Exploring Unknown Structured Environments

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Abstract

This paper presents perceptual algorithms for corridor navigation, door detection and entry that can be used for exploration of an unknown floor of a building. The algorithms are fairly robust to sensor noise, do not use odometric data, and can be implemented on a low end PC. The primary sensor used is a laser range scanner.

Introduction

Many practical robot applications require navigation in structured but unknown environments. Search and rescue missions, surveillance and monitoring tasks, urban warfare scenarios, are all examples of domains where autonomous robot applications would be highly desirable. Deploying robots in such scenarios is expected to reduce the risk of losing human lives (Blitch 1999).

One scenario, for example, would be a biohazard detection mission, where a robot or a team of robots would be deployed to enter and navigate an unknown building to search and report the existence of any hazardous materials. Although the building layout may be unknown, it is safe to assume that the building will consist of several floors, where each floor will have one or more corridors, and each corridor will have several rooms whose entrance doors are located on the corridor.

This paper presents several perceptual algorithms that exploit available structure to allow mobile robots to navigate through corridors, detect doors, and enter rooms. In combination the algorithms can be used for exploration of an unknown floor of a building in the absence of any map. The algorithms are fairly robust to sensor noise, do not rely on odometry, and are computationally efficient. The primary sensor used is a laser range scanner. The algorithms presented here have been demonstrated successfully at the DARPA Tactical Mobile Robotics (TMR) Demonstration in Rockville, Maryland in September 2000.

Related Work

Lu and Milios (Lu & Milios 1997a; 1997b) have previously described algorithms for robot pose estimation with laser data. The approach that they take is registration and matching. Their technique relies on constraint-based search to align a current laser frame with a map built from previous laser scans. The alignment of range scans is computationally expensive and can be unnecessary when navigating in a structured environment.

Other researchers (Fox *et al.* 1999) have used laser range scanners for map building and robot localization. Their approach relies heavily on the assumption that the features of the environment used for localization are not changing over time. Therefore, it is not robust to changes in the environment (e.g., opening and closing doors) which may disorient the robot causing it to decrease its localization certainty. Consecutive localizations can take time which may not always be available in a warfare scenario.

The office delivery mobile robot Xavier (Simmons *et al.* 1997) was capable of entering rooms in order to deliver or pick up printouts that users requested over a web-based interface. Xavier used a neural network and camera images to position itself in front of a door in order to enter a room. The whole process was discrete rather than continuous.

The approach presented in this paper for door entry uses a behavior similar to the docking motor schema described in (Arkin & Murphy 1990). This schema allows the robot to enter the room rapidly while traveling on a smooth semi-arc trajectory (see Figure 2). The robot never stops to make sure it is on the right track.

Mission Specification

The *MissionLab* mission specification system (Endo *et al.* 2000) was used as a test-bed for the biohazard survey experiments (see Experiments Section for details). *MissionLab* allows a robot mission to be specified graphically in terms of a finite state acceptor (FSA). Figure 1 shows the FSA used for the biohazard detection mission. We present perceptual algorithms that support the *ProceedAlongHallway* and *GoThroughDoor* behavioral assemblages. An assemblage is a collection of low-level behaviors aggregated in support of a task.

The behavioral assemblage *ProceedAlongHallway* is composed of the motor schemas *StayInHallway*, *MoveDownHallway*, and *AvoidObstacles*. *StayInHallway* directs the robot in a direction orthogonal to the centerline of the hallway. It requires as input the width of the hallway and the

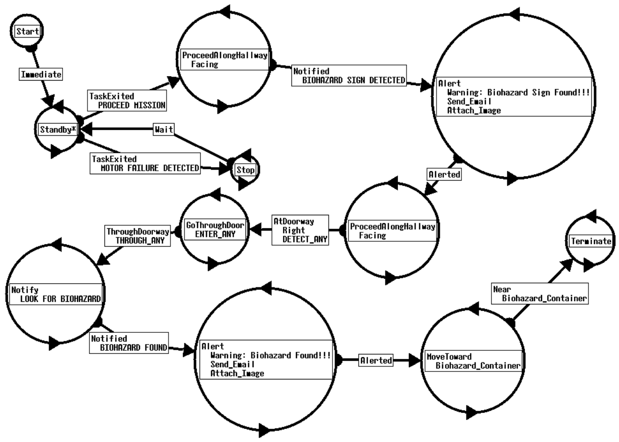

Figure 1: Finite State Acceptor describing a biohazard detection mission at a high level.

angle between the centerline of the hallway and the current robot heading. *MoveDownHallway* moves the robot parallel to the centerline of the hallway. The angle to the centerline alone is sufficient input for this motor schema. *AvoidObstacles* repulses the robot from obstacles. Each of the three schemas produces a vector as its output. The vectors are adjusted according to gain values supplied by the user.

