Cooperative Target Tracking in a Distributed Autonomous Sensor Network

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Abstract— **This paper describes an investigation into the control of multiple, cooperating autonomous sensor platforms operating in a marine sensor network. Distributed sensors allow us to view phenomena of interest from multiple, simultaneous vantage points, creating significant processing gain from the spatial diversity. The major objective of this paper is to describe a framework for adaptive and cooperative control of the autonomous sensor platforms in such a network. This framework has two major components, an intelligent sensor that provides high-level state information to a behavior-based autonomous vehicle control system and a new approach to behavior-based control of autonomous vehicles using multiple objective functions that allows reactive control in complex environments with multiple constraints. Experimental results are presented for a 2-D target tracking application in which a pair of fully autonomous surface craft using simulated bearing sensors acquire and track a moving target. From these results, it is readily seen that there is the potential for potent synergy from the cooperation of multiple sensor platforms.**

I. Introduction

Mobile sensor platforms working in coordination offer distinct advantages. They may each have different payloads, sensors, and endurance capabilities. A network of small, inexpensive platforms with low-performance sensors may be able to use its spatial diversity to outperform systems using single, very expensive, high-performance sensors. The use of multiple platforms also may allow one platform to stay at the surface, with a higher bandwidth link to other robotic or human operated vehicles, while one or more other platforms operate under the surface at varying depths to optimize their sensor-oriented tasks. Network survivability is also enhanced as the loss of one or even possibly several inexpensive sensors can be absorbed with the redundancy inherent in such a network We are motivated by the following scenario: two networked sensor vehicles are in operation, both fitted with passive, towed sensor arrays. Both vehicles will detect and cooperatively track an unknown target. Both vehicles begin in patrol mode in separate portions of the operating area in order to optimize their sensor coverage. The two vehicles work together to track underwater objects by communicating target bearing and track estimate information between themselves via acoustic modem. The vehicles will then position themselves with respect to the target in a formation designed to minimize the uncertainty in the target track estimate.

While coordinated marine vehicles have their advantages, they present challenges in their joint control to reach their combined potential. Inter-vehicle communication is limited in bandwidth and carefully allocated. Any kind of central continuous control is likely infeasible. In multi-vehicle joint exercises involved with sensing dynamic phenomena, it may not be practical or effective to think in terms of a single vehicle state space to which proper actions can be assigned a priori.

In this work we address these challenges by presenting a novel architecture consisting of a network of sensor platforms each with an intelligent sensor supplying high-level environmental state data to a new type of behavior-based control system that is more suited to reactive control with multiple constraints than previous behavior-based implementations. We then present experimental validation of this work using three fully autonomous surface craft.

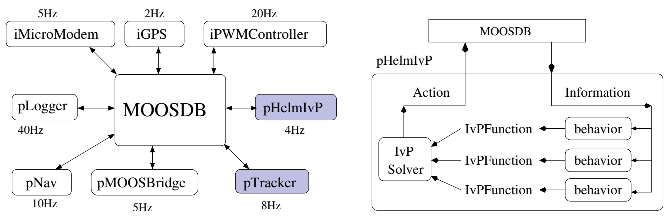
II. Technical Approach

In this section we present our general autonomy architecture and how the particular components that reflect the contribution of this work fit into that architecture. The outline for experimental validation is also discussed.

A. The MOOS-IvP Autonomy Architecture

This work uses the MOOS-IvP architecture for autonomous marine vehicle control. MOOS-IvP is composed of the Mission Oriented Operating Suite (MOOS), a open source software project for coordinating software processes running on an autonomous platform, typically under GNU/Linux. MOOS-IvP also contains the IvP Helm, a behavior-based helm that runs as a single MOOS process and uses multi-objective optimization with the Interval Programming (IvP) model for behavior coordination, [1].

