Obstacle Detection and Avoidance for an Autonomous Surface Vehicle using a Profiling Sonar

Hordur K. Heidarsson and Gaurav S. Sukhatme

Abstract— We present an experimental study of a mechanically scanned profiling sonar for Autonomous Surface Vehicle (ASV) obstacle detection and avoidance. We extract potential obstacles from echo returns and suggest a scanning strategy for sonar in this application. We demonstrate with simulations (driven by data collected in the field) the potential for an ASV to rely solely on sonar data to navigate and avoid obstacles in a lake and harbor environment.

I. INTRODUCTION

Obstacle avoidance is a fundamental and extensively studied topic in robotics. Many different approaches exist to solving the problem, some commonly used approaches are the Vector Field Histogram (VFH) [3], the Dynamic Window Approach [7] and occupancy grid methods [6].

For Autonomous Surface Vehicles, ASVs, the most commonly used sensors for obstacle avoidance are laser range finders and cameras. In this paper we explore the use of an active acoustic sonar, commonly used on Autonomous Underwater Vehicles (AUVs) but usually only used for bathymetric profiling on ASVs.

For Autonomous Surface Vehicles the literature dealing with the obstacle detection and avoidance problems [8] [1] typically focuses on above-surface obstacles. In some environments, *e.g.,* waters with reefs or lakes with shallow banks, there is a need for the detection of sub-surface obstacles. Since most above-surface obstacles have a sub-surface presence as well, sub-surface sensing can complement the above-surface sensing. In comparison to vision-based methods, sonar can work in all lighting conditions while cameras might not. Some weather conditions (*e.g.,* rain) degrade the performance of laser range finder-based or camera-based methods.

For AUVs, obstacle avoidance is mainly performed using a forward looking sonar [11]. The problem can be solved in a similar way for a surface vehicle but there are some important differences. On an ASV, the sonar is looking right under the water-air boundary which could be problematic. Thermal gradients that make sonar sensing difficult are often present close to the surface. Finally the ASV is subject to rolling and pitching due to wave action at the surface. This causes the sonar beam to be pointed up towards the water-air boundary or down towards the bottom. Experience suggests that sonar data gathered at the near-surface is more noisy

than data gathered at depth. This requires the sonar data processing to be robust to noise.

This paper focuses on the use of a single-beam mechanically-scanning profiling sonar, mounted facing forward on an ASV. The purpose is to detect (and avoid) obstacles. A profiling sonar has a cone-shaped beam that is well suited to detect near surface obstacles that are relevant to an ASV. AUVs are usually equipped with an imaging sonar or side-scan sonars that have a fan-shaped beam. The fan shaped beam would not be ideal for an ASV as it can get unwanted echo returns from the seabed and will likely not work well in shallow waters. When moving in an unknown area (*e.g.,* a harbor or close to reefs or banks) the sonar can be pointed forward, then repositioned for profiling when in an area that is deemed safe. While we focus on a single beam sonar here, we expect this work should be directly applicable to multi-beam sonar with similar characteristics. However, a multi-beam sonar deliver something more similar to an image, so image processing techniques will likely be much more beneficial in the multi-beam case.

We start by presenting a sonar data processing pipeline to extract obstacles from the sonar imagery. We then show results from data gathering in the field using a profiling sonar mounted on an ASV. Finally we demonstrate the usability of sonar for obstacle avoidance on ASVs by simulations that incorporate the data gathered in the field.

II. RELATED WORK

Many ASVs have been designed and developed in recent years, some of them are equipped with radar or cameras for obstacle sensing [4] [5], but none of them use sonar for this purpose.

ASV literature that specifically deals with the obstacle avoidance problem [8] [1] focuses on obstacle detection for above-surface obstacles. Larson *et al.*navigate an ASV with the help of vision and radar [8], and Bandyophadyay *et al.*use a laser range finder to perform obstacle avoidance in Singapore harbor. Benjamin *et al.*broadcast positions of ASV to avoid collisions between them [2] without any sensing. In related work, the group at JPL [15] has investigated vision-based methods for target tracking on the water surface. Martins *et al.*use vision to dock with an AUV [10]. Leedekerken *et al.*[9] do mapping on an ASV by combining data from LIDARs above surface and sonar below surface.

