Robots in crowds - being useful while staying out of trouble

Ladislau Bölöni, Saad Ahmad Khan and Saad Arif
Dept. of Electrical Engineering and Computer Science
University of Central Florida
Orlando, Florida
lboloni@eecs.ucf.edu

Abstract

In this paper we are considering an autonomous robot moving purposefully in a crowd of people (a marketplace). The robot should take into consideration the *social costs* of its movement, expressed in terms of violation of the personal space of the humans, blocking their path or even making physical contact with them. On the other hand, the full avoidance of any social cost might jeopardize the mission of the robot - in a sufficiently dense crowd, movement is impossible without violating at least some social norms. The individuals in the crowd, including the robot, periodically encounter *micro-conflicts* where they need to change their behavior to avoid large social costs (such as bumping into each other). We model the resolution of micro-conflicts as a series of games where the payoffs integrate the social and mission costs of the action choices. We show that human behavior corresponds to a strategy which is not necessarily optimal on a single-game basis; instead, it reflects the personality and social status of the person and the psychological requirement of consistency in behavior. We describe a robot behavior which classifies the strategy used by the opponent in the micro-conflict and chooses an appropriate counter-strategy which takes into account the urgency of the robot's mission.

Introduction

Marketplaces are complex environments where physical obstacles are combined with crowds of people. The individual members of the crowd move in a purposeful way: move from one shop to another, stop at various landmarks or head towards the exit along a pre-planned but not rigidly fixed trajectory. We will say that the individuals have a *mission* with a specific value and urgency. The movement of people in such environments is governed by social norms: they are not supposed to violate each other's personal space, block each other's intended direction of movement or physically bump or push each other. The social norms for physical movement depend on the culture and social setting. Different cultures define the personal space of an individual differently, and put different penalty on physical contact. Whether movement in a certain environment can be performed without violating any social norm depends on the density of the crowd: beyond a certain density, an individual which tries to avoid any violation of personal space will not make any advance at all. Groups of individuals moving in dense crowds will enter into *micro-conflicts* if following their planned trajectory would create an unplanned, large social cost through physical collision or severe violation of personal space. The attribute *micro* illustrates the fact that these conflicts are normally resolved in several seconds: one or more participants will alter their speed and/or path, reducing the social cost to an acceptable level.

In this paper we consider the case of an autonomous robot which moves in such an environment. The robot, just like the human participants, has a mission which can be expressed in physical terms. For instance, the mission might be to reach a certain landmark by a certain time, to follow one or more humans at a certain distance, or to maintain its position in a team formation while moving in the crowd. At the same time, the robot needs to stay out of trouble: it must avoid violating the social norms which govern the crowd, taking into account the local social and cultural norms. Part of this can be achieved through path-planning: the robot can plan its path around landmarks and try to avoid dense crowds. Dynamic path replanning, using algorithms such as focussed D*(Stentz 1995) or D*-lite (Koenig and Likhachev 2005) can allow the robot to avoid large, persistent crowds of people. Occasional micro-conflicts with human participants, however are unavoidable, and the urgency of the robots missions makes it unfeasible for the robot to be always the one which "gives way". In general, the robot must avoid violating the social norms, but it should be able to accept some social costs, if it is necessary to achieve its mission.

To successfully participate in micro-conflicts, the robot needs to have an operational model of the social costs and mission costs as perceived by the local society and the individual participants. Furthermore, it needs to have a model of the strategies deployed by the human participants when participating in the micro-conflicts, such that it can develop effective counter-strategies which either mimic or extend those used by humans.

A multidimensional cost model

One way to quantify the decision making process of humans in social settings is by taking into consideration the costs and benefits of certain actions. For our scenario, we assume two large classes of costs: *social costs* depend on the social norms governing the environment and the participants while *mission costs* depend on the specific goals of the human or robot. For humans, the social costs are rooted in the psychology and social conditioning. While robots, naturally, do not have these factors, in order to be accepted by humans as natural participants in the crowd, they need to emulate the human behavior as closely as possible (Nakauchi and Simmons 2002; Walters et al. 2005; Pacchierotti, Christensen, and Jensfelt 2005). Thus, we will assume that humans and the robots use the same cost types (but their values, naturally, can be different).

