A Laboratory Exercise - Unmanned Vehicle Control and Wireless Sensor Networks

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Abstract

With the ever decreasing cost of processors and electronics in general, wireless sensor networks (WSNs) are increasingly being utilized for environmental measurements. Different WSN topologies will allow different sensor coverage and energy utilization options for a given application. These WSNs can then be used as “extra eyes and ears” for an unmanned vehicle traversing the environment. A vehicle’s path and control can be improved by using the WSN more efficiently to ensure proper vehicle operation in the given application.

At Texas A&M University-Kingsville, a new lab exercise for an unmanned surface vehicle has been created for students to demonstrate how the sensor network improves the vehicle’s control and path planning. A simple sensor model is implemented in the exercise. The physics-based model is analyzed for the vehicle. A “simulated sensor” input from the WSN results in the development of the control of the vehicle system during the laboratory exercise. Then the students compare the corresponding closed loop control system with and without the WSN input in a path planning application. The closed loop system is simulated with MATLAB software tool. The lab exercise demonstrates to the students the increased utilization of WSNs for various applications such as control systems.

1. Introduction

Increased student involvement with the design process and more immediate feedback in the form of two dimensional (2D) and three-dimensional (3D) simulation environments such as Autonomous Unmanned Vehicle (AUV) workbench [1]-[3] or MATLAB results in improved understanding of and engagement in the material. Problem based learning (PBL) continues to be a successful method for increasing student involvement [4]-[8]. The students are provided with an open problem where the students are expected to explore a path planning technique based on potential fields where regions of attraction and repulsion will represent waypoints (goals) and obstacles, respectively. Once the obstacle course is modeled, a simulated robot or unmanned vehicle must reach the goal based on the potential fields present in the region of operation and avoiding obstacles [9]. The details of the problem description are presented in Section 2. Results are included in Section 3. Conclusions are presented in Section 4. The Bibliography follows at the end of the paper.

2. Problem Description

The laboratory exercise and students’ tasks based on an open problem are described as follows: “In this assignment, students will explore a path planning technique based upon potential fields. Goals or waypoints will be represented by regions of attraction while obstacles will be modeled by repulsive potential field regions. A simulated model of a robot or unmanned vehicle such as the unmanned surface vehicle (USV) Sea Fox will proceed to the goal based upon the potential fields present in the region of operation [9].” Utilizing a Wireless Sensor Network (WSN), the USV’s planned path can be modified possibly resulting in a more direct path. The WSN which in this case uses a simple sensor model increases knowledge about obstacles and the environment.
2.1 USV Model

A more detailed description (6 degree of freedom (DOF) model) of the following equations for a USV model can be found in [8]-[12]. The model presented here assumes that the USV motion will occur in the horizontal plane with relatively calm conditions which reduces the number of equations required to model the USV. “The USV model in the horizontal plane can be utilized … assuming that the roll, pitch, and heave can be ignored. This results in three equations

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\psi}
\end{bmatrix} =
\begin{bmatrix}
\cos \psi & -\sin \psi & 0 \\
\sin \psi & \cos \psi & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
u \\
v \\
r
\end{bmatrix},
\]

where the x (surge) and y (sway) are motion directions with velocities along the x and y defined as u and v [9].” Figure 1 depicts the horizontal plane model.

![Figure 1](image-url)

**Figure 1 – Horizontal Plane Model for USV [10]-[12] (\(\chi\) - course angle; \(\psi\) - heading angle; \(\beta\) - sideslip angle)**

Equations for the course angle \(\chi\), heading angle \(\psi\) and sideslip angle \(\beta\) are given below in (2) [10]-[12]. Given no sideslip angle, the course and heading angles will be the same.

\[
\begin{align*}
\chi &= \psi + \beta \\
\beta &= \tan^{-1}\left(\frac{v}{u}\right) \\
U &= \sqrt{u^2 + v^2}
\end{align*}
\]

2.2 Proportional Integral Derivative (PID) Controller

In the laboratory exercise, the students are introduced to the proportional integral derivative (PID) controller as a solution for the USV control system. “If one assumes a PID controller, the closed-loop control system for the Sea Fox horizontal plane model can be as shown in Figure 2.
The commanded course angle (assuming no side slip) is $\psi$. This angle will be given by the path planning algorithm to reach the desired goal location after going through each waypoint [9].”

