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# Multi-Vehicle Testbed for Decentralized Environmental Sensing

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*Abstract*— **In this paper we present our multi-vehicle testbed that was designed for verification and validation of cooperative control algorithms involving environmental sensing. Two cooperative control algorithms: prioritized multi-sensing behavior, and a distributed adaptive algorithm for nonholonomic sensor networks are qualitatively verified using our multi-vehicle testbed. The multi-vehicle testbed allows for a straightforward transition from simulation to experimenting on actual hardware and has the flexibility to interface various types of sensors, vehicles, as well as enable indoor and outdoor experiments.**

## I. INTRODUCTION

Recently in the literature much attention has been paid to the development of mobile robot teams capable of accomplishing various tasks through cooperation which would be very inefficient if done by a single robot. Among the recent advances in mobile robots is the idea of a dynamic or reconfigurable sensor network, where each robot is equipped with sensors that are capable of measuring some parameter of the environment and able to reconfigure the network configuration based on these measurements. Through cooperation the robot team should accomplish different tasks such as optimal sensor coverage, target tracking, or spatial distribution mapping. Some motivating and practical applications include search and rescue operations [1], [2], target detection [3], [4], and hazardous contaminations [5] to name a few.

Although much attention has been paid to creating cooperative control algorithms for dynamic sensor networks less attention has been paid to the validation and verification of these control algorithms on experimental hardware. The focus of this paper is to expand our current experimental testbed to accommodate environmental sensing applications.

To facilitate the development of novel cooperative control algorithms specifically for environmental sensing, monitoring, and mapping, we extend our current multi-vehicle testbed to enable a quick turnaround from simulations of the control algorithms to actual hardware implementation.

With this addition, limitations in the cooperative control algorithms can be identified and subsequently addressed in further research. This approach to verification and validation facilitates cooperative control algorithms that are implementable in real-wold scenarios.

The addition to our multi-vehicle testbed consists of four Pioneer P3-AT mobile robots each equipped with an environmental sensor suite. The multi-vehicle testbed was designed to interface various types of sensors as well as various numbers of vehicles and types. Sensors and robots can be added and removed on the fly based on user need. Also, the multi-vehicle testbed is able to carry out indoor as well as outdoor experiments.

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### A. Sensor Network Background

Recent research in sensor networks concentrates on creating a sensor network that can adapt to its environment. In this sense, the trend is towards reconfigurable sensor networks. Addressing reconfigurable sensor networks is typically done by utilizing mobile sensor platforms to adapt to the environment, [6] and [7]. Mobile robots give the network the ability to react to changes in the environment through their mobility by placing sensors to more interesting areas or places that may lack sensor coverage due to spatial configurations or possible sensor failures. Mobile robots also allow the network to verify or disregard abnormal (noisy) data coming from a sensor by reconfiguring so that a second sensor can obtain data to compare with.

Much of the research in reconfigurable sensor networks focuses on surveillance and tracking tasks. The goal in these applications is to identify and track targets moving within the area the sensor network covers. In [6], Huntwork *et al.*, create a sensor network with both mobile sensor platforms as well as stationary sensors. The network is not assumed to be configured in any optimized fashion, so mobile sensors are used when a target is no longer visible by the stationary sensors, or cannot be tracked at an adequate resolution.

Cortés, Martínez, and Bullo [8] and [9], use gradient climbing algorithms to distribute sensor platforms in an optimal fashion over the area in question to address spatial distribution of the sensor platforms. Robot agents follow gradients that maximize a static density function that is weighted by a sensor performance function. The area is divided up among the agents using Voronoi partitions. Hussein and Stipanovic [10] use a gradient climbing method for control of the sensor network as well, but without having to partition the area among the team members, which reduces computational overhead.

A large part of research in reconfigurable sensor networks is mostly concerned with issues related to monitoring, surveillance, and target tracking, but there are also applications beyond a pure surveillance or tracking [7]. Mobile sensor platforms can be used as reconfigurable sensor networks for mapping spatial distributions of physical quantities [11]. We envision controlling a multi-robot team to map these physical quantities, where the sensor network is reconfigured on-line based on the information from the sensed environment.

