

5 Mobile Robot Localization

5.1 Introduction

Navigation is one of the most challenging competences required of a mobile robot. Success in navigation requires success at the four building blocks of navigation: *perception*, the robot must interpret its sensors to extract meaningful data; *localization*, the robot must determine its position in the environment (figure 5.1); *cognition*, the robot must decide how to act to achieve its goals; and *motion control*, the robot must modulate its motor outputs to achieve the desired trajectory.

Of these four components (figure 5.2), localization has received the greatest research attention in the past decade and, as a result, significant advances have been made on this front. In this chapter, we explore the successful localization methodologies of recent years. First, section 5.2 describes how sensor and effector uncertainty is responsible for the difficulties of localization. Then, section 5.3 describes two extreme approaches to dealing with the challenge of robot localization: avoiding localization altogether, and performing explicit map-based localization. The remainder of the chapter discusses the question of rep-

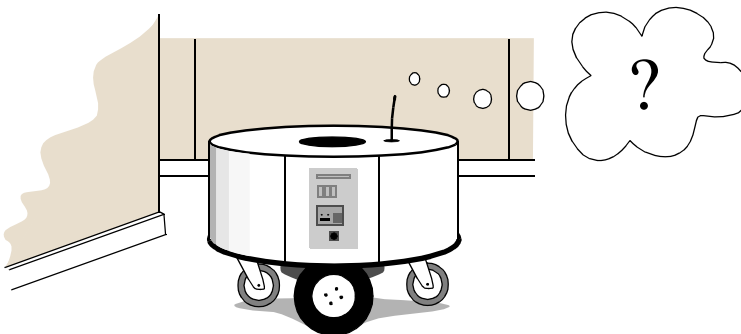


Figure 5.1
Where am I?

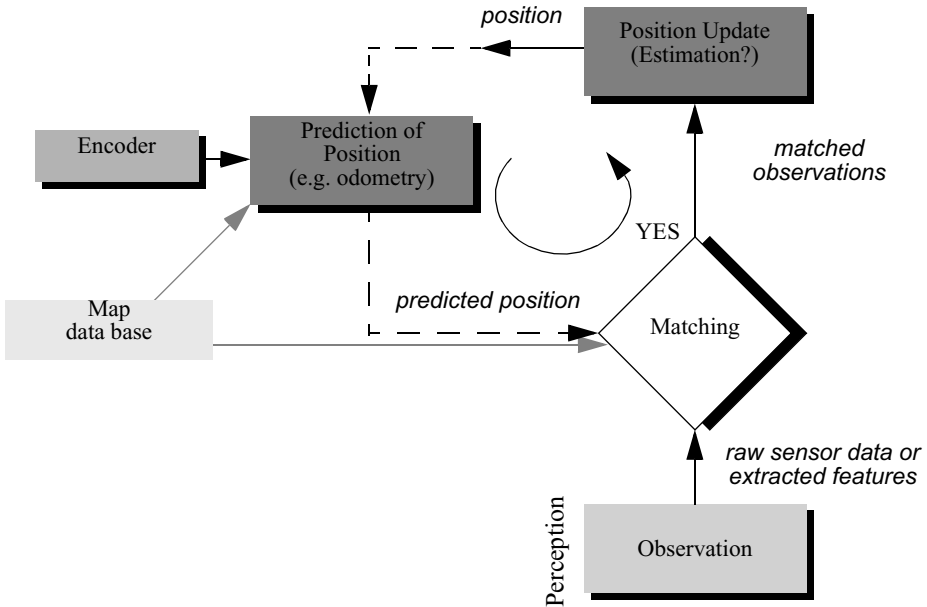


Figure 5.2
General schematic for mobile robot localization.

resentation, then presents case studies of successful localization systems using a variety of representations and techniques to achieve mobile robot localization competence.

5.2 The Challenge of Localization: Noise and Aliasing

If one could attach an accurate GPS (global positioning system) sensor to a mobile robot, much of the localization problem would be obviated. The GPS would inform the robot of its exact position, indoors and outdoors, so that the answer to the question, “Where am I?”, would always be immediately available. Unfortunately, such a sensor is not currently practical. The existing GPS network provides accuracy to within several meters, which is unacceptable for localizing human-scale mobile robots as well as miniature mobile robots such as desk robots and the body-navigating nanorobots of the future. Furthermore, GPS technologies cannot function indoors or in obstructed areas and are thus limited in their workspace.

