

# Coverage and Active Localization for Monitoring Invasive Fish with an Autonomous Boat

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**Abstract**—Carp is a highly invasive, bottom-feeding fish which pollutes and dominates lakes by releasing harmful nutrients. Recently, biologists started studying carp behavior by tagging the fish with radio-emitters. The biologists search for and localize the radio-tagged fish manually using a GPS and a directional antenna. We are developing a novel robotic sensor system in which the human effort is replaced by autonomous robots capable of finding and tracking tagged carp.

In this paper, we report the current state of our system. We present a new coverage algorithm for finding tagged fish and active localization algorithms for localizing them precisely. In addition to theoretical analysis and simulation results, we report results from field experiments.

## I. INTRODUCTION

Invasive fish, such as the common carp, pose a major threat to the ecological integrity of freshwater ecosystems around the world. Presently, these fish are controlled using non-specific toxins which are expensive, ecologically damaging, and impractical in large rivers and lakes. Recent studies in small lakes have established that common carp aggregate densely at certain times and regions within the lakes [1]. Their population can be controlled by targeting these aggregations using netting. To predict the locations of aggregations within a lake, biologists surgically implant radio tags on some fish, and use radio antennas to track them periodically (Figure 1). Manually locating tagged fish in large, turbid bodies of water is difficult and labor-intensive. Our goal is to build a robotic system to automate this tedious manual task.

In our previous work [2], we demonstrated the feasibility of finding radio-tagged carp using a custom-made, catamaran-style autonomous robot. Our current system features a new boat (Figure 1) and improved system architecture, presented in Section III.

We perform the task of locating tagged fish in two phases: *search* and *localization*. The goal in the search phase is to find a location of the robot from which the tag can be sensed. In the localization phase, the goal is to accurately estimate the location of the fish. We developed a new search algorithm suitable for finding tagged carp under the assumption that they loiter in their home ranges for long periods of time [3]. In Section IV we present this algorithm, its analysis, and results from a field trial.

In Section V, we first present a method to robustly obtain a bearing measurement towards a tag using a directional radio antenna. We then propose three strategies to compute locations from which to obtain bearing measurements from, so as to localize stationary tagged fish precisely. These strategies were

previously presented in [4] with experiments performed for a ground robot. We report additional experiments using our boat. Finally in Section VI, we report results from field experiments where the robot executed both search and localization phases for locating reference tags and radio-tagged fish.

## II. RELATED WORK

Recent years have witnessed the development of many environmental monitoring systems which use aquatic robots. Applications include tracking dynamic phytoplankton [5] and collecting biological and environmental data from stationary sensors [6], [7]. The recent survey by Dunbabin and Marques [8] provides an excellent overview of such systems.

The search problem is closely related to the robotic coverage problem which has received significant attention (c.f. [9]). We introduce a new version of the problem in which regions scattered in the lake must be covered, as opposed to the whole lake. We present a constant-factor polynomial-time approximation algorithm for this problem (see e.g. [10] for more on approximation algorithms).

In the localization phase, we perform active, bearing-only target localization. In one of the earlier works on this problem, Hammel et al. [11] used the determinant of the Fisher Information Matrix (FIM) as the objective function to be maximized, and numerically computed an optimal open-loop trajectory for a robot in the case where measurements are obtained continuously. The resulting trajectory follows a spiral shape, but is an open-loop trajectory which does not depend on the actual measurements the robot obtains. Frew [12] presented a feedback strategy for tracking targets with bearing measurements obtained using monocular vision. The strategy is based on a state-exploration tree, and a trajectory is obtained using breadth-first search for the minimum uncertainty. Recently, Zhou and Roumeliotis [13] considered the active localization problem for a team of robots capable of taking range and/or bearing measurements towards a moving target. They consider maximum speed and minimum sensing range constraints, and plan for the next best sensing location using the trace of the posterior covariance matrix as the uncertainty measure.

What differentiates our problem from these works is that each measurement in our system takes a long time, and the uncertainty in measurements is considerably larger. We address these factors in our strategy by using the best worst-case behavior as our objective function, and limit the number of measurements as part of our planning process.