### B. Related Experimental Testbeds

We expand on our original testbed [12] COMET, to include mechanisms that allow for environmental sensing which enable validation and verification of cooperative control algorithms that depend on measurements of the sensed environment. The original COMET testbed consisted of ten all-terrain vehicles which are based on the Tamiya TXT-1 chasis. The COMET testbed is used for validation of cooperative control algorithms, however in its first generation lacked environmental sensing capabilities.

Along the same lines, the experimental testbed at the GRASP Laboratory at the University of Pennsylvania [13] was designed for large-scale multi-robot systems for experimental validation of distributed robot applications in a strictly indoor environment. This testbed was specifically designed to address situations such as formation control, search and pursuit of targets of interest, and cooperative manipulation tasks.

In a similar design to the testbed presented in this paper, the authors of [14] utilize a group of 16 SwarmBots to validate a coverage control algorithm that is based upon information of the sensed environment. Sensory information was simulated during one of the experiments to compare the performance against a known ground truth then during a second experiment sensory information was taken from onboard light sensors.

The GRASP testbed is more tailored for validating control algorithms such as formation control, search and pursuit of targets, and cooperative manipulation, rather than sensing environmental data which is the focus of our testbed. Also, the group of SwarmBots use only a single source of data rather than data from multiple spatial distributions in the environment which our current testbed is equipped to handle.

## II. Hardware Description

### A. Vehicle Description

The Pioneer P3-AT stores up to 252 Wh of hot-swappable batteries. The P3-AT can reach speeds of 0.8 m/s and carry a payload of up to 30 kg as well as climb a steep 45% gradient. Also, laser-based navigation options, integrated inertial correction to compensate for slippage, GPS, bumpers, gripper, vision, stereo rangefinders, and compass options are available commercially for the P3-AT [15].

Our current testbed can accommodate laser-based navigation, GPS navigation, as well as gripper/manipulator tasks. Although this paper concentrates on experiments conducted with the Pioneer P3-AT robots, our testbed also contains ten all-terrain vehicles which are based on the Tamiya TXT-1 chasis as well as a Drangonflyer X-Pro quadrotor and two AscTec Hummingbird quadrotors.

### B. Environmental Sensor Suite

The environmental sensor suite consists of a Phidgets 8/8/8 USB interface I/O board capable of measuring eight digital and eight analog inputs and capable of driving eight digital outputs. The Phidgets I/O board can accommodate pressure, temperature, humidity, light intensity, and magnetic field sensors as well as many others.

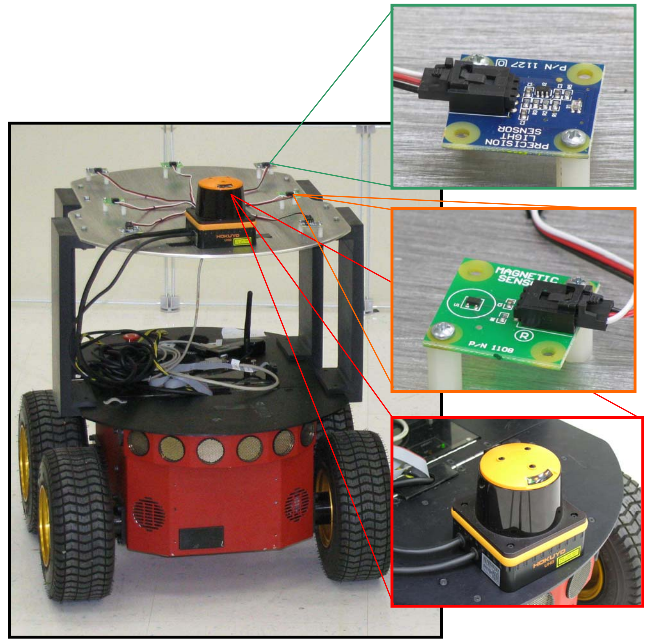

Fig. 1. Pictured are four precision light sensors (top) three magnetic sensors (middle) and a Hokuyo UHG-08LX laser range finder (bottom) all mounted on a custom fixture that is attached to a robot.

