# A Scenario for Planning Visual Navigation of a Mobile Robot

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## Introduction

We can classify visual navigation of a mobile robot into two different scenarios. One scenario is given by the world that is out of the scope of our sensing capabilities. We call this world the dark world. In general the robot's goal will be in the dark world. In order to do better than a simple random walk, the robot needs some kind of internal representation that allows it to calculate a long-term plan.

On other hand, we have our local position, where we can perceive the world directly through our perception capabilities. We call this scenario the bright world. The main issue about the bright world is that any event in it can have an immediate impact on the performance of the robot. In order to deal with the intrinsic uncertainty and dynamic of the bright world we need appropriate reactive behaviors. These behaviors should be able to couple sensing and action in a synchronized way, in order to allow safe and intelligent navigation.

We believe that one of the main challenges of planning for a mobile robot is to develop suitable techniques to deal with the constraints and requirements of each scenario. These techniques should be combined to generate a consistent plan. In this extended abstract we present some of the ideas that we are currently pursuing for the visual navigation of our robots. First we present some ideas about a possible approach for motion planning. Then we support these ideas by analogies with biological systems, and a simplified implementation on a real robot.

## The Dark World

One of the more critical parts about planning in the dark world is the internal representation. One good internal representation is a topological graph of visual natural landmarks augmented with odometry and visual servoing information. In this graph, nodes represent landmarks and edges represent spatial relation among these landmarks.

We distinguish two types of landmarks: position and navigation landmarks. *Position landmarks* are given by a specific set of known visual features of the environment. These landmarks provide the robot with an absolute world-centered coordinate system. The robot uses this system to position itself with respect to the external world, and to continuously recalibrate its internal odometry. *Navigation landmarks* provide visual servoing information to the robot. Using this type of landmarks the robot can navigate between points using the landmarks as a reference for heading direction. Examples of navigation landmarks are a corridor wall in an indoor scene, and a distant mountain in an outdoor scene.

In this way, position landmarks represent the nodes of the topological graph, while odometry and navigational landmarks form the edges that connect neighboring position landmarks. The system should be able to build, and continuously maintain, this representation.

Much of previous works about navigation using landmarks have only been based on position landmarks. Even though these are important, especially to construct and to sign the correct path, navigational landmarks can also be very useful. For example humans make intensive use of navigational landmark behaviors such as walking on sidewalks, road following, and servoing to building entrances.

Given the natural lack of total invariance for the landmark detection (e.g. different point of view), the topological graph should be given as a probabilistic graph. The planning should not only optimize shortest path, but also the feasibility of successfully traversing a path given by conditional probabilities. In the case of position landmarks high probabilities should be given to landmarks with clear visual features, such as a particular texture or color. In the case of navigational landmarks and odometry, each edge of the topological graph should receive a joint probability. All these probabilities should be updated dynamically. Bayesian networks and Markov chains can be some candidates to maintain this probabilistic topological graph. In [8] partial Markov chains were used to plan the path of a mobile robot using a topological graph. Even though this implementation was especially customized for an office-building environment, this work is a good example of the performance and complexities involves in a probabilistic approach.

## The Bright World

In the bright world visual navigation should be guided by a set of reactive behaviors that allow the robot to preserve safety and move with a reasonably intelligent intention (e.g. move to the goal, run away from dangerous situations, and prefer areas with easily identifiable landmarks).

Among the reactive behaviors we can distinguish general navigation behaviors, for example a potential field algorithm that move the robot to the goal while avoiding obstacles. Also we can distinguish task specific behaviors, such as a street crossing behavior for an outdoor robot, and a turn away from stairs behavior for an indoor wheeled robot. Finally we can distinguish active sensing behaviors, such as to prefer motions through areas with greater number of visual features.

In contrast to the dark world, the reference coordinate system of the bright world should be centered on the robot. This can facilitate the estimation of distance with respect to self-motions. In this way, distances should be given not only with respect to metric coordinates, but also with respect to self motion skills and time to contact.

## Biological Support

So far biological vision systems are the only ones able to achieve robust navigation on natural environments. Here evolution has left its mark, in a world where reaction time and timing perception were a matter of surviving.

In the biological world, insects provide one of the most basic examples of a robust visual navigation system. Insects are able to navigate around a 3D cluttered world, avoiding obstacles, recognizing paths, landing in many places, taking off to avoid capture, and so on.

Several studies show that insects move around their environment helped by internal dead reckoning skills and the recognition of natural landmarks. These studies show that instead of building an accurate 3D visual representation of these landmarks, insects identify the landmarks using simple visual cues such as color, position, orientation, and relative change of size from different points of view. Insects achieve the correct navigation by minimizing the difference between the learned and the current perceived features of the landmark. In [1] bees were trained to recognize their home place using a cylindrical landmark. When the size of the learned cylinder was changed the bees searched further from a cylinder that was larger than the one that they were accustomed to see, and closer to one that was smaller. This suggests that the landmark size was the cue used for the bees to find their home place. Also this experiment shows that insects use landmarks as a visual servoing reference, and as a positioning system.

Humans also navigate in the world using dead reckoning, and memories of learned landmarks and their spatial relations. Dead reckoning estimations are given by knowledge about the calibration of self motion with respect to spatio-temporal variations relating objects in the surrounding [7]. In the case of landmark, studies based on the vision for action and vision for perception paradigm [5] show that humans use landmarks with two purposes: positioning and servoing.

To illustrate this, consider the way that humans navigate to a goal. First, using an internal representation of the environment one constructs a path to the goal given by spatial relation of clear features of the environment. For example “Go straight until you see the tall building, then at the corner turn to the right and so on… ”. Then at execution time one uses a series of learned behaviors mostly based on the use of navigational landmarks such as walking on side walks, corridor following, and so on. One executes this plan until the goal is reached, or until some unexpected features or internal dead reckoning alarm indicate that something is wrong, in which case one re-plans.

## Sage

Recently we implemented a simplified version of the navigation scheme described above on our robot Sage. Sage is a robot that daily navigates the Dinosaur Hall of the Carnegie Museum of Natural History in Pittsburgh, Pennsylvania. Using its internal odometry and visual capabilities, everyday Sage is able to successfully give tours to the museum visitors.

In order to simplify the perception problem, we modified the museum environment, installing 4 artificial landmarks in strategic positions. These landmarks consist of squares areas of 12x12 inches with a special hue print that can easily and robustly be recognized by the vision system. At any time just one landmark is on the bright world of Sage. Sage uses this landmark as a navigation landmark that indicates the right heading direction. Also every time that Sage returns to its initial position, it can recalibrate his internal odometry using a position landmark. In contrast to the navigation landmarks, the position landmark has a small black square in front of the hue

patch. Estimating the position of the projection of the black square on the hue patch, Sage can accurately recalibrate its internal odometry.

Two times a day Sage feels hungry. Using a small version of the position landmark, Sage can dock itself to an electrical socket, servoing its motion with a precision greater than 2 mm.

The navigational system of Sage presents some of the features mentioned above. The long term planning is given by a sequential plan based on the internal knowledge about the spatial location of the artificial landmarks. Also, the reactive planning is given by an obstacle avoidance behavior that uses the visible landmark as the right heading direction. Even though Sage-world is a simplified deterministic version of the scenario described above, its success has encouraged our research efforts. Currently we are working on visual routines to recognize natural landmarks, and to replace sonars in the detection of obstacles. In the future we expect to be able to provide Sage with a reliable natural navigation system.

**References**

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