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SELF DRIVING CAR PATH PLANNING MODIFICATION WITH RESPECT TO RAPID EMERGENCY VEHICLE DETECTION

Tatoglu, Akin[1]
Autonomous Mobile Robotics Lab
University of Hartford, Mechanical Engineering
West Hartford, CT, USA

King, Eoin[2]
Acoustics Program and Lab
University of Hartford, Mechanical Engineering
West Hartford, CT, USA

ABSTRACT

Self-driving cars and mobile robots utilize visual sensors including cameras and Lidars to perceive the environment. Same data is utilized to generate a 3D map for localization, path planning and obstacle avoidance purposes. These vehicles are also expected to modify their path plans rapidly when an emergency vehicle such as a fire truck or an ambulance is approaching. Required steps include an early detection, determining and maneuvering to a safe spot to park. However, these steps are challenging with a visual perception only system since it requires a direct view without an obstacle in between. At this research effort, we formalized a set of experiments to analyze the robustness of location and velocity vector prediction quality of a robot equipped with a transducer array. Detection and mapping algorithms work simultaneously to mark safe and unsafe routes. Case studies include single and two robots settings with stationary, constant velocity and acceleration motion profiles while occluding planes are placed to simulate a direct and T section occlusions. Accuracy for both systems are compared with plots. It is shown that direction estimation is sufficient enough to modify the occupancy grid rapidly prior to emergency vehicle reaches to a close proximity.

Keywords: Robotics, Path Planning, Acoustic Cues
I-INCE Classification of Subject Number: 76

1. INTRODUCTION

Self-driving cars and mobile robots utilize visual sensors including cameras and Lidars to perceive the environment. Same data is utilized to generate a 3D map for localization, path planning and obstacle avoidance purposes. These vehicles are also expected to modify their path plans rapidly when an emergency vehicle such as a fire

[1] tatoglu@hartford.edu
[2] eoking@hartford.edu

truck or an ambulance is approaching. Required steps include an early detection, determining and maneuvering to a safe spot to park. However, these steps are challenging with a visual perception only system since it requires a direct view without an obstacle in between.

A typical autonomous mobile robot application uses a stochastic process such as an Extend Kalman Filter (EKF) based Simultaneous and Localization and Mapping (SLAM) techniques. This approach concurrently generates a map and attempt to localize the observer –a robot— within this map. It first calculates a controller input and predict the error. Then, it actually executes the controller input and re-calculate the error with respect to surrounding objects called landmarks [1-2-3-4]. A sample 2D and 3D map generated by our research platform is shown in Fig. 1. We used ROS (Robot Operating System) and executed Gmapping and Octoslam algorithms for localization and mapping purposes. While Gmapping uses a 2D occupancy grid, Octomap registers both occupied and unoccupied volume. [5-6].

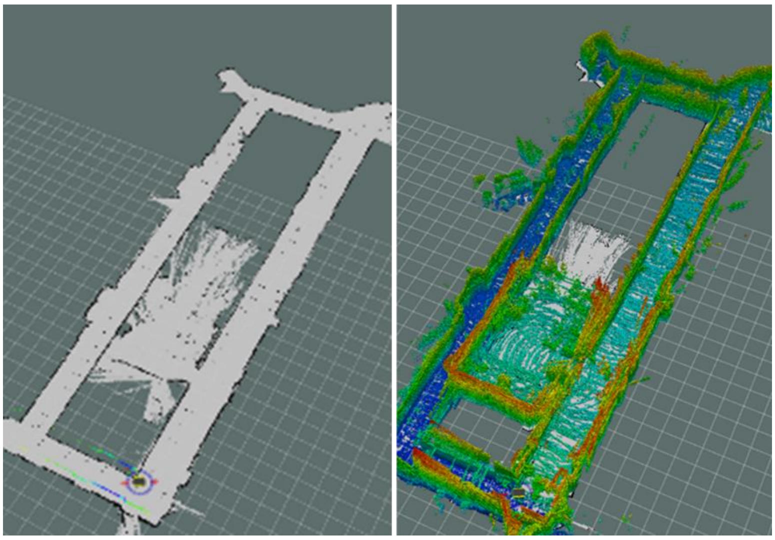

Figure 1. Left: 2D Map, GMapping. Right: 3D Map, OctoSLAM.