The behavioral assemblage *GoThroughDoor* consists of *EnterDoorway* and *AvoidObstacles* schemas. *EnterDoorway* uses a docking schema (Arkin & Murphy 1990) to compute the instantaneous force on the robot relative to the door. The schema requires three points to compute the vector response: two end points of the door to enter and a point on the far side of the door that the robot should move towards (Figure 2).

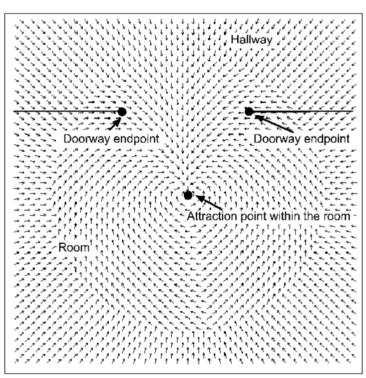

Figure 2: The docking motor schema used to enter rooms.

Perceptual Algorithms

We are motivated by the approach of (Gibson 1979) and use affordance-based percepts to interpret sensor data. For example, a door for the robot is defined as an affordance for passage; a corridor is an affordance for navigation.

Corridor Detection

We begin with the assumption that hallway parameters (width and angle with respect to the robot) can in fact be determined from a single laser reading. This is a fairly strong but generally true assumption. Two factors contribute to this result. First, hallways have distinct features; long, straight, parallel walls. Second, the laser range scanner is extremely accurate[1] allowing proper perceptual algorithms to detect these features.

The SICK LMS[2] 200 used in our experiments has a field-of-view of 180 degrees and returns 361 distance readings (two per degree). These distances are converted in software to Cartesian coordinates to form a laser frame $F = < p_1, p_2, ..., p_{361} >$, where each p_i is a point in $2D$. A local coordinate system is imposed on the laser frame such that p_{181} is always on the x-axis, p_1 on the $-y$ axis, and p_{361} on the $+y$ axis. All calculations that follow are relative to the origin of this coordinate system. Angles calculated relative to the sensor are calculated with respect to the x-axis.

Since corridors consist of long, straight walls, it is expected that many of the laser rays will intersect these walls, yielding a frame with a large number of relevant data points. It only needs to be determined which points fall along these walls. Figure 3 shows a laser frame taken in a corridor with two open doors.

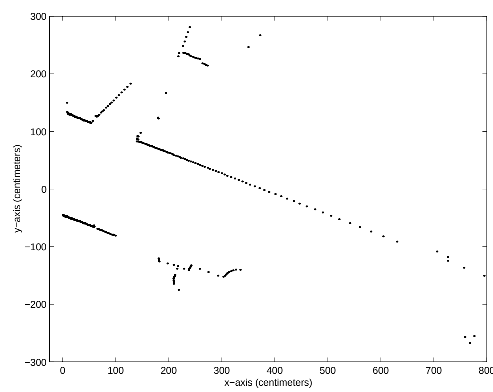

Figure 3: A Single frame of laser scanner data, positioned at the origin.

To determine which points fall along the two parallel walls a voting scheme is adopted. Each point p_i is allowed to vote for the dominant orientation of the corridor. The points cast their vote by observing the local orientation, determined by a small neighborhood of points around them, and declaring it the dominant orientation. The orientation with the most votes is declared the orientation of the hallway. This is done by fitting a line L to the local neighbor-

[1]Maximum error of +/-3 cm per 80 meters.

[2]SICK is an industrial sensor engineering company. The Laser Measurement System (LMS) calculates the distance to an object using the time of flight of pulsed light. A rotating mirror deflects the pulsed light beam to many points in a semi-circle. The LMS 200 has a serial port interface, a peak power demand of 35 Watts, and costs approximately five thousand dollars.

hood of points about p_i. A line, L, in 2D can be described by two parameters ρ and ϕ, where ρ is the perpendicular distance to the line L and ϕ is the angle from the positive x-axis to that perpendicular of L (Figure 4).

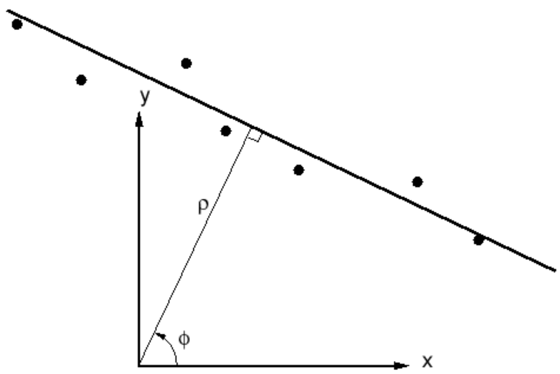

Figure 4: Best fit line for a set of points.