A MOOS community contains processes that communicate through a database process called the MOOSDB, as shown in Fig. 1(a). MOOS ensures a process executes its “Iterate” method at a specified frequency and handles new mail on each iteration in a publish and subscribe manner. The IvP Helm runs as the MOOS process pHelmIvP (Fig. 1(b)). Each iteration of



(a) A MOOS Community (b) The pHelmIvP process

Fig. 1. The IvP Helm runs as a process called pHelmIvP in a MOOS community. MOOS may be composed of processes for data logging (pLogger), data fusion (pNav), actuation (iPWMController), sensing (iGPS), communication (pMOOSBridge, iMicroModem), and much more. They can all be run at different frequencies as shown.

the helm contains the following steps: (1) mail is read from the MOOSDB, (2) information is updated for consumption by behaviors, (3) behaviors produce an objective function if applicable, (4) the objective functions are resolved to produce a single action, and (5) the action is posted to the MOOSDB for consumption by low-level control MOOS processes. The behaviors responsible for sensor platform control in the tracking application are discussed in Section IV.

B. The Logical Sonar Sensor

The logical sonar sensor consists of the physical acoustic sampling hardware as well as algorithms that abstract the real-time data into higher forms of information suitable for a behavior-based control system. Because of the distributed MOOS architecture, the actual sensor and processing algorithms (MOOS processes) may well reside in a separate vehicle payload from the main vehicle control computer. The tracking vehicles in this work use a set of tracking algorithms that run in a single MOOS process called pTracker (see Fig. 1(a)). This process subscribes to target bearing data from the MOOS database. The bearing data is either produced by another MOOS process interfaced with a physical bearings-only sensor, or the bearing data is produced by an alternative MOOS process that simulates bearings-only sensor data. The pTracker process then produces and posts track solution information to the MOOSDB to be consumed by any other MOOS process. Feedback from the platform behaviors is available for dynamically changing the sensor parameters in response to the platform state. More information on the algorithms for the pTracking process is given in Section III.

III. Bearings-Only Object Tracking

In order to track a moving object from a set of discrete sensor observations, one must first decide on the kinematic model used to describe the object's motion. In this work, a constant-velocity model was chosen because it is one of the simplest to describe mathematically and because estimating the motion of a constant velocity target using a bearings-only sensor is a classical problem in target motion analysis. In typical passive ranging applications, however, the state parameters for the target track are estimated using a set of observations from a single moving sensor platform. With only one sensor, both temporal and spatial diversity in the sensor measurements are needed to estimate the target track. In this work, we will estimate the target track parameters using simultaneous measurements from two spatially distributed sensors from which an immediate solution of the target position can be formed. Successive position estimates will then be used to estimate the target's velocity components.

A. 2D Target Position Triangulation

Triangulating the position of an object using passive angle measurements is common in a number of fields including optics. Most analysis, however, assumes fixed sensors triangulating fixed or moving targets or moving sensors estimating the position of a fixed target [2]. In this work we now consider the position estimation for a moving target from a moving sensor platform. In this section, we will follow the analysis as developed in [2] for the 2D target position estimation and the subsequent error analysis. Given the coordinate frame shown

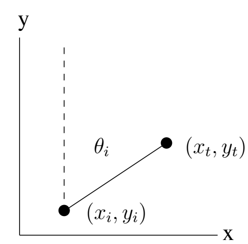


Fig. 2. Coordinate frame for 2D multi-sensor tracking.

in Fig. 2 with target location $(x_t[n], y_t[n])$ and sensor positions $(x_i[n], y_i[n])$ for the discrete time interval $n = 0, 1, \ldots, N$, the relationship between the position of the i^{th} sensor and its measured target bearing θ_i at time n is given by

$$\tan\theta_i[n] = \frac{x_t[n] - x_i[n]}{y_t[n] - y_i[n]} \tag{1}$$

The solution to (1) for the general case of I sensors can be written in matrix form as

$$\begin{bmatrix} \vdots \\ x_i[n] - y_i[n]\tan\theta_i \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots & \vdots \\ 1 & -\tan\theta_i[n] \\ \vdots & \vdots \end{bmatrix} \begin{bmatrix} \hat{x}_t[n] \\ \hat{y}_t[n] \end{bmatrix} \tag{2}$$

