Learning When to Fail: Contingency Plans for Crowd Navigation

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***Abstract*— When navigating in the presence of humans, mobile robots need robust, efficient ways of dealing with highly stochastic dynamic obstacles. This problem is often addressed by building a (implicit or explicit) model of possible human trajectories and planning the robot's motion based on this model to avoid collisions. We call this a *success controller*. However, such controllers typically assume that their goal is feasible, without considering cases in which humans may move to block the robot's path. This can lead to the robot simply stopping, continuously replanning to an infeasible goal, or, in the worst case, colliding with a pedestrian. This work seeks to explicitly address this deficiency by creating a classifier that examines the robot's trajectory to determine whether or not it believes the robot can efficiently achieve its goal point. Additionally, we develop a *failure controller* that the robot executes if the classifier determines that it cannot reach its goal. This controller safely guides the robot to a different location from which it can replan. We show that this failure controller results in fewer intrusions near people in a crowded scene than simply relying on the success controller.**

I. INTRODUCTION

Pedestrian crowds present a challenging navigation environment for a mobile robot. The robot must comply with latent social rules governing its trajectory while simultaneously reaching its goal in a reasonable amount of time. As robots move into closer contact with humans, advanced methods for navigation in crowds will gain increased importance. Probabilistic planners, which make navigation plans in the belief space, show potential to make headway in this problem and have demonstrated success dealing with uncertainty [1] like that experienced navigating in a crowd. To form their plans, these planners rely on smaller atomic actions which are strung together to form an overall trajectory. Some of these actions are learned by presenting the robot with its starting pose and a waypoint pose and running simulations with pedestrians or other agents [2]. In general, these controllers guiding each action deal with unexpected situations in which their original trajectory to their waypoint becomes infeasible by simply replanning or stopping altogether. Replanning in some cases may take too long to avoid an imminent collision. Additionally, when the waypoint becomes completely unreachable, replanning or stopping may result in a more costly trajectory than simply abandoning it and seeking a safe location from which the higher level planner can generate a new trajectory to the overall goal. We address this issue by developing a failure controller aimed explicitly at motion control for the robot when it has no goal.

Some text

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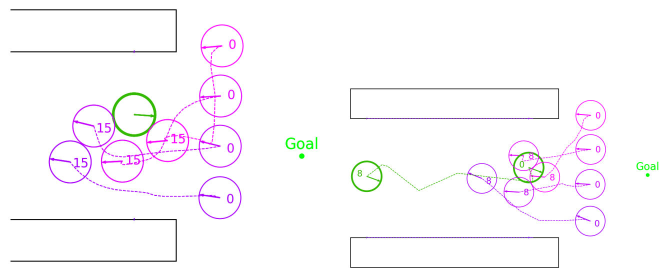


(a) (b)

Fig. 1: The green circle represents the robot, the blue circles represent different humans and the black polygons represent the walls of the corridor. The arrows indicate the heading of each agent. Only the initial and final locations of each object are shown. The numbers indicate the time step at which the snapshot was taken. This is an example of a situation in which the robot stopping (a) will cause more collisions and intrusions than following a failure controller which in this case simply moves the robot along the corridor out of the way of humans (b).

Developing such a controller is useful because it gives long term planners a contingency plan at planning time so they can more efficiently explore the search space. The failure controller itself also helps ensure that the robot obeys a safe policy even when it has no waypoint to navigate to. For example, in some situations like that in Figure 1a, staying still will cause the robot to be a hindrance to the humans and it will likely intrude into their personal space. Moving away to a different area of the scene would give the robot a safer place to replan from.

This work facilitates combining learning with planning for long term crowd navigation by providing a reinforcement learning based failure controller and a supervised learning based predictor for determining when to use it. Specifically, this paper assumes that an existing probabilistic planner uses a set of motion primitives and controllers to create navigation plans. The set of controllers includes some to execute complex behaviors that interact with pedestrians. Each of these controllers has some probability of success which is associated with one goal and trajectory, and some probability of failure which is associated with a different trajectory. Success cannot be guaranteed for the controllers because the surrounding humans may interact with the robot or each other in unexpected ways. Note that the failure controller's objective differs from that of a traditional navigation planner in that the failure controller is not given an explicit goal; rather, it attempts to extract the optimal goal and trajectory from its environment.

