Chemical Plume Tracing Experimental Results with a REMUS AUV

Jay A. Farrell
University of California, Riverside
Department of Electrical Engineering
Riverside, CA 92521
farrell@ee.ucr.edu

Wei Li
California State University - Bakersfield
Department of Computer Science
Bakersfield, CA 93311
wli@cs.csubak.edu

Shuo Pang
University of California, Riverside
Department of Electrical Engineering
Riverside, CA 92521
spang@ee.ucr.edu

Richard Arrieta
SPAWARSYSCEN-San Diego, Code 2744
Ocean Technology Branch
San Diego, CA
arrieta@spawar.navy.mil

Abstract—Olfactory-based mechanisms have been hypothesized for biological behaviors including foraging, mate-seeking, homing, and host-seeking. Typically, olfactory-based mechanisms proposed for biological entities combine a large-scale orientation behavior based in part on olfaction with a multisensor local search in the vicinity of the source. Long-range olfactory based search is documented in moths at ranges of 100-1000 m and in Antarctic procellariiform seabirds over thousands of kilometers. Autonomous underwater vehicles (AUVs) capable of such chemical plume tracing feats would have applicability in searching for environmentally interesting phenomena, unexploded ordinance, undersea wreckage, and sources of hazardous chemicals or pollutants.

This article presents an approach and experimental results using a REMUS AUV to find a chemical plume, trace the chemical plume to its source, and maneuver to reliably declare the source location. The experiments were conducted in November 2002 at San Clemente Island, California using a plume of Rhodamine dye developed in a turbulent fluid flow (i.e., near shore ocean conditions).

***Index Terms*—Autonomous vehicles, behavior based planning, chemical plume tracing.**

I. INTRODUCTION

Olfactory-based mechanisms have been hypothesized for a variety of biological behaviors [1, 2, 3]: homing by Pacific salmon [4], foraging by Antarctic procellariiform seabirds [5], foraging by lobsters [6, 7], foraging by blue crabs [8], and mate-seeking and foraging by insects [9, 10]. Typically, olfactory-based mechanisms proposed for biological entities combine a large-scale orietation behavior based in part on olfaction with a multisensor local search in the vicinity of the source. The long-range olfactory based search is documented in moths at ranges of 100-1000 m [11] and in Antartic procellariiform seabirds over 1000 km [5].

This article presents a algorithm that replicates these Chemical Plume Tracing (CPT) feats in autonomous vehicles. The goal of the autonomous vehicle is to locate the source of a chemical that is transported in a turbulent fluid flow. The basic idea of CPT is illustrated in Figure 1. A vehicle is constrained to maneuver within a region referred to as the OpArea. Within the OpArea the vehicle should search for a specified chemical. If the chemical is detected, the vehicle should trace the chemical plume to its source and accurately declare the source location. Such autonomous vehicle capabilities have applicability in searching for environmentally interesting phenomena, hazardous chemicals, and pollutants.

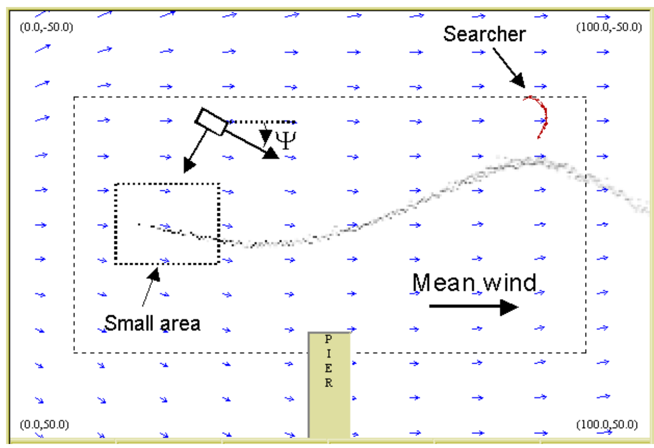

Figure 1. Depiction of a vehicle (not to scale) performing chemical plume tracing. The array of blue arrows indicate the direction and relative magnitude of the flow at the tail of the arrow. The numbers in the four corners are the coordinates of the corners. The meandering gray-scale trail is the plume. The chemical source is at (20,0) m. The start of the searcher trajectory is the curved red path in the upper right.

