# Active Perception
## *Improving Perception Robustness by Reasoning about Context*

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Abstract: Existing machine perception systems are too inflexible, and therefore cannot adapt well to environment uncertainty. We address this problem through a more dynamic approach in which reasoning about context is used to actively and effectively allocate and focus sensing and action resources. This *Active Perception* approach prioritizes the system's overall goals, so that perception and situation awareness are well integrated with actions to focus all efforts on these goals in an optimal manner. We use a POMDP (Partially Observable Markov Decision Process) framework, but do not attempt to compute a comprehensive control policy, as this is intractible for practical problems. Instead, we employ *Belief State Planning* to compute point solutions from an initial state to a goal state set. This approach automatically generates action sequences for sensing operations that reduce uncertainty in the belief state, and ultimately achieve the goal state set.

# 1 INTRODUCTION

Existing machine perception systems do not adapt well to environmental uncertainty because their components are statically configured to operate optimally under very specific conditions. As a result, information flow in such systems is bottom up, and generally not guided by knowledge of higher level context and goals.

If higher level goals, context, or the environment change, the specific conditions for which the static configuration is intended may no longer hold. As a result, the static systems are prone to error because they cannot adapt to the new conditions. In addition to their inflexibility, existing machine perception systems are often not well integrated into the autonomous and systems to which they provide information. As a result, they are unaware of the autonomous system's overall goals, and therefore, cannot make intelligent observation prioritization decisions in support of these goals.

We address these shortcomings by using a more dynamic approach in which reasoning about context is used to actively and effectively allocate sensing resources. This *Active Perception* approach prioritizes the system's overall goals, so that perception and situation awareness are well integrated with actions to focus all efforts on these goals. Active perception draws on models to inform context-dependent tuning of sensors, to direct sensors towards phenomena of greatest interest, to follow up initial alerts from cheap, inaccurate sensors with targeted use of expensive, accurate sensors, and to intelligently combine results from sensors with context information (gists) to produce increasingly accurate results.

Consider the problem of changing a flat tire on a car. This has been a "textbook" problem for PDDL generative planning systems (Fourman, 2000), and also a challenge problem in the Defense Advanced Research Project Agency (DARPA) ARM project (Hebert et al., 2012). There are significant challenges in building an autonomous system that can perform this task entirely, or even one that would just assist with the task (Figure 1). Such a system would have to be able to determine the vehicle type (Figure 2), whether a tire is actually flat (Figure 3), and what an appropriate sequence of repair steps should be (Figure 4). It would have to be able to solve many subproblems, such as reliably finding a wheel in an image. The system would have to be able to work in many different environments, a great range of lighting conditions, and for a comprehensive set of vehicle types.

We consider the sub-problem of reliably finding the wheels of a vehicle in an image. We show how the use of top-down, model-based reasoning can be used to coordinate the efforts of multiple perception


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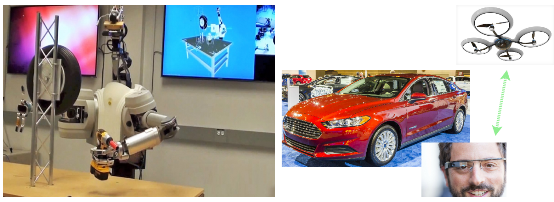


(a) Fully autonomous system using robot. (b) Semi-autonomous advisory system.

Figure 1: Intelligent machine perception would be needed for both a fully autonomous system (a), and a semi-autonomous advisory system (b). The latter might include observation drones, and Google glasses (Bilton, 2012) to guide a human user in the repair.

(a) Truck (b) SUV (c) Sedan

Figure 2: Vehicle type, and ultimately, make and model, are useful things for the perception system to know (or to discover).

(a) Tire is flat. (b) Tire is under-inflated. (c) Tire is OK.

Figure 3: The perception system must be able to determine whether a tire is really flat, and which one it is.

(a) Wheel chock. (b) Remove wheel.