Emergency sirens are used to inform drivers about various types of approaching emergency vehicles which is the only acoustic cue [7]. Most of these sirens vary between 500Hz and 3,000Hz. Thus, throughout this project tests are performed with a sound source made up of 500-3000Hz pink noise. Our goal is to incorporate this data to path planning algorithm of a mobile robot or self-driving car to improve the safety. We had used our mobile platform shown in Fig. 2. A transducer array is mounted on top of it to conduct multiple experiments using beamforming techniques to predict the location of the sound source. At the second experiment, we used another tracked robot to study the behavior of the response while both observer and source are in motion. Finally, overall system is tested with multiple types of obstacle locations. Following sections discuss the background of the technique and rig assembly as well as details of the experimental setup and results.

3. MICROPHONE ARRAY ASSEMBLY

We had logged the received data with a high resolution DAQ and the time lag between signals is used to determine the source angle with a technique called the time-of-distance-arrival (TDOA). Algorithm utilizes the time difference between received signals to solve a multi variable system. The solution to the systems is used at the following triangulation step. The angle of incidence θ, is calculated from x = s cosθ, where s is the microphone spacing and x, 2x, etc is determined from the measured time delay as shown in Fig. 3.

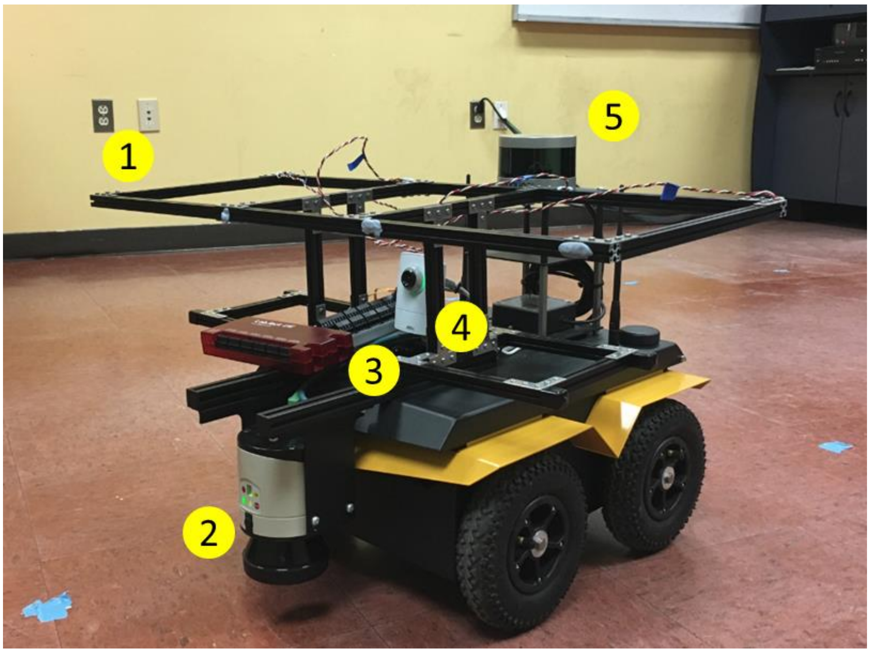

Figure 2. Mobile Platform: 1) Transducer array, 2) Front Lidar, 3) DAQ, 4) Camera, 5) 3D Lidar

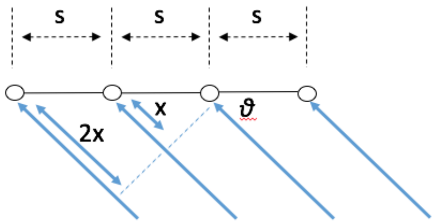

Figure 3. The angle of incidence from an array of four microphones.

The system consists eight MEMS transducers four on the left and four on the right, illustrated in Fig. 4. They are assembled in parallel for a practical calculation process. Type of the omnidirectional microphones are ADMP401, Analog Devices and there is 0.3 m. spacing between channels. Mobile data acquisition systems used is a LabJack USB Analog to Digital converter with 3.3V voltage regulators.