But, looking beyond the limitations of GPS, localization implies more than knowing one’s absolute position in the Earth’s reference frame. Consider a robot that is interacting with humans. This robot may need to identify its absolute position, but its relative position

with respect to target humans is equally important. Its localization task can include identifying humans using its sensor array, then computing its relative position to the humans. Furthermore, during the *cognition* step a robot will select a strategy for achieving its goals. If it intends to reach a particular location, then localization may not be enough. The robot may need to acquire or build an environmental model, a *map*, that aids it in planning a path to the goal. Once again, localization means more than simply determining an absolute pose in space; it means building a map, then identifying the robot's position relative to that map.

Clearly, the robot's sensors and effectors play an integral role in all the above forms of localization. It is because of the inaccuracy and incompleteness of these sensors and effectors that localization poses difficult challenges. This section identifies important aspects of this sensor and effector suboptimality.

5.2.1 Sensor noise

Sensors are the fundamental robot input for the process of *perception*, and therefore the degree to which sensors can discriminate the world state is critical. *Sensor noise* induces a limitation on the consistency of sensor readings in the same environmental state and, therefore, on the number of useful bits available from each sensor reading. Often, the source of sensor noise problems is that some environmental features are not captured by the robot's representation and are thus overlooked.

For example, a vision system used for indoor navigation in an office building may use the color values detected by its color CCD camera. When the sun is hidden by clouds, the illumination of the building's interior changes because of the windows throughout the building. As a result, hue values are not constant. The color CCD appears noisy from the robot's perspective as if subject to random error, and the hue values obtained from the CCD camera will be unusable, unless the robot is able to note the position of the sun and clouds in its representation.

Illumination dependence is only one example of the apparent noise in a vision-based sensor system. Picture jitter, signal gain, blooming, and blurring are all additional sources of noise, potentially reducing the useful content of a color video image.

Consider the noise level (i.e., apparent random error) of ultrasonic range-measuring sensors (e.g., sonars) as discussed in section 4.1.2.3. When a sonar transducer emits sound toward a relatively smooth and angled surface, much of the signal will coherently reflect away, failing to generate a return echo. Depending on the material characteristics, a small amount of energy may return nonetheless. When this level is close to the gain threshold of the sonar sensor, then the sonar will, at times, succeed and, at other times, fail to detect the object. From the robot's perspective, a virtually unchanged environmental state will result in two different possible sonar readings: one short and one long.

The poor signal-to-noise ratio of a sonar sensor is further confounded by interference between multiple sonar emitters. Often, research robots have between twelve and forty-

eight sonars on a single platform. In acoustically reflective environments, multipath interference is possible between the sonar emissions of one transducer and the echo detection circuitry of another transducer. The result can be dramatically large errors (i.e., underestimation) in ranging values due to a set of coincidental angles. Such errors occur rarely, less than 1% of the time, and are virtually random from the robot's perspective.

In conclusion, sensor noise reduces the useful information content of sensor readings. Clearly, the solution is to take multiple readings into account, employing temporal fusion or multisensor fusion to increase the overall information content of the robot's inputs.

5.2.2 Sensor aliasing

A second shortcoming of mobile robot sensors causes them to yield little information content, further exacerbating the problem of perception and, thus, localization. The problem, known as *sensor aliasing*, is a phenomenon that humans rarely encounter. The human sensory system, particularly the visual system, tends to receive unique inputs in each unique local state. In other words, every different place looks different. The power of this unique mapping is only apparent when one considers situations where this fails to hold. Consider moving through an unfamiliar building that is completely dark. When the visual system sees only black, one's localization system quickly degrades. Another useful example is that of a human-sized maze made from tall hedges. Such mazes have been created for centuries, and humans find them extremely difficult to solve without landmarks or clues because, without visual uniqueness, human localization competence degrades rapidly.

In robots, the nonuniqueness of sensor readings, or *sensor aliasing*, is the norm and not the exception. Consider a narrow-beam rangefinder such as an ultrasonic or infrared rangefinder. This sensor provides range information in a single direction without any additional data regarding material composition such as color, texture, and hardness. Even for a robot with several such sensors in an array, there are a variety of environmental states that would trigger the same sensor values across the array. Formally, there is a many-to-one mapping from environmental states to the robot's perceptual inputs. Thus, the robot's percepts cannot distinguish from among these many states. A classic problem with sonar-based robots involves distinguishing between humans and inanimate objects in an indoor setting. When facing an apparent obstacle in front of itself, should the robot say "Excuse me" because the obstacle may be a moving human, or should the robot plan a path around the object because it may be a cardboard box? With sonar alone, these states are aliased and differentiation is impossible.