Figure 4: Repair steps include stabilizing the car (a), getting the spare tire and tools, jacking up the car, removing lug nuts and wheel (b), and installing the new wheel.

algorithms, resulting in more robust, accurate performance than is achievable through use of individual algorithms operating in a bottom-up way.

## 2 PROBLEM STATEMENT

Given one or more *agents* operating in an environment, and given that the agents do not directly know the state of the environment, or even, possibly, parts of their own state, and given a goal state for the environment and agents, the problem to be solved is to compute control actions for the agents such that the goal is achieved. In this case, an agent is a resource capable of changing the environment (and its own) state, by taking action. An agent could be a mobile ground robot, a sensing device, or one of many parallel vision processing algorithms running on a cluster, for example. Given that there is uncertainty in the state, an agent must estimate it based on (possibly noisy) observations. Based on the agent's best estimate of the current state, it should take actions that affect the state in a beneficial way.

The actions, themselves have some uncertainty; they do not always achieve the intended effect on the state. The agents must take both state estimate uncertainty, and action uncertainty into account when determining the best course of action. Actions can also have cost. The agents must balance the cost of actions against the reward of reduced uncertainty and progress towards the goal when deciding on actions.

This problem presents significant challenges. First, the overall state space can be very large. Second, the state space is generally hybrid; it includes discrete variables, such as hypotheses for vehicle type, as well as continuous variables, such as position of a wheel. Third, significant parts of the state space may not be directly measurable, and must be estimated based on observations. Fourth, the effect of some actions on state may have uncertainty. Fifth, the agents must take many considerations into account when deciding on actions: they must take into account the uncertainty of the state estimate, the uncertainty of the action effect on the state, the cost of the action, and the benefit of the action in terms of reducing uncertainty and making progress towards the goal.

Note that some actions are performed to improve situational awareness, and some actions are performed to change the state of the agent and/or environment, to achieve an overall goal (for example, jacking up a car so the tire can be changed). The autonomous system should judiciously mix both types of actions so that the situational awareness is sufficient to achieve the goal. In particular, a good sequence of control actions is one that minimizes cost, where cost attributes include both state uncertainty, as well as cost of the action itself. Note, also, that it is typically not necessary for the system to exhaustively resolve all state uncertainty; it just needs to be certain enough to achieve the overall goal.

The problem is stated formally as follows. Let $S = \{S_e, S_a\}$ be the state space, where $S_e$ is for the environment, and $S_a$ is for the agent; let $A$ be the set of agent actions, and $O$, the set of observations. A state transition model represents state evolution probabilistically as a function of current state and action: $T : S \times A \times S \mapsto [0,1]$. An observation model represents likelihood of an observation as a function of action and current state: $\Omega : O \times A \times S \mapsto [0,1]$. A reward model represents reward associated with state evolution: $R : S \times A \times S \mapsto \mathbb{R}$. Given an initial state $s_0$ and goal states $s_g$, the problem to be solved is to compute an action sequence $a_0, \ldots a_n$ such that $s_n \in s_g$, and $R$ is maximized. Note that this problem formulation, expressed in terms of a single agent, is easily extended to allow for multiple agents.

## 3 BACKGROUND AND RELATED WORK

A *Partially Observable Markov Decision Process* (POMDP) (Monahan, 1982) is a useful framework for formulating problems for autonomous systems where there is uncertainty both in the sensing and actions. A POMDP is a tuple $\langle S, A, O, T, R, \Omega, \gamma \rangle$ where $S$ is a (finite, discrete) set of states, $A$ is a (finite) set of actions, $O$ is a (finite) set of observations, $T : S \times A \times S \mapsto [0,1]$ is the transition model, $R : S \times A \times S \mapsto \mathbb{R}$ is the reward function associated with the transition function, $\Omega : O \times A \times S \mapsto [0,1]$ is the observation model , and $\gamma$ is the discount factor on the reward. The *belief state* is a probability distribution over the state variables, and is updated each control time increment using recursive predictor/corrector equations. First, the *a priori* belief state (prediction) for the next time increment, $\bar{b}(s_{k+1})$, is based on the *a posteriori* belief state for current time increment.