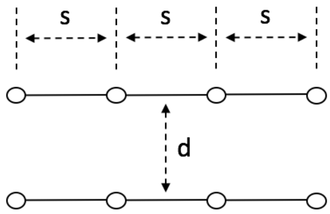

Figure 4. Transducer assembly

4. EXPERIMENTAL SETUP

Experiments were performed in three distinct environments; with controlled and uncontrolled environments with and without obstacles.

4.1 Controlled Setting (Anechoic Chamber)

A preliminary study in an anechoic chamber at the University of Hartford (qualified for free-field measurements for one-third octave bands of 100 Hz and above per ISO 3745-2003 [8]) is conducted to model microphone behavior in a controlled environment. Sound source used was A Genelec 8030A loudspeaker. The frequency response of this loudspeaker is flat or within a negligible 1 dB for an angular variation of 15° on either side of its acoustical axis. The distance between source and the receiver was 3 m. and the array was rotated to measure angular behavior of the system.

4.2 Uncontrolled Setting without Obstacles (Outdoors)

Similar tests were conducted outdoors without any obstacle in between the transmitter (Robot-1) and the transducer rig (Robot-2). Both mobile systems displaced at a constant but different velocities towards each other starting from 15 m. distance. Both mobile robots and angle of incident variable are illustrated in Fig. 5. Figure 6 presents another scenario tested.

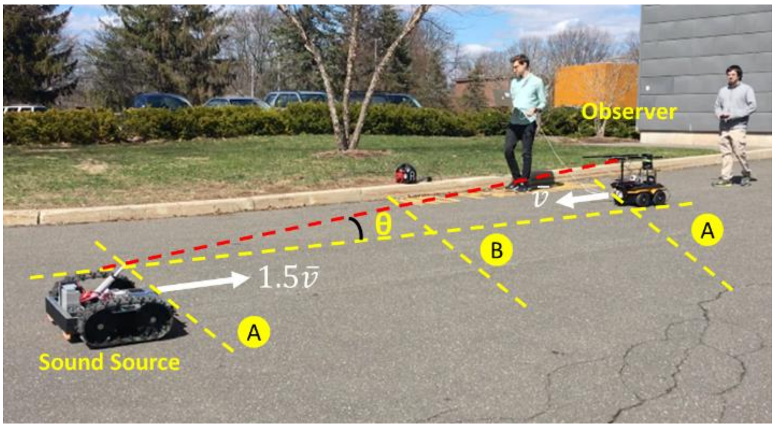

Figure 5. Multi robot outdoor experiment robots moving towards each other without obstacles in between.

Figure 6. (1) Sound source in motion with a siren, (2) Observer mobile robot.

4.3 Indoor Setting with Obstacles (Indoors)

At this third experiment, a panel to simulate an obstacle and/or T section is placed at multiple different locations between source and receiver. The experiment is conducted indoor and a sound source with multiple drivers is used to generate a white noise. Sound source, robot and obstacle are illustrated in Fig. 7.