The contributions of this work are:

1) A classifier that determines whether or not a robot is likely to reach its goal in a given scene.
2) A failure controller that safely guides the robot to a stable position from which it can initiate replanning.

The design philosophy taken by this approach separates controllers for individual actions from the long term planner. This means the results presented here could easily be adapted to work with any planner.

The remainder of this paper is organized as follows.

The code of our approach is available here: `https://github.com/patricknaughton01/LearnController`.

II. RELATED WORK

Several methods use explicit models of human behavior to achieve smooth, predictable robot navigation among pedestrians. Trautman et al. model the interaction between the robot and pedestrians as an extension of an interactive Gaussian process that accommodates multiple goals [3]. The social forces model treats humans and the robot in question as masses subject to Newtonian dynamics and applies fictitious forces to them to predict and plan trajectories [4]. It recomputes these forces and their effects on robot motion at each time step to determine how the robot should move. These techniques however rely on hand-crafted models of human behavior to achieve their results and handle unexpected or uncooperative human actions by simply replanning using the same model. The social forces model in particular does not demonstrate robust navigation plans and will sometimes exhibit oscillatory behavior in more crowded or narrow areas [4].

Another approach uses inverse reinforcement learning to learn latent, possibly stochastic social rules humans observe when navigating in crowds [5]. This method uses example trajectories recorded from humans or gathered from teleoperated runs. This approach however is extremely unlikely to observe failed trajectories where a human attempts to execute some navigation plan and is forced to completely abort their initial goal. If a human attempts to overtake someone else, for example, they have many contingency options in the case where the other person is either intentionally or unintentionally uncooperative. For example, they could use verbal communication or body language to more explicitly communicate their intentions, options which are not available to many mobile robots. For this reason, inverse reinforcement learning will likely be unable to formulate a useful model for navigation when situations such as these occur.

Reinforcement learning has successfully been applied to the social robot navigation problem using a variety of different models [6], [2]. Reinforcement learning is particularly suited to this application as noted in [6] because it is extremely difficult to specify what the optimal action for a robot to take is, but it is comparatively easy to alert the robot when it performs a socially unacceptable or unsafe action. Previous work has focused on using reinforcement learning to develop policies that generate optimal (in terms of time) paths to a robot's goal in the presence of humans or other autonomous agents. These policies however generally assume the goal is reachable and do not make contingency plans if that assumption turns out to be incorrect. Additionally, the agent is explicitly given a goal to reach by the experimenters; we wish to navigate in the case of failure at which point there is no obvious goal.

The above methods all either deal with failure at execution time by simply replanning or do not consider failure to reach the goal at all. We depart from this paradigm by designing a controller specifically targeted at producing trajectories when the robot's original goal is no longer reachable.

III. PROBLEM STATEMENT

We consider a robot that strings together different motion primitives and controllers to generate a navigation policy to reach some overall goal. Motion primitives are basic actions the robot can take which are guaranteed to succeed, for example, drive forward one meter. Controllers are more complicated actions that may fail, for example, barging past a group of pedestrians. These controllers can be used by the robot in specific situations to navigate in a scene. We refer to the controller that guides the robot a *success controller*. This work is concerned with detecting and handling the failure of these controllers. Specifically, we develop a *failure controller* that corresponds to a given success controller. This failure controller directs the robot if it is determined at execution time that the success controller is unlikely to achieve its goal.

Additionally, we would like to rigorously determine at execution time whether or not the success controller is likely to succeed. In this framework, the robot can decide at each time step whether it should begin using the failure controller. Once it switches to the failure controller, it cannot switch back to the success controller until the planner generates a new plan.

IV. APPROACH

We begin with a fixed success controller. In this work, we consider one specific controller for barging into a group of people at the end of a corridor. While the experiments and results here only concern this controller, the framework can be extended to include other controllers as well, for example, to overtake or cross in front of pedestrians. To characterize the state of the robot, an initial matrix is constructed with the same number of rows as there are agents and obstacles in the scene (including the robot). Each row of the matrix takes the form $(d_x, d_y, s_{\text{pref}}, h, r, v_x, v_y, p'_x, p'_y, v'_x, v'_y, r', d, r_{\text{sum}})$ where

- d_x and d_y are the x and y distances from the robot to the goal.
- s_{pref} is the preferred speed of the robot.
- h is the heading of the robot w.r.t. the global coordinate frame.
- r is the radius of the robot.
- v_x and v_y are the x and y velocities of the robot w.r.t. the robot's coordinate frame.