We start with an overview of the system and present our search and active localization strategies in Sections IV and V respectively.

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Fig. 1. **Left:** Fish biologists manually tracking carp. **Center:** Targeted removal of the carp aggregation in Lake Lucy, MN, USA, using a large under-ice seine. Over 95% of all carp in this lake were captured in 4 hours. Photos courtesy of Peter Sorensen. **Right:** Robotic boat during coverage experiments at Lake Keller, MN, USA. A directional loop antenna can be seen mounted on a pan-tilt unit.

### III. SYSTEM DESCRIPTION

Our system consists of an autonomous robotic boat with on-board sensors, radio tags and receiver, and a directional antenna. We discuss each of these in turn.

#### A. Robotic Boat

The hull of our robotic platform (Figure 1) is the *QBoat* designed by Oceanscience<sup>1</sup>. The *QBoat* has dimensions of 182cm  $\times$  71cm, and can carry a payload of approximately 40kg. The boat is capable of a maximum speed of 1.65m/s. An on-board 12V, 30Ah NiMH battery allows approximately two hours of continuous operation.

The electronics on-board the boat (Figure 2) consist of a laptop running high-level software, an Atmel micro-controller board for low level interface, radio receiver equipment (described in the following section), a digital compass and a Garmin 18x Global Positioning System (GPS) unit. We also have a remote override radio control system that can directly control the boat, if desired.

We have a modular software architecture based on the Robot Operating System (ROS), comprising of packages for navigation, localization, simulation, and reading sensor data. ROS allows remote monitoring of data from another computer on the shore via an ad-hoc network formed with the on-board laptop. At the core of the navigation package is the implementation of a waypoint navigation algorithm reported in our previous work [2], with an EKF-based localization routine similar to the catamaran solution presented in [14]. The electronics and software can be easily transferred to other platforms. In fact, in winter we move the system to a ground robot used on frozen lakes [4].

#### B. Radio Tag and Receivers

For sensing the fish, we use radio tags manufactured by Advanced Telemetry Systems (ATS)<sup>2</sup>. A complete fish sensing system by ATS consists of radio tags, a loop antenna connected to a radio receiver, and a data logger which provides the computer interface for the receiver. Each radio tag emits a short pulse roughly once per second. The radio antenna (shown on top of the boat in Figure 1) is used to detect these pulses.

The radio receiver reports the received signal strength of the pulse. However, the signal strength is not directly useful

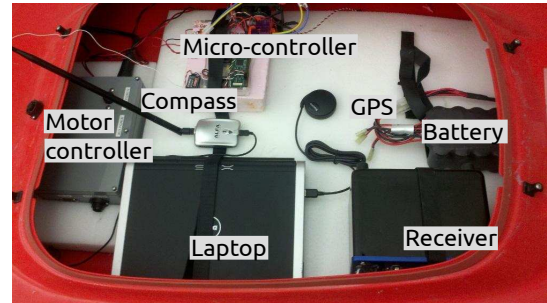


Fig. 2. Top view of the electronics compartment: On-board electronics comprises of a laptop, GPS, micro-controller board, batteries, digital compass, motor controller, and radio receiver.

in determining the distance to the tag, as it also depends on the unknown depth of the fish, conductivity of the water, and the remaining battery-life of the tag. Therefore we rely only on the directional nature of the antenna, and obtain a bearing measurement towards the tag. Our method for estimating the bearing is presented in Section V.

The tag on each fish is assigned a unique frequency. The receiver can be programmed to tune in on one or more frequencies. In the search phase, we program the receiver to loop through a list of frequencies of tagged fish present in the lake. To reliably detect a pulse from a tag, the receiver needs to stay tuned on the corresponding frequency for more than one second since the tags emit pulses at about 1Hz. After detecting a radio tagged-fish in the search phase, we program the receiver to tune only to the corresponding frequency and switch to the localization phase. In the search phase, described in the next section, we do not rotate the antenna or obtain bearing measurements, since the goal of this phase is only to detect the presence of a tag.