Ribas *et al.*[13] did Underwater SLAM using a mechanically scanning imaging sonar mounted forward on an AUV. Similar to our work, the sensing focused on walls and obstacles around the vehicle. Williams *et al.*[14] fused sonar

H. K. Heidarsson is with the Robotic Embedded Systems Lab and the Department of Electrical Engineering, University of Southern California, Los Angeles, CA 90089, USA heidarss@usc.edu

G. S. Sukhatme is with the Robotic Embedded Systems Lab and the Department of Computer Science, University of Southern California, Los Angeles, CA 900089, USA gaurav@usc.edu

imagery with vision to do bathymetric SLAM with an AUV on the Great Barrier Reef.

III. SONAR DATA PROCESSING

A. Data processing

Sonars typically return data in the form of a vector where each element corresponds to the echo return strength for a given time interval. This corresponds to a distance based on the time of flight of the echo. The intervals are equally divided along the configured range of the sonar. The sonar range can be varied by changing the frequency and the pulse length of the sonar along with some signal processing parameters. The top plot of figure 1 shows a typical data return from the sonar. This particular one has 500 bins distributed over 30 m, and each bin can take on a value between 0 and 127. The larger the value, the stronger an echo was received from that distance. One can see that very strong echos were received from objects 12 m and 22 m away.

We developed a simple processing pipeline of the sonar data that would be able to work for reactive obstacle avoidance. We process and hand off all measurements to the obstacle avoidance algorithm as soon as they are made. This precludes us from buffering scans (and processing them *e.g.,* as an image). Instead we process each echo return sequentially. The processing of a sonar return is as follows.

First we segment the return into low and high strength values. Similar to what is done when segmenting images, we create a smoothed histogram of the data and look at the modes of the distribution. Usually there is a significant mode in the low echo return strength. If there are objects in the sonar beam, there will usually be some smaller modes as well. We find the second largest mode in the data and pick a threshold between the initial mode and the second one. If there is only a single mode in the data, we look for the first plateau and use its location as our threshold. (first non-negative difference value). Using the selected value, we threshold the sonar return data. Following that we find local maxima separated by some minimum distance.

To ensure that we are not getting sporadic high echoes *e.g.,* due to turbulent water, we perform a comparison with the previous sonar return. For each local maximum, we apply a similarity metric to the windowed location of both returns as well as the whole return. We use the ratio of the similarity metrics as a confidence metric for the detected obstacle. If the maximum was a sporadic effect, it should not occur in both returns and will therefore have low similarity. The similarity metric used is defined as follows: $similarity(a,b) = \cos(\theta) = \frac{a \cdot b}{\|a\| \cdot \|b\|}$.

The metric range to the obstacle is then calculated based on the return bin number and the aforementioned sonar wave parameters that affect the range. Finally, the coordinates of the obstacle in the global coordinate frame are found using the GPS position of the ASV along with bearing information from the IMU and the angle of the sonar head when the obstacle was detected.

Algorithm 1: Sonar echo return processing

Require: Sonar echo return vector, x, previous vector, y
1: $h \leftarrow histogram(x)$
2: $m \leftarrow smooth(h)$
3: $m \leftarrow addNoise(m)$ {We add small noise so plateaus will have mininma }
4: $t \leftarrow findFirstLocalMinima(m)$ {Use the index of minima as threshold }
5: **for** $i = 1$ to length(x) **do**
6:      **if** $x(i) \leq t$ **then**
7:          $x(i) = 0$
8:      **end if**
9: **end for**
10: $x \leftarrow smooth(x)$
11: $[peaks, values] \leftarrow findLocalMaxima(x, minDist)$ { Find all local maxima, with a minimum distance between }
12: $c \leftarrow similarity(x, y)$ { Find the similarity of the two measurements }
13: $conf = []$
14: **for** $i = 1$ to length($peaks$) **do**
15:      $a \leftarrow window(i, windowSize) \cdot x$ { Isolate the peak with a window}
16:      $b \leftarrow window(i, windowSize) \cdot y$
17:      $conf(i) \leftarrow similarity(a, b)/c$
18: **end for**
19: **return** $(peaks, values, conf)$

