Human-Aware Motion Planning: Using HMMs for Avoidance of Moving Obstacles

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***Abstract* --- We propose an alternate solution to avoiding moving obstacles in human-aware motion planning that will be more accurate in knowing when to calculate a new path for the robot by using Hidden Markov Models (HMMs). The HMMs are used to determine the probability of the human obstacle and the robot reaching a certain position in the robot's current path at the same time. If there is a high chance of them occupying a position at the same time, only then will the robot need to calculate a new path towards its destination. This is different from the known implementation that detects changes in the human's position and orientation and calculates a new path if those changes are over a certain threshold. From our experiments, we found that using HMMs in obstacle avoidance significantly reduces the amount path calculations by more than three times while maintaining the same level of perceived safety and efficiency in navigation as previous works.**

Keywords --- motion planning, mobile robot, obstacle avoidance, hidden markov models, human, navigation, motion tracking

1. INTRODUCTION

Human aware motion planning takes into account all humans within the collaborative space as the robot navigates towards a specific destination. Using cost functions for the positions in the space and motion tracking systems, human aware motion planning has been researched in previous works. In the previous research of human aware motion planning, the main focus was put on the ability of the robot to navigate towards the target human in a safe and visible manner [1]. However, it also looks at the other humans and keeps track of where they are to avoid collisions. Knowing that the navigation towards the destination using a minimum cost path has undergone much research and experiments, we decided to focus more on the path replanning aspect in human aware motion planning.

More specifically, we designed a new method of replanning for avoiding moving humans in the collaborative workspace. This new method would make more efficient use of the motion tracking data for collision avoidance by applying more constraints to the algorithm that would result in the removal of unnecessary path planning. With this decrease in calculation complexity, the robot would spend less resources making calculations to find a new path unnecessarily. Our new method will make use of Hidden Markov Models in order to achieve this.

We will then evaluate our new method by comparing its ability to navigate in a collaborative space with a moving human to the ability of the original method. Through observations of our method in action and safety surveys of the a human participants' feelings during the interaction, we attempt to determine if using HMMs makes the interaction safer, better avoids collisions, and decreases the complexity of calculations.

2. RELATED WORK

The main source of inspiration for our project is the research done in *A Human Aware Mobile Robot Motion Planner* [1]. The paper describes the development of a motion planning algorithm used by a mobile robot to navigate the environment towards a human destination while taking into account the safety and visibility of that particular human. Within their motion planning algorithm, they laid out the space as a two-dimensional grid with each cell of the grid being assigned a cost based on the safety and visibility constraints for the target human. With the costs, the robot would plan a minimum cost path to the minimum cost point using the A* search algorithm. Additionally, in their algorithm, to avoid moving obstacles within the space, the robot would calculate a new path on-the-fly. However, the decision to replan the path is done by checking if any human detected by their visual detection and laser sensors moved 0.2 meters or 0.3 radians. While this method of deciding on whether or not to replan is fast and simple, we believe that its accuracy of detecting possible collisions is low and leads to many recalculations of a new path when there isn't a need to. In this method, a new path has a high chance of being calculated since the threshold values are low. Therefore, it will replan anytime a human turns or takes a step in the collaborative space even if they are not near the robot or moving towards its path.

For our project, we tried to replicate as much of their human-aware motion planning algorithm as possible from the specifications detailed in the paper. We had the space laid out into a two-dimensional grid and assigned each cell in the grid a cost based on its safety and visibility to a specified human. We also used the A* search algorithm to find the minimum cost path to the minimum cost point in the grid. Additionally, we used their constraints for replanning in the non-HMM condition for our experiments and will try compare it with our new method that uses HMMs. On the other hand, we chose to not implement hidden zones, use visual detection, and deal with multiple humans moving around in the navigation space. Furthermore, our version of the cost functions for safety and visibility and the replanning algorithm may differ as the actual functions and replanning algorithm were not stated in the paper.

3. SYSTEM DESIGN

Our system has three main components - an iRobot Create, a Vicon System, and a laptop running ROS and Python. The iRobot Create will be the robot that navigates the grid space using a human aware motion planner. Since we are focusing on the robot's capability to to safely avoid a moving obstacle with and without the use of HMMs for replanning, the robot we used did not need many capabilities aside from being able to move around the environment and interact with the code running on a laptop for calculations. We designed the robot's step size to be around 0.5 meters. While it would have been better to have a larger and more human-like robot to give a more realistic interaction, the only mobile robots available to us were the iRobot Create and Sphero. As the iRobot was larger in size and closer in width to a human, we believed that it was the better robot for our social navigation experiment.