### IV. SEARCH AND COVERAGE

The first phase of our monitoring task is to search for all tagged fish in the lake. One of the current models for carp mobility suggests that each fish moves to its preferred region in the lake during day time, and remains in that region for long periods of time [3]. To increase the efficiency of our system, we restrict the search to only those regions of the lake which are likely to contain the fish (Figure 3). We assume that these regions are connected in the sense that there is a path between any two points. We also assume the fish remain stationary

<sup>1</sup><http://www.oceanscience.com/>

<sup>2</sup><http://atstrack.com>

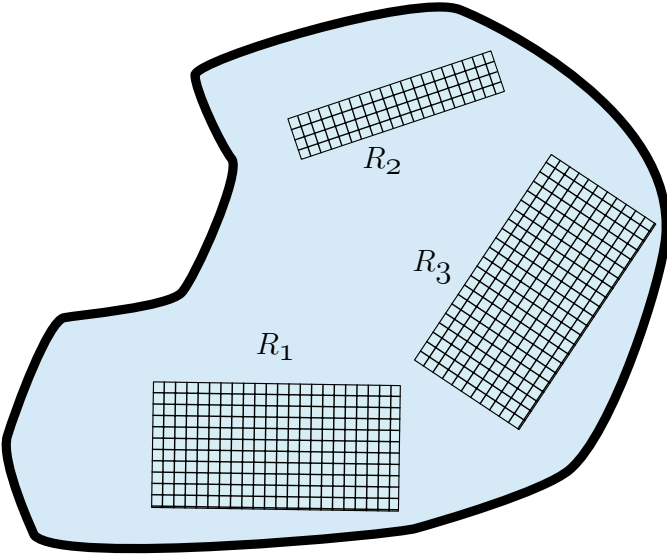


Fig. 3. We incorporate domain knowledge to restrict the search region for the fish to a given set of regions, e.g.  $R = \{R_1, R_2, R_3\}$ . A simple approach of discretizing these regions and finding a TSP tour becomes infeasible when the regions are large.

for the duration of covering a region and reduce the search problem to a coverage problem.

The radio antenna has limited sensing range. A given robot path is said to cover a point if the point lies within the sensing range of the robot at some instance along the path. The coverage problem can be defined as follows: *Given a set of connected regions  $R = \{R_1, R_2, \dots, R_n\}$ , find a minimum length tour which covers every point in each region  $R_i \in R$ .*

A possible approach for solving this problem is based on the Traveling Salesperson Problem (TSP). We can discretize each region with a resolution dependent on the sensing range (Figure 3), and compute a TSP tour of this set of points. However, approximation algorithms for TSP usually require a metric graph, which is typically represented as a complete graph whose vertex set is the point set to be covered. In such a representation the number of edges is quadratic in the number of points. As the lake size or the sampling granularity increases, maintaining and operating on this large graph can become infeasible.

The coverage problem defined above is a generalization of Euclidean TSP and consequently NP-Hard. Next, we present a general approach for solving the coverage problem and show that the length of the path using this approach does not deviate significantly from the length of an optimal tour.

#### A. Algorithm Description

Our general approach is composed of two steps. First, we compute a tour  $\tau_R$  that visits all the regions in  $R$  exactly once. We say that region  $R_i$  is *visited* if *any* point in  $R_i$  is visited by the tour. The tour  $\tau_R$  imposes an ordering on the regions, and defines (possibly same) entry and exit points for each region. The entry and exit points are where  $\tau_R$  intersects a region for the first and the last time. Such a tour is not necessarily

a solution to the original problem, since it is not guaranteed to cover all points in each region. We compute a coverage tour  $C_{R_i}$  for each region  $R_i \in R$  independently, starting and finishing at the entry and exit points for each  $R_i$ . The final tour  $\tau$  is constructed by augmenting the coverage tours of each region to the visiting tour  $\tau_R$ .