B. Scanning strategy

Multi-beam sonars can return a whole sector polar image at once, while single-beam sonars can only measure at one angle at a time. Often the sonar head is mechanically rotatable, so measurements can be taken at many angles, one angle at a time. One drawback of this is the relatively slow scanning speed of the sonar when gathering a view of its surroundings, especially when considering the narrow conical sonar beam($2.1°$). To address this, we limit the scanning sector of the sonar to only scan in front of the ASV. This can further be addressed by varying the sector width with the speed of the ASV, making the sector narrower when moving fast and enlarging it when moving slower with the goal of trying to keep the distance travelled between scanning in front of the ASV relatively constant and to gather more data from the surroundings when safe to do so. Our sonar unit, for example, is able to scan at approximately 10 Hz. With a step size of $2.4°$, it takes approximately 3.75 s to perform a $90°$ sector scan. In that time, an ASV such as ours is able to move 6 m at full speed, which is higher than the worst case detection range we have experienced for some obstacles, so such obstacles could go undetected until too late. The relationship between the distance covered during a full scan, d, the sector width, w, and the speed, v is:

$$d = \frac{w \cdot v}{s \cdot r} \Rightarrow w = \frac{d \cdot s \cdot r}{v}$$

where s is the sonar step size and r is the sonar scanning rate.

This is illustrated in figure 2 for a fixed guaranteed cover of 5 m, with $r = 10$ and $s = 2.4$. This means, if we want to perform a scan straight ahead every 5 m, we have to follow
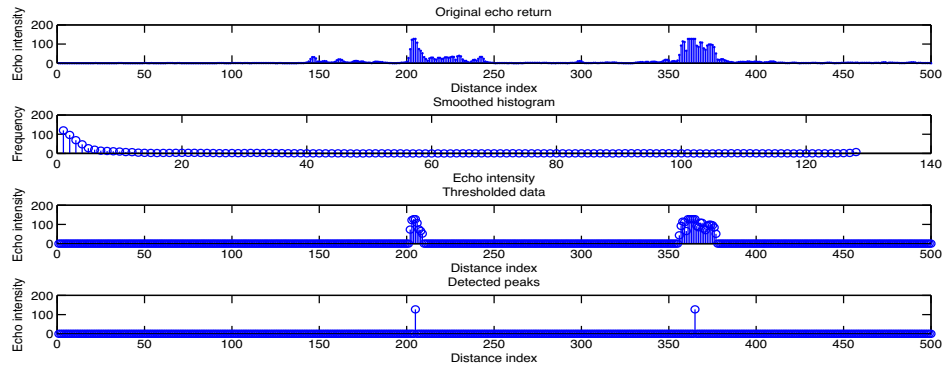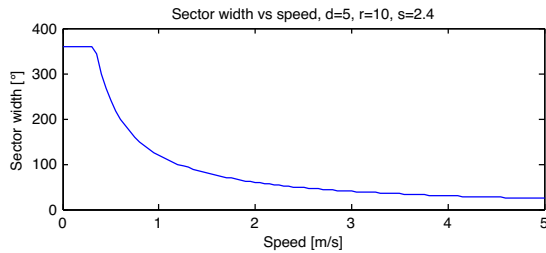

Fig. 1. Sonar echo return processing

Fig. 2. Sonar scanning sector vs ASV speed for guaranteed coverage 5m in front of ASV.

the curve for the sector width. We can see that with these parameters, when moving at 0.5 m/s, we can have a sector of 240 degrees, which reduces to 120 degrees for 1 m/s and then further to 75 degrees for 1.6 m/s.