A special aluminium plate and mounting system was created to interface the environmental sensor suite. The plate and mounting system allows for multiple sensor configurations as well as the ability to mount multiple accessories on each robotic platform. Figure 1 shows the custom built aluminum plate with four precision light sensors and three magnetic sensors. Also shown is a Hokuyo UHG-08LX laser range finder. The addition of the custom plate and mounting brackets allow for a quick swapping of sensors and accessories to address a variety of experimental tests. The experimental testbed has its own dedicated IEEE 802.11 WLAN, which provides a low-latency network that is used by the robotic platforms for communication as well as for Player server/client communications.

## III. Player/Stage/Gazebo/USARSim Interface

One of the most widely used robotics software packages is the Player/Stage/Gazebo (PSG) [16]. The PSG project consists of libraries that provide access to communication and interface functionality on robot hardware. The robot "server" Player, provides an architecture where multiple modules, also known as drivers, can be written independently and connected via a custom middleware that relies on TCP communication. Users write "client" applications (control algorithms) that connect to and command modules (drivers) running on a Player "server." Additionally, PSG provides a 2D simulator, Stage, and a 3D physics-based simulation environment Gazebo. Additionally USARSim [17] is a highfidelity simulator of robots as well as environments which is based upon the Unreal Tournament game engine which can be used with a Player "server." USARSim allows for realistic robotic environments with kinematically accurate robot models. These simulators provide a transparent transition from simulation code using a virtual environment to the actual robot hardware.

## IV. Control Algorithms

### A. Prioritized Multi-Sensing Behavior

In [18], we propose a decentralized coordination algorithm that allows a team of sensor-enabled robots to navigate a region containing non-convex obstacles and take measurements within the region that contain the highest probability of having "good" information first. This approach is motivated by scenarios where prior knowledge of the search space is known or when time constraints are present that limit the amount of area that can be searched by a robot team. One very practical application is that of a hazardous contamination in the environment. With some prior knowledge of where the contamination may have occurred, the coordination algorithm allows for prioritizing searching/sensing efforts. An outline of the control algorithm is described below.

1) (*Voronoi region*) Determine the Voronoi partitioning based on robot positions.
2) (*Global optimization*) Apply the Monte Carlo optimization method over robots Voronoi partition on the Probability Of Detection (POD) map.
3) (*Check feasibility*) Determine if the goal point is reachable by solving the shortest-path problem from the graph that creates the navigation function. If goal point is not reachable then go to Step 2 and determine next best possible goal point.
4) (*Navigation function*) Create a modified navigation function with the goal point.
5) (*Control actuation*) Apply a gradient descent control based on the modified navigation function.
6) (*Local map update*) For all points that are inside the sensing radius $R$, update the POD map.
7) (*Global map update*) Each robot communicates with its neighbors and exchanges its current position. All robots update their local maps with all other robots local maps to create a synchronized global map.
8) (*Termination*) Check if $t \geq T_{search}$ if true, stop. Else goto Step 1. $T_{search}$ is taken to be the time allowed for the search.

As an extension to [18] we introduce the idea of a multi-sensing framework, where robotic platforms are equipped with more than one sensing modality. This multi-modal approach becomes very practical in such applications as search and rescue or hazardous contaminations where more than one factor may play a role in decision making.

From our previous work [18] we have shown how to prioritize searching/sensing efforts through the use of a probability of detection map. To address the multi-sensing framework we propose the use of logistic regression to express the contributions of each sensing modality and its factor on the overall probability of detection (POD) map. This approach allows one to weigh a particular sensing behavior over another depending on need or usefulness of the sensing data.

The logistic function is defined in the following way,

$$f(y) = \frac{1}{1+e^{-y}}, \tag{1}$$

where $y$ is defined as

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_k x_k. \tag{2}$$

In equation (1), the output represents the probability of a particular outcome. For our purposes $f(y)$ in (1) represents the probability of finding useful information at a particular point in the area or interest. In (2), the parameters $\alpha_1, \alpha_2, \ldots, \alpha_k$ are the regression coefficients which describe the contribution of the risk factors, $x_1, x_2, \ldots, x_k$. $\alpha_0$ represents the probability of finding useful information given all risk factors are equal to zero. For our purposes risk factors will be different sensors probability of detection maps. In this sense, through logistic regression we are able to fuse a variety of different sensing objectives (POD maps) into a single objective that is weighted based on user need or the mission objective. Figure 2 shows a one-dimensional example of combining multiple POD maps. Notice that although the map represented by the blue line has the highest POD value initially, when combined with the other POD maps it has the lowest POD value. This is due to its regression coefficient, which is taken to be $0.6$. In this way, although there is a good indication that some useful information may be there, it may not be a primary objective of the mission. Through this linear regression technique the user can bias what the robots should search/sense first but also allow the possibility of searching/sensing secondary objectives if time permits.