$$\begin{aligned} \bar{b}(s_{k+1}) &= \sum_{s_k} Pr(s_{k+1}|s_k, a_k)\, \hat{b}(s_k) \\ &= \sum_{s_k} T(s_k, a_k, s_{k+1})\, \hat{b}(s_k) \end{aligned} \tag{1}$$

Next, the a posteriori belief state (correction) for the next time increment, $\hat{b}(s_{k+1})$, is based on the a priori belief state for next time increment.

$$\begin{aligned} \hat{b}(s_{k+1}) &= \alpha\, Pr(o_{k+1}|s_{k+1})\, \bar{b}(s_{k+1}) \\ &= \alpha\, \Omega(o_{k+1}, s_{k+1})\, \bar{b}(s_{k+1}) \end{aligned} \tag{2}$$

$$\alpha = \frac{1}{Pr(o_{k+1}|o_{1:k}, a_{1:k})} \tag{3}$$

These equations work well given that the models are known, and given that the control policy for selecting an action based on current belief state is known. Unfortunately, computing these, particularly the control policy, is a challenging problem. Value iteration (Zhang and Zhang, 2011) is a technique that computes a comprehensive control policy, but it only works for very small problems. An alternative is to abandon computation of a comprehensive control policy, and instead, compute point solutions for a particular initial state and goal state set.

A promising technique for this is *Belief State Planning* (Kaelbling and Lozano-Pérez, 2013), which is based on generative planner technology (Helmert, 2006). A key idea in this technique is the use of two basic actions for a robotic agent: move and look. A move action changes the state of the robot and/or environment; it may move the robot in the environment, for example. A look action is intended to improve the robot's situational awareness.

The move action is specified using a PDDL-like description language.

```
Move(lstart, ltarget)
  effect: BLoc(ltarget, eps)
  precondition: BLoc(lstart, moveRegress(eps))
  cost:  1
```

The variables lstart and ltarget denote the initial and final locations of the robot. The effect clause specifies conditions that will result from performing this operation, if the conditions in the precondition clause are true before it is executed. Cost of the action is specified in the cost clause. The function BLoc(loc, eps) returns the belief that the robot is at location loc with probability at least (1 - eps). The moveRegress function determines the minimum confidence required in the location of the robot on the previous step, in order to guarantee confidence eps in its location at the resulting step:

$$moveRegress(eps) = \frac{eps - p_{fail}}{1 - p_{fail}} \tag{4}$$

where $p_{fail}$ is the probability that the move action will fail.

The look action is specified as follows:

```
Look(ltarget)
  effect: BLoc(ltarget, eps)
  precondition: BLoc(lstart,
                   lookPosRegress(eps))
  cost:  1 - log(posObsProb
                   (lookPosRegress(eps)))
```

The lookPosRegress function takes a value eps and returns a value eps' such that, if the robot is believed with probability at least 1 eps' to be in the target location before a look operation is executed and the operation is successful in detecting ltarget, then it will be believed to be in that location with probability at least 1 eps afterwards.

$$lookPosRegress(eps) = \frac{eps(1 - p_{fn})}{eps(1 - p_{fn}) + p_{fp}(1 - eps)} \tag{5}$$

