Intent Communication between Autonomous Vehicles and Pedestrians

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***Abstract*— Some of the problems with autonomous vehicles include communication with other vehicles, the technological capabilities of the environment around them, and the passengers in the vehicle. For example, people crossing the street usually look to the driver to make sure they have been seen and it is clear that they can cross. This paper seeks to fill the gap that exists with intent communication between pedestrians and autonomous vehicles. Initially, there is an experimental setup that creates a feedback loop between an autonomous golf cart and pedestrians using LED lights, an LED word display, and speakers. Once the pedestrians have been detected via LIDAR, a command is given through the word display and the lights. The command to be given is based on the probabilities of different actions a pedestrian might take. Along with the experiment, simulations are run to test different learning algorithms that will be able to predict pedestrian intent. The current simulation is based on a POMDP using SARSOP. In future work, the simulation will use a belief-state MDP to reduce calculation time.**

I. Introduction

Vehicle-human communication is an area that has been less researched than vehicle to vehicle communication. Pedestrians are everywhere that cars are and they have to be accounted for. The problem is that the intent communication between autonomous cars and pedestrians is unclear compared to the communication between drivers and pedestrians. Intent implies that the actions a person or machine are going to take are understood by those around them. People tend to be skeptical of fully autonomous vehicles.

Humans are unable to predict what the vehicle might do because there arent any natural cues to check for. The vehicles are unable to predict what pedestrians might do because human behavior is complex and not entirely predictable. Both the golf cart and pedestrian have no way of determining if one of them will stop or continue moving. To address this problem, this project will develop a system for intent communication between autonomous vehicles and pedestrians using an autonomous golf cart as the test machine. The autonomous golf cart will be able to communicate its intent to the pedestrians around it, determine what actions the pedestrian might take and their intent, and adjust the golf carts actions accordingly.

To model the environment, a partially observable Markov Decision Process (POMDP) will be implemented to assist the golf cart with pedestrian intent identification. A POMDP is the appropriate model for this type of problem because the intent of the pedestrians may not be fully available to the autonomous vehicle based on observations alone. To keep computing time to a minimum, the POMDP will be modeled as a belief-state Markov Decision Process (MDP). This assumption is made based on the fact that there are a limited number of actions that both the golf cart and pedestrians could possibly take. The assumption was based on the responses of a survey of 50 people with no previous involvement in the research.

The key contributions of this paper are:

- A feedback loop between pedestrian and golf cart intent
- Clear and accurate communication from the golf cart to pedestrians about what action it intends for the pedestrian to perform
- A simulation of a POMDP that shows the difference intent communication makes compared to no intent communication

II. Related Work

Human-robot interaction (HRI) is a wide field of study. Current research in HRI has had a focus on identifying and learning how to distinguish different human gestures [1], [2], [3], [4], [5], [12]. This research has focused on the different ways robots or machines can learn what to expect from humans in terms of intent based on learned gestures. A problem with gestures is that they have to be taken in context of what is happening in the environment in which the robot and human are working together in. Gestures also have the problem of memory allocation when it comes to a robot learning more and more of them. The memory problem for gestures has to do with the fact that gestures have to be taken in context, unlike with the proposed solution which already assumes that the pedestrians are acting with respect to the golf cart. Another limitation is that the previous research has usually only focused on hand gestures. Hand gestures can be dependent on what the rest of the body is doing. Using gestures to determine human intent also leaves the problem of how the human will interpret what action the robot is going to take or what request the robot will ask of the human.

A key issue in HRI is the trust in automation. In [7], [9], [10], [11], [13], the problem of humans trusting robots is explored. When a person doesnt trust another person, they have a significantly low probability of believing what they are being told. This concept applies to humans listening to machines. People are skeptical of automated machine as they are, but when one of these machines begins operating alongside them, they become much more critical of the requests of the machine [10]. The problem with building trust between machines and humans lies in the way that they communicate.

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Without clear explicit or implicit communication, humans are likely to ignore the requests of the robots.