A further addition to this scanning strategy is to have a high level controller or the obstacle avoidance algorithm on the vehicle give direction cues to the sonar based on the position of the goal. For example, if the ASV is traveling alongside some long obstacle, unable to head straight in its goal direction because the obstacle is blocking, it can be beneficial to center the scanning sector slightly towards the obstacle instead of straight forward. This will give better coverage of the obstacle and might reduce the chance of missing a traversable gap. Of course, care has to be taken to not rotate the scanning sector too much as not to loose coverage in the direction of travel.

IV. EXPERIMENTAL PLATFORM

A. Hardware

The experimental platform used is the Autonomous Surface Vehicle (ASV) designed by the University of Southern California's Robotic Embedded Systems Laboratory (Fig. 3). The ASV is an Ocean Science QBoat-I hull of length 2.1 m and 0.7 m wide at the widest section. The ASV is actuated by two electrical motors and rudder and is capable of speeds up to 1.6 m/s.

The ASV has an onboard 1.6GHz Intel Atom computer. For navigational sensing it is equipped with a u-blox EVK-5H GPS unit, which provides position updates at 2 Hz, and

a Microstrain 3DM-G inertial measurement unit (IMU) with built in magnetometer/compass, sampled at 50 Hz. The ASV also has WiFi to communicate with other ASV's as well as for operating it. For operational safety, the ASV is equipped with an RC fail-safe so an operator can always take over control with a remote control when deemed necessary.

For the trials described in this paper, the ASV was equipped with an Imagenex 881L Profiling Sonar mounted facing forward as pictured in Figure 4. The 881L is a single-beam mechanically scanned multi-frequency sonar with a full scale range from 1 m to 100 m.

B. Software

The ASV is controlled by software built using the open-source framework Robot Operating System (ROS) [12]. The framework provides a structured communications layer on top of the running operating system and a variety of tools to aid in experimental robotics. The software for the robot is split into small components called nodes. Each node performs a specific task and communicates directly to other nodes using messages.
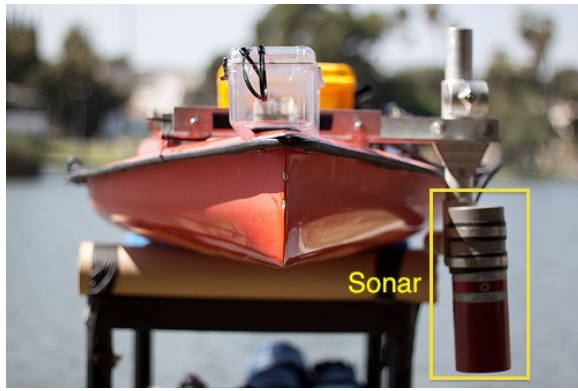

Fig. 3. Knarr, one of the USC test ASVs

Fig. 4. The Imagenex 881L Profiling Sonar mounted at the side of the ASV.

V. EXPERIMENTAL RESULTS

A. Swimming pool experiments

As discussed before, sonar is extensively used for obstacle avoidance on AUVs, but mounting a sonar facing forward on an ASV is different in several ways. Since the sonar is mounted just below the surface, effects of waves and disturbances in the water causing the ASV to tilt will frequently make the sonar tilt towards the bottom or towards the air-water boundary. To investigate the effects the air-water boundary and to verify some properties of the sonar we performed experiments in an indoor swimming pool. The swimming pool allowed us to have good control over what the sonar was seeing and to have an accurate ground truth on distances.

The swimming pool used for the tests was in indoor pool at the University of Southern California. Its dimensions are 23 m long by 18 m wide. The sonar unit was mounted on a pole suspended into the water 40 cm from the bank of the pool.