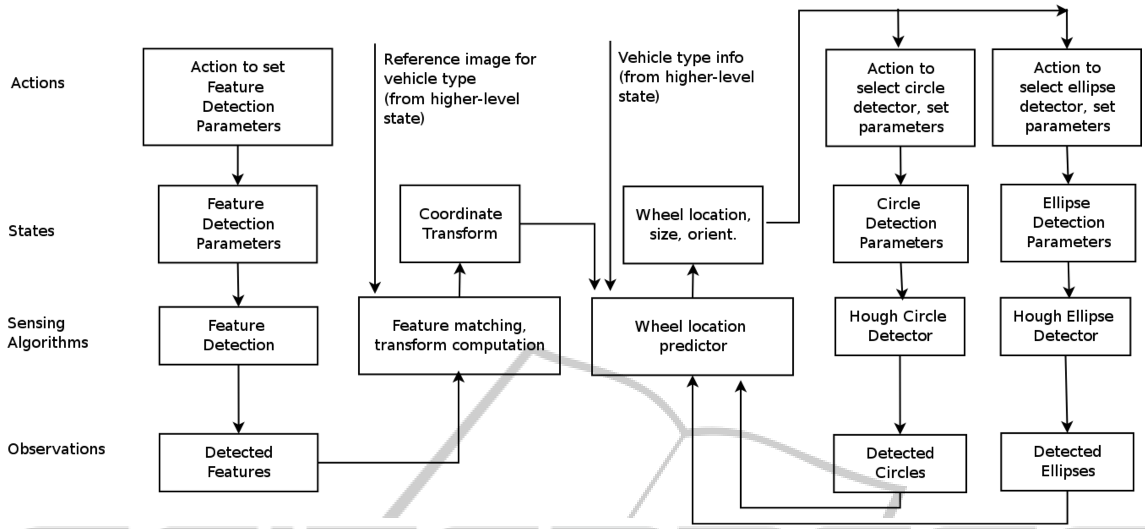



Figure 5: Data flow architecture for wheel finding components.

where $p_{fn}$ and $p_{fp}$ are the false negative and false positive observation probabilities.

In terms of the POMDP belief state update, the move action corresponds to the predictor (Eq. 1), and the look action corresponds to the corrector (Eq. 2).

For the observations, we make extensive use of two types of feature detection algorithms: *Speeded Up Robust Features* (SURF) (Bay et al., 2008), and *Hough Transforms* (Duda and Hart, 1972). Neither of these algorithms, used individually, is satisfactory for solving the wheel detection problem robustly. However, when used together, in an Active Perception framework, they beneficially reinforce each others' hypotheses, allowing for more reliable performance.

# 4 APPROACH

When evaluating approaches to this problem, it is useful to consider what an architecture for the sensors and state estimation components should look like if it were designed by a human expert (Figure 5). Each sensing algorithm can use the current belief state as input, and can also adjust belief state as output.

This organization based on actions, observations, and belief state fits well with the POMDP formalism. As stated previously, we avoid value iteration approaches (Zhang and Zhang, 2011), and instead compute point solutions. Our approach automatically synthesizes architectures such as the one in Figure 5, and generates action sequences for sensing operations that reduce uncertainty in the belief state, and ultimately achieve the goal state set.

We use three main sensing actions: SURF Match, SURF Match Other Wheel, and Hough Ellipse Match. Each of these actions has preconditions (requirements for current belief state), and post conditions (effects on belief state). SURF Match uses the SURF algorithm to perform a preliminary detection of a wheel in an image. SURF Match Other Wheel attempts to find the second wheel, also using SURF, given that the first wheel has been detected. This action also performs vehicle pose estimation, and refines the prediction of where the wheels are. Hough Ellipse Match uses either a Hough Circle or Hough Ellipse transform algorithm to refine the wheel location estimates.

The sequence of actions is computed using a *generative planner*. Given the high uncertainty in our problem, the traditional approach of generating a plan and executing it in its entirety is not suitable. Instead, we adopt a *receding horizon control framework* in which a plan is generated based on the current belief state, but only the first action of this plan is executed. After the action, the belief state is updated based on observations, and an entirely new plan is generated. The process then repeats with the first action from this new plan being executed. This approach is computationally intensive, but it ensures that all actions are based on the most current belief state.