- p'_x and p'_y are the x and y coordinates of the other agent w.r.t. the robot's coordinate frame.
- v'_x and v'_y are the x and y velocities of the other agent w.r.t. the robot's coordinate frame (note, this is not relative to the robot's velocity, just relative to its rotation).
- r' is the radius of the other agent.
- d is the Euclidean distance between the robot and the other agent.
- r_{sum} is the sum of the radii of the robot and the other agent.

The first five components of each row are referred to as the robot's `self_state` because they pertain specifically to the robot.

This is augmented by a series of occupancy maps, one for each human and obstacle in the scene and one for the robot itself. Each occupancy map is centered on and aligned with its respective agent and their heading and is discretized into a number of squares. Each square indicates in a binary fashion whether or not it contains an object. Each square also contains the average velocity of all the objects within that square (simply set to 0 if the square is unoccupied). In our case, each occupancy map is discretized into 16 (4x4) 1 unit squares. This collection of occupancy maps and information about the robot's dynamics form the robot's *state*. Note that the dimensions of the state matrix will vary depending on the number of humans and obstacles in the scene.

This combined state is used as the input to a neural network. We model our architecture off of that presented in [2] in order to handle the variable input sizes, as the input matrix changes size based on the number of people and obstacles in the scene. This architecture was shown to produce good results for robotic navigation in the presence of pedestrians in [2]. In addition, we include an LSTM at the end of our network so that the robot can learn relationships between successive states. Figure 2 shows the overall architecture of the model. The output of the network has five nodes which are interpreted as the x and y coordinates of the mean, the x and y standard deviations, and the correlation between x and y of a Gaussian distribution of the next location of the robot conditioned on its current state. At execution time, we then feed this network its current state and attempt to move to the mean of this distribution in the next time step.

We trained this neural network on 1000 successful trajectories in which the robot can feasibly reach its goal. These trajectories were generated using the RVO2 library [7] [8]. We trained using an Adam optimizer with a learning rate of 0.005 and the negative 2D log-likelihood loss for 500 epochs. This controller was trained with a very high dropout percentage of 0.5 in each MLP. Because the success controller is not the focus of this work, we only used scenes containing four people and two obstacles. Figure 3 shows an example of a trajectory generated by the final controller.

We split the remaining approach into two distinct parts: First, we consider just determining whether or not the robot should switch to its failure controller. Given this classifier, we then develop a failure controller that, starting from the

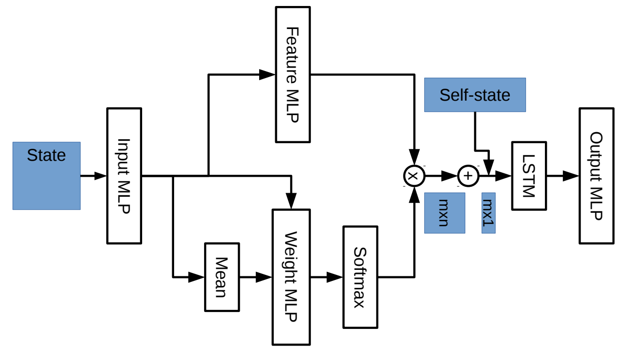


Fig. 2: Model architecture of the neural network used to control the robot. Variable sized inputs are handled by summing a weighted vector across the people and obstacles.

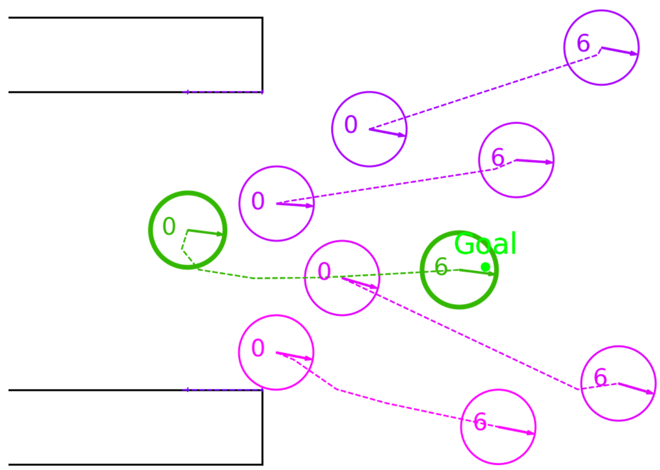


Fig. 3: Example of a successful trajectory. When executing the barge in success controller, the robot expects the humans in the scene to disperse to let it through.

state at which the classifier reports we have failed, attempts to learn a policy that guides the robot to a safe location from which to replan.