An initial approach to designing an autonomous vehicle plume-tracing strategy might attempt to calculate a concentration gradient, with subsequent plume tracing based on gradient following; however, gradient-based algorithms are not feasible in environments with medium to high Reynolds numbers [12, 13]. At medium and high Reynolds numbers, the evolution of the chemical distribution in the flow is turbulence dominated [14]. The result of the turbulent diffusion process is a highly discontinuous and intermittent distribution of the chemical [12, 15]. A dense array of sensors distributed over the area of interest and a long (i.e., several minutes) time-average of the output of each sensor is required to estimate a smooth (time-averaged) chemical distribution [16, 17] suitable for gradient-based calculations. However, the required dense spatial sampling and long time-averaging makes such an approach inefficient for implementation on a vehicle. In addition, even decameters from the odor source in the direction of the flow the gradient is too shallow to detect in a time-averaged plume. For an 'instantaneous' plume, the gradient is time-varying, steep, frequently in the wrong direction, and its evaluation would require numerous sensors. Therefore, gradient following is not practical.

The instantaneous odor distribution is distinct from the time-averaged plume [12, 13]. The major differences include: the time-averaged plume is smooth and unimodal while the instantaneous plume is discontinuous and multimodal; the time-averaged plume is time invariant while the instantaneous plume is time-varying. Instantaneous concentrations well-above the time-averaged concentration will be detected much more often than predicted by the time-averaged plume model. The fact that instantaneous concentrations well-above the time-average are available at significant distances from the source is one of reasons that olfaction is a useful long distance sensor [18]. A challenge in using olfaction on autonomous vehicles is to design effective algorithms to determine the odor source location even though the odor source concentration is not known, the advection distance of the detected odor is unknown, and the flow varies with both location and time.

Various studies have developed biomemetic robotic plume-tracing algorithms based on olfactory sensing. Belanger and Willis [19] presented plume tracing strategies intended to mimic moth behavior and analyzed the performance in a computer simulation. Grasso et al. [20, 21] evaluated biomimetic strategies and challenge theoretical assumptions of the strategies by implementing biomimetic strategies on their robot lobster. Robots that replicate biological approaches for plume tracing are also described in [22, 23, 24]. Li et al. [25] developed, optimized, and evaluated counter-turning strategies inspired by moth behavior. The fundamental aspects of these research efforts are sensing the chemical, sensing or estimating the fluid velocity, and generating a sequence of searcher speed and heading commands such that the resulting motion is likely to locate the odor source. In each of these articles, the algorithms for generating speed and heading commands use only instantaneous (or very recent) sensor information. Typical orientation maneuvers include: sprinting upwind upon detection, moving crosswind when not detecting, and manipulating the relative orientation of a multiple sensor array, either to follow an estimated plume edge or to maintain the maximum mean reading near the central sensor.

This article extends plume tracing research by presenting a complete strategy for finding a plume, tracing the plume to its source, and maneuvering to accurately declare the source location; and, by presenting results from successful, large-scale, in-water tests of this strategy. The assumptions made herein relative to the chemical and flow are that the chemical is a neutrally buoyant and passive scalar being advected by a turbulent flow. The autonomous vehicle (or robot) is assumed to be capable of sensing position, concentration, and flow velocity. The concentration sensor is a binary detector. We solve the plume-tracing problem in two dimensions. A main motivation for implementing the algorithms in two dimensions is the computational simplification achieved; however, neutral buoyancy of the chemical or stratification of the flow [26] will often result in a plume of limited vertical extent, which may be approximated as two-dimensional.