To implement this receding horizon control framework, we use an architecture consisting of four main components: Executive, Planner, Sensor Actions, and Belief State Updater, as shown in Figure 6. The Executive manages the receding horizon control process. It maintains the current belief state, and the goal state set. At each control loop iteration, it passes these to the Planner. The Planner, if successful, returns a plan consisting of actions that transition the system from the current state to a goal state, if there are no disturbances. The Executive takes the first action from the plan and executes it by dispatching the appropriate sensor operation. The sensor operation produces an observation, which is used to update the belief state. The process then repeats.

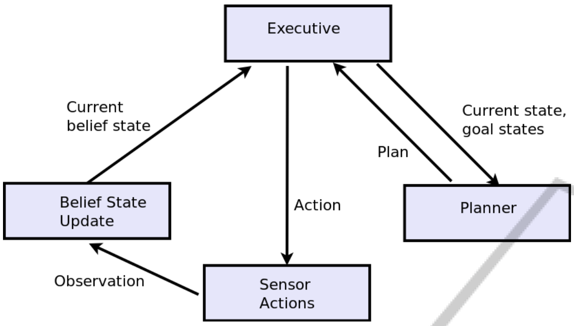



Figure 6: Receding Horizon Control Architecture for Active Perception.

# 5 IMPLEMENTATION

The Executive component implements the top-level receding horizon control loop, coordinating the activities of the planner and sensor components. Algorithm 1 shows pseudocode for the Executive. The algorithm begins by initializing the belief state according to the a priori probabilities, and performing other initialization (Line 1). Belief state for a discrete state variable is represented as a *Probability Mass Function* (PMF) over the possible values of the probabilistic variable. Belief state for a continuous state variable is represented using a *Gaussian Probability Distribution Function* (Gaussian PDF) with a specified mean and variance. This could be extended to a representation using a mixture of Gaussians, in order to approximate more complex, non-Gaussian PDFs.

The receding horizon control loop begins at Line 5. The first step is to invoke the generative planner in order to determine the next action. A generative planner requires, as one of its inputs, the current state in a deterministic form. The belief state, however, is represented in a probabilistic form, so it first has to be converted to a deterministic form using MostLikelyState (Line 6). The input to the generative planner includes the determinized state, as well as the goal state set. The Executive generates *domain* and *problem* PDDL files, and then executes the planner (Line 7). The planner generates a result file containing a plan, which the Executive reads.

The planner may fail to generate a plan, in which case, the algorithm returns failure. If the planner is successful in generating a plan, the executive dispatches the first action (Line 11). The action (sensor operation) generates an observation. The belief state is updated based on this observation (Line 12). The algorithm terminates if the goal has been achieved, or the maximum number of iterations has been exceeded.

**Algorithm 1:** `Executive`.

**Input**: a-priori-belief-state-probabilities, goal-state-set
**Output**: goal-achieved?

```
                    /* Perform initialization.    */
1  belief-state ←
   InitializeBeliefState(a-priori-belief-state-probabilities);
2  goal-achieved? ← false;
3  max-iterations ← 1000;
4  iteration ← 0;
                    /* Begin control loop.    */
5  while not goal-achieved? do
6      current-state ← MostLikelyState(belief-state);
7      plan? ← GeneratePlan(current-state, goal-state-set);
8      if not plan? then
9          return ;
10     action ← First(plan?);
11     observation ← Dispatch(action);
12     belief-state ← UpdateBeliefState(observation);
13     goal-achieved?
       ← CheckGoalAchieved(belief-state, goal-state-set);
14     iteration ← iteration + 1;
15     if iteration > max-iterations then
16         return ;
```