A. Determining When To Switch

In order to rigorously determine whether or not the success controller is likely to succeed (and thus, whether or not we should switch to the failure controller), we train an additional neural network that has the same architecture as the original. However, it attempts to learn a target function that predicts the distribution of previous locations of the robot given the robot's current state and the fact that the robot is on a trajectory that leads to its goal. It is trained on $10,000$ trajectories generated by the success controller in scenes where the success controller can reach its goal. This network however does not receive the robot's full state, rather, it only observes the robot's *self state*. This was done so that we could train the network by only showing it successful trajectories without the uncertainty in its prediction exploding when it observes unsuccessful ones.

At execution time, we utilize this network's prediction to perform a statistical p-test with an α value of 0.05. At each time step we construct the error ellipse given by the Gaussian distribution represented by the reverse predictor that contains $1-\alpha$ of the distribution's probability mass. We perform this same test on the robot's current position given the distribution predicted by the success controller in the previous time step. By default, we assume that the trajectory will be successful and switch to the failure controller only if one of these tests fails.

B. Failure Controller

For the failure controller, we need to address a somewhat novel formulation of the navigation problem in that the robot now has no specific goal it is trying to reach. Once the failure controller gets invoked, the robot has determined that it is unlikely to reach its goal. Because it is impossible to explicitly define optimality in this framework, we formulate this as a reinforcement learning problem $\langle \mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma \rangle$ with an infinite set of states $\mathcal{S}$, a finite set of actions $\mathcal{A}$, state transition matrix $\mathcal{P}(s_t, a_t, s_{t+1})$, reward function $\mathcal{R}(s_t, a_t, s_{t+1})$ and discount factor $\gamma \in (0,1)$ [9] and model the robot as a Markovian agent. Rather than define a set of states constituting a goal, we define a reward function that punishes actions we determine to be undesirable.

Our reward function is split into three parts: $\mathcal{R}_{\text{collision}}$, $\mathcal{R}_{\text{movement}}$, and $\mathcal{R}_{\text{smoothness}}$. The overall reward the robot observes is simply the sum of these three components. Equations 1, 2, and 2 show how these values are calculated. Note that each term is computed (where appropriate) with respect ot each agent and obstacle in the scene. This means that an action that causes a collision with two agents receives a collision reward of -2, not just -1. We apply the $\mathcal{R}_{\text{movement}}$ and $\mathcal{R}_{\text{smoothness}}$ rewards so that, other things equal, the robot will prefer to remain stationary and move in straight lines at consistent velocities that are more predictable for other humans in the scene.

$$\mathcal{R}_{\text{collision}} = \begin{cases} -1 & d < 0 \\ -0.25 & 0 \le d < 0.2 \\ 0 & else \end{cases} \tag{1}$$

$$\mathcal{R}_{\text{movement}} = \begin{cases} 0 & a_t = 0 \quad (remain\ still) \\ -0.01 & else \end{cases} \tag{2}$$

$$\mathcal{R}_{\text{smoothness}} = \begin{cases} 0 & a_t = a_{t-1} \vee a_{t-1} = 0 \\ -0.01 & else \end{cases} \tag{3}$$

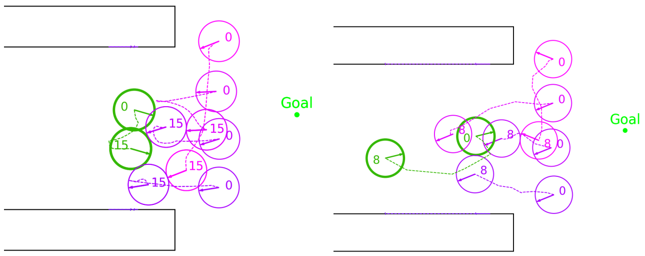
We then define a $Q_\pi(a_t, s_t)$ function that represents the total expected discounted return achieved by executing action a_t from state s_t and thereafter following policy π.

$$Q_\pi = \sum_{k=0}^{\infty} E[\gamma^k \mathcal{R}(s_{t+k}, \pi(a_{t+k} \mid s_{t+k}), s_{t+k+1})] \tag{4}$$

We represent this function with a deep neural network and use the Deep Q-learning algorithm with experience replay developed in [10] to obtain an estimate of the optimal Q function. We utilize an ϵ-greedy policy with an ϵ that linearly decays from _ to _ over _ episodes. We set $\gamma = 0.9$ and train using the Adam optimizer with learning rate 0.001.