II. BEHAVIOR BASED PLANNING

A behavior-based planning strategy is an efficient means to navigate an autonomous system in an uncertain environment. A *behavior* is a mapping of sensor inputs to a pattern of motor actions. A set of behaviors can be used to achieve a task if a mechanism for coordinating the behaviors is also available.

In the late 1970's and early 1980's, Michael Arbib began to investigate models of animal intelligence from the biological and cognitive sciences point-of-view to gain alternative insight into the design of advanced robotic capabilities [27]. At nearly the same time, Valentine Braitenberg studied methods by which machine intelligence could be evolved by using sensor-motor pairs to design vehicle systems [28]. Later, a new generation of AI researchers began exploring the biological sciences in search of new organizing principles and methods of obtaining intelligence. This research resulted in the reactive behavior-based approaches. Rodney Brooks' subsumption architecture is the most influential of the purely reactive paradigms. Its basic idea is to describe a complex task by several behaviors, each with simple features [29]. Design of a behavior-based planner includes two significant steps. First, the designer must formulate each reactive behavior quantitatively and implement the behavior as an algorithm. Second, the designer must define and implement a methodology for coordinating the possibly conflicting commands from the different behaviors to achieve good mission performance.

Various coordination approaches have been proposed. For example, each behavior can output a command and a priority. Traditional binary logic can be used to select and output the command with the highest priority. An alternative coordination approach is to use artificial potential fields [30]. A drawback to either approach is that formulating and coordinating the reactive behaviors requires significant pre-mission simulation and testing. These are ad-hoc processes and may need to be re-addressed each time new behaviors are added or existing behaviors are changed. In some applications, these tuning parameters depend heavily on environmental conditions. Another alternative that has been suggested is to train an artificial neural network (ANN) to perform the behavior coordination [33]. However, this approach would require some mechanism for determining 'correct' coordination decisions for each training scenario and would provide no guarantee that all coordination situations are properly trained [31]. Fuzzy logic can improve the performance of reactive behavior coordination [32, 33, 34] by providing a formalism for automatically interpolating between alternative behaviors.

Behavior based design methodologies are bottom-up approaches to the design of an intelligent system. Observed behaviors with simple features are analyzed and synthesized independently. In this paper, we describe the behaviors and coordination mechanism that were used to solve the problem of chemical plume tracing strategy for an autonomous underwater vehicle.

III. CPT PLANNER

The location of pheromone-emitting females by flying male moths is considered a remarkable case of odor-guided navigation. The AUV behaviors described herein were inspired by biological behaviors observed in moths and other biological entities [25].

The CPT behaviors include: Go-To, Find-Plume*,* Track-Plume (Track-in and Track-out)*,* Reacquire-Plume and Fly-By behaviors. In addition, to ensure the safety of the vehicle, we implement a cage function that was responsible for not allowing the vehicle to leave the rectangular OpArea defined by $x \in [x_{\min}, x_{\max}]$ and $y \in [y_{\min}, y_{\max}]$.

The vehicle is equipped with sensors to detect the vehicle location, fluid flow, and the chemical concentration. The control commands for the vehicle are speed and heading. Figure 2 shows a behavior-switching diagram for behavior coordination during vehicle operation. The following subsections describe the logic for generating the heading commands within each behavior.

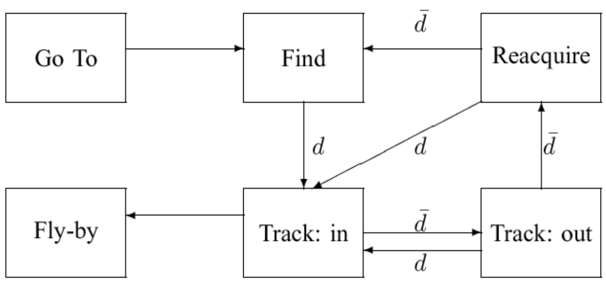

Figure 2. Behavior Switching Diagram. The symbol d denotes a behavior switch that occurs when chemical is detected. The symbol $\bar{d}$ denotes a behavior switch that occurs when chemical is not detected for some time interval.