The Planner component is implemented using *Fast Downward* (Helmert, 2006), a state of the art generative planner that accepts problems formulated in the PDDL language (McDermott et al., 1998). A PDDL problem formulation consists of a *domain* file, and a *problem* file. The domain file specifies types of actions that can be used across a domain of application such as logistics, manufacturing assembly, or in this case, finding wheels in an image. The domain file is fixed; it does not change for different problems within the domain. Thus, this part of the formulation was generated manually, and is not modified by the Executive. The problem file, on the other hand, contains problem-specific information such as initial and goal states. Therefore, it must be generated specifically for any new problem. The Executive generates this file automatically, based on knowledge of the goal and belief states. The following PDDL domain file fragment shows the definition of the SURF Match action in PDDL.

```
(:action SURF-match
  :parameters
    (?w ?p ?bsv)
  :precondition
```

```
  (and (belief-state-variable ?bsv)
       (pose ?p) (wheel ?w)
       (for-wheel ?w ?bsv)
       (at-pose ?p ?bsv)
       (at-belief-level
         belief-level-one ?bsv))
:effect
  (and (at-belief-level
         belief-level-two ?bsv)
       (increase
         (total-cost)
         (feature-observation-cost ?p))))
```

The precondition clause specifies that the belief state variable value for a particular pose and wheel must be at belief level one in order for this operation to be tried. The effect clause specifies that the belief level increases to belief-level-two if the operation succeeds. The cost for the operation is also added to the total cost. The other sensor actions are specified in the PDDL domain file in a similar manner.

We now describe in more detail the three sensor actions: SURF Match, SURF Match Other Wheel, and Hough Ellipse Match. The SURF Match action uses the SURF (Speeded Up Robust Features) algorithm (Bay et al., 2008) to attempt to identify wheels by matching a wheel in a reference image with a wheel in the target image. The SURF algorithm is scale invariant, but is somewhat sensitive to large changes in orientation. Therefore, multiple reference images are used, including ones for different orientations (Figure 7). The orientations in the reference images correspond to the orientations of the discrete belief state variables.

(a) +2 (b) +1 (c) 0 (d) -1 (e) -2

Figure 7: Wheel reference images, corresponding to different orientations.

The SURF Match action is not highly reliable; it can miss detecting a wheel, especially if the target image is noisy, and it can falsely detect objects that are not wheels. Also, due to the symmetry of wheel images, the SURF Match algorithm does not provide a very accurate estimate of the pose (position and orientation) of the wheel in the target image. Thus, the SURF Match action is used to attempt to achieve a rough initial match, the goal being to move from low to medium confidence estimates, and set the stage for the use of the other sensor actions to improve the estimates.

The SURF Match Other Wheel sensor action is similar to the SURF Match action, but assumes that one wheel position estimate already exists. It uses this information, along with a number of gists (assumptions), to try to find the other wheel. In particular, it is assumed that the action is observing the left side of the car, and that the car is on level terrain.

If the SURF Match Other Wheel action is successful in finding the other wheel, then it uses the position estimates of both wheels to estimate the pose of the car. The sensor action uses projective geometry, combined with a number of additional gists, to estimate the positions of each wheel in the world coordinate frame, given the image position estimates. These gists are: 1) the height of the camera; 2) the focal length of the camera; and 3) the size of the wheel. All of these are reasonable gists; a ground robot or UAV would know the focal length of its camera, as well as its height. Given previous gists for vehicle type, the size of the wheel can be determined from the vehicle type's spec data.

Once the position estimates of each wheel in the world coordinate frame are known, simple trigonometry is used to determine orientation of the car, particularly, its yaw (rotation about the vertical axis). This estimate is the continuous counterpart to the discrete belief state variables for orientation. The continuous and discrete variables inform and reinforce each other as part of the belief state update mechanism.

The Hough Ellipse Match sensor action uses Hough transforms (Duda and Hart, 1972) to determine wheel position in an image with a high degree of accuracy. This action is computationally expensive, but has the potential to give very accurate estimates, when supplied with good parameters. Thus, this action is used after the other, less expensive sensor actions have developed a good hypothesis about the wheel pose.

The computational expense of the Hough transform algorithm rises as the number of parameters increases. Therefore, the ellipse variant is more expensive than the circle variant. For this reason, the Hough Ellipse Match sensor action first checks whether estimated orientation (yaw angle) of the car is small, indicating that the car side is facing the camera directlym ub wgucg case the circle variant is used.