![Simple PID Feedback Control System](image)

Figure 2. Simple PID Feedback Control System [8]-[10] – modified from [13]

The PID controller can be discrete or analog for the given application. In this case the students simulated a path planning algorithm that utilizes potential fields to determine the course in MATLAB. The simulation required a discrete PID implementation to move the USV given the potential fields’ path planning files that were utilized by the students. The transfer function for the PID controller can be represented by Equation (3)

$$G_{PID} = \frac{K_D s^2 + K_{prop} s + K_I}{s} = \left(\frac{K_{prop}}{s} + \frac{K_I}{s} + sK_D\right),$$

(3)

where $K_{prop}$ is the proportional constant, $K_I$ is the integral constant, and $K_D$ is the derivative constant. A discrete PID controller can be implemented through MATLAB simulation as in (4) [13],

$$r(k) = r(k-1) + K_1 e(k) + K_2 e(k-1) + K_3 e(k-2)$$

(4)

where

$$e = \psi_{command} - \psi$$

$$K_1 = K_{prop} + K_I \Delta t + K_D / \Delta t$$

$$K_2 = -K_{prop} - 2K_D / \Delta t$$

$$K_3 = K_D / \Delta t$$

(5)

The discrete PID controller is then described by a set of equations as shown in (5) in which only the previous two values of the error $e$ and the control input $r(k-1)$ need to be stored in order to calculate the control input $r(k)$.

**2.3 Potential Fields**

There are many path planning techniques in the literature. In this assignment students applied a potential fields path planning algorithm. The path planning method supplies the commanded course angle to the USV movement control. In this method, waypoints or goals are considered to be objects of attraction and obstacles are considered as objects of repulsion. Using a simple model, the equations to describe these two sets of objects are as in (6) and (7) below [14]-[16]:

$$G_{PID} = \frac{K_D s^2 + K_{prop} s + K_I}{s} = \left(\frac{K_{prop}}{s} + \frac{K_I}{s} + sK_D\right),$$

$$r(k) = r(k-1) + K_1 e(k) + K_2 e(k-1) + K_3 e(k-2)$$

$$e = \psi_{command} - \psi$$

$$K_1 = K_{prop} + K_I \Delta t + K_D / \Delta t$$

$$K_2 = -K_{prop} - 2K_D / \Delta t$$

$$K_3 = K_D / \Delta t$$

(6)

(7)
Repulsion: (Obstacles)

\[
U_{\text{obst}} = \begin{cases} 
    k_{\text{obst}}(D - d_{\text{obst}})/D & \text{if } d_{\text{obst}} \leq D \\
    0 & \text{if } d_{\text{obst}} > D 
\end{cases} 
\]

\[U_{\text{obst}} = \sum_{i} U_{\text{obst}}\]  \hspace{1cm} (6)

Given

i) \( k_{\text{obst}} > 0 \),

ii) \( d_{\text{obst}} \) is the distance from a point in the potential field to the obstacle,

iii) \( D \) is the maximum distance of the obstacle’s repulsion influence and

iv) Repulsion drops linearly as a function of distance.

Attraction: (Goals or waypoints)

\[
U_{\text{att}} = k_{\text{att}} \left( (x_{\text{position}} - x_{\text{goal}})^2 + (y_{\text{position}} - y_{\text{goal}})^2 \right) 
\]

(7)

Given

i) \( k_{\text{att}} > 0 \),

ii) \( (x_{\text{position}}, y_{\text{position}}) \) and \( (x_{\text{goal}}, y_{\text{goal}}) \) are a point and the goal position in the potential field

This means the attraction is a function of the Euclidean distance. Thus obstacles will repel the USV and goals will attract the USV. The total potential field is then found by the Equation (8) as follows [14]-[16]:

\[
\text{PotentialField} = -\nabla U_{\text{att}} - \nabla U_{\text{obst}} 
\]  \hspace{1cm} (8)

Simulations for an obstacle potential field in 2D and 3D are depicted in Figures 3 and 4, a 2D potential field for waypoint 2 is shown in Figure 5, and a unified waypoint 2 and obstacle potential field is shown in Figure 6. Figure 7 depicts the path for the USV traveling from the starting point to waypoint 1.
2.4 Sensor Model