Several tests were performed with different types of obstacles in the water. The sonar unit was tilted both upwards and downwards to investigate the effect of the air-water boundary and bottom on the sonar data. Tilting the sonar upwards (up to $10°$) did not significantly affect the sonar, the detection range for obstacles was only shortened by 1-2 m. This happens because the angle of incidence with which the sound waves hit the water-air boundary is so large that majority of the energy is reflected forward.

B. Echo Park Lake experiments

We collected data in Echo Park Lake in Los Angeles. The lake has both shallow and steep banks and has several floating islands and a fountain. At the North end of the lake there are some nets attached to floats that are not safe to traverse with an ASV.

In figure 5 we can see that the banks of the lake were detected properly by the sonar. Also noteworthy is that at the North end of the lake, the nets and floats were detected by the sonar and deemed to be obstacles. The submerged net would unlikely to have been detected by a camera vision
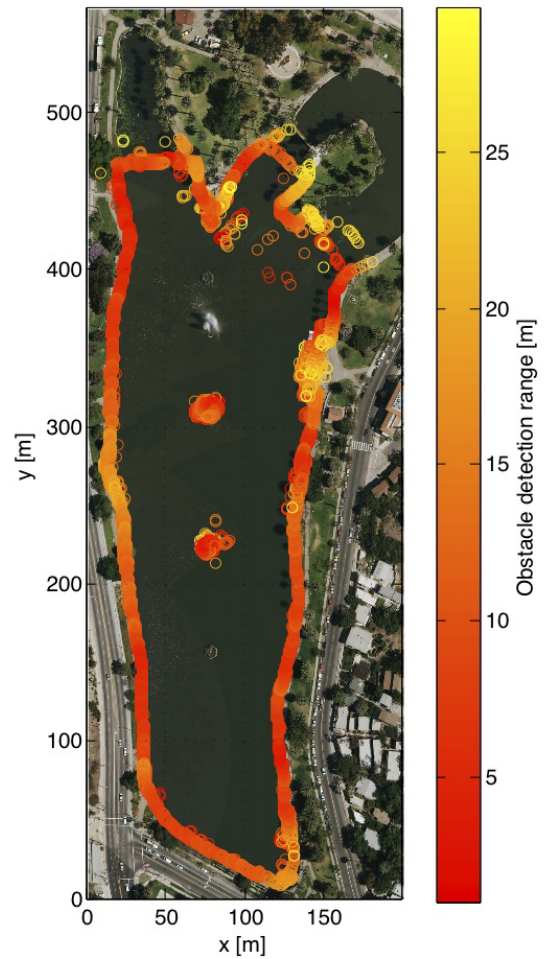

Fig. 5. Detected obstacles plotted on top a satellite image of Echo Park Lake. The boat performed a sideways scan while driven around the whole lake and around the islands.

system, and almost certainly not by a laser range finder, thereby demonstrating one of the benefits of using a sonar for obstacle sensing.

C. King Harbor, Redondo Beach experiments

We performed further experiments at the mouth of the King Harbor Marina, Redondo Beach, CA. Just as in the Echo Park experiments, the ASV was remotely piloted and data recorded for post processing. The harbor had many floating docks supported by pillars as well as walls, rocky banks and of course boats. The environment was much more dynamic than Echo Park Lake as many boats were moving through the mouth of the harbor. Another difference from Echo Park Lake was the amount of tilting of the ASV due to wave action. This did not have a significant effect on our ability to detect obstacles in the environment.