### B. Adaptive Algorithm for Nonholonomic Sensor Networks

Having a density function of a measurable phenomenon we can employ dynamic sensor networks to get an estimation of the concentration. In our particular case a group of nonholonomic vehicles equipped with sensors are distributed in an unknown area and position themselves near optimally over the sampling space estimating the available sensory information. The sensory function is assumed to be dynamic (*e.g.,* an oil spill [19] or a forest fire [20]).

The work of Schwager *et al.,* presented in [14] and [21] consists of implementing a stable and decentralized coverage control law over a population of mobile sensors to solve a facility location problem [22] by using centroidal Voronoi tesselations. A consensus algorithm is used to propagate the measurement information through the sensor network using an adaptation law with a gradient estimator [23]. The theoretical framework in [22] is developed for a distributed controller considering holonomic vehicles.

In this paper, on the other hand, we propose a nonlinear polar controller to drive a team of nonholonomic agents. The control algorithm for each robot is organized as follows.

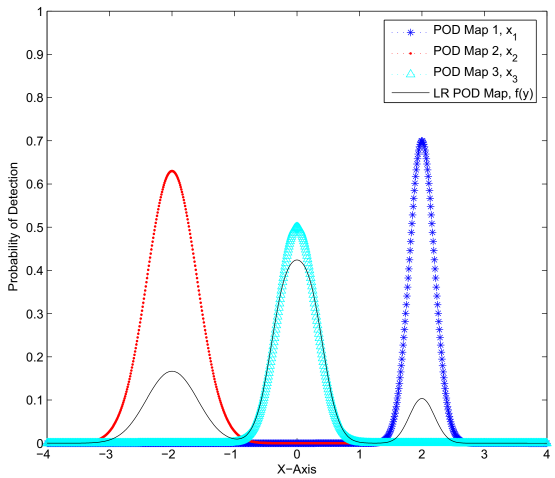


Fig. 2. One-dimensional example of the linear regression algorithm. Three POD maps (red (circles), cyan (triangles), blue (asterisks)) with high probabilities of containing good information at $x = -2, 0,$ and 2 respectively, are combined into a single one-dimensional POD map (black (solid line)) that reflects the overall mission objective. LR POD Map (black (solid line)) in the legend corresponds to the overall POD map after the linear regression step. Here the POD map with the lowest probability (cyan (triangles)) is the most important to the mission objective which is reflected after the linear regression is done.

1) (*Voronoi region*) Determine the Voronoi partitioning based on robot positions.
2) (*Density function measurement*) Take a measurement of the density function from the environmental sensors.
3) (*Gradient estimator*) Approximate the calculation of a gradient estimator using difference equations to parameterize the density function.
4) (*Consensus error*) Calculate the consensus error vector to calculate the adaptation law using the gradient estimator output.
5) (*Center of mass*) Approximate the center of mass of the Voronoi region based on the estimated density function.
6) (*Polar coordinate conversion*) Carry out the axis translation and trigonometric conversions to obtain the polar coordinate position.
7) (*Control actuation*) Apply the nonlinear polar control law to drive the robots to the center of mass of its Voronoi region.
8) (*Change of estimate parameters*) Check for a problem dependent condition to change the estimate parameters. This is useful for dynamic density functions.
9) (*Termination*) Check if a problem dependent time condition is fulfilled. If true, stop. Else goto Step 1.

To carry out the simulation and the experiments related to our controller, we use a population of four robots to sense a concentration of yellow light in a rectangular sampling space of $4.7\text{m} \times 6.6\text{m}$ . The sampling space was divided in a $8 \times 8$ grid where the geometric centroid of each rectangular cell corresponds to the mean of a bidimensional Gaussian function given by

$$\mathcal{K}_i = 0.5e^{\frac{-(q-\mu_i)^2}{2\sigma_i^2}}, \tag{3}$$

with $\sigma_i = 0.7$ m.