# 6 RESULTS AND DISCUSSION

## 6.1 Negative Results using Individual Sensor Algorithms

The SURF algorithm is susceptible to error, particularly when there is a significant difference in orientation between the wheel in the reference and target images. Figure 8 shows a weak match result due to this problem. Figure 9 shows an incorrect match, also due to this problem.

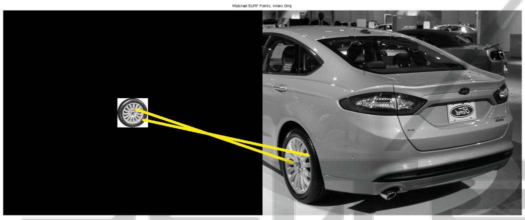


Figure 8: The significant difference in wheel orientation between the reference and target images results in a match of only two points. This does not give a very good estimate of wheel position.

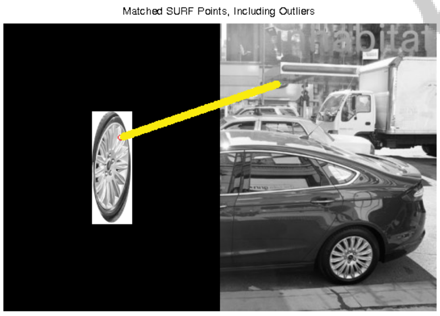



Figure 9: The significant difference in wheel orientation between the reference and target images results in a bad match (false positive).

For this reason, our system uses multiple wheel reference images, at different orientations. Which to use is informed by the belief state variables.

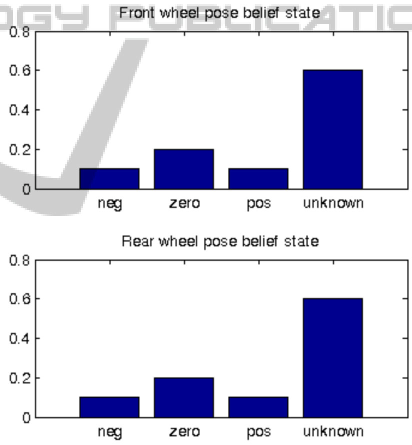
Figure 10 shows what can easily happen when the Hough Ellipse algorithm is used with insufficient guidance. Instead of finding a wheel, the algorithm has found an elliptical form in the car's grill. Sufficiently constraining the expected ellipse parameters solves this problem.

## 6.2 Example Test Cases

For the first test case, the target image is as shown in Figure 11. The a priori belief state for the discrete wheel poses is shown in Figure 12 (values for car pose belief state are similar). This indicates that the poses

Figure 10: With insufficient guidance, the Hough algorithm finds an ellipse in the car's grill (highlighted in green), rather than finding the wheel.

Figure 11: Target image for test case 1.




(a) Wheel

Figure 12: Wheel pose, a priori belief state.

are largely unknown, with a slight bias to the zero pose.

The first control step iteration, based on this belief state, yields the following plan from the PDDL planner.

```
1. SURFMatch(front-wheel pose-zero)
2. SURFMatchOtherWheel(front-wheel pose-zero)
3. HoughEllipseMatch(rear-wheel pose-zero)
```

The Executive performs the first of these actions, yielding a successful match, as shown in Figure 13. Based on this, wheel pose estimates are updated; the hypothesis for zero pose for the front wheel is strengthened.

The second control step iteration, based on this

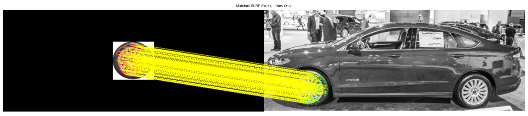


Figure 13: Successful SURF match to front wheel.

updated belief state, yields the following plan from the PDDL planner.

```
1. SURFMatchOtherWheel(front-wheel pose-zero)
2. HoughEllipseMatch(rear-wheel pose-zero)
```

The Executive performs the first of these actions, yielding a successful match, as shown in Figure 14. Based on this, wheel and car pose estimates are updated to further strengthen the zero pose hypothesis.