A. Behavior: Go-To

The Go-To behavior issues heading commands that will direct the vehicle from its current location to a target location. For example, during mission start-up, the vehicle is dispatched from its home location to an area of interest before starting to search for plume. Also, the vehicle returns to its home after it declares the source of odor. Chemical detection information is ignored during the Go-To behavior. The Go-To behavior uses the following formula to calculate the commanded heading ψ and velocity v :

$$\psi = \text{atan}\,2((y_g - y_c),(x_g - x_c))$$

$$v = v_c$$

where atan2 is a four quadrant arctangent function, (x_g , y_g) are coordinates of the target location, (x_c , y_c) are the coordinates of the current vehicle location, and v_c is a constant speed command set as a mission parameter.

B. Behavior: Find Plume

Prior to tracing a plume, the plume must be found (i.e., chemical detected for the first time). Table 1 contains pseudo-code for the finding behavior. In Table 1, $d\theta_{upflow} = 125$ deg and $d\theta_{downflow} = 60$ deg are, respectively, the upflow and downflow search offsets. The `sign` function is defined as

$$\mathbf{sign}(x) = \begin{cases} 1 & x >= \mathbf{0} \\ -1 & x < \mathbf{0} \end{cases}.$$

When the search area is large and there is not prior information about the source location (i.e., uninformed search), this behavior may consume a significant amount of time. Therefore, once chemical is detected, we try to maintain intermittent contact with the plume so that it is unlikely that the vehicle will re-enter this behavior.

Table 1. Finding Time Behavior

```
Behavior::find_plume( )
{
   if(odor conc. < threshold){
      if( x_c > X_max ){
         upflow_search = 1;
      }
      if( x_c < X_min ){
         upflow_search = 0;
      }
      if(( y_c > Y_max ) or ( y_c < Y_min ))
         η = sign(( Y_max + Y_min )/2 - y_c );
      if(upflow_search)
         ψ = η* dθ_upflow ;
      if(not upflow_search)
         ψ = η* dθ_downflow ;
      v = v_c ;
      return plume_finding;
   }
   else
      return track_plume;
}
```

C. Behavior: Reacquire

If the searcher loses contact with the plume for greater than λ s, then the behavior switches to one that is likely to reacquire contact with the plume so that the searcher does not need to revert to the (resource-consuming) plume-finding behavior. The searcher will revert to the plume-finding behavior if the plume is not re-contacted within *N_re* repetitions of the reacquisition trajectory.

The reacquire behavior is implemented using on a clover leaf shaped trajectory, as in Figure 3. The clover leaf center is last location at which odor was detected: (x_{last} , y_{last}). The parameter d_{leaf} determines the size of the leaves. This pattern was selected as it yields significant search in all directions relative to the last detection point and it is achievable within the vehicle maneuvering constraints. Table 2 shows the pseudo code for this strategy.

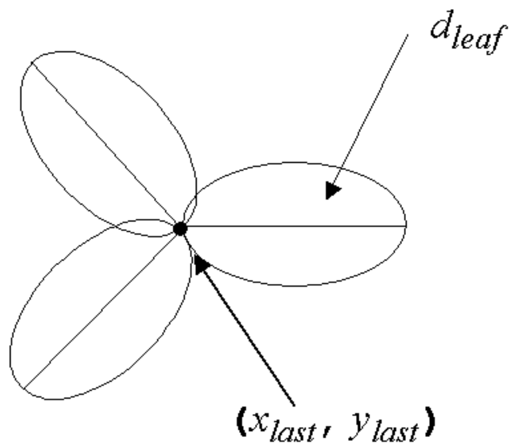

Figure 3. Clover leaf trajectory of the Reacquire Behavior.

In Table 2, *N_re* is the number of cloverleaf patterns repeated prior to giving up and reverting to the find behavior. Cloverleaf is a function that issues the heading commands require for the vehicle to follow the trajectory shown in Figure 3.