We now analyze the performance of this algorithm. Let  $OPT$  be an optimal tour which visits *and* covers all the regions in  $R$  in minimum time. Let  $\tau_R^*$  be the optimal tour which visits all the regions in  $R$ . Since  $OPT$  also visits all the regions in  $R$ , we have  $|OPT| \geq |\tau_R^*|$ , where  $|\tau|$  denotes the length of tour  $\tau$ . Let  $C_{R_i}^*$  be the optimal coverage tour for a region  $R_i$ .  $OPT$  covers every region in  $R$  therefore, we have  $|OPT| \geq \sum_{R_i \in R} |C_{R_i}^*|$ .

Suppose we use an  $\alpha$ -approximation algorithm for computing  $\tau_R$ , and a  $\beta$ -approximation algorithm for finding the coverage tour of each region. Then the tour  $\tau$  obtained by visiting the regions according to the order given by  $\tau_R$ , and covering each region independently when it is visited, has a cost of at most  $\alpha|\tau_R^*| + \sum_{R_i \in R} \beta|C_{R_i}^*|$ . Equivalently,

$$|\tau| \leq \alpha|\tau_R^*| + \sum_{R_i \in R} \beta|C_{R_i}^*| \leq \alpha|OPT| + \beta|OPT|$$

$$\therefore |\tau| \leq (\alpha + \beta)|OPT|$$

Therefore, this approach costs at most a factor  $(\alpha + \beta)$  of an optimal algorithm.

We now present algorithms for the two components of the strategy: computing a tour that visits the regions and covering the regions with specified entry and exit points.

#### B. Visiting the Regions: TSPN and the Zookeeper Problems

Computing a tour  $\tau_R$  that visits all the regions depends on the geometric properties of the regions. This problem is commonly known as TSP with neighborhoods (TSPN). Most geometric instances of the TSPN problem are NP-Hard. In general, we can use constant-factor approximation algorithms for TSPN such as [15] to find  $\tau_R$  and  $\alpha$ .

In our application, it is reasonable to model the lake as a simply-connected region, i.e., without any holes. Further, regions of interest where the fish may lie are usually close to the shore. If the regions are convex polygons touching the boundary of a simply-connected lake then the tour can be computed using the so-called zookeeper's route [16]. This special case of the TSPN can be solved optimally ( $\alpha = 1$ ) in polynomial time due to the following lemma.

*Lemma 1 ([16]):* Let  $R = \{R_1, R_2, \dots, R_i, \dots, R_n\}$  be a set of convex regions located along the perimeter of a simply connected polygon  $P$ . There exists an optimal solution for visiting the regions in  $R$  which visits them in the order they appear along the boundary of  $P$ .

Once the ordering of the regions is known, the shortest tour visiting all regions can be calculated using dynamic programming. The exact solution is given in [16]. We use a simpler solution by discretizing the boundary of the regions for determining the entry and exit locations for each region. We build a table  $C(i, s_i)$  which stores the length of a tour that







value for the leaf nodes is defined as the determinant of the simulated posterior covariance matrix stored at that node. The min-max value for all MAX nodes is the max of min-max values of its children, and that for non-leaf MIN nodes is min of min-max values of its children.

During execution, the robot chooses the MAX node with the minimum min-max value as next sensing location at each iteration. The MIN node is chosen as per the actual bearing obtained. Since we use discrete measurement samples, there might not be a node with bearing exactly equal to the actual measurement. In addition, there is uncertainty associated with the position of the robot itself. Hence, we use the Bhattacharya Distance [18] to find a MIN node with posterior covariance closest to the covariance after the measurement update.

### C. Simulations and Experiments

We first compared the performance of the three active localization strategies in simulation. We ran 100 random trials with the true tag 25m away from the starting position of the robot in each trial. A grid with side length 3m was used to generate sensing locations for 3 measurements. We generated noisy bearing measurements by corrupting the true bearing with Gaussian noise ( $\sigma = 15^\circ$ ).

The mean errors for FIM, Greedy, and Enumeration tree were 6.30m, 5.98m, and 5.73m, and the mean determinant of the final covariances were 54.81, 40.59, and 48.36 units respectively. The poor performance for the FIM strategy can be attributed to the fact that it is an open-loop strategy which depends on the initial estimate. Further, it computes locations which minimize the lower bound on final uncertainty of an “efficient estimator” (i.e. estimator whose variance is equal to the CRLB). Since EKF is not an efficient filter, there is no guarantee that it would achieve this lower bound. On the other hand, the Enumeration tree and the Greedy compute the actual covariance of the EKF estimator and pick the location which would minimize its determinant.