To train our agent, we ran 1000 episodes in which the robot begins by executing its success controller. However, the humans in the scene move in such a way to prevent the robot from barging in. Namely, they move into the corridor towards the robot rather than dispersing to allow it through. Once the reverse predictor determines that the robot has failed, the robot begins executing an ϵ-greedy policy and stores transitions in its replay buffer. At each time step, the reward achieved by the robot is computed and its policy is updated. After 10 time steps, the current episode ends and another one is started. The failure controller moves for 10 time steps regardless of how long the success controller moved.

Algorithm 1 summarizes the overall navigation policy of the robot. t_s is the maximum number of time steps the success controller can run for, and t_f is the same for the failure controller. Note that dropout remains on for both the success controller and reverse predictor at inference time. This is so that we can sample the networks' outputs multiple time to find the variance of their predictions and thereby estimate the network's epistemic uncertainty. This is then added to the data uncertainty which the model directly outputs [11]. S is the number of samples to draw from these networks when deciding where to move to next. c is the confidence value to use when performing the p-test to determine whether or not the robot has failed. Here, $G^{(c)}(\mu, \Sigma)$ denotes an error ellipse that contains c fraction of the probability mass of $\mathcal{N}(\mu, \Sigma)$.



(a) (b)

Algorithm 1 Detect And Handle Failure

function EXECUTE(t_s, t_f, S, c)
  Initialize C_s, P_r, and C_f
  Initialize $F \leftarrow false$
  for $t = 1..t_m$ **do**
    Observe s_t
    Sample S times from C_s, compute μ_s and Σ_s
    $G_s = \mathcal{N}(\mu_s, \Sigma_s)$
    Move towards μ_s, observe s_{t+1}
    Sample S times from P_r, compute μ_r and Σ_r
    $G_r = \mathcal{N}(\mu_r, \Sigma_r)$
    if $s_{t+1} \notin G_s^{(c)} \wedge s_t \notin G_r^{(c)}$ **then**
      $F \leftarrow true$
      break
    end if
  end for
  if F **then**
    for $t = 1..t_f$ **do**
      Observe s_t
      Compute μ_f and Σ_f from $C_f(s_t)$
      Move towards μ_f
    end for
  end if
end function

V. EXPERIMENTS

To evaluate the effectiveness of our framework, we ran two sets of experiments. In one, the reverse predictor is completely disabled so that the robot continues to execute its success controller regardless of what the people in the scene do. The episode ends after 15 time steps or after the robot reaches its goal, whichever comes first.

In the other set, the robot begins by executing its success controller and only switches to the failure controller when the p-test performed by the reverse predictor fails. If the robot executes the success controller for 10 time steps without triggering the reverse predictor's failure condition, it is cut off and the failure controller is allowed to run. If the robot reaches its goal, this episode is simply thrown out. After the failure controller initiates, it executes for 5 time steps before the episode ends.

VI. RESULTS

We used versions of the metrics presented in [12], which were designed to evaluate robot motion in crowds, to compare the two frameworks' effectiveness. These metrics are the length of the trajectory, time elapsed, angular distance traveled (computed as total change in heading between time steps), the number of collisions incurred and the number of intrusions incurred. Here, the robot is considered intruding on a human if it comes within $0.2m$ of the human. Similarly to how the reward function is computed, we count collisions (and intrusions) in each time step according to the number of humans or obstacles the robot is colliding with in that step.

TABLE I: Metrics comparing trajectories generated by a robot with no failure controller to a robot using the presented controller. The data here are averages across 1000 runs for both cases.

	No Failure Controller	Failure Controller (Ours)
Length	**3.92**	4.27
Angle	**4.80**	6.08
Time	13.50	**8.30**
Collisions	0.86	**0.18**
Intrusions	15.21	**5.60**

VII. CONCLUSIONS

ACKNOWLEDGMENT

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