This system of nonlinear equations can be solved using general least-squares methods such as Gauss-Newton and Levenberg-Marquardt. For the problem under consideration in this work, we limit ourself to the case of two sensors for which the exact solution at any time step n can be be written as

$$\hat{x}_t = \frac{x_2\tan\theta_1 - x_1\tan\theta_2 + (y_1 - y_2)\tan\theta_1\tan\theta_2}{\tan\theta_1 - \tan\theta_2} \tag{3}$$

$$\hat{y}_t = \frac{y_1\tan\theta_1 - y_2\tan\theta_2 + x_2 - x_1}{\tan\theta_1 - \tan\theta_2} \tag{4}$$

B. Variance of the Target Position Estimate

One of the most important pieces of information needed to develop the proper behaviors for a sensor-adaptive system is the relationship between the target motion and the variance of the parameter estimates for the process under observation. From (3) and (4) it is apparent that the uncertainty in the target position estimates will be influenced by three factors:

1) The uncertainty of the sensor positions $(x_i[n], y_i[n])$
2) The uncertainty of the bearing measurements $\theta_i[n]$
3) The positions of the sensors with respect to the target

The sensor position uncertainties we model as Gaussian distributions with variance σ^2_{pos} equal and uncorrelated in both the x and y directions. The measurement uncertainties we also model as Gaussian distributions with variance σ^2_θ equal and independent of sensor platform. The usual method for finding the variances of (3) and (4) would be to take the expectation

$$var(\hat{x}) = E[(\hat{x} - x)^2)] \tag{5}$$

Given the complexity of the functional forms for (3) and (4) however, no closed form solution for (5) can be calculated. In this case, one can derive the error propagation equations by performing Taylor series expansions of (3) and (4) as given in detail for this application in [2]. Using the above assumptions with regards to the uncertainties for sensor position and bearing measurements, a first-order approximation to the target position uncertainties can be given as

$$\sigma^2_{x_t} \approx C_1\sigma^2_{pos} + C_2\sigma^2_\theta \tag{6}$$

$$\sigma^2_{y_t} \approx C_3\sigma^2_{pos} + C_4\sigma^2_\theta \tag{7}$$

where C_1, C_2, C_3, and C_4 are coefficients given as

$$C_1 = \left(\frac{\partial x_t}{\partial x_1}\right)^2 + \left(\frac{\partial x_t}{\partial x_2}\right)^2 + \left(\frac{\partial x_t}{\partial y_1}\right)^2 + \left(\frac{\partial x_t}{\partial y_2}\right)^2 \tag{8}$$

$$C_2 = \left(\frac{\partial x_t}{\partial \theta_1}\right)^2 + \left(\frac{\partial x_t}{\partial \theta_2}\right)^2 \tag{9}$$

$$C_3 = \left(\frac{\partial y_t}{\partial x_1}\right)^2 + \left(\frac{\partial y_t}{\partial x_2}\right)^2 + \left(\frac{\partial y_t}{\partial y_1}\right)^2 + \left(\frac{\partial y_t}{\partial y_2}\right)^2 \tag{10}$$

$$C_4 = \left(\frac{\partial y_t}{\partial \theta_1}\right)^2 + \left(\frac{\partial y_t}{\partial \theta_2}\right)^2 \tag{11}$$

The derivatives needed to calculate (8) through (11) are derived in [2]. Coefficients C_1 and C_3 measure the contribution of the sensor position error to the target location error while coefficients C_2 and C_4 measure the contribution of the bearing measurement error to the target location error. From an analysis of these equations, the following observations can be made with regard to the effect of sensor platform motion on the variance of the target position estimates:

1) The largest influence on $\sigma^2_{x_t}$ and $\sigma^2_{y_t}$ is the sensor separation angle $(\theta_1 - \theta_2)$ with minimum variance at a separation angle of 90 degrees rising to infinity at separation angles of 0 degrees and 180 degrees.
2) The influence of the bearing measurement error rises linearly with the sensor to target range. The bearing measurement error will also rise with the sensor to target range due to the reduction in the received signal to noise ratio when using a real acoustic array.
3) The 90 degree rotation between the plots of the coefficients for the variances of $\hat{x}_t$ and $\hat{y}_t$ indicate that uncertainty in one spatial direction can be minimized with a corresponding increase in uncertainty in the other spatial direction.