Several approaches have been taken to address the issues in HRI intent communication. A novel approach, shown in [15], is to use haptic feedback. This approach would not be applicable to the autonomous golf cart problem because the goal is to keep the pedestrians and golf cart from making physical contact. Other approaches such as in [8], [23] use gaze direction detection or vocalizations from the robot or human to determine the intent of either party. This doesnt account for when the human has become distracted or if they have lost interest in working with the robot. The humanoid approach has been a popular one in current research on HRI. In [14], [17], [20], [21], [22] the focus is on ways that robots can learn from human-human interactions and create models based on these observations. Some use machine sounds specific to the work being done to the deliver a message to the humans and others continue to use gestures, gaze direction detection, or other human-like behaviors to determine intent.

Very little of the research focuses on the loop of intent communication between robot and human. Most of the research in HRI has focused on the robot learning the intent of the human and the human learning to eventually trust the robot. In [6], assistive free flyers (AFFs) are used in an environment where humans are also moving around. This research uses primitives to make the motion of the AFFs more natural to humans so that they could be aware of where it is going. It doesnt address how the communication intent between both humans and AFFs will be clearly defined. Another approach can be seen in [25] and [26]. In these papers, they include an approach that makes it possible to solve POMDPs online and in real time as well as enable to the vehicle to predict the movements of pedestrians. This approach doesnt include a clear way for the vehicle to communicate its intent with the pedestrians. The research in [16], [18], [19] address how partially observable Markov Decision Processes (POMDPs) and Markov Decision Processes (MDPs) can be used to model the uncertainty inherent in intent communication. With POMDPs, the literature addresses a limited number of actions a human could take which drastically decreases the applicability of these methods due to the increases in communication complexity. Another issue with POMDPs is the amount of time required to calculate a solution. The problem with the strictly MDP model is that the assumption of full observability of the humans intent at all times, which is unrealistic.

The problem that this research hopes to address is to create an explicit communication channel between robot and human intent. Through the review of relevant literature, it has been found that intent communication has commonly been limited to either the robot learning the humans intent or the human understanding the robots intent. This is the problem this research hopes to address with the autonomous golf cart by enabling both parties to be aware of each others intent. To avoid the potential psychological issues that have been seen, the research will focus on keeping peoples perception of the golf cart as a machine or tool.

III. Problem Formulation

The goal of this research is to accurately predict the intent of pedestrians as the golf cart approaches them and have the golf cart adjust its speed and direction accordingly. The golf cart will relay information about its intent via an LED word display and LED light strips to indicate the desired pedestrian action. There will also be a heads-up display (HUD) system inside of the golf cart to show passengers that the cart is aware of the obstacles around it and that it knows how to avoid them. The hypothesis is that since people associate certain colors to certain feelings, they will be able to better understand the golf carts intent. The lights are also used to catch peoples attention to make sure they see the cart approaching them. The LED word display will be able to explicitly communication the golf carts intent using pictures, words, or a combination of the two. To accomplish this, an algorithm will be created that models the intent of both the pedestrian and the golf cart.

A. Belief-State Markov Decision Process

The intent of pedestrians has uncertainty associated with it due to the unpredictability of humans. Due to this uncertainty, a POMDP-based model would be appropriate. Because of the time constraint imposed by real-time calculations of POMDPs, this model, like others, will be based on a belief-state MDP. This simplification can be done because of the fact that there are a limited number of actions the golf cart can take and there are also a limited number of actions pedestrians will take.

The model of the intent communication between the golf cart and pedestrians will be based on the following belief-state MDP tuple:

$$\langle B, A, \tau, r, \gamma \rangle \tag{1}$$

where:

- B: the set of belief states over the POMDP states
- A: the same finite set of actions as the POMDP
- τ: the belief state transition function
- r $\in$ BxA $\Rightarrow$ R: the reward function on belief states
- $\gamma \in$ [0,1] : the discount factor
- τ (b,a,b') = $\sum$Pr (b'| b,a,o) $\cdot$ Pr (o| a,b) where:

$$Pr\,(o \mid a, b) \tag{2}$$

is provided from the POMDP:

$$\sum \text{Pr}(b' \,|\text{b,a,o}= \begin{cases} 1 & b' \\ 0 & otherwise \end{cases} \tag{3}$$

To construct a realistic belief-state to be used in later work, a survey was conducted to determine the potential actions pedestrians might take when encountered with an autonomous golf cart and the probabilities of those actions. Based on the survey of 50 people with no affiliation to the research, potential pedestrian actions were gathered and their probabilities were calculated. The goal of the survey was to narrow down the number of actions pedestrians might take when they encounter a golf cart that might not have a person operating it and to use their responses to determine what kind of communication system would perform the task well and help people to feel more receptive of autonomous vehicles so that they will be more likely to perform what the vehicle asks of them. Some of the questions asked include:

- What would you do if you saw a car approaching you without a driver?
- How would this make you feel?
- What would make you feel more comfortable around this type of vehicle?