With the Vicon system, we tracked the pose of the moving human obstacle within the grid to determine their current position and orientation for calculations. We retrieved sensor data on the human by having the human carry a helmet with 6 sensor markers tracked by the Vicon system. The helmet was carried rather than worn since the Vicon system was not as consistent in tracking data at high altitudes. The Vicon system's space was a 6 meter by 6 meter grid that went from -3 meters to 3 meters in both the x direction and the y direction. The laptop running ROS and Python has a node to communicate with and control the robot as well as retrieve the sensor data from the Vicon system. The robot is connected to the laptop through bluetooth connection while the Vicon system is connected to the laptop by using a specific wireless network in the lab.

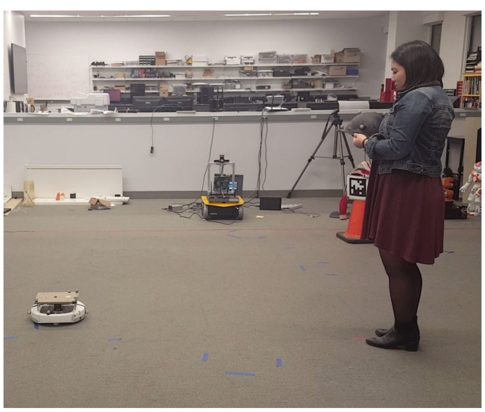

Fig. 1: *Participant carries helmet with sensors and starts to move while robot goes to destination.*

3.1 Motion Planner Implementation

With ROS and Python, we implemented our own customized version of the human-aware motion planner based on the implementation details defined in the *A Human Aware Mobile Robot Motion Planner* paper [1]. The motion planner first initializes the space it will navigate by transforming it into a 2D grid where each cell in the grid corresponds to the size of one step for the robot which is 0.5 meters. Once the grid is initialized, the cost for each cell is calculated based on the safety and visibility functions we defined. The safety constraints were based on the robot's distance from the target human. We gave the cell the human was in a very high cost and as the cell became farther from the human, the cost of the cell decreased. The visibility constraints were based on how much the human would have to turn his head to see the robot. Therefore, we assigned the cost for each cell to be the angle the human would have to rotate to see the robot. Then, to get the total cost of the cell, we would sum up its safety and visibility costs.

With a cost assigned to each cell, the minimum cost cell is found and chosen as the destination of the robot. Then, a path from the robot's current state to the destination is found by using the A* search algorithm. In the A* search algorithm, we use the Euclidean distance between two points on the grid as the heuristic function. Once the path is calculated, the path is sent to the robot who moves to the specified cells to reach the destination. After each step, the robot gets the motion tracking data from the Vicon system and uses it to determine whether or not it needs to plan a new path to avoid colliding with the human moving in the grid space. The obstacle avoidance algorithms and conditions are described in more detail in the next section. Finally, once the robot reaches its destination, it turns to face the target human it would interact with.

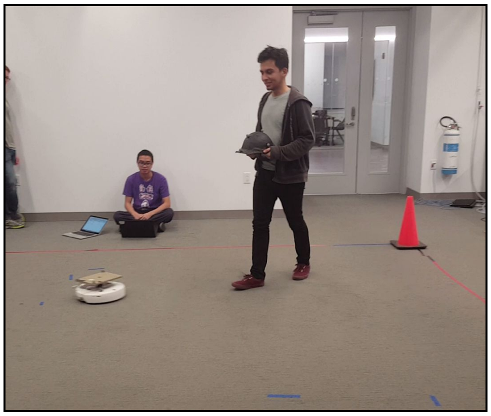

Fig 2: *Participant moving towards robot while it calculates a new path to avoid him*

3.2 Obstacle Avoidance

For our system, we implement two methods of obstacle avoidance - using Hidden Markov Models and not using Hidden Markov Models. In both cases, the robot will first gather the initial sensor data to calculate the initial human aware path to the minimum cost position near the human goal. The human obstacle is accounted for by increasing the cost of the cell on which the human is on as well as its neighbors. These costs are increased by a very large amount so that the robot would avoid those positions when looking for a minimum cost path. The reason for increasing the costs of the neighboring cells was to account for the human's faster movement and lessen the probability of collisions due to errors and rounding of sensor values.