Figure 6 shows the detected obstacles plotted on a satellite image from Google Earth. There is a good match between the detected obstacles and the image and apart from the encircled markers, there are almost no sporadic readings,
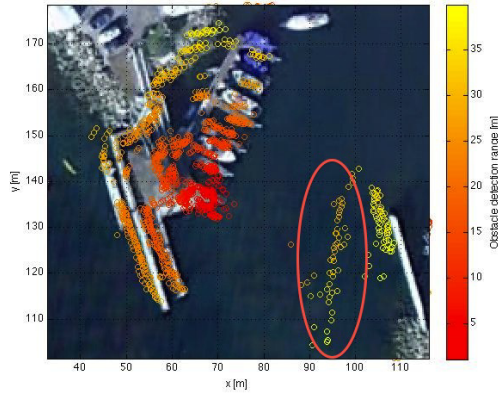
Fig. 6. Detected obstacles overlaid on top of a satellite image of the mouth of the harbor. The encircled markers are the result of a large boat coming in to the harbor.
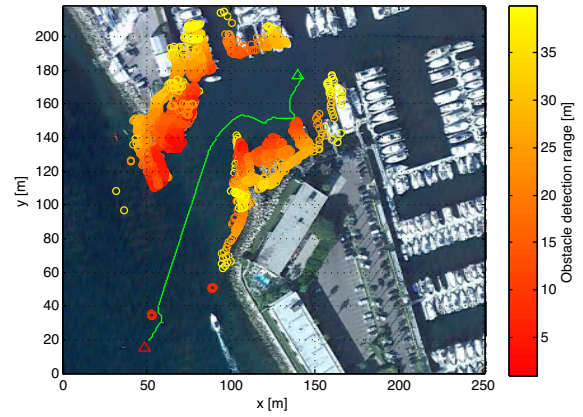

Fig. 7. Simulated trajectory of the ASV exiting the harbor. The green triangle marks the starting position, the red triangle is the goal position, the colored circles are the sonar data inputs and the green line is the ASV trajectory.

demonstrating how effectively we manage to reject noise. The encircled markers represent echo returns from a large vessel that passed by. Due to its low speed, there were consistent consecutive measurements so they were not rejected due to lack of similarity.

VI. SIMULATIONS

To verify that our approach works for obstacle avoidance we conducted a series of simulations where we have used sonar echo data recorded at King Harbor Marina and at Echo Park Lake. We implemented the VFH algorithm [3] for obstacle avoidance and rely on the sonar for sensing. The sonar data was segmented as described earlier. With each data point we store the range from which it was originally detected. We have removed echo returns from ships and boats that were entering and exiting the harbor at the time of recording since the simulation does not deal with the temporal aspect of the collected data. The VFH algorithm is not given any obstacle or map information *a priori*, instead we simulate the mechanical sweeping of the sonar and only pass on obstacles that are hit by the sonar beam in simulation. Obstacles are only sensed if they are within the associated original sensing range and once an obstacle is found in the beam, further obstacles that might also be in the beam are ignored. This ensures that the simulation treats obstacles similar to real operation. One drawback of this is that in the simulation, some obstacles may be detected later than they should if the ASV was close to them in the data collection. In the simulation, the ASV speed has been limited to 1 m/s and the turning rate limited to a realistic value. The sonar scanning sector is set to 90 degrees, centered around the front of the ASV.

In figures 7, 8, 9 we show a simulated trajectory where the ASV exits/enters the King Harbor Marina. In the first task, the simulated ASV is able to exit the marina without any collisions. As the figure shows, several obstacles were avoided during the length of the trajectory. The obstacle near the end of the trajectory is a buoy which could not

be properly detected by the sonar from more than 5 m away. This explains why the ASV comes close to it before turning around it. In the second and third tasks, the ASV enters the marina from two different starting positions. In both cases, the ASV successfully navigates around obstacles on the way, making it safely in to the marina.
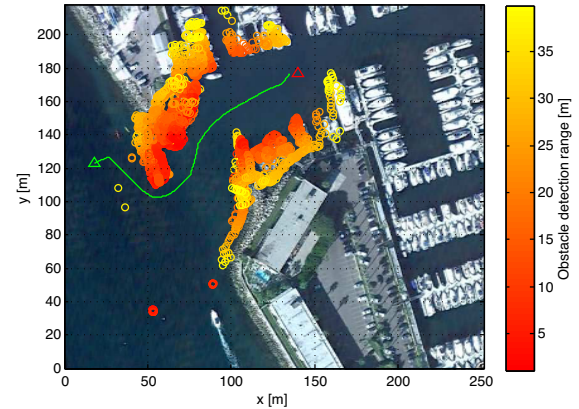

Fig. 8. Simulated trajectory of the ASV entering the harbor from the west. The green triangle marks the starting position, the red triangle is the goal position, the colored circles are the sonar data inputs and the green line is the ASV trajectory.