Table 2: Pseudo Code for Reacquire Behavior

```
Behavior::reacquire( )
{
  if(odor conc. < threshold){
     if(n < N_re) {
        if(cloverleaf(n) == done){
           n++;
           return reacquire;
        }
        else
           return plume_finding;
   }
   else {
     n = 0;
     return track_plume;
   }
}
```

D. Behavior: Track-in and Track-out

Once the vehicle detects the plume concentration over a threshold, the vehicle switches to the tracking behavior. This behavior attempts to trace the plume towards the source location. Due to the turbulent fluid flow, the sensed concentration is an intermittent signal. To address the intermittency, we implement this behavior in two cases: Track-in and Track-out. The pseudo-code is shown in Table 3, where *T_last* is the last time at which chemical was detected and t is the present time.

Table 3: Pseudo Code for Plume Tracking Behavior

```
Behavior::track_plume( )
{
   if((t – T_last) < λ)
   {
      if(odor conc. >= threshold)
      {  // Track in
         ψ= flow_dir + 180;
      }
      else
      {  // Track out
         ψ = flow_dir + 180 ± β(t);
      }
      v = v_c ;
      return track_plume;
   }
   else
   {
      return reacquire;
   }
}
```

In the Track-in case, the vehicle moves upflow directly so that the vehicle can approach the plume source quickly. In Track-out case, the vehicle moves upflow with an angle $\beta(t)$. The sign preceding $\beta(t)$ is selected to attempt to force the search to cross the plume [25].

E. Behavior: Fly-by

The Fly-by maneuver was not used in the November 2002 series of experiments. It may be used in future experiments. The purpose of the Fly-by is to drive the vehicle past the declared source location along a trajectory optimized for data acquisition by an auxiliary sensor (video or sidescan sonar). Such auxiliary sensor information is useful source verification, identification, and ground truth location information. For example, Figure 7 shows a prototype mission where a flyby is used to acquire sidescan imagery of a location identified via CPT.

F. Behavior: Cage

The Cage behavior has two responsibilities. First, if the vehicle leaves the area of operation, the Cage behavior overrides the heading command of any of the other behaviors with a heading command along the inward pointing Normal vector to the nearest boundary. This heading should return the vehicle to the operational area. Second, if the vehicle is more than 30 m outside the operating envelope, then the Cage must abort the mission.

G. Behavior Coordination

Behaviors A through E were switched based on Boolean logic as indicated in the pseudo-code of each behavior. Only one of Behaviors A through E was active at any given time. Behavior F, when active, will override any of the other behaviors.

H. Source Declaration

The source declaration is not a separate behavior. Instead, it is a function that is called at the end of the Track-Out behavior. Each time that the Track-In ends, the last detection point is added to a list. That list is sorted according to distance along the direction of the flow. Along as the vehicle is making progress up the plume, the first points on the list will be widely separated. When the first three points on the list differ in the direction of the flow by less than 4 meters, then the most upflow point on the list is declared as the source location.

IV. IN-WATER RESULTS

The CPT algorithms described herein were tested in November 2002 at San Clemente Island onboard a REMUS vehicle. The chemical plume for these tests was Rhodamine dye. The REMUS was equipped with a fluorimeter for chemical detection. This set of tests included 15 vehicle runs. The first 7 runs (MSN001—MSN006) involved parameter tuning, testing and revision of algorithms. The main revisions concerned the logic for reliably declaring a source location. On the last 8 runs (MSN007—MSN010r3), the source location was successfully declared 7 times.

The declared source locations are shown in Table 4. For MSN007r2—MSN009, the flow was to the southeast at approximately 135 deg relative to magnetic north. For MSN010r1—MSN010r3, the flow was to the northwest at approximately 330 deg. Between the various runs, the vehicle starting location was varied. As the data shows, in each case the AMP succeeded in finding the source and declaring the source location. Due to the fact that the chemical source is on the bottom and the vehicle is driving at a nonzero altitude, the chemical will not be detected in the immediate vicinity of the source. The chemical will only be detected at a distance in the downflow direction that is sufficient for the chemical plume to rise to the altitude of the vehicle. Therefore, the declared source location is known to be some distance downflow from the source. This downflow direction is known, but the distance is not known since the distance depends on environmental factors. Therefore, the likely source location is within a long narrow rectangle. The long edge is parallel to the flow. The downflow narrow edge is centered on the declared source location.