The light concentration is considered a time-varying density function $\phi(q,t) = \mathcal{K}(q)^T a(t)$ where the parameter vector $a(t)$ is a piece-wise constant function $a(t) : \Re_+^m \mapsto \Re_+^m$ and is right continuous. Also, we assume that $\lim_{t\to\infty} a(t) = a_c$ where $a_c \in \Re_+^m$ is a constant value *i.e.,* the density function reaches a stable state.

We assume that the adaptation law rate and the angular and linear speed of the agents are fast enough to follow the slow dynamics of the density function.

The Voro++ library is used to calculate the Voronoi tessellation vertices, and the numerical integral for the centroid equation was approximated by Riemann summations discretizing the inside of the polygons in a $8 \times 8$ grid and adding the volumes of the hexahedra corresponding to every division. In both control algorithms presented, the partitioning of the space is done based on location of the robots only.

## V. Results

### A. Simulations

To simulate the prioritized multi-sensing behavior and adaptive sensor network algorithm, we use the Player/Stage interface which utilizes software drivers for the Pioneer P3-AT robots that mimic their physical behavior when interacting in an environment. Because of the realistic feedback of the Player/Stage interface, the actual experimental environment was roughly reconstructed in a two dimensional representation. During simulation as well as in the actual hardware experiment we opted to use magnetic and light sources for the multi-sensing behavior and multiple light sources for our adaptive algorithm.

This allows for simulations in Stage to behave very closely to the actual hardware experiments, which allows for a quick turnaround from simulation to experiments. Although hardware drivers are available for the Phidgets Interface Kit in Stage there does not exist software drivers for accessing data from a "virtual" sensor. To overcome this setback during simulation we choose to create "virtual" sensor data for the magnetic and light sources. The "virtual" sensor data for both the magnetic and light sources come from Gaussian functions where sensor values are based on the current robot positions. In this way we are able to simulate the physical environment through Stage but also the sensing environment.

### B. Experiments

Both the prioritized multi-sensing behavior and adaptive algorithm for nonholonomic sensor networks were implemented on our multi-vehicle testbed for qualitatively verification. However, our multi-vehicle testbed also allows for more rigorous verification and validation if need be. A short video showing snapshots of the experiments accompanies this paper.

*1) Prioritized Multi-Sensing Behavior:* The two spatial distribution quantities that our sensors are measuring are magnetic intensity as well as light intensity. Sensor measurements taken by the robots are subject to noise, however a detailed investigation of the affect of noisy measurements on the algorithms is out of the scope of this paper. A large magnet is placed at $(.5\text{m}, -1.5\text{m})$ and a light source is emanating directly above $(0\text{m}, 2\text{m})$ in the search space. The magnetic source used during the experiment was a "C" shaped ferrite magnet placed in a box, which is capable of producing a magnetic intensity of 126 gauss at a distance of 40cm. The light source used for the experiment was a 100W flood lamp placed 2.5m above the ground. Also two obstacles were placed in the search area to show the collision avoidance capability of the control algorithm.

Laser range finders are used only for obstacle avoidance. Localization currently is done through odometry, however a Vicon motion capture system is currently being installed. The sensed data is coupled with an (x,y) coordinate that corresponds to a point in the world coordinate which is subject to localization errors. To minimize localization errors, the prioritized multi-sensing behavior was only run for 30 iterations. This was long enough to verify the qualitative behavior of the algorithm.

Figure 5 shows the initial POD map used for the experiment. Each robot first calculates its own Voronoi partition based on its position as well as its neighbors. Next the point that has the highest probability of containing "good" information is calculated. For our experiment "good" information represents a magnetic or light source. We notice also in Figure 5 that after 30 iterations of the algorithm the POD map has been reduced by a factor of two. Figure 3 shows the points in the search space that the robots took measurements from, in other words, where the highest probability of obtaining good magnetic or light readings.