A least-squares approach is used to fit a line to the neighborhood of points. A closed form solution exists and can be calculated efficiently (Lu & Milios 1997a). The size of the local neighborhood was empirically determined to be 7. Smaller values for the neighborhood can cause the lines to be overly sensitive to small changes in contour and noise, while larger values incur more computation with little gain in performance.

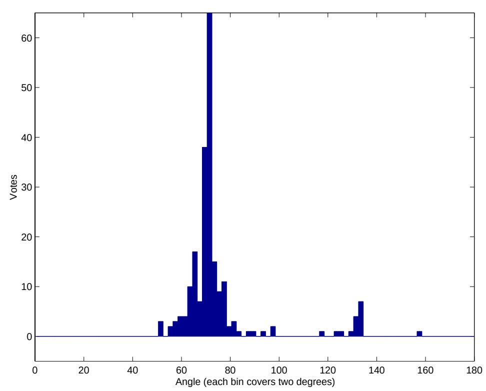

Figure 5: Histogram for the dominant hallway angle for Figure 3. Each bin corresponds to a two degree interval.

Step 1. A line is fit through each data point. To be more precise, for each data point p_i in a laser frame F, a best fit line L_i is found for the set of data points $\{p_j \in F : i-3 \leq j \leq i+3\}$.

Step 2. A histogram is calculated over all ϕ_i. After all (ρ_i, ϕ_i) pairs have been calculated, a histogram over ϕ_i is computed. For a typical hallway and a laser scanner position within the hallway, the histogram will have two large humps corresponding to the two opposing walls. Exploiting the fact that the walls are parallel, or near parallel, the two humps can be merged if all ϕ_i outside the range $[0, 180]$ are rotated by 180 degrees. In this way, angles corresponding to parallel lines will now be overlapping. Figure 5 shows the ϕ histogram for the laser frame displayed in Figure 3.

Step 3. The hallway angle is selected. A triangle filter is used to smooth the histogram and the dominant angle in the histogram is selected. This is the angle between the perpendicular to the left-hand wall and the laser scanner. The angle between the perpendicular to the right-hand wall and the sensor is 180 degrees larger. This latter angle, labeled H_ϕ, is the one used in subsequent calculations. The bin size of the histogram was selected to be two degrees and the triangle filter used was $[0.1,\ 0.2,\ 0.4,\ 0.2,\ 0.1]$.

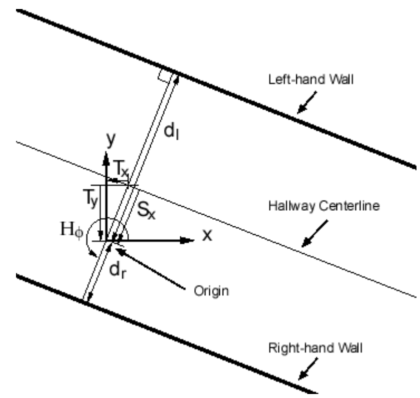

Figure 6: Hallway transformation parameters.

Step 4. The winning points are divided into two sets. The width of the hallway will be estimated from those points that voted for the winning hallway angle. These points can be divided into two sets corresponding to the left and right wall: L and R. The set L consists of points p_i for which $\phi_i \in [0, 180]$. The set R consists of points p_i for which $\phi_i \in [-180, 0]$.

Step 5. The distance to each wall is calculated using a histogram method. A histogram is calculated over ρ_i for each of the two sets. Triangle filtering is again used. The most common value is selected from each histogram. Let d_l be the distance to the left-hand wall calculated from the set L, and let d_r be the distance to the right-hand wall calculated from the set R.

Step 6. The width of the hallway is calculated. Then the width of the hallway, H_w, is the sum of the two distances: $H_w = d_l + d_r$.

Step 7. The location of the robot within the hallway is calculated. The distance between the laser scanner and the hallway centerline, can also be calculated: $S_x = d_l - H_w/2$. The sign of this variable determines whether the robot is to the right (positive) or to the left (negative) of the centerline. There is now sufficient information to navigate along the hallway. Let the laser scanner be positioned at the front center of the robot and oriented in the same direction. Then the angle of the hallway local to the robot is -$H_\phi - 90$. The width of the hallway is H_w and the robot is located S_x units away from the hallway centerline.

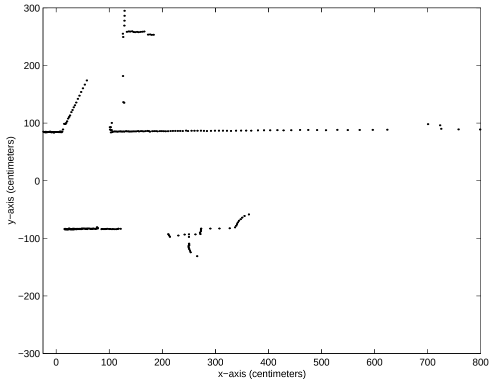

Figure 7: Aligned laser scan data.