These observations will be used in Section IV to develop the autonomous vehicle behaviors designed to cooperatively track a moving target with two sensor platforms with a goal of minimizing the target localization errors subject to other constraints on the platform motion.

C. Target Velocity Component Estimation

Having derived the necessary analysis to be able to estimate the instantaneous position of a target from two simultaneous bearing measurements, we would like to filter these noisy measurements as well as estimate the target's velocity components from successive position estimates. A number of techniques are available to do this but the extended Kalman filter was chosen for its speed, with available CPU cycles being limited on small, autonomous platforms. Even though this is a non-optimal estimation technique, good performance was obtained as shown in Section VI. The full derivation of the Kalman filter equations can be found in [3].

IV. The IvP Helm and Vehicle Behaviors

Here we describe the use of multi-objective optimization with interval programming and the primary behaviors used in this experiment. For further examples of this approach, although with different missions and behaviors, see [4], [5].

A. Behavior-Based Control with Interval Programming

By using multi-objective optimization in action selection, behaviors produce an *objective function* rather than a single preferred action ([1], [6], [7]). The IvP model specifies both a scheme for representing functions of unlimited form as well as a set of algorithms for finding the globally optimal solution. All functions are piecewise linearly defined, thus they are typically an *approximation* of a behavior's true underlying utility function. Search is over the weighted sum of individual functions and uses branch and bound to search through the combination space of pieces rather than the decision space of actions. The only error introduced is in the discrepancy between a behavior's true underlying utility function and the piecewise approximation produced to the solver. This error is preferable compared with restricting the function form of behavior output to say linear or quadratic functions. Furthermore, the search is much faster than brute force evaluation of the decision space, as done in [7]. The decision regarding function approximation accuracy is a local decision to the behavior designer, who typically has insight into what is sufficient. The solver guarantees a globally optimal solution.

Although the use of objective functions is designed to coordinate multiple simultaneously active behaviors, helm behaviors can be easily conditioned on variable-value pairs in the MOOS database to run at the exclusion of other behaviors. Likewise, behaviors can produce variable-value pairs upon reaching a conclusion or milestone of significance to the behavior. In this way, a set of behaviors could be run in a plan-like sequence, or run in a layered relationship as originally described in [8].

B. The Waypoint Behavior

The waypoint behavior is responsible for moving the sensor platform from one point to another along the shortest path. The behavior is configured with a list of waypoints and produces objective functions that favorably rank actions with smaller detour distances along the shortest path to the next waypoint. This behavior is used by the target vehicle in the experiments to form a constant velocity motion, for example, and multiple waypoints can be sequenced together to form platform motion along arbitrary polygons.The objective function for this behavior is three-dimensional over course, speed, and time.

C. The Orbit Behavior

The Orbit behavior is responsible for providing a patrol capability in which the vehicle will orbit a fixed point. Given an orbit center, the behavior dynamically determines a list of waypoints to form the orbit. Parameters to this behavior allow the choice of clockwise/counter-clockwise orbits as well as the number of waypoints in the orbit path and the vehicle speed. The objective functions for this behavior are identical to the standard waypoint objective functions described in Section IV-B.

D. The ArrayTurn Behavior

The ArrayTurn behavior is responsible for providing a vehicle turning motion such that sensor platforms with acoustic line arrays can determine which side of the array the target is on. This behavior requires tight integration with the acoustic sensor which signals when the left/right ambiguity has been cleared. The objective function for this behavior is one-dimensional over course and bimodal, with the modes centered around the two possible course choices which are ninety degrees from the vehicle's course when the behavior is activated (he course fix). The mode that is centered at the course closest to the vehicle's current course is weighted in order to prevent frequent oscillation between the two modes.