Figure 4 depicts the magnetic and light intensity maps after 30 iterations of the control algorithm. We see that indeed the highest intensity values coincide with locations of the magnetic and light sources respectively. We also notice that two of the robots were taking measurements that coincided with the magnetic and light sources, however the third robot was taking measurement that did not coincide with any source. This shows the dependence of the control algorithm on prior information. Although the experiment was only ran for 30 iterations, in simulation it is observed that the third robot would eventually make its way towards one of the other robots to help reduce the POD map or begin reducing the POD map in areas that have yet to be reduced.

*2) Adaptive Algorithm for Nonholonomic Sensor Networks:* For the experiments we use four Pioneer P3-AT robots as the one shown in Figure 1. The light is measured by four precision light sensors fixed to the top of the aluminum plate. The robots location is controlled through the odometry system embedded in the robots which involves a gyroscope and wheel encoders.

In Figure 6 we show the behavior of the euclidean distance between the robots and the centers of mass of their Voronoi partitions, and the consensus error which is an indicator of the similarity of the parameter estimation between the robots. Notice in both cases that the robots are reducing their average distance to the centroids and the averaged difference of the estimate parameter.

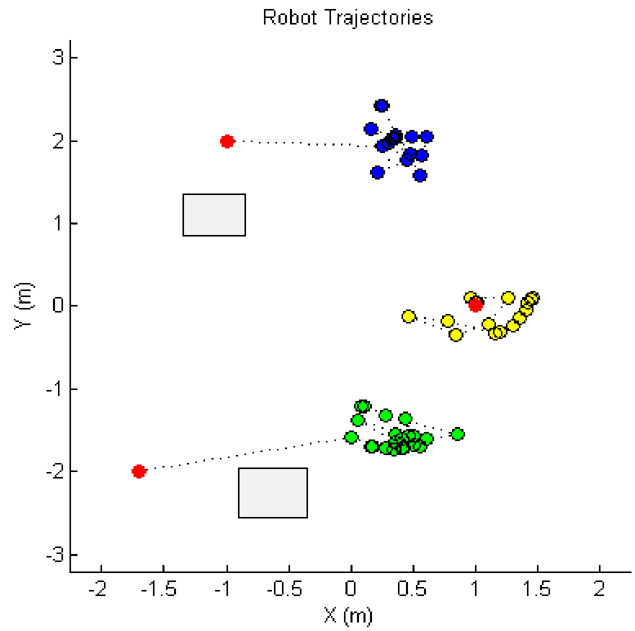


Fig. 3. The robot trajectories during the experiment. The red dots indicate the robot initial positions and the colored dots indicate the places that sensor data was taken, i.e. the areas with the highest probability of detection based on each robots voronoi partition.

The plots in Figure 6 are affected by the noise of the sensor measurements and the numeric approximation of the centroid integrals. We show a filtered version of the signal in red that illustrates the convergence.

Furthermore, the effect of the adaptive law approximation is evident again in Figure 6, where the constant value intervals correspond to the moment the robots are traveling to their Voronoi cell centroid. The discontinuous edges correspond to the moment the robots take a light measurement and calculate the new centroids. Measurements are not continuous, rather taken when the robots reach the desired position.

Figure 7 depicts the average estimated light distribution obtained by the robots during the experiment, before and after the light concentration was moved in the search space.

## VI. CONCLUSIONS AND FUTURE WORKS

In this paper we presented our multi-vehicle testbed for environmental sensing and included experimental results from two cooperative control algorithms, prioritized multi-sensing behavior and a distributed adaptive algorithm for nonholonomic sensor networks. The testbed provides an easy transition from simulation to experimentation and has the flexibility to be easily reconfigured to allow for a variety of experiments involving measurements from the environment.