In this student assignment a simple sensor model and WSN is assumed. The original information about the obstacles and environment may be incomplete. The wireless sensor network and onboard sensors will augment the environment information allowing for better USV control, path planning and navigation. Sensor networks exhibit a power advantage by utilizing multi-hop communication to connect two nodes that might be distant as depicted in Figure 8 as compared to a direct communication between A and B [17].
Thus each node in the WSN will communicate with its neighbor for node A to communicate with node B. Each node in the communication link, however, will consume energy to receive the data and there will be communication overhead to handle the message at each node [17]. The WSN energy consumption and communication overhead is ignored here as this is assumed to be the WSN topology utilized in the simulation due to its simplicity and coverage. This simple model can also exhibit interference if four adjacent nodes (first with second and third with fourth) need to communicate as the wireless signals can interfere with each other. The sensing model that is utilized in this student assignment is a binary representation as shown in Figure 9. Any event that occurs inside the sensing radius \( r \) will be detected while anything outside the radius will not.

A more realistic model would be a probabilistic model [17]. The communication and sensing ranges are not necessarily equal for a particular sensor node hardware choice. There are numerous WSN topologies where each exhibits different sensor coverage and energy consumption. Multi-hop communication will generally be used to reduce energy consumption as discussed before [17]. Figure 10 shows a uniformly distributed sensor network in the USV application area that is utilized in this assignment. The potential field can then be updated based upon new information from the WSN. Utilizing information from WSN allows a more direct path to be planned as depicted in Figure 11. These are representative plots of the students’ assignment. The students could modify the obstacle and waypoint locations and the number of obstacles as well as the radius of influence.
3. Results

Students were asked in the assignment the following questions [9]:

[1] How does the simulation run if you add more obstacles?
[2] How does the simulated path planning compare without the sensor information ... and with the sensor information...? (Note the last plot) plots both USV paths.
[3] What did you learn in this lab [9] and the previous lab [8]?

The students commented on adding more obstacles to the point that the USV could not complete its path since it would be blocked if there was not a minimum distance between obstacle repulsion fields. This occurred since the USV movement control file did not include a maneuver to reverse the USV or to randomly turn the USV to attempt a new direction whenever the USV could not move forward. Both would be easily added to the MATLAB simulation. An example student group answer for question 1 is “If you add more obstacles, the simulation takes longer because it tries to stay away from the obstacles while being attracted to the goals.” One of the student groups’ answers for question 2 is “Without the sensor information, ..., the USV was not able to detect the movement appropriately and changed directions from vertical to horizontal as starting point.” Another student group stated on question 2 that “Without the sensor, the sea fox would get stuck and be unable to fix its path to the goal points.”

As can be seen in Figure 11, the updated potential field could allow the USV to traverse the path if more space was determined to be available between obstacles. In Figure 11 the path with sensor input is also shorter and more direct which was indicative of many of the simulated updated potential fields. Many students also commented on learning more about MATLAB and its capabilities. An example student group answer for question 3 is “In this and the previous lab we learned that matlab ... can simulate real life systems based on a Simulink model.”

Figure 11. USV Paths With and Without Sensor Input
4. Conclusions

In this problem based learning exercise that uses the USV model and closed loop control system from the previous lab [8], [10], the students simulated potential field path planning. The path planning method supplied the commanded course angle to the USV course angle closed loop control system which was designed in the previous lab [8] and is discussed in [10]. The students modified the potential field MATLAB files given to them by the instructor to change obstacle locations, number of obstacles and waypoint locations. The files included the basic potential field path planning and USV movement. The movement control file also included a PID controller. The students could modify the included PID parameters to match their designed PID controller from the previous lab [8]. The students have successfully studied potential field path planning and PID control. The lab demonstrates to students the increased utilization of WSNs for use in various applications such as control systems.

Students commented that if they added too many obstacles, the USV’s path would become blocked. This occurred since the USV movement control file did not include a mechanism to back the USV up or to randomly turn the USV to attempt a new direction. Both will be easy additions to the MATLAB simulation in the future.

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