The demographic of the survey included students on campus between the ages of 18-22, faculty on the Oklahoma State University campus between the ages of 30-70, and people with no affiliation to the university between the ages of 14-65. There were five pedestrian actions identified ranging from moving out of the way to trying to get in the car. With this information, the belief-state of the MDP, **B**, was composed. Based on the typical operations of a golf cart, the action space, **A**, has also been determined. The transition function, τ, will be calculated based on the reward function, **r**, to determine the appropriate action for the golf cart to take.

B. Partially Observable Markov Decision Process

Due to time limitations, the belief-state MDP was not used for this portion of the research. It will be utilized in the future work of the project. To begin the experiment, a POMDP model will be used. The SARSOP algorithm created in [24] will be used to execute the modeled POMDP. In this paper, the POMDP model is completely defined. The tuple:

$$\langle S, A, O, T, Z, R, \gamma \rangle \tag{4}$$

which includes the possible states, actions, and observations are defined based on the world that the golf cart will be tested in. The POMDP will be used to show the difference in computation time and optimal policy between this method and the belief-state MDP.

IV. Methodology

Before the intent communication algorithm is implemented on the real golf cart, it will first be tested in a gridworld simulation. The simulation will be based on the data collected from the survey and knowledge about the operational environment. While the simulations are being conducted, psychologists will be consulted to determine the best colors to use in the LED light strip to convey the intent of the golf cart as well as what words, phrases, or pictures should be streamed across the LED word display. As of now, the word display shows the simple messages of either STOP or PLEASE CROSS. The HUD system will also be tested to see how accurately it can highlight pedestrians and show the carts intended action.

After the simulations have been completed using SARSOP, the algorithm will be optimized based on the results. The simulations are based on the vehicle determining the intent of the human based on a probabilistic model created from the survey discussed earlier. Once the simulations and optimizations are completed, the algorithm will be implemented onboard the golf cart and the LED light strip, word display, and HUD system will be interfaced with the correct computers. The algorithm will then be tested in a structured environment to see how accurately it will be able to predict the intent of pedestrians and how well it will be able to relay its intent. After several trials have been conducted, the algorithm will further be optimized. Once the final optimization is complete, the golf cart will be used in a real world environment.

V. Results

A. Description of the Experiment

The algorithm for intent communication has been designed based on a POMDP given the reward and transitions models:

$$R\left(a,b\right) = \sum_{s \in S} r\left(a,s\right) \cdot b\left(s\right) \tag{5}$$

$$p\left(s' \mid a,b\right) = \sum_{s \in S} p\left(s' \mid a,s\right) \cdot b\left(s\right) \tag{6}$$

$$b\left(s\right) = p\left(s\right) \tag{7}$$

In these equations, R(a,b) represents the reward given an action, a, in the belief-state, b, r(a,s) is the reward associated with the action in the current state, s, p(s' |a,b) defines the probability that we will transition to the next state, s, given the action and the belief-state, p(s'| a, s) defines the probability we will transition to the next state given the action and current state, and b(s) represents the probability distribution over the world states. For this algorithm, the belief-state was constrained based on the responses from the survey and knowledge about the environment the golf cart will be operating in.

In addition, based on the probabilities of potential actions a pedestrian might take, one obstacle was added that can move like a pedestrian. For example, in the gridworld, it would be the equivalent of a block possibly moving in front of our car or deciding to remain in its current position. This obstacle will move different ways each time the simulation is run. To determine how well the algorithm is able to detect and successfully react to a pedestrian, the simulation will perform 2000 Monte Carlo runs. Each time the golf cart moves through the gridworld, it has a reward of -5 if it gets within one grid-space of a pedestrian and a reward of 1 for each transition it doesnt hit a pedestrian. The SARSOP algorithm used in the Approximate POMDP Planning Toolkit (APPL) [24] will be the testing ground for this simulation. The algorithm was run to test how well it would perform with and without the intent communication between the golf cart and pedestrian and with the pedestrian moving according to the given probabilities. There was one obstacle placed in the simulation. The obstacle had a probability of either moving in front of the car, moving into the same grid-space as the car, or not moving at all. The following plots show how well the golf cart and pedestrians were able to communicate intent.