Finally, in figure 10, we show a simulated trajectory from Echo Park Lake, where the simulated ASV successfully navigates around two islands situated in the lake. The islands are floating, tethered to the lake bottom. The detection range results for these were mixed but in the navigation simulation, the ASV is still able to react to it in time.

VII. CONCLUSIONS AND FUTURE WORK

In this work we performed an initial experimental investigation into the use of a forward-facing profiling sonar for obstacle avoidance on an ASV. We developed a simple processing pipeline for data returned by the sonar and
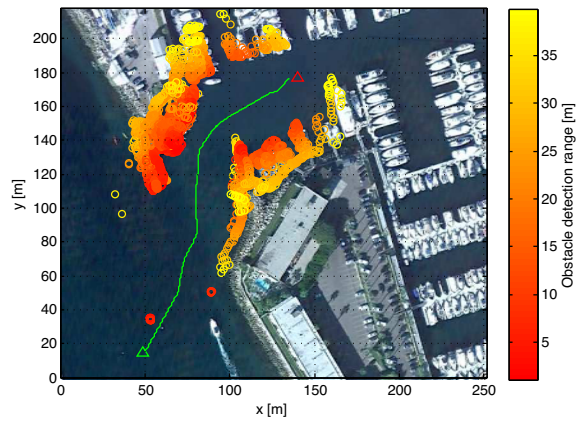
Fig. 9. Simulated trajectory of the ASV entering the harbor from the south-west. The green triangle marks the starting position, the red triangle is the goal position, the colored circles are the sonar data inputs and the green line is the ASV trajectory. The first obstacles detected are not sporadic readings as one might think, but are actually navigational buoys.
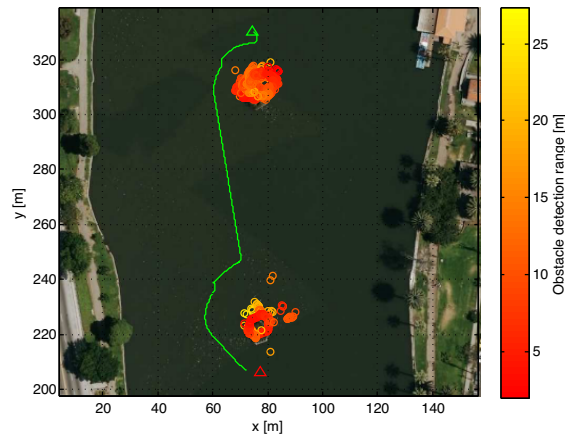

Fig. 10. Simulated trajectory of the ASV in Echo Park Lake. The green triangle marks the starting position, the red triangle is the goal position, the colored circles are the sonar data inputs and the green line is the ASV trajectory. The two big obstacles in its way are floating islands tethered to the lake bottom.

performed tests to verify the design. The tests were also aimed at exploring the feasibility of using the sonar close to the water-air boundary. We were able to detect all obstacles that we tried, but with varying detection range. We have used the data gathered in the field to build a simulation which was used to demonstrate that the use of sonar for this type of critical sensing is indeed possible.

While this work provides initial evidence that sonar provides sufficient information for obstacle avoidance and avoidance, more work is needed to quantify the effects of vehicle pitch and roll as well as expected error rates for commonly found environments. This work is in progress. We are also addressing the case of dynamic obstacles. In future work we plan to add an above-surface sensor, camera or a laser range finder, to the setup allowing the detection of obstacles to be made more robust. Complementary sensing

will allow obstacles to be classified as being floating/residing above the water, floating on the water or submerged below the water. As many obstacles have presence both above and below the water surface, fusing data from both sensors could provide more accurate estimates of obstacles.

VIII. ACKNOWLEDGEMENTS

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