The source declaration locations reported in Table 4 are calculated based on the REMUS navigation system. That system uses buoy-mounted transponders. Changes in the buoy locations, due for example to changes in flow, affect the accuracy of the reported locations. For this set of experiments, there is no ground-truth source location for comparison. In future tests, we will use sidescan sonar to obtain an independent ground-truth source location in the same coordinate system.

Trajectory and chemical detection data for three runs is shown in Figure 4 – Figure 6. In each of these figures, the red curve indicates the vehicle trajectory. Each blue x indicates the location of a chemical detection. The green line indicates the boundary of the OpArea. In Figure 6, the black dot indicates the declared source location. For this set of experiments, a camera was in the water and focused on the chemical source. The camera caught the vehicle operating near the source on many occasions. One image is shown in Figure 8.

Table 4. Declared source locations and flow information for the last seven runs.

Run ID	Declared Source Location		Flow	
	Latitude	Longitude	cm/s	degree
MSN007r2	32N58.859	118W32.247	7-10	135
MSN008r1	32N58.847	118W32.249	7-9	129
MSN008r2	32N58.851	118W32.262	3-6	130
MSN009	32N58.849	118W32.259	4-10	150
MSN010r1	32N58.858	118W32.278	3-12	320
MSN010r2	32N58.849	118W32.269	5-7	340
MSN010r3	32N58.848	118W32.252	3-6	320

One of the lessons learned in this experiment is that the altitude control algorithm achieves an altitude above the commanded altitude when the water depth is increasing (offshore direction) and an altitude below the commanded altitude when the water depth is decreasing (onshore direction). Since the plume is near the bottom, the vehicle was more likely to detect when traveling toward the shore than when traveling away from the shore. This is shown in Figure 5 where the vehicle drives over the plume on an offshore heading. Later in the run, chemical is detected at the same location when the vehicle has an onshore heading.

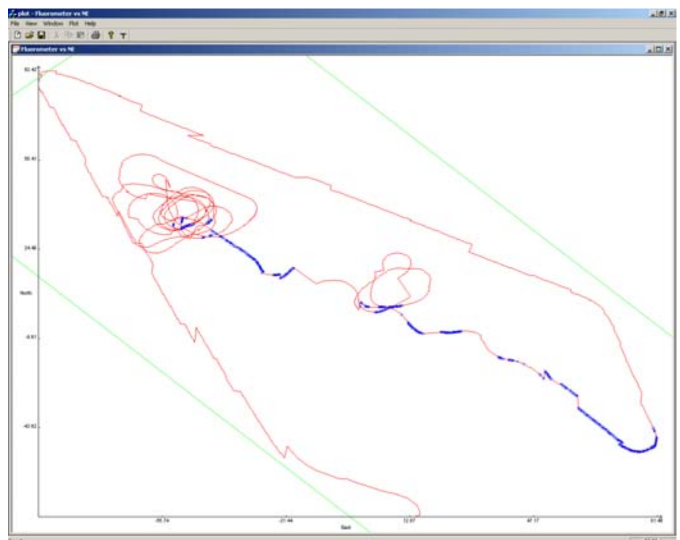

Figure 4. CPT MSN004 data for t in [800,1400] s. This time period includes FIND, TRACK, REACQUIRE, and DECLARE behaviors.

V. CONCLUSION

This article has described chemical plume tracing algorithms and presented successful in-water experimental demonstration of chemical plume tracing on a REMUS class AUV. For these experiments, the OpArea was 250-300 m along shore and 100 m cross-shore. Plumes were tacked for over 100m. These are the largest area CPT experiments and longest plume tracking experiments known to the authors. Future experiments will (1) increase the size of the OpArea, (2) add post-declaration maneuvers, (3) add the ability to obtain ground truth source locations, (4) add the ability to accommodate multiple sources.