Modeling the social costs of moving in crowd

We will model the social costs of moving in the crowd by a number of geometrical zones associated with the opponent agents. An agent incurs costs whenever it enters into one of these zones. The zones are not necessarily circular, they move and change orientation with the agents. The costs associated with these zones are justified by psychological models of human perception, and they must be calibrated for the individuals as well as for the culture.

For the work in this paper we consider three zones:

Physical contact zone: represented by the actual physical size and shape of the human or robot agent. Violating this zone means physical contact and carries a large social cost.

Personal space: is the spatial region which a person (and by extension, a robot) regards as psychologically his (Hall and Hall 1969). Within the personal space, we model the personal distance (1-1.5 ft) and the social distance (3-4 ft). The cost decreases towards the outside of the area, becoming zero outside the social distance perimeter.

Movement cone: the movement cone represents the space where the human or the robot made public its intention to move. For the purpose of this paper, we consider the movement cone as circular pie extending from the agent in the current direction of movement, for a radius equal of 3 seconds movement with the current speed. The movement cone is only relevant for a mobile agent. By violating the movement cone, the opponent forces the agent to change its movement, unless it accepts a high social cost by violating the personal space or even the physical space.

We are using a model where the social costs are additive across the cost types and for the multiple agents. For instance, if the agent violates more than one agent's personal space, it will occur the sum of the costs. On the other hand we retain only the maximum social cost for each micro-conflict.

We need to consider the relationship of these social costs to similar geometric models used in robot navigation. For instance, the movement cone concept is related to that of collision cone (Chakravarthy and Ghose 1998), while the personal space can be perceived as similar to potential field methods (Ge and Cui 2002; Huang 2009; Lamarche and Donikian 2004; Waydo and Murray 2003). These models are a direct input to the movement control of the robot, for instance in the choice of the velocity vector (Guy et al. 2009; Van den Berg, Lin, and Manocha 2008; Van Den Berg et al. 2011). In contrast, the social costs are not a direct input to the movement control: instead, they provide input to the high level decision making. For instance, an agent might decide to move ahead, even if this leads to a high social cost or even a collision. Naturally, once the high level system.

Modeling mission costs

We assume that the participants in the crowd have tasks to accomplish, thus any delay caused by a micro-conflict comes with a mission cost.

For a *non-urgent* mission, the mission can still be achieved at an arbitrarily later time - thus the mission cost of a delay is proportional with the delay. For *urgent* missions, the delay reduces the probability of mission success, thus the cost of the delay escalates in time.

For the purpose of this study we assume that the human participants have non-urgent missions. The mission of the robot is to follow its owner in the crowd. Repeated delays in the resolution of a micro-conflict make the robot fall more and more behind, modeled with a mission cost which for every new second of delay considers the full amount of time the robot is behind its owner. On the other hand, the robot is able to catch up with its owner between micro-conflicts (or equivalently, the owner will wait for the robot to catch up). Other assumptions are, of course, possible, but they are beyond the scope of this paper.

Micro-conflicts and resolution strategies

Micro-conflicts

A micro-conflict is a situation in the movement of an agent in the crowd where the next planned action of the agent has a significant, unexpected social cost by violating the zones of one or more opponent. For the current work we will only consider micro-conflicts with exactly two participants. Furthermore, we assume that micro-conflicts will be attended to in the reverse order of their maximal costs (which means in dense crowds, agents will ignore lower stake micro-conflicts until the ones with higher stakes are resolved).

The answer of the agent to a micro-conflict involves the consideration of other alternatives to the currently planned movement: the agent might stop, continue moving with a different speed (faster or slower) or it can replan its trajectory. In this paper we model this choice with a two-player one-move game. The move C (collaborate) corresponds to the player stopping, while the move D (defect) corresponds to the agent moving on its currently planned path. This model can account for a slow-down (by alternating C and D moves), but it does not cover the options of accelerating or changing the movement path.

The payoffs of the game are given by the total costs incurred by the players for the various combinations of moves. The games are not, in general, symmetric, as the cost functions differ from agent to agent.