Although the Enumeration Tree performs better than the Greedy strategy, the performance gains are not significant to warrant the extra computational time. Hence, we decided to use the Greedy strategy on our system in field experiments. To test the system we conducted field trials with a reference tag submerged in a lake at a known position. The results from one such trial are shown in Figure 7. Sensing locations  $r_4, r_5, r_6$  were obtained by running the Greedy strategy. The resulting  $1-\sigma$  uncertainty ellipses are shown (in blue) along with the tag estimates (as red crosses). The true location of the tag is marked by a black star. The final error of this triangulation was 1.21m, with  $1-\sigma$  bounds of 3.3m and 2.7m in the  $x$  and  $y$  directions, respectively.

The field experiments demonstrate that our system is capable of localizing stationary reference tags reliably. Next, we present complete field experiments where the robot executed both the *search* and *localization* phases.

## VI. FIELD EXPERIMENTS

In this section, we report results from two field tests conducted at Lake Gervais in MN, USA. In the first test, a

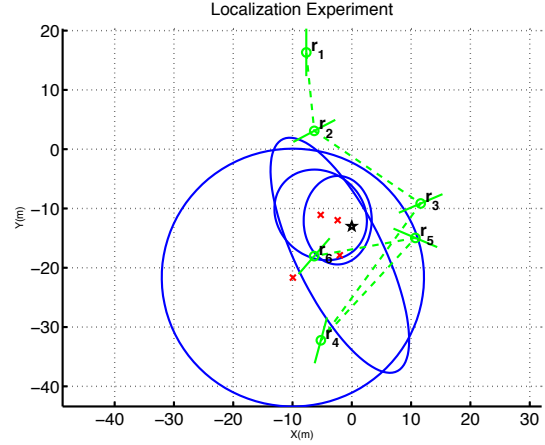


Fig. 7. Localization experiments with the Greedy strategy. Ellipses shown encompass the  $1-\sigma$  uncertainty after each measurement. We use the second measurement to disambiguate which side the tag lies from bearing obtained at  $r_1$ . Bearing measurements are shown as solid green lines.

reference tag was deployed at a known location. In the second test, we searched for tagged fish present in the lake.

Figure 8 shows results from the first experiment with a reference tag deployed at the location marked in Figure 8(b). The robot executed the coverage pattern while continuously monitoring the radio antenna on the frequency of this reference tag. After detecting signal from this radio tag at  $r_1$  (Figure 8(c)), the robot switched from the search phase to the localization phase.

During the localization phase, the robot executed the Greedy strategy with  $k = 2$  measurements, in addition to the two initialization measurements taken at  $r_1$  and  $r_3$ . The measurement at  $r_2$  is used to distinguish which side of the bearing at  $r_1$  the fish is located by comparing their signal strengths. The robot then moved to  $r_4$  and  $r_5$  and obtained bearing measurements as shown. The  $1-\sigma$  uncertainty ellipse after each step is also shown. After completing the localization, the robot continued to cover the rest of the regions. The robot covered a total path of approximately 2km in 49min.

The second field trial (Figure 9) was conducted in the same lake without a reference tag. We programmed the robot to search for frequencies corresponding to actual radio-tagged fish present in this lake. While searching the first region, the robot detected one of the frequencies in the list, executed the localization strategy, and returned to the search plan. Figure 9(b) shows the coverage path followed by the robot. The red box marks the area where the robot followed the localization strategy to obtain additional bearing measurements and localize the unknown tag. Figure 9(c) shows a closeup of the localization phase. Since this was an actual radio-tagged fish, the ground truth is unknown.