After the robot takes the first step in the initial path, it will then decide if it should replan the path to the destination. To replan, it first gathers sensor data from the Vicon system. For the Vicon data, we round the x and y coordinates of the positional data to the nearest 0.5 meter interval and the orientation data to the nearest 45° angle interval before using them in our algorithm. This rounding is done since our algorithm deals with the use of discrete values to get the cost of a cell and get the relevant transition and emission probabilities for HMMs. Following the retrieval of sensor data, the cells whose costs were increased at the previous step are decreased back to their cost when the human was not present. After this, the algorithm then reaches the part where the calculations performed at each step differ for whether or not HMMs are used in the replanning method.

The method not using HMMs is similar to the obstacle avoidance method described in previous work [1]. This method uses the human's current position and orientation collected from the Vicon system and checks if the human has at least moved 0.2 meters or 0.3 radians from their previous pose. If a change in pose that surpassed those thresholds was detected, the robot would replan for a new path from its current position that avoids the human. This new path is found by using the A* algorithm but with the human's new position and its neighbors having increased costs. Once the new path is calculated, the robot takes the next step and repeats the process again.

For our new method that uses HMMs, we have transition and emission probabilities for our calculations. The transition probabilities between two cells on the grid is the probability of the human moving to that spot in the next step given the current position. Thus, for a given cell, the transition probabilities between cells not adjacent to it is 0. The remaining probability for that cell is divided evenly amongst the 8 neighboring cells and the cell itself as the human can move in any direction they want or stay in their current position. The emission probabilities are based on the probability of having previously been in a particular cell and facing a certain direction given the human's current position. These probabilities make the assumption that the human is more likely to move to a cell in the direction they are facing. Therefore, we give the highest probability to the neighboring cell that is directly in front of the direction the human was facing. The next highest would go to the cells diagonally in front of the direction the human was facing. The remaining probability given that particular cell is distributed evenly among the other neighbors of the previous cell and itself. Both the transition and emission probabilities take into account cells that do not have all 8 neighbors by reweighting the probabilities appropriately.

With these probabilities, we find the probability of the robot and human colliding within 2 moves. To do these, we get the human's current position and the robot's 2nd move in the current path and check if they are neighbors or have any neighbors in common. If they are neighbors, the human can stay still for one step of the robot and then move into the robot's next position. If they have a common neighbor, then the human can take two steps and end up on the robot's path. For all of these possible human paths consisting of two moves that will lead to the robot's 2nd move, we calculate the probability of them actually occurring using HMMs. For the unobserved directions of future moves by the human that are used in emission probabilities, we assume that the human moved directly forward from the previous cell since this is the sequence for each path that will result in the highest probabilities. The final probabilities for each sequence of 2 moves by the human were found to mostly be between 0.04 and 0.05. Thus, we set a threshold value of 0.045 and would calculate a new path for the robot only if any of the sequences had a probability higher than the threshold. The new path is found by increasing the costs of the neighbors of the human's current position and the second move of the robot and using the A* search algorithm.

4. METHODS

4.1 Participants

Ten graduate students from Cornell University were chosen without compensation to participate in this study. Due to time constraints, we chose to only conduct this study on ten volunteer participants. There were no significant differences between our experimental conditions due to factors such as age or gender. Of the ten participants, 3 were female and 7 were male. The ages of the subjects ranged from 21 to 23 years.

4.1 Experiment Conditions

For the experiment, we have two different conditions, robot path planning using HMMs to predict collisions and not using HMMs to predict collisions. This means that we will have the robot navigate to a goal while it uses two different algorithms to decide when it has to plan a new path to the goal. The algorithm not using HMM-based collision prediction will be our control, as it mimics the same algorithm used for the robot to decide to plan a new path towards the goal given in the previous work for human-aware motion planning [1]. The purpose of our experiment is to assess the perceived safety and computational load given by our new approach to detect possible collisions.