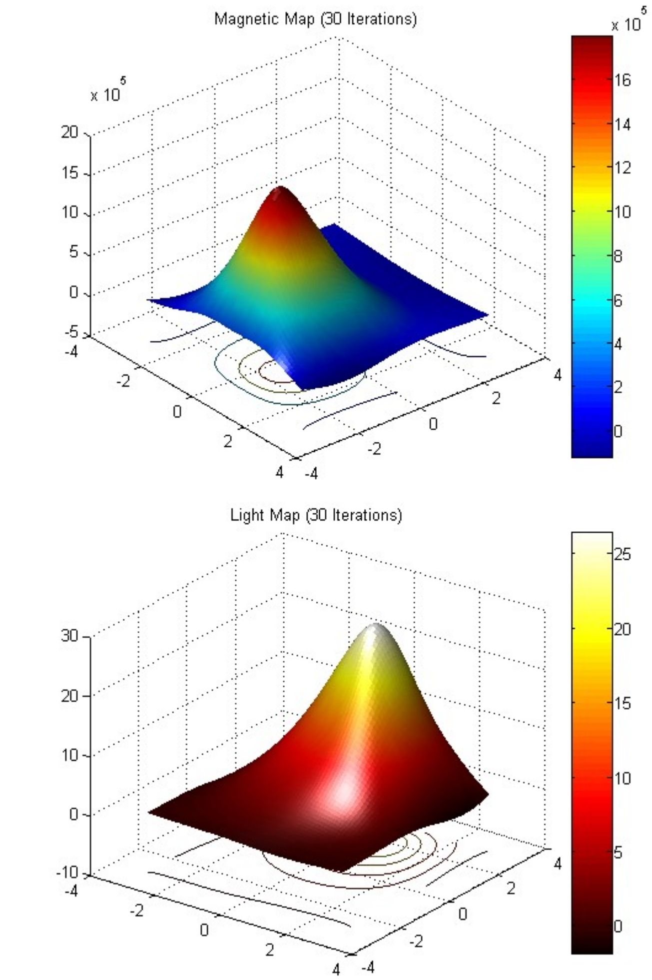


Fig. 4. The top figure shows the magnetic intensity map 30 iterations of the cooperative control algorithm. We see that the highest concentration of the magnetic field is near (.5m,-1.5m). The bottom figure shows the light intensity map after 30 iterations of the cooperative control algorithm. We see that the light is concentrated near (0m,2m).

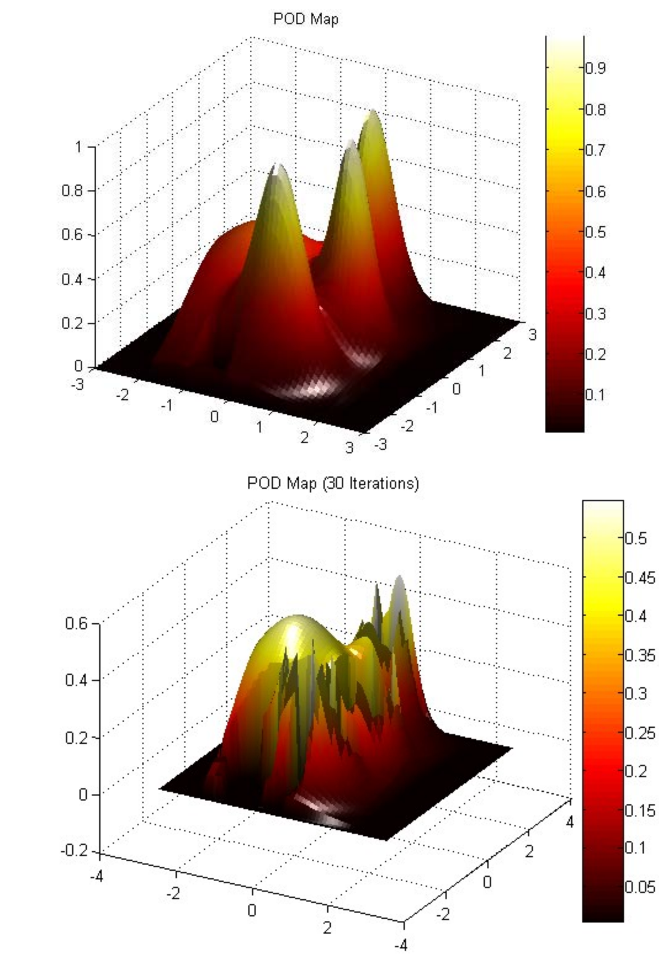


Fig. 5. The top figure shows the probability of detection map which reflects the likelihood of detecting "good" information in the region. The bottom figure shows the probability of detection map after 30 iterations of the control algorithm. Notice that the probability of detection has been reduced significantly, from about .95 to nearly .5.