As a note, for these games it is more convenient to speak in terms of cost minimization rather than payoff maximization. Rigurously, the payoffs are the costs with a negative sign.

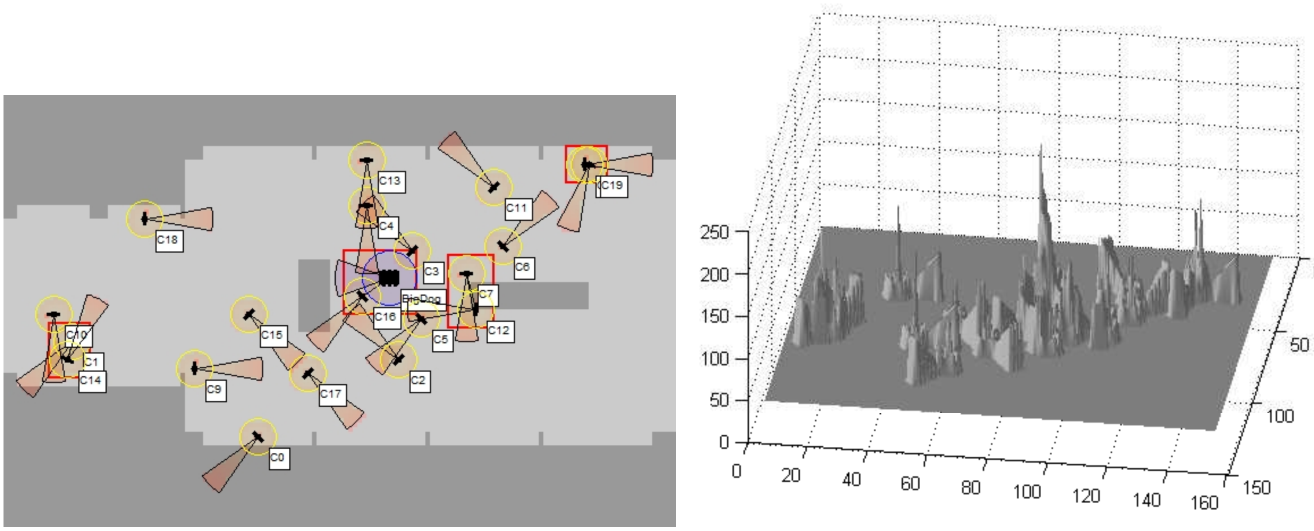


Figure 1: A moment in the scenario of the robot navigating a crowd of people on the market. The left screenshot shows the visualization of the scenario in the simulator at time $t = 21sec$. The right diagram shows the cummulative social cost at that particular moment. The goal of the robot can be interpreted as an attempt to move while keeping to the "valleys" of this constantly changing surface.

The life cycle of a micro-conflict

A game can be technically created among any pair of agents. However, if the agents are sufficientlly far away from each other, the moves (D,D) will have no cost in the game. The agents enter into a micro-conflict when the (D,D) move pair has a non-zero cost for at least one of the agents. The conflict is *resolved* when the (D,D) move pair will have again a zero cost.

A micro-conflict is not necessarily resolved in a single game. It normally requires a series of games, each with a specific set of costs. Even if the two agents play (C,C) which means that they start the next game from the same physical position, the costs of the new game might change if one of the agents has an urgent mission, which would change the mission component of the cost. Figure 2 shows the evolution of the games played during a hand-crafted micro-conflict where a robot and a human are heading to a collision course on right-angle trajectories.

It is impossible to predict the nature of the games which will occur during a micro-conflict. The agents heading on a collision course will at some moment encounter some variation of a Hawk-Dove game, where in the case of a (C,D) or (D,C) play the player moving D will have an advantage, but a (D,D) move will have a large cost for both players. It is not necessary, however, for each of the games encountered during the resolution of a micro-conflict to be Hawk-Dove games.