E. ArrayAngle Behavior

The ArrayAngle behavior is responsible for holding a vehicle course such that sensor platforms with acoustic line arrays will have the array as close as possible to broadside with the target given the other constraints on vehicle motion. The objective function for this behavior is one-dimensional over course and bimodal, with the modes centered around the two possible course choices that keep the array oriented at broadside with respect to the target. The mode that is centered at the course closest to the vehicle's current course is weighted in order to prevent frequent oscillation between the two modes.

F. Formation Behavior

The formation behavior is responsible for maintaining two sensor platforms in formation in a track and trail scenario behind the target using the current target position estimate as a virtual leader. The optimal formation consists of the sensor platforms maintaining a ninety degree angle with respect to the target position estimate while trailing at a fixed trail distance r. The objective functions for this behavior are three dimensional over course, speed and time. It should be noted that the separation is computed using the current position of the other sensor platform which is also calculating the separation angle. This can lead to dynamic instability problems if there is not enough damping in the vehicle motion.

V. Experimental Scenario and Configuration

Experimental validation of the architecture and algorithms for cooperative sensor platform control in the sensor-adaptive tracking application was conducted using two autonomous kayaks as mobile sensor platforms and a third kayak acting as a moving object to be tracked. The kayaks are proxies for autonomous underwater vehicles (AUVs) used in upcoming follow-on experiments. The experiments were conducted using a test range available on the Charles River near MIT.

A. Simplifying Assumptions

Two significant simplifying assumptions were made. First, as a proxy for the towed acoustic array sensor, the GPS position of the sensed vehicle was communicated over an 802.11b wireless connection to the sensor vehicles. The sensor vehicles converted this information into bearings-only sensor data using a simulator which provided bearing data to the MOOS database just as the intelligent sensor currently in use on the AUVs would do. The second simplification was the use of the 802.11b wireless connection as a proxy for communications via acoustic modem between the sensor vehicles.

B. The Marine Vehicle Platforms

The autonomous surface craft used in this experiment are based on a kayak platform. Each is equipped with a GPS unit providing position and trajectory updates at 1 Hz. The vehicles are also equipped with a compass but the GPS provides more accurate heading information, and is preferred, at speeds greater than 0.2 m/s. Each vehicle is powered by 5 lead-acid batteries and a Minn Kota motor providing both propulsion and steerage. The vehicles have a top speed of roughly 2.5 meters per second. See [9] for more details on this platform. Each kayak is equipped with the distributed MOOS architecture and IvP Helm as described in Section II-A.

C. Scenario

The experimental scenario begins with the deployment of two sensor vehicles into separate patrol orbits where they remain until a target detection occurs. At some point, the target kayak begins its motion into the target area. When it enters into the target area (Fig. 3), it will begin broadcasting its GPS location to the sensor vehicles whose sensor simulators will convert the position information into target bearings. Vehicle two's bearing data will then be transmitted to vehicle one where it will be combined with vehicle one's bearing information to form the target track. The target track information will then be broadcast back to vehicle two and both vehicles will use the track information to position themselves with respect to the target using the formation described in Section IV-F. After a predetermined amount of tracking time, tracking will be declared over and the sensor vehicles will return to their patrol orbits to await another target.

VI. Experimental Results

Fig. 3 shows the vehicle motion for an experimental tracking mission with autonomous kayaks with two tracking vehicles and one target vehicle. The objective of this mission is to execute the scenario described in Section V-C where two sensor vehicles cooperatively track the target vehicle.

Fig. 4 depicts the target position estimates produced by the MOOS process pTracker overlaid onto the actual target track for the period in which the target vehicle was operating in a constant velocity scenario. As can be seen, excellent position estimates were obtained, especially compared with the tracking results obtained using a single sensor platform to track a constant velocity target as detailed in [10]. The gaps in the estimates as seen in the figure were due to communications breaks when no bearing estimates from vehicle two were received by vehicle one. As can be seen, even with the communications breaks, position estimation results were generally very good.