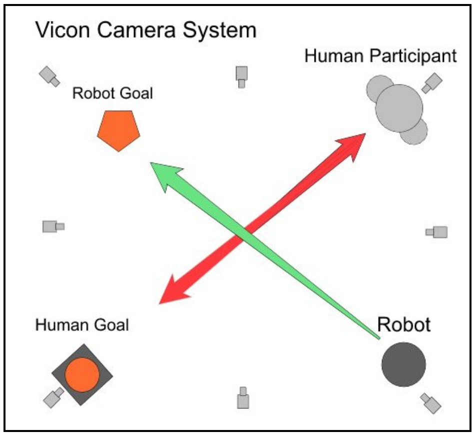

Fig. 3 *This shows the layout for the experiment.*

4.2 Procedure

Each participant was brought into the room with the overhead Vicon system cameras. They performed the experiment separately in 10 minute time slots and given instructions. The initial environment setup for each participant was identical. The robot was initially positioned on coordinate (2.5, 0) with an initial direction of 0 radians. The goal was placed at (-0.5, -2.5) with a randomized direction. The human subject starts on the origin at (0, 0) and they are told to walk to (3, -3) and back to the origin at a moderately slow pace. Their goal position and start positions were marked with a cone and tape respectively (see **Fig 1**). All coordinate measurements are taken in meters as that is the unit used by the Vicon system to record positions. In order to capture the participant's position, each participant was instructed to hold the helmet at waist level and notified that wearing the helmet on their head would result in inaccurate measurements of position and pose. Participants were additionally instructed to keep the helmet pointing in the direction that they are facing to ensure an accurate direction reading.

Our experimental conditions are within-subject since each subject will conduct the experiment two times with a survey following each run to evaluate the perceived safety of each implementation. For the first run, the participants were given a short demo of an appropriate walking pace and notified that they would be filling out a short survey after each run. They were also notified that they must participate in two separate runs of the experiment, but not that there are differing conditions. For each participant, whether or not the robot used HMM collision detection for the first run was randomized to reduce ordering effects. The second run would then be the condition that was not used for the first run. The survey used for our experiment was taken from the Godspeed questionnaire series [2]. The specific questions pertain to the fifth series of the Godspeed questionnaire that has to do with perceived safety by evaluating the emotional state of the subject. For each run, we asked three semantic differential scale questions with a scale from 1 to 5. The semantic differential scale questions were between anxious and relaxed, calm and agitated, and quiescent and surprised for questions 1, 2, and 3 respectively.

For each run, we log the time it takes from when the robot computes its initial path and the time at which the robot arrives in the goal position. We also have a counter to keep track of the number of times the robot plans the path to the goal regardless of if the resulting path is the same as the previous path. As long as a path is planned again, we increment the counter as it still takes time to compute the optimal path, even if the optimal path does not change. Additionally, we manually log the observed number of collisions that occur between the human participant and the robot for each run.

4.3 Results and Evaluation

Evaluation of our experiment comes down to analyzing our results from our objective metrics in the form of observations and logging and our subjective metric in the form of a questionnaire. Our observation of whether or not collisions occurred will be used to analyze the of the safety of our collision detection method. The observation we are looking at during each run is if a collision occurred. If a collision is observed, we note it down and at the end we can look at the total number of times collisions occurred for each condition. The data logged about the total completion time can be used to measure how efficient each algorithm was in getting the robot to where it has to go. The number of paths calculated gives us a good idea of the workload difference as calculating a new path using the A* algorithm is more costly than calculating the probabilities for collision using HMMs where the probability distributions could be precomputed. Finally the questionnaire results will give us an idea about the perceived safety of each condition and how they compare to each other.

5. ANALYSIS

5.1 Results

An independent samples t-test on the two conditions - using HMMs and not using HMMs - revealed that there was a significant difference between the total number of path calculations with a p-value of 0.001. HMM True correlates to our condition where we use HMMs in computing when the robot should calculate a new path and HMM False correlates to the condition where we are not using HMMs in determining when to calculate a new path. The mean for the HMM True condition was 1.2 while the mean for the HMM False condition was 3.9. This is consistent with our hypothesis that using HMMs will decrease the amount of work done by the system to calculate new paths. The mean values for total number of path calculations, travel time, and scores for the semantic differential sentiments are shown in Table 1. Table 2 shows that of the different variables measured, there was only a significant difference between total number of path calculations.