Modeling the human opponent: Strategy consistency and choice of strategies

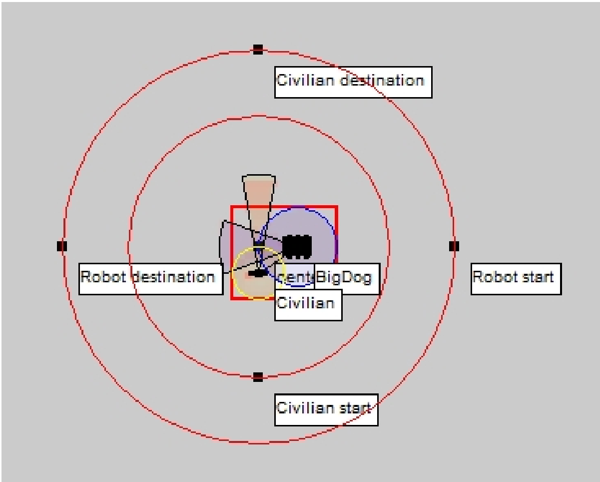
We call strategy the algorithm used by an agent to determine its choice of move in a given game. Restricting our considerations to a single game, game theory would tell us to choose a move which maximizes our payoffs with the assumption that the opponent also plays the perfect strategy. As the games in the micro-conflicts are not zero-sum, this would correspond to a *maximin strategy* (risk minimization).

However, this is not an accurate model of human behavior, because the human game-playing strategy takes into consideration other factors beyond the current game. First of all, crowd participants will encounter many micro-conflicts over time, each micro-conflict consisting of several games. Human psychology rewards perceived consistency and predictability and there is a social cost of being perceived in having an erratic behavior.

Second, beyond the micro-conflict games costs, the agents behavior must be consistent with other social values such as dignity, politeness, "face" and other metrics. The first implication of all this is that instead of choosing a strategy for the individual games, the agents will choose *meta-strategies* which they will follow consistently across the games of the micro-conflict. Meta-strategies can contain stochastic elements, considerations of factors outside the current game (such as the history of the games in the micro-conflict or predictions of future games).

The existence of stable meta-strategies means that the players can, to a certain degree, predict the moves of the opponents. Under these conditions, maximin is not an optimal strategy - stochastic expectation maximization strategies can yield a better value in the long run.

The next questions involves whether humans use mixed strategies in micro-conflicts. It is well known that for Hawk-Dove games the only symmetric Nash equilibrium is a mixed strategy equilibrium. On the other hand it had been argued that the randomness involved by mixed-strategies is not the normal way for humans to operate: humans do not perform



Game at t=8.0 (moves: R: C, H: D)

Civilian \ BigDog	C	D
C	38.268 1.000	13.500 22.535
D	12.500 1.000	37.268 18.750

Game at t=9.0 (moves: R: D, H: C)

Civilian \ BigDog	C	D
C	25.768 20.750	2.000 37.268
D	0.000 24.535	24.768 12.500

Game at t=10.0 (moves: R: D, H: D)

Civilian \ BigDog	C	D
C	25.768 2.000	2.000 0.000
D	0.000 2.000	24.768 0.000

Game at t=11.0 (moves: R: D, H: D)

Civilian \ BigDog	C	D
C	1.000 2.000	2.000 0.000
D	0.000 2.000	0.000 0.000

Figure 2: A hand-crafted single-conflict scenario between a robot and a human. The screenshot of the scenario (above) at time t=7.0 and four individual games at times t=8.0 to t=11.00 as they appear during the resolution of the micro-conflict.

mental coin-tosses, and even if they would want to, they have difficulty generating random outcomes without external physical means. In the particular case of micro-conflicts, however, we can safely assume the existence of mixed strategies as there is sufficient randomness both in the lack of knowledge about the exact game (the Harsányi interpretation (Harsanyi 1973)) as well as in the uncertainty about the strategy of the opponent (Aumann and Brandenburger 1995).

Modeling human meta-strategies

One of the characteristics of human meta-strategies is that humans enter into micro-conflicts with a clear view of what type of resolution they would prefer. These strategies not only determine the behavior of a specific human player, but they also provide information to the other players. The use of a specific meta-strategy in the case of a human is signalled through the physical movement itself. In human-to-human interaction there are a number of other means through which this communication can happen: there is a priori information which can be inferred from social status, previous acquaintance and physical characteristics. In addition to this, human players can perform communication during the micro-conflicts using social signalling(Vinciarelli, Pantic, and Bourlard 2009) or even natural language. These communication means, however, are not available for human-to-robot interaction.