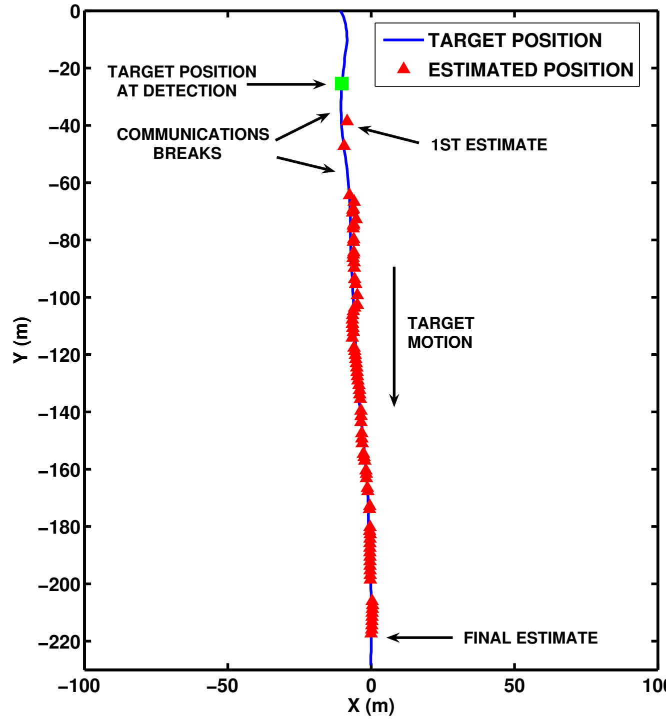


Fig. 4. Target track solution results. This figure depicts the target position estimates produced by the MOOS process pTracker overlaid onto the actual target track for the period in which the target vehicle was operating in a constant velocity scenario. As can be seen, excellent position estimates were obtained, especially compared with the tracking results obtained using a single sensor platform to track a constant velocity target as detailed in [10]. The gaps in the estimates as seen in the figure were due to communications breaks when no bearing estimates from vehicle two were received by vehicle one.

VII. Conclusions

We have demonstrated a method for sensor-adaptive control of autonomous marine vehicles in an autonomous oceanographic sampling network and shown its suitability for controlling multiple, cooperating heterogeneous sensor platforms. The results show that our proposed method combining a behavior-based, multiple objective function control model with a sensor providing high-level state information about the process being sampled is a viable method for adaptive sampling of transitory ocean phenomena in which fast reaction time is necessary. In complex environments where such vehicles may have to contend with unknown and situations like obstacle avoidance while still maintaining sensing performance, the state space for the vehicle control is much too large for a world-model approach and a behavior-based approach such as described in the paper is indicated. This approach does not come without penalty, however. The parameter tuning and weighting needed for multiple, interacting behaviors to provide reasonable performance under complex conditions is not trivial at this stage. Our work in this area continues with an application requiring autonomous underwater vehicles with real array sensors to detect and track moving underwater targets as well as tracking applications using N sensor platforms possibly tracking multiple simultaneous contacts.