In the simulations, the intent of the golf cart was provided to the pedestrian based on the observation of the pedestrian's motion. With intent communication, the pedestrian reacted to the golf cart's intent, i.e. either stopped or crossed. Without intent communication, the pedestrian continued on the path they were taking without accounting for the golf cart's approach. The plots show that with or without the intent communication, convergence takes about the same number of iterations or approximately 100 seconds. The pedestrian movement probabilities remained the same throughout both simulations.

When intent communication was included, the reward converged to a higher value than when intent wasnt included. When the intent wasnt communicated between the golf cart and the pedestrian, the reward was noticeably lower and it took longer to converge on the final value. The problem with the slower convergence is that the golf cart may not have an adequate amount of time to react to pedestrians or it might not correctly react to pedestrians. It is possible that the navigation without intent communication could converge to a potentially higher value, but given the time constraint in a real world environment, navigation with intent communication has an advantage.

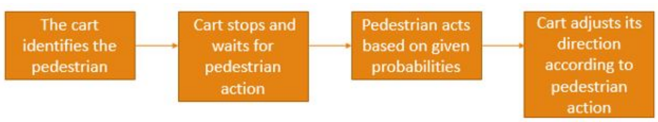

Fig. 1: Navigation with Intent Communication Diagram. The intent is shown to be communicated when the golf cart anticipates a pedestrian action and displays a message accordingly.

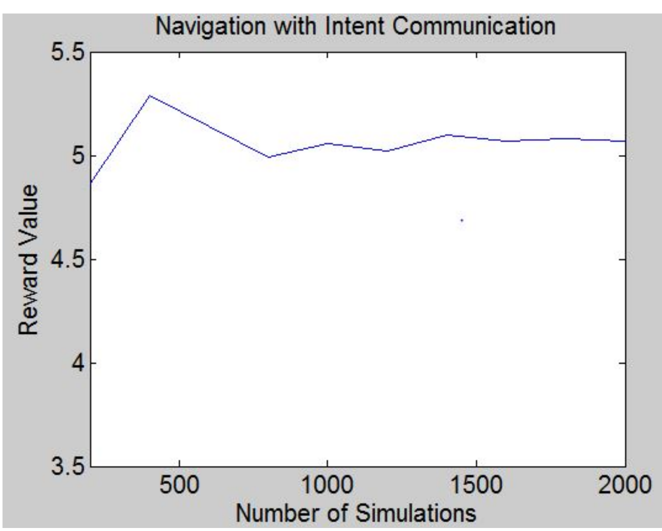

Fig. 2: Navigation with Intent Communication Results. Shows how intent communication causes the POMDP to converge to a reward value based on the given inputs.

Fig. 3: Navigation without Intent Communication Diagram. When intent commuication isn't taken into consideration, the golf cart can identify the pedestrian, but it shows no interest in changing its path with respect to what the pedestrian could do.

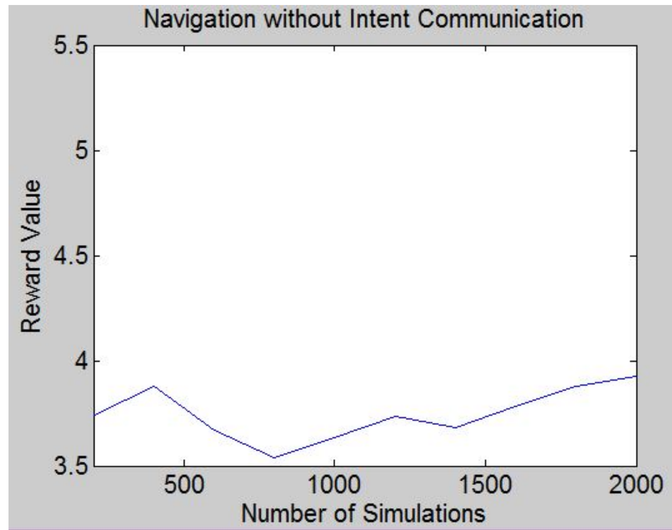

Fig. 4: Navigation without Intent Communication Results. Shows how the POMDP responds when intent communication is removed. The reward value is lower and it has yet to converge.