We will consider four meta-strategies. For each, we will describe the *intent* of the agent A when encountering agent B, followed by its expression in terms of costs.

MS1 **Respectful:** I am going to give B a wide berth. Agent A tries to avoid any social cost in the interaction with B, playing C for all games unless the predicted costs are very low.

MS2 **Tight-after:** I am going to let B pass, but pass very close behind him. This can be modeled by a stochastic model where the agent plays with a high confidence that the opponent plays D (in our model, 0.75).

MS3 **Tight-front:** I am going to cross in front of B (but will avoid direct physical contact). This can be achieved by a stochastic strategy which weights the opponent's predicted choice with a high confidence that the opponent plays C (in our model, we assume a probability of 0.75).

MS4 **Bully** The agent decides to minimize its mission costs, ignoring almost all social costs. The assumption behind this model is that this behavior will make the opponent play C, thus keeping the costs low.

These meta-strategies can be transformed into a specific mixed strategy for each individual game encountered by the agent in the resolution of the micro-conflict. Note that although these meta-strategies are not optimal, certain combinations can yield near optimal social costs for the overall micro-conflict. The encounter between a bully and a respectful agent will yield a low social cost through the restraint of the respectful agent. However, the series of C moves by the respectful agent implies a high delay and thus a high mission cost for it.

Another observation is that the high level intent in the meta-strategy might not necessarily be accomplished. If both agents use Tight-front, naturally, only one of them can pass first. What will happen is that depending on the geometric configuration, there will come a moment when the other agent's cost for the D move will outweigh all other considerations, and it will need to play C, allowing the other agent to pass first. Nevertheless, the series of moves will be different from that of an agent which would have played Tight-after.

Adapting the robot strategy against the human opponent

There is a strong motivation for the robot to play a meta-strategy which is, at least superficially, similar to that of humans. Furthermore, if the robot can make the assumption that the human will play a consistent meta-strategy from a certain set (such as the MS1 …MS4 strategies outlined above), it can try to infer what strategy the opponent uses and choose an advantageous counter-strategy. As we have seen, human players have various means of social signalling to communicate their chosen strategy. If the robot lacks the ability to communicate in a similar way, it needs to rely exclusively on the information gleamed from game-play.

We have implemented a framework which adapts the meta-strategy deployed by the robot to the opponent, by classifying the opponent based on the opponents moves. This is performed by performing a series of simulated plays from the opponent's perspective using four internal simulated agents which conform to the four human meta-strategies. The results of the simulated plays are compared to actual play performed by the opponent, and their match updates the classification of the opponent.

The output of the classifier allows the robot to adapt its behavior to the opponent, by probabilistically predicting the next move of the opponent, and using it to weight the costs of its own moves. For instance, if the agent classifies its opponent as a Bully, the agent only needs to consider the costs of the (C,D) and (D,D) move pairs, knowing that the opponent always plays D.

Experimental results

In the following we describe the results of a series of experiments involving the behavior of a robot in a crowd. The experimental scenario involves a marketplace in a Middle-Eastern country. The area is a narrow space surrounded with shops whose entrances serve as landmarks, as well as internal obstacles. A number of shoppers perform purposeful movement, which involves visiting shops for a shorter or longer times. The path chosen by the individuals balances the length of the path with the avoidance of the obstacles and large groups of people. Micro-conflicts are resolved through a succession of games with the four meta-strategies described in the previous section. We assume that the meta-strategies of the individuals are distributed as follows: 10% Respectful, 30% Tight-after, 50% Tight-front and 10% Bully. A game which is "stuck", in the sense that both sides play C for three times in a row, are resolved through path re-planning, by considering the opponent as an obstacle and calculating an avoiding path.