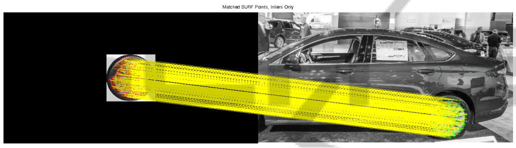


Figure 14: Successful SURF match to other (rear) wheel.

The third control step iteration, based on this updated belief state, yields the following plan from the PDDL planner.

```
1. HoughEllipseMatch(rear-wheel pose-zero)
```

The Executive performs the first of these actions, yielding a successful match, as shown in Figure 15. In this case, because the pose hypothesis is pose zero (indicating that the camera is directly facing the car), the circle rather than ellipse variant of the Hough transform is used. The history of rear wheel pose belief state values over the control iterations is shown in Figure 16. The zero pose belief increases with successive iterations (observations), whereas the pos and neg pose beliefs decrease.

For second test case, the target image is as shown in Figure 17. As before, the planner generates a plan assuming pose zero, based on the a priori belief state. The SURF matches succeed, even though the reference image for pose zero does not exactly match the wheels in the car due to its angle. After the SURF match other wheel action, the pose estimate is improved, resulting in a belief state where pose -1 is most likely. The Hough ellipse match action knows that with this pose, the circle variation of the algorithm will not work, so it uses the ellipse variation, with bounds on aspect ratio and rotation informed by the car pose estimate. This results in a successful match, as shown in Figure 18. The history of rear wheel pose belief state values over the control iterations is shown in Figure 19. The zero pose belief is


Figure 15: Successful Hough ellipse match to rear wheel (match highlighted in green).

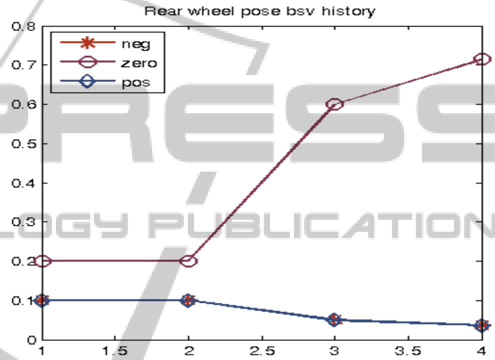



Figure 16: Evolution of belief state for rear wheel pose variable (neg, zero, and pos values).

Figure 17: Target image for test case 2.

initally the highest, but after the SURF match other wheel action (iteration 2), it drops, along with the pos pose belief, while the neg pose belief increases.

The focus of our efforts thus far has been on the sub-problem of finding a wheel in an image. This has led to an emphasis on "look" actions, but no incorporation of "move" actions (actions that change the state of the environment). We believe that the approach we have developed is well suited for incorporating move as well as look actions, with the generative planning component intelligently combining both types of actions. This would allow for testing with more general kinds of problems, where the goal is more than purely a perception goal, but rather, involves achieving an environment goal.

Figure 18: Successful Hough ellipse match, using ellipse rather than circle variation of the algorithm.

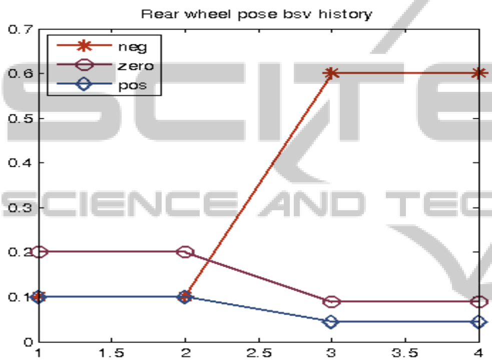



Figure 19: Evolution of belief state for rear wheel pose variable, example test case 2.

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