VI. Conclusion

The key contributions of this work are: a direct feedback loop between the cart and the human, and clear communication between the golf cart and human.

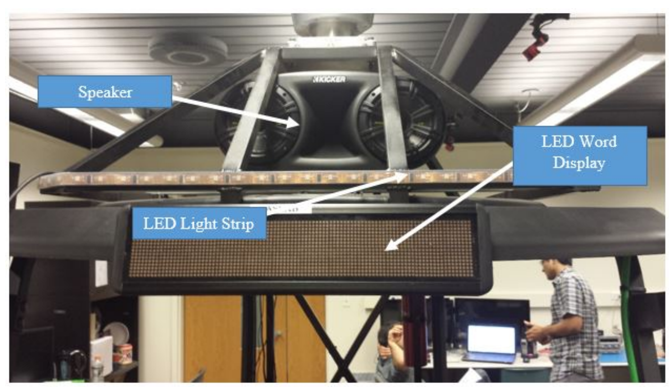

Fig. 5: Picture of experimental setup.

Based on the literature this is the first attempt at solving this problem in this manner. In previous works, there havent been many clear attempts at creating the feedback loop between autonomous vehicle and pedestrian. They have mostly been based on experiments with the humans and machines interacting directly. The papers that had more of a mathematical foundation were limited in the number of actions a person could take [18], [19] or the MDP was idealistic and had no POMDP backing [16]. The benefit of the proposed algorithm is that it will take into account a given belief-state drawn from the original POMDP instead of directly solving a POMDP or creating too idealistic of a model based on an MDP. The simulation run allowed for 9 states to be recorded with the potential for more. The approach seen in [25] and [26] has similar elements, but is currently missing the ability for the vehicle to communicate with pedestrians in an easy to understand manner.

The LED light strips and word display were not bright enough to be seen in direct daylight. The suggested solution is to replace these components with laser lights to create a lane around the golf cart and to project symbols in front of the golf cart. The current solution has been to mount LED lights onto the front of the cart to signal which direction the cart intends to go and stop lights to indicate the cart is coming to a stop. By incorporating the LED lights and word display, the feedback between the golf cart and human should be clear. Because there are a limited number of actions the golf cart will ask of the human, there are few opportunities for a miscommunication to take place. To further decrease the opportunities for miscommunication, a HUD system has been included to communicate the carts intent to passengers which helps to establish trust in the vehicle. The idea is that if the people inside the vehicle appear confident, the pedestrians will be more likely to pay attention the carts indicators.

A. Future Work

The future work for this project includes updating the belief-state MDP algorithm to learn to better predict pedestrian movements, make the algorithm execute faster by potentially using parallelization to search states more efficiently, implement the algorithm on the golf cart, possibly include voice cues to the pedestrians, and to create better visualization systems on the exterior of the golf cart.

REFERENCES

[1] Nehaniv, Chrystopher L., et al. "A methodological approach relating the classification of gesture to identification of human intent in the context of human-robot interaction." Robot and Human Interactive Communication, 2005. ROMAN 2005. IEEE International Workshop on. IEEE, 2005.

[2] Breazeal, Cynthia, et al. "Effects of nonverbal communication on efficiency and robustness in human-robot teamwork." Intelligent Robots and Systems, 2005.(IROS 2005). 2005 IEEE/RSJ International Conference on. IEEE, 2005.

[3] Lee, Christopher, and Yangsheng Xu. "Online, interactive learning of gestures for human/robot interfaces." Robotics and Automation, 1996. Proceedings., 1996 IEEE International Conference on. Vol. 4. IEEE, 1996.

[4] Wang, Tian-Shu, et al. "Unsupervised analysis of human gestures." Advances in Multimedia Information ProcessingPCM 2001. Springer Berlin Heidelberg, 2001. 174-181.

