Narrow corridor	8.51	**13.1747**	**27.92**	**0.7222**	0.5481	**12.8807**	13.2372	30.8850	0.4845	**0.0277**
Wide space	8.5137	**9.5454**	**19.8133**	0.7222	0.1212	**9.8575**	9.6781	22.2517	**0.8274**	**0.0182**

TABLE I

MEAN VALUES OF THE METRICS OVER 10 REPETITIONS. ipl: INITIAL PATH LENGTH, tpl: TRAVERSED PATH LENGTH, ct: COMPLETION TIME OF THE EXPERIMENT, d_{min}: MINIMUM DISTANCE BETWEEN HUMAN AND ROBOT DURING THE EXECUTION OF THE TRAJECTORY IN THE GIVEN EXPERIMENT. α: LENGTH DEVIATION FACTOR.

framework to Pepper[7] robot and used it for this study. Since the main objective is to study the navigation framework, we used the OptiTrack[8] motion capturing system to track the humans. The localization of the robot in the map is done using the standard localization technique based on ArUco[9] markers.

We have conducted two experiments to check the capabilities and improvements in HATEB-2. In the first experiment, shown in Fig. 10, the human moves along his path without blocking the way for the robot. It can be seen from Fig. 10, the robot continues to navigate on the same side and follow a path similar to the initially planned path. We can also observe the band tightening in Fig. 10 (d) as the human is close to robot. In the second experiment, the human goes out of his path and blocks the robot's planned path. Two kinds of scenarios are possible depending on how the human acts in this setup. If the human goes very close to the robot, the robot has to backup before resolving the entanglement problem. In the other case where human is at a nominal distance from the robot, only entanglement resolution happens. These two cases can be seen in the video[6]. However, we have presented only the first scenario in this section as it brings out more capabilities of the system and also due to space constraints. This is shown in Fig. 11. In Fig. 11 (f), human goes very close to the robot and hence the robot backs off (Fig. 11 (g)) before resolving the entanglement. Finally, the entanglement is resolved (Fig. 11 (h)) and the robot proceeds to its goal.

[7]https://www.ald.softbankrobotics.com/en/pepper
[8]http://www.optitrack.com/
[9]https://chev.me/arucogen/

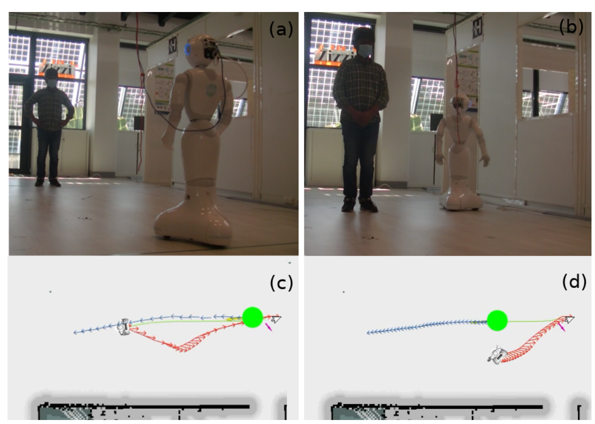

Fig. 10. Human follows his path without disturbing the robot. (a) Initial positions (b) Intermediate positions. (c) & (d) are the trajectories at (a) & (b) respectively. In (d), the band tightening can be seen as the robot is close to the human. Red: Robot Trajectory, Blue: Human Trajectory

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a new framework combining reactive planning and decision making to handle human-robot co-navigation, called, HATEB-2. This framework includes three different modes of planning, namely Single Band, Dual

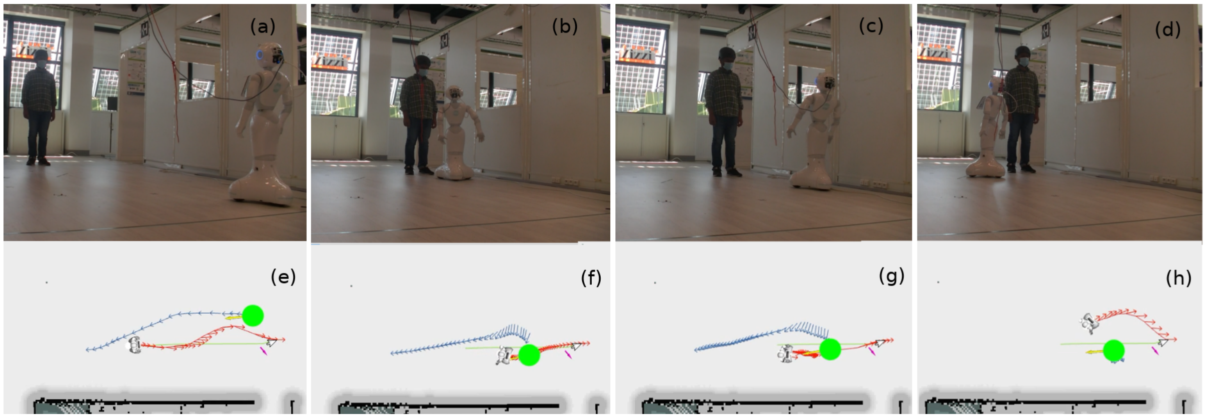

Fig. 11. Entanglement resolution in a real-world scenario. Here the human goes out of his path and blocks the robot's planned path (f). While trying to block the path, he moves very close to the robot as it can be seen from (f). Therefore, the robot backs off (g) before resolving the entanglement and finding an alternative path (h). (a)-(d) represent different positions of the robot during the experiment, and (e)-(h) show the planned trajectories at these positions. Red: Robot Trajectory, Blue: Human Trajectory

Band and VelObs. Switching between these modes allows for solving many complex human-robot cooperative navigation problems. We have presented details of these different modes of planning, and also talked about the modifications made in HATEB before including it into HATEB-2. These modifications remove some of the drawbacks of HATEB apart from the improvements. We have also presented the improvements made in human prediction and estimation. Finally, we performed several experiments in various intricate situations and then provided a detailed analysis of the results. Results show that HATEB-2 have an overall better performance. The framework was ported to real robot platform and results were presented. As a part of future work, we plan to extend this framework by including more modalities. Further, we also plan to include improved human predictions and better models for humans.

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