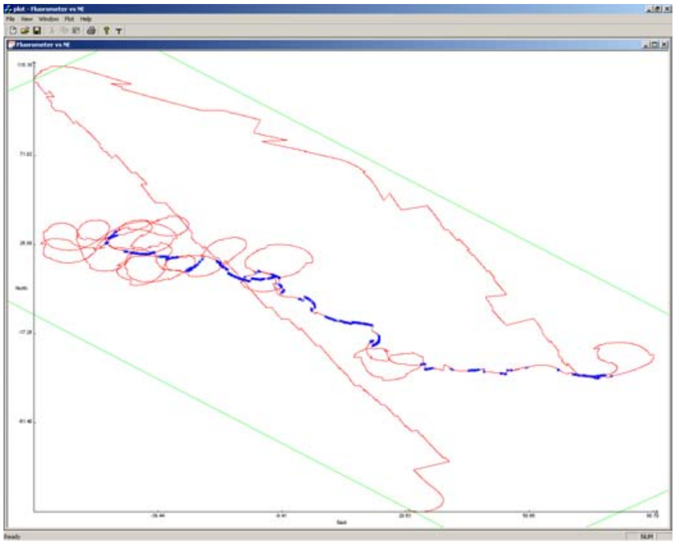

Figure 5. CPT MSN006 for t in [520, 1800] s. This time period includes FIND, TRACK, REACQUIRE, and DECLARE behaviors.

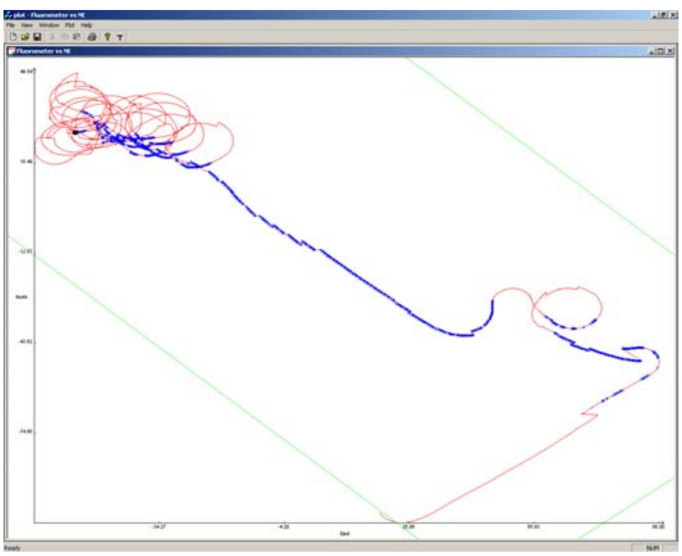

Figure 6. CPT MSN007r2 for t in [440,1190] s. This time period includes FIND, TRACK, REACQUIRE, and DECLARE behaviors. The black dot indicates the declared source location.

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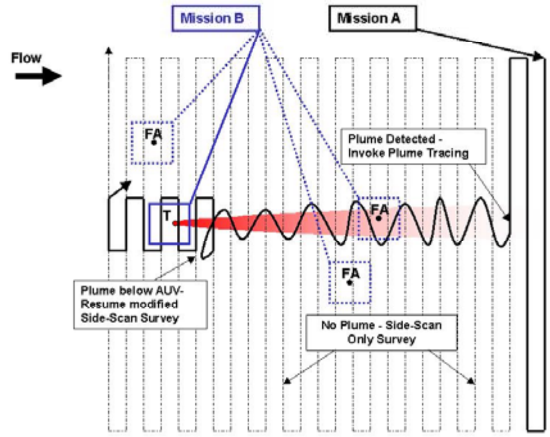

Figure 7. A prototype CPT mission with Flyby.