[5] Pavlovic, Vladimir I., Rajeev Sharma, and Thomas S. Huang. "Visual interpretation of hand gestures for human-computer interaction: A review."Pattern Analysis and Machine Intelligence, IEEE Transactions on 19.7 (1997): 677-695.

[6] Szafir, Daniel, Bilge Mutlu, and Terrence Fong. "Communication of intent in assistive free flyers." Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction. ACM, 2014.

[7] Croft, D. Kuli EA. "Estimating intent for human-robot interaction." IEEE International Conference on Advanced Robotics. 2003.

[8] Strabala, Kyle, et al. "Learning the communication of intent prior to physical collaboration." RO-MAN, 2012 IEEE (2012): 968-973.

[9] Lyons, Joseph B., and Paul R. Havig. "Transparency in a human-machine context: Approaches for fostering shared awareness/intent." Virtual, Augmented and Mixed Reality. Designing and Developing Virtual and Augmented Environments (2014): 181-190.

[10] Salem, Maha, et al. "Would You Trust a (Faulty) Robot?: Effects of Error, Task Type and Personality on Human-Robot Cooperation and Trust." (2015).

[11] Rakotonirainy, Andry, Ronald Schroeter, and Alessandro Soro. "Three social car visions to improve driver behaviour." Pervasive and Mobile Computing 14 (2014): 147-160.

[12] Papageorgiou, Constantine, and Tomaso Poggio. "Trainable pedestrian detection." Image Processing, 1999. ICIP 99. Proceedings. 1999 International Conference on. Vol. 4. IEEE, 1999.

[13] Eyben, Florian, et al. "Emotion on the roadnecessity, acceptance, and feasibility of affective computing in the car." Advances in human-computer interaction (2010).

[14] Shah, Julie, et al. "Improved human-robot team performance using chaski, a human-inspired plan execution system." Proceedings of the 6th international conference on Human-robot interaction. ACM, 2011.

[15] Kucukyilmaz, Ayse, Tevfik Metin Sezgin, and Cagatay Basdogan. "Physical Communication of Intent: A Haptic Negotiation Framework for Human-Robot Interaction." (2012).

[16] McGhan, Catharine, Ali Nasir, and Ella Atkins. "Human intent prediction using markov decision processes." Infotech@ Aerospace 2012 (2012): 2.

[17] Ivaldi, Serena, et al. "Perception and human interaction for developmental learning of objects and affordances." Humanoid Robots (Humanoids), 2012 12th IEEE-RAS International Conference on. IEEE, 2012.

[18] Matignon, Latitia, Abir-Beatrice Karami, and Abdel-Illah Mouaddib. "A Model for Verbal and Non-Verbal Human-Robot Collaboration." AAAI Fall Symposium: Dialog with Robots. 2010.

[19] Karami, A-B., Laurent Jeanpierre, and A-I. Mouaddib. ”Human-robot collaboration for a shared mission.” Human-Robot Interaction (HRI), 2010 5th ACM/IEEE International Conference on. IEEE, 2010.

[20] Boerkoel Jr, James C., and Julie A. Shah. ”Planning for flexible human-robot co-navigation in dynamic manufacturing environments.” International Conference on Human-Robot Interaction (HRI), Proceedings of Human Robot Interaction Pioneers. 2013.

[21] Yi, Daqing, and Michael A. Goodrich. ”Supporting task-oriented collaboration in human-robot teams using semantic-based path planning.” Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series. Vol. 9084. 2014.

[22] Joosse, Michiel, Manja Lohse, and Vanessa Evers. ”Sound over matter: the effects of functional noise, robot size and approach velocity in human-robot encounters.” Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction. ACM, 2014.

[23] Clair, Aaron St, et al. ”Speech, Gesture, and Space: Investigating Explicit and Implicit Communication in Multi-Human Multi-Robot Collaborations.” AAAI Spring Symposium: Multirobot Systems and Physical Data Structures. 2011.

[24] Kurniawati, Hanna, David Hsu, and Wee Sun Lee. ”SARSOP: Efficient Point-Based POMDP Planning by Approximating Optimally Reachable Belief Spaces.” Robotics: Science and Systems. Vol. 2008.

[25] Bandyopadhyay, Tirthankar, et al. Intention-Aware Pedestrian Avoidance

[26] Bandyopadhyay, Tirthankar, et al. Intention-Aware Motion Planning