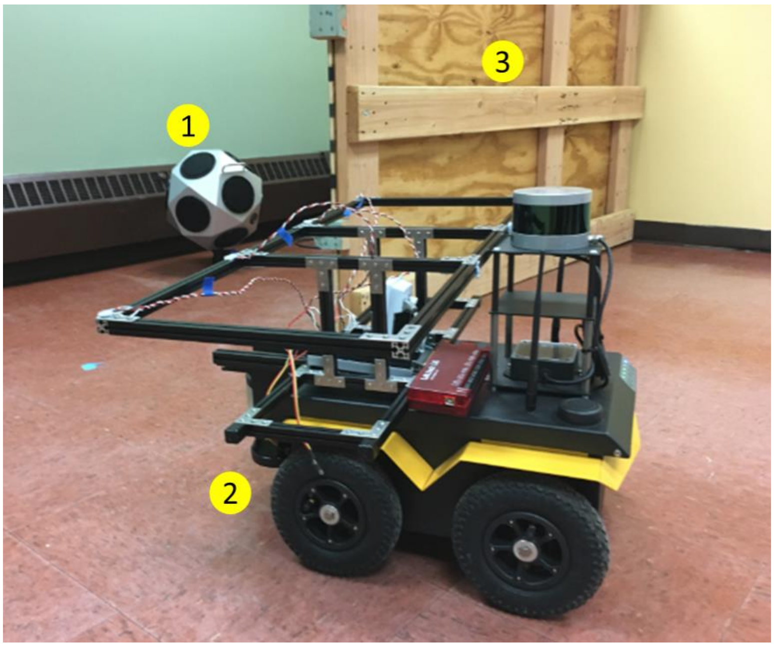

Figure 7. 1) Sound Source, 2) Mobile Rig, 3) Obstacle Panel

5. RESULTS

5.1 Controlled Setting (Anechoic Chamber)

Results from both left and right channels are plotted in Fig. 8. Figure 9 represents the angular response of the transducer. The similar behavior of the response signals shows that it is possible to determine the location with a reasonable error.

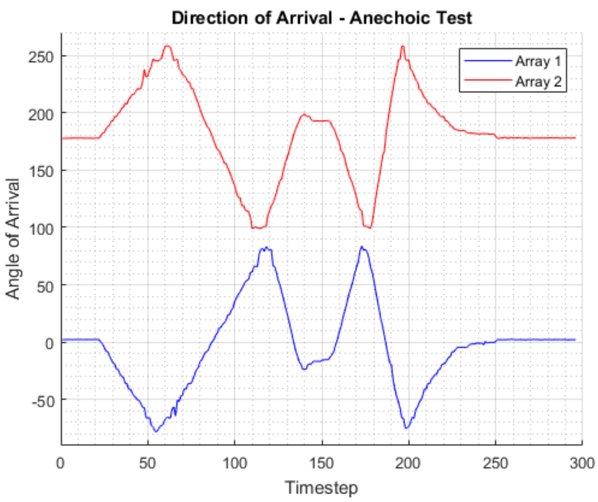

Figure 8. Results from both linear arrays, recorded simultaneously as array is manually rotated in front of sound source

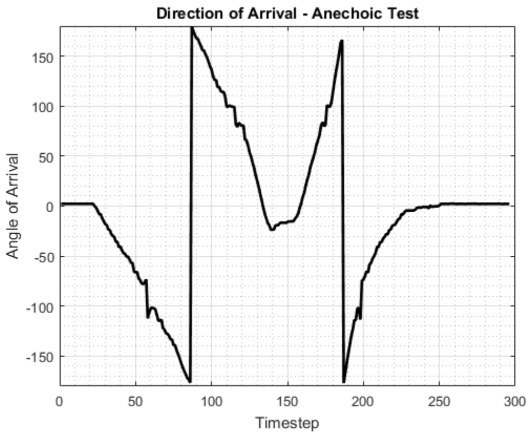

Figure 9. Results from each line array may be combined to yield a 360º angle of arrival coverage.

5.2 Uncontrolled Setting without Obstacles (Outdoors)

The source robot started traversing towards each other {A} with an initial angle of -75º and ended about +75º . The intersection point of lines {B} in Fig. 10 represent the closest point of robots.

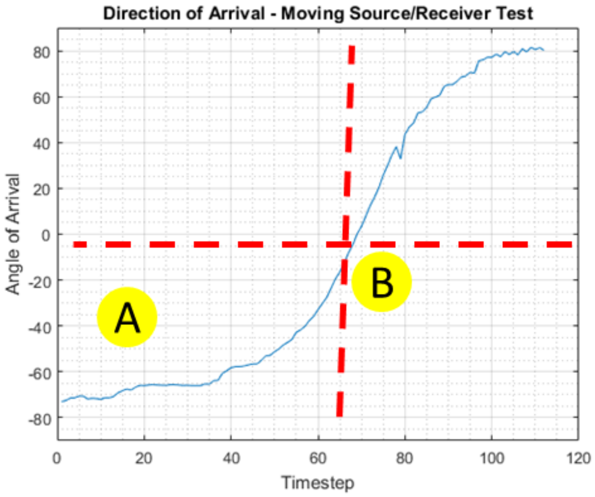

Figure 10. Moving source and receiver outdoor test. Starting and the closest points are marked with letter A and B respectively

5.3 Controlled Setting with Obstacles (Indoors)

The source robot traversed in a room and generated a 2D map with GMapping algorithm. The map and actual dimensions robot created is shown in Fig. 11.