In this baseline scenario we consider the presence of a patrol of peacekeeping soldiers traversing the market while being accompanied by a Boston Dynamics Big Dog robot(Raibert et al. 2008). The mission of the robot is to follow the soldiers through the crowd as closely as possible, while "staying out of trouble". The soldiers can change their movement at any time, triggering frequent path replannings, for which we use the D*-lite algorithm (Koenig and Likhachev 2005). The robot participates in micro-conflicts in the same way as the human participants. Naturally, the robot's personal space and physical space is different from that of a human (a Big Dog robot is larger than a human). In addition, the robot's mission cost escalates with any delay - that's is successive C plays within the same micro-conflict will become more and more costly.

We have run experiments with the robot using one of five meta-strategies (Respectful, Tight-after, Tight-front, Bully and the Adaptive strategy). Each experiment has been repeated 20 times, and the results averaged. Figure 3 shows two sets of measurements illustrating the performance of the robot on these metrics.

The left diagram shows the maximum social cost for each micro-conflict. The Bully strategy incurs the highest cost in a consistent way. However, there is little consistent difference between the remaining strategies. The Adaptive strategy performs among the best or very close to the best for a number of points (at crowd sizes of 25, 30, 40, 45 and 60) but in the middle of the group for others, and in two occasions (65 and 70) beats only the Bully strategy. Overall, this illustrates the fact that the probabilistic inference of the opponents behavior (coupled with the stochastic nature of the meta-strategies themselves) can occasionally lead to wrong choices, even if they work on the average case.

The right diagram on Figure 3 shows the sum of the mission costs for each scenario. Intuitively, this number is the sum of the meters the robot falls behind the patrolling soldiers for each scenario. For this metric, the different meta-strategies are more clearly separated: as expected, the Bully strategy occurs a cost of zero, as it will never concede priority. It is followed by the Tight-front, Adaptive, Tight-after and, at large distance, by the Respectful strategy.

Taking into consideration the fact that the goal of the robot is to balance its mission goals with the desire to minimize social costs, we can conclude that the Adaptive meta-strategy and the Tight-front meta-strategy are significantly better than the other strategies considered (Bully, Tight-after and Respectful) which fail at one or the other requirements.

The relative closeness of the performance of these two meta-strategies is an interesting result of our studies. We conjecture that a consistent Tight-front strategy will incur public perception costs not necessarily captured in the physical model of social costs, so for a practical implementation, the Adaptive strategy will be preferable. Nevertheless, if the requirements for opponent classification are missing, the Tight-front meta-strategy represents a close fallback.

Conclusions

In this paper we described a method for the navigation of a robot in a crowd of people with purposeful movements. Inevitably, the robot will enter into micro-conflicts with the human participants, which can be resolved through a series of games. We described a number of meta-strategies which model human behavior, as well as an adaptive strategy for the robot which is based on the classification of the opponent's meta strategy. Natural extensions of this work include the consideration of games with more than two choices (corresponding to speedup, slowdown and evasive maneuvers) as well as the impact of social signalling between the participants.

References

Aumann, R., and Brandenburger, A. 1995. Epistemic conditions for nash equilibrium. *Econometrica: Journal of the Econometric Society* 1161–1180.

Chakravarthy, A., and Ghose, D. 1998. Obstacle avoidance in a dynamic environment: A collision cone approach. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on* 28(5):562–574.