Door Detection

The technique for doorway detection relies on the definition of a door as an affordance for passage. It looks for openings in the hallway that are within some acceptable width. In the experiments, fifty centimeters was used for the minimum doorway width and two meters for the maximum. These numbers were used to accommodate our RWI urban robot (Figure 8). A larger or smaller robot may have very different acceptable ranges of doorway widths.

Step 1. All points in the frame are transformed so that the hallway centerline coincides with the x-axis. This step allows for efficient detection of openings in the two walls, since the walls will now be horizontal. This transformation requires a translation of $(\cos(H_\phi) * S_x, \sin(H_\phi) * S_x)$ followed by a rotation of $-H_\phi - 90$, where again H_ϕ is the angle between the laser scanner and the perpendicular to the right-hand wall. The wall positions are now (0, -$H_w/2$) and (0, $H_w/2$) and the new laser scanner position is (0,-S_x). Figure 7 displays the laser frame after the translation and rotation have been performed.

Step 2. Openings in the wall are detected using a box filter. To detect openings a box filter of size 50 cm x 50 cm is passed along each wall at 5 cm offsets. For each filter position the number of points that fall within the box is counted. Consecutive regions with zero points are merged to form a potential door opening. The width of that opening is checked against the acceptable door widths specified earlier.

Step 3. False positives are eliminated. This method can generate false positives, however, due to obstacles located between the laser and the wall. To eliminate this problem the laser frame is checked for points that are closer to the laser scanner than the expected position of the wall and fall in the same viewing angle as the opening. If such points are found the opening is rejected. The coordinates of the two endpoints of the opening (which can be represented as a line segment) are tracked continuously, transformed into coordinates local to the robot, and fed to the *EnterDoorway* motor schema during doorway entry.

Experiments

The experiments described in this section were conducted during the DARPA TMR Demo in Rockville, Maryland in September 2000. The site for our demo portion was inside a firefighters' training facility, also known as the *Burn Building* (Figure 9). The conditions inside the building were quite different from the pristine environments found in many robotics labs. Most walls (both corridor and room walls) were not precisely straight due to the routine incinerate/extinguish exercises that have been going on for more than a decade in that building. Light was very limited and the air was quite dusty.

Figure 8: The RWI Urban Robot equipped with a SICK laser scanner and a Sony pan/tilt/zoom camera.

Nevertheless, the RWI Urban robot (Figure 8) was up to the test. Its mission was to start from one end of the building, navigate down the corridor, find a room that is labeled as one containing biohazard materials, enter that room, find the hazardous material, and navigate towards it. If a biohazard is found, the robot sends a picture of the material back to the human operator. The room in question was labeled with a biohazard sign (Figure 8). A bucket labeled 'biohazard' was used for the biohazard material. To detect the sign and the bucket the robot used simple color tracking. A Newton Labs Cognachrome board performing real time color blobbing was used to do the tracking. The size and position of the blob was used for detection. This simple technique serves as a place holder for a more sophisticated sensor that would be able to detect a biohazard directly.

Total Missions	Successes	Failures	Mean Run Time	STD
32	29	3	62.3 seconds	5.6 seconds

Table 1: Summary of the experimental results.

Thirty-two missions were attempted during a two day period before the demo day. Of those twenty-nine were successful - 91% success rate. Two mission failures were caused by unreliable detection of the biohazard due to the limited light in the building, which caused the computer vision code to fail. One failure resulted from an unsuccessful

Figure 9: The Burn Building in Rockville, MD: site of the DARPA TMR Demo.

attempt to enter the door. Table 1 summarizes the results of the experiments.

The corridor and door detection algorithms performed exceptionally well since the laser range scanner is not affected by the amount of light present in the environment. In fact, the same mission (without the biohazard sign detection) was run successfully in complete darkness.

Summary

This paper described perceptual algorithms for corridor navigation, door detection and entry that can be used for exploration of an unknown floor of a building. The algorithms use the inherent structure in building design to extract a few parameters needed for correct navigation. To navigate down a corridor, for example, the robot needs to know only the width of the corridor and the angle between the centerline of the corridor and its current heading. To enter a door, the robot needs to know only the two endpoints of the doorway. The algorithms presented in this paper use a laser range scanner to detect these parameters. Experimental results presented above show that this technique is quite reliable. In fact, the same motor schemas and perceptual algorithms have been used without modification to control a Nomad 200 robot that has a completely different drive mechanism than the Urban robot.

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