Future work entails further development of the multi-vehicle testbed to enable experiments with both ground and aerial vehicles with environmental sensing capabilities, as well as the development of novel cooperative control algorithms that make use of both ground and aerial vehicles for environmental sensing, monitoring, and mapping. Another avenue of future research is in the connectivity of the robot team. In these algorithms connectivity was assumed, in a more realistic setting, this assumption may not hold. We hope to incorporate some aspects of communication constraints in future algorithms to better model the real-time nature of the robot communication network.

## VII. ACKNOWLEDGMENTS

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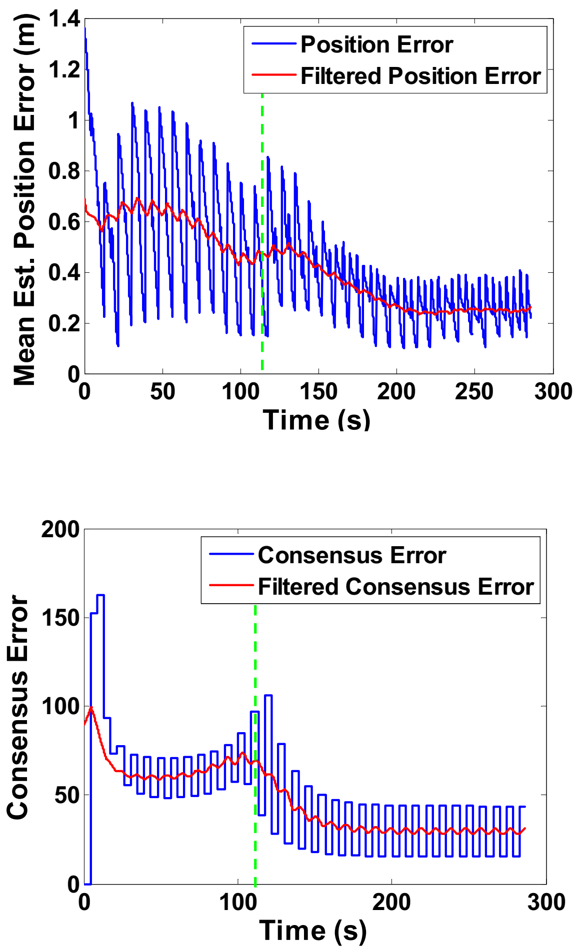


Fig. 6. Plots the averaged euclidean distance between the robots centers of mass of their Voronoi cell (top) as well as a plot of the consensus error (bottom).

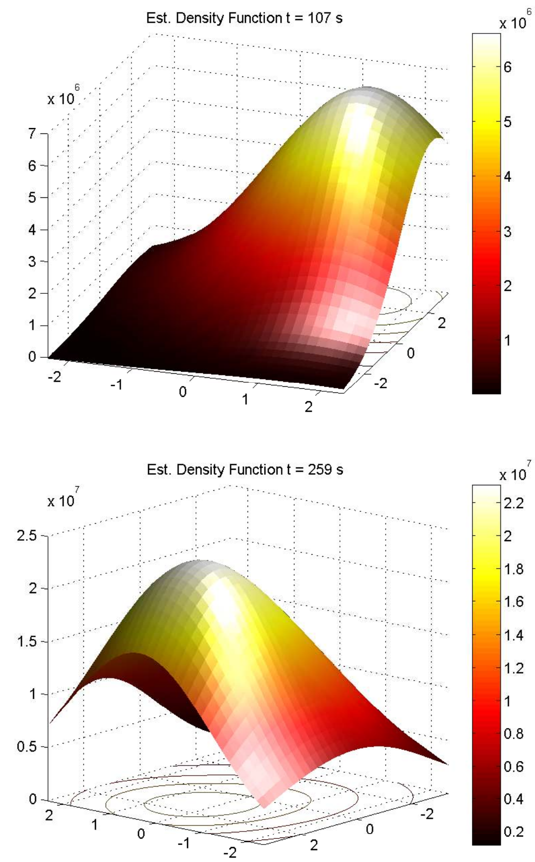


Fig. 7. Estimated density function averaged over the four robots. The light distribution in the plots corresponds with the concentration of light in the search space.

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