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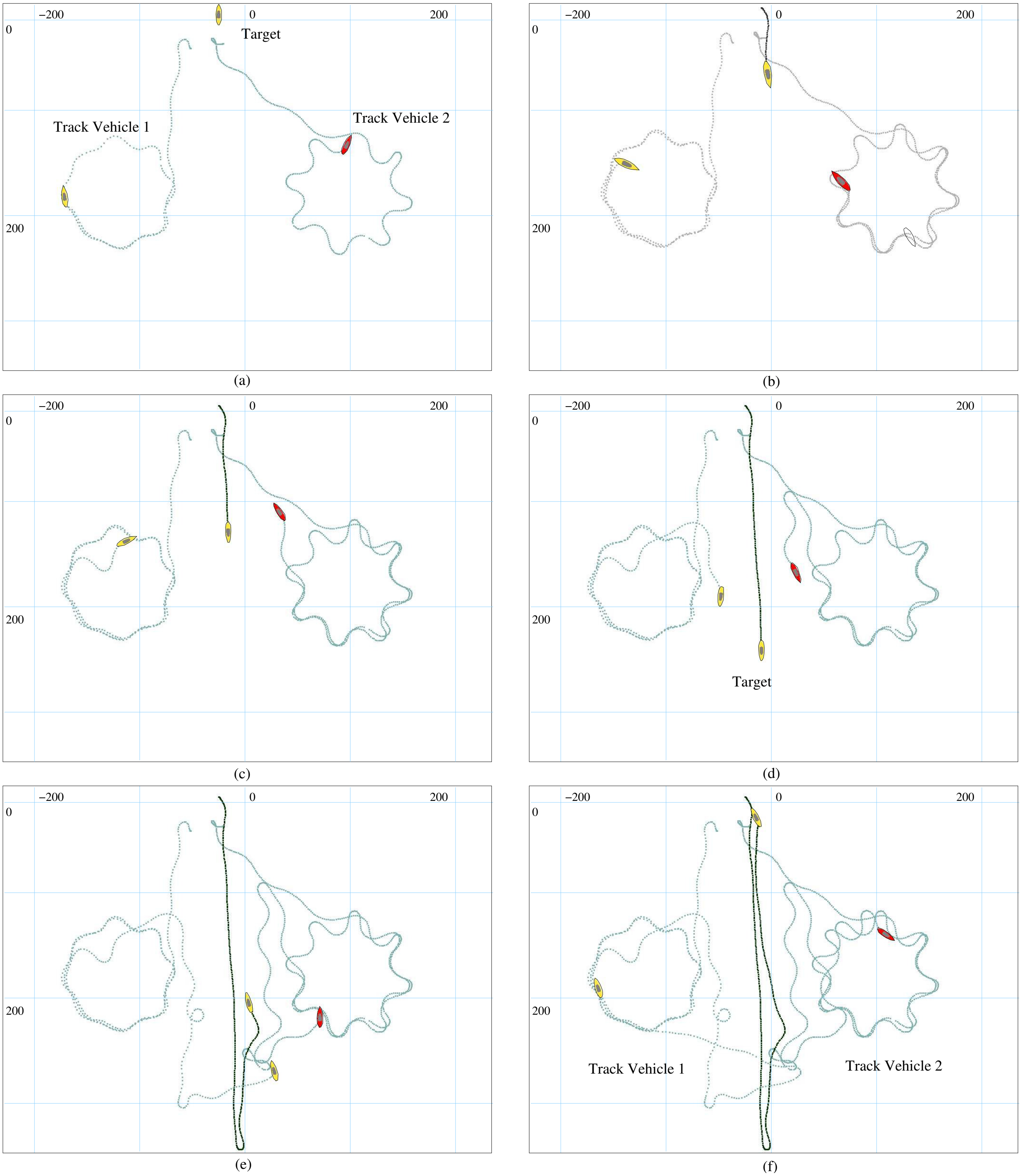

Fig. 3. A rendering of the experimental results. In (a) two tracking vehicles (both autonomous kayaks) are deployed and executing their Orbit behaviors to patrol in two separate regions. Note that tracking vehicle two is exhibiting signs of a rudder control problem. In (b) the target vehicle is deployed and has just entered the "sensor region" where it begins to transmit its position data to the tracking vehicles for use in the bearing simulators. The tracking vehicles have just activated their ArrayTurn behaviors for determining which side of the sensor array the target is on. In (c) the tracking vehicles have just sufficiently resolved the left-right ambiguity and have begun executing their Formation behaviors using the target position estimate as a virtual leader. In (d) both the tracking vehicles have moved into formation behind the target. In (e), the target unexpectedly turned for home before the sensor vehicles have finished tracking, violating the constant velocity assumption and confusing the tracking system. In (f) both vehicles are back on-station and awaiting any further unknown objects or vehicles to come through its sensor field. The target vehicle has returned to the dock.