The problem posed to navigation because of sensor aliasing is that, even with noise-free sensors, the amount of information is generally insufficient to identify the robot's position from a single-percept reading. Thus techniques must be employed by the robot programmer that base the robot's localization on a series of readings and, thus, sufficient information to recover the robot's position over time.

5.2.3 Effector noise

The challenges of localization do not lie with sensor technologies alone. Just as robot sensors are noisy, limiting the information content of the signal, so robot effectors are also noisy. In particular, a single action taken by a mobile robot may have several different possible results, even though from the robot's point of view the initial state before the action was taken is well known.

In short, mobile robot effectors introduce uncertainty about future state. Therefore the simple act of moving tends to increase the uncertainty of a mobile robot. There are, of course, exceptions. Using *cognition*, the motion can be carefully planned so as to minimize this effect, and indeed sometimes to actually result in more certainty. Furthermore, when the robot's actions are taken in concert with careful interpretation of sensory feedback, it can compensate for the uncertainty introduced by noisy actions using the information provided by the sensors.

First, however, it is important to understand the precise nature of the effector noise that impacts mobile robots. It is important to note that, from the robot's point of view, this error in motion is viewed as an error in odometry, or the robot's inability to estimate its own position over time using knowledge of its kinematics and dynamics. The true source of error generally lies in an incomplete model of the environment. For instance, the robot does not model the fact that the floor may be sloped, the wheels may slip, and a human may push the robot. All of these unmodeled sources of error result in inaccuracy between the physical motion of the robot, the intended motion of the robot, and the proprioceptive sensor estimates of motion.

In odometry (wheel sensors only) and dead reckoning (also heading sensors) the position update is based on *proprioceptive* sensors. The movement of the robot, sensed with wheel encoders or heading sensors or both, is integrated to compute position. Because the sensor measurement errors are integrated, the position error accumulates over time. Thus the position has to be updated from time to time by other localization mechanisms. Otherwise the robot is not able to maintain a meaningful position estimate in the long run.

In the following we concentrate on odometry based on the wheel sensor readings of a differential-drive robot only (see also [4, 57, 58]). Using additional heading sensors (e.g., gyroscope) can help to reduce the cumulative errors, but the main problems remain the same.

There are many sources of odometric error, from environmental factors to resolution:

- Limited resolution during integration (time increments, measurement resolution, etc.);
- Misalignment of the wheels (deterministic);
- Uncertainty in the wheel diameter and in particular unequal wheel diameter (deterministic);
- Variation in the contact point of the wheel;

- Unequal floor contact (slipping, nonplanar surface, etc.).

Some of the errors might be *deterministic (systematic)*, thus they can be eliminated by proper calibration of the system. However, there are still a number of *nondeterministic (random)* errors which remain, leading to uncertainties in position estimation over time. From a geometric point of view one can classify the errors into three types:

1. Range error: integrated path length (distance) of the robot's movement
→ sum of the wheel movements
2. Turn error: similar to range error, but for turns
→ difference of the wheel motions
3. Drift error: difference in the error of the wheels leads to an error in the robot's angular orientation

Over long periods of time, turn and drift errors far outweigh range errors, since their contribution to the overall position error is nonlinear. Consider a robot whose position is initially perfectly well-known, moving forward in a straight line along the x -axis. The error in the y -position introduced by a move of d meters will have a component of $d \sin \Delta\theta$, which can be quite large as the angular error $\Delta\theta$ grows. Over time, as a mobile robot moves about the environment, the rotational error between its internal reference frame and its original reference frame grows quickly. As the robot moves away from the origin of these reference frames, the resulting linear error in position grows quite large. It is instructive to establish an error model for odometric accuracy and see how the errors propagate over time.

5.2.4 An error model for odometric position estimation

Generally the pose (position) of a robot is represented by the vector

$$p = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \quad (5.1)$$

For a differential-drive robot the position can be estimated starting from a known position by integrating the movement (summing the incremental travel distances). For a discrete system with a fixed sampling interval Δt the incremental travel distances $(\Delta x; \Delta y; \Delta\theta)$ are

$$\Delta x = \Delta s \cos(\theta + \Delta\theta/2) \quad (5.2)$$