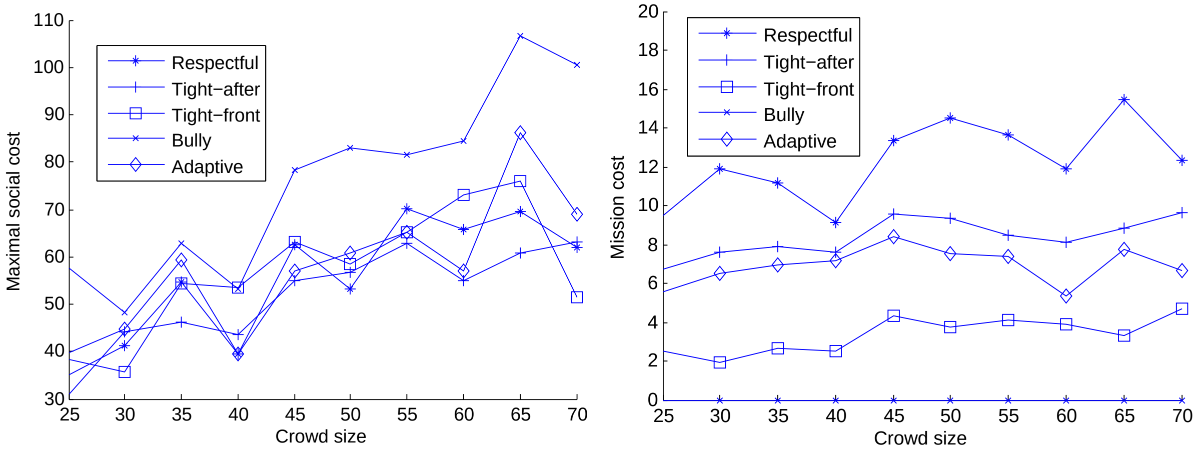


Figure 3: Experimental results. Left diagram: sum of the maximum social costs / micro-conflict. Right diagram: sum of the mission costs.

Ge, S., and Cui, Y. 2002. Dynamic motion planning for mobile robots using potential field method. *Autonomous Robots* 13(3):207–222.

Guy, S.; Chhugani, J.; Kim, C.; Satish, N.; Lin, M.; Manocha, D.; and Dubey, P. 2009. Clearpath: highly parallel collision avoidance for multi-agent simulation. In *Proc. of the 2009 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, 177–187. ACM.

Hall, E., and Hall, E. 1969. *The hidden dimension*. Anchor Books New York.

Harsanyi, J. 1973. Games with randomly disturbed payoffs: A new rationale for mixed-strategy equilibrium points. *International Journal of Game Theory* 2(1):1–23.

Huang, L. 2009. Velocity planning for a mobile robot to track a moving target: a potential field approach. *Robotics and Autonomous Systems* 57(1):55–63.

Koenig, S., and Likhachev, M. 2005. Fast replanning for navigation in unknown terrain. *IEEE Transactions on Robotics* 21(3):354–363.

Lamarche, F., and Donikian, S. 2004. Crowd of virtual humans: a new approach for real time navigation in complex and structured environments. In *Computer Graphics Forum*, volume 23, 509–518.

Nakauchi, Y., and Simmons, R. 2002. A social robot that stands in line. *Autonomous Robots* 12(3):313–324.

Pacchierotti, E.; Christensen, H.; and Jensfelt, P. 2005. Human-robot embodied interaction in hallway settings: a pilot user study. In *IEEE Int. Workshop on Robot and Human Interactive Communication*, 164–171. IEEE.

Raibert, M.; Blankespoor, K.; Nelson, G.; Playter, R.; et al. 2008. Bigdog, the rough–terrain quadruped robot. In *International Conference of Automatic Control*, 10823–10825.

Stentz, A. 1995. The focussed $\hat{d^*}$ algorithm for real-time replanning. In *International Joint Conference on Artificial Intelligence*, volume 14, 1652–1659.

Van Den Berg, J.; Guy, S.; Lin, M.; and Manocha, D. 2011. Reciprocal n-body collision avoidance. *Robotics Research* 3–19.

Van den Berg, J.; Lin, M.; and Manocha, D. 2008. Reciprocal velocity obstacles for real-time multi-agent navigation. In *IEEE Int. Conf. on Robotics and Automation*, 1928–1935.

Vinciarelli, A.; Pantic, M.; and Bourlard, H. 2009. Social signal processing: Survey of an emerging domain. *Image and Vision Computing* 27(12):1743–1759.

Walters, M.; Dautenhahn, K.; Koay, K.; Kaouri, C.; Boekhorst, R.; Nehaniv, C.; Werry, I.; and Lee, D. 2005. Close encounters: Spatial distances between people and a robot of mechanistic appearance. In *5th IEEE-RAS Int. Conf. on Humanoid Robots*, 450–455.

Waydo, S., and Murray, R. 2003. Vehicle motion planning using stream functions. In *IEEE Int. Conf. on Robotics and Automation*, volume 2, 2484–2491. IEEE.