For total number of collisions, there were only 3 total collisions recorded, with 2 of them recorded during the HMM False case and 1 of them recorded during the HMM True case. All collisions observed were with separate participants. Since there were so few number of collisions, there was no significant difference found between both conditions.

	t	df	p	Cohen's d
Total Number of Path Calculations	8.786	18.00	< .001	3.929
Anxious–Relaxed	0.808	18.00	0.430[a]	0.361
Calm–Agitated	−0.210	18.00	0.836	−0.094
Quiescent–Surprised	0.000	18.00	1.000	0.000
Travel Time	−0.815	18.00	0.426	−0.364

Table 1: Independent sample t-test on dependent variables.
Only Total Number of Path Calculation has a p-value < 0.05.

	Group	N	Mean	SD	SE
Total Number of Path Calculations	HMM False	10	3.900	0.738	0.233
	HMM True	10	1.200	0.632	0.200
Anxious–Relaxed	HMM False	10	4.000	1.155	0.365
	HMM True	10	3.500	1.581	0.500
Calm–Agitated	HMM False	10	2.300	0.823	0.260
	HMM True	10	2.400	1.265	0.400
Quiescent–Surprised	HMM False	10	2.600	1.265	0.400
	HMM True	10	2.600	0.966	0.306
Travel Time	HMM False	10	20.491	2.307	0.730
	HMM True	10	21.511	3.221	1.019

Table 2: Mean and Standard deviations for dependent variables

5.2 Discussion

The most significant result in our experiment is that we found that the condition of not using HMMs to determine when to compute a new path resulted in almost three times as many path calculations when compared to the case where HMMs is used. This is important because most methods of computing the optimal path are quite costly in terms of computation, especially as the workspace area gets larger.

The travel time recorded showed that the mean travel time for the HMM False condition was shorter than that of the HMM True condition, however this difference was not shown to be statistically significant. Additionally, the means only differ by one second time difference and in an approximately 3x3 square meter workspace, that may not make too much of a difference.

Observed collisions between the two conditions do not really tell us much because these collisions were probably due to the fact that we did not take into account velocity of the human in our model. By not taking into the account the velocity of the human, if the human moves too fast, we will not be able to incorporate the new positional data before the robot finishes its step and therefore, a collision occurs. Although only 3 actual collisions occurred between the subjects and the robot, there were also many times in which the robot would've collided with the human if the human did not continue walking thus again showing the inconsistency of our system. However, this was the best we could do given the time and resource limitations.

Analysis of our survey results reveal that for the calm-agitated and quiescent-surprised semantic differential questions, the means were close to the middle for all conditions. However, the anxious-relaxed case seems to fall closer to relaxed at 4.0 and 3.5 for the HMM False and HMM True conditions respectively. Although there was no significant difference found using a series of individual sample t-tests between the conditions, it seems that most of the participants were more relaxed than anxious when dealing with the near robot experience. This could be due to the fact that all participants come from a technical background at the graduate level of university. Overall, the perceived safety of both conditions seem to be about the same.

Although these were the results we found in this experiment, we have to keep in mind of the possible reasons these results may not be directly applied to all cases. First is the problem of accurately computing the movements of the robot. We had some issues accurately providing commands to the robot to turn at certain angles, which would leave the robot off of its intended calculated path a little bit. Another reason why our experiment may not have seen much of a difference between the two conditions is that we did not take into account velocity of the human when computing our probability of collisions in the HMM condition. This could be a problem because although our subjects were told to walk at a relatively slow pace, their speed and stride differ from subject to subject and therefore, our algorithm cannot accurately predict future collisions if the human is moving too fast into the robots path before the robot reads the data again. We also used relatively large areas to create the grid space where all the costs and paths were computed. In our experiment, we used cell sizes of 0.5 x 0.5 meters.

6. CONCLUSIONS

Between using HMMs and not using HMMs in human-aware motion planning obstacle avoidance, we have found that using HMMs significantly reduces the number of path calculations in this controlled experiment. However, there does not seem to be a significant difference in the perceived safety and efficiency of the robot’s navigation in both conditions. For future and continuing work, we may want to implement the system with continuous values and take into account human velocity to make the system more robust and accurate. A more accurate model of the system would allow us to then better predict human-robot collisions and evaluate the efficacy of using HMMs to predict human-robot collision in human-aware motion planning. Additionally, we can try to use a more human-like robot to see how a larger robot would affect the perceived safety of the interaction or have more human obstacles to simulate a more realistic environment.

7. REFERENCES

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