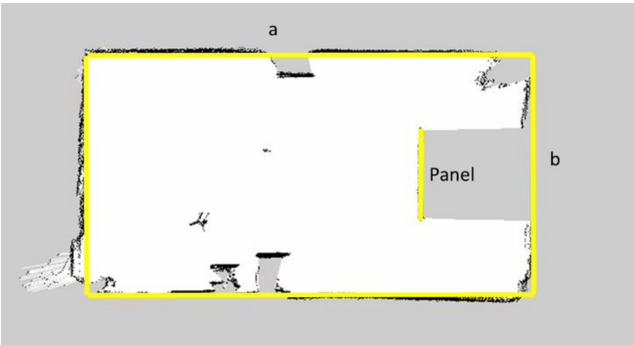

Figure 11. GMapping output with actual dimensions detected. Panel: 196.215cm., Lengths a: 948.372cm., b: 509.470cm.

The goal is to identify the approximate location of the sound source. However, the challenging signal processing step is to drop reflected signals from the surroundings – such as the walls and the panel itself. Our initial reflectivity model resulted with Fig. 12 illustrating detected beams. While initial model successfully identified main reflected signals, it couldn't recover from all of the obstacle related signals.

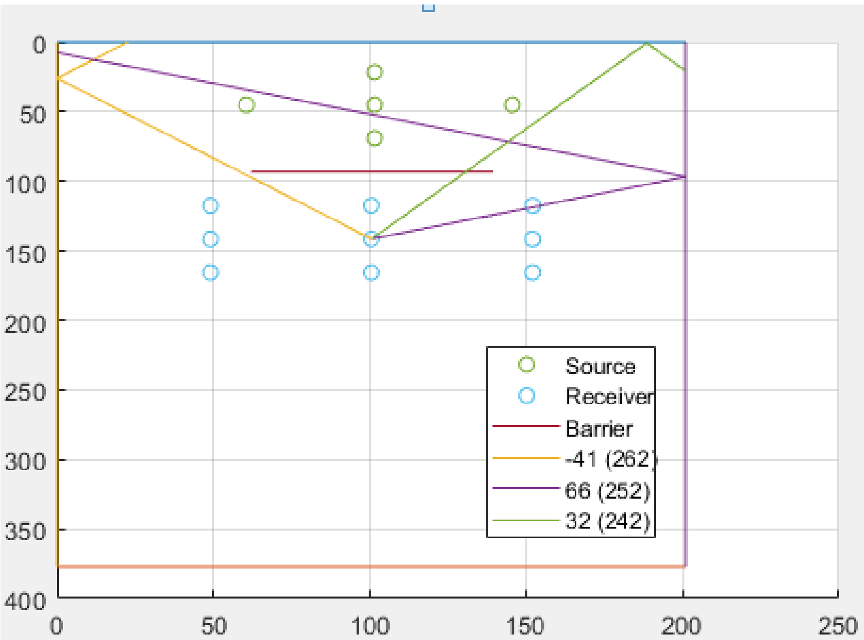

Figure 12. Detected direct and reflected signals, superimposed on GMapping generated robot map.

6. CONCLUSION AND FUTURE WORK

Self-driving cars and autonomous mobile robots generate a path plan with respect to created map of the environment. During the process, it might need to slightly modify its path with respect to other vehicle behavior. However, if there is an emergency vehicle in close proximity, time constrains are aggressive and vehicles are expected to find a safe spot to park the car immediately. In this study, we investigated the possibility of the early detection of emergency vehicles while they can't be visually observed. The goal is to let the processing unit have more time to safely calculate an appropriate modified route.

We conducted three different experiments to study the transducer behavior, two car scenario without and with obstacles. The results show that location of the approaching vehicle could be predicted even with outliers. At the next step of our research, we will modify our reflectivity model to increase the accuracy of sound localization and implement a machine learning based outlier detection to drop faulty signals.

7. REFERENCES

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