## VII. CONCLUSION

We presented a novel system for monitoring radio-tagged invasive fish. We divided the monitoring task into two sub-tasks of finding the tagged fish and localizing them accurately. For the first task, we presented an algorithm for finding a tour whose length is at most a constant factor away from an optimal



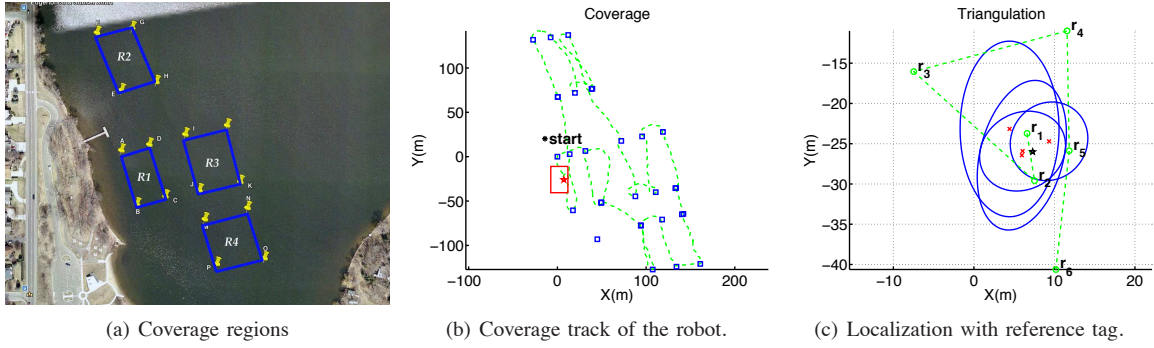


Fig. 8. A field trial on Lake Gervais, MN. The robot covered the regions via the path shown in the middle figure. On the right, a closeup of the localization of a reference tag is shown. The true location of the reference tag is marked with a black star. The red box in the middle figure corresponds to the triangulation area on the right.

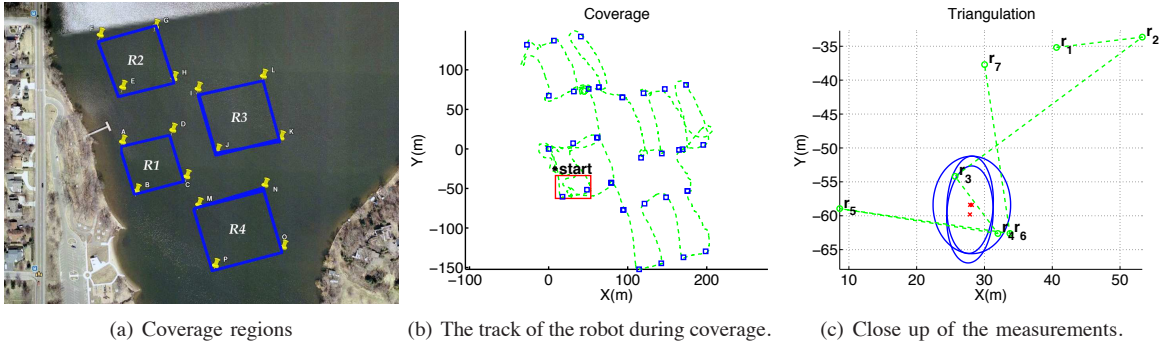


Fig. 9. Field experiments at Lake Gervais, MN. Figure 9(a) shows the areas we wish to cover. The computed search path and the trajectory executed by the robot are shown in Figure 9(b). Upon detecting a tag, the robot executed a localization strategy as shown in Figure 9(c). Because the robot attempted to triangulate a tagged fish, we do not know the true location of the tag.

tour. For localizing the tagged fish, we first showed how the bearing of the tag can be estimated by using measurements obtained by rotating a directional antenna. Next we addressed the problem of actively choosing sensing locations to reduce localization uncertainty. We compared three algorithms in simulations and field experiments, and incorporated the most effective one into our system. We concluded the paper with additional field trials.

While the initial results are encouraging, there is significant future work including developing fish mobility models and corresponding search and tracking algorithms. We plan to use multiple boats to improve the coverage time and localization uncertainty. Additional issues faced when building such a system (e.g. communication and coordination) must be addressed. Finally, we plan to use our system in larger lakes and help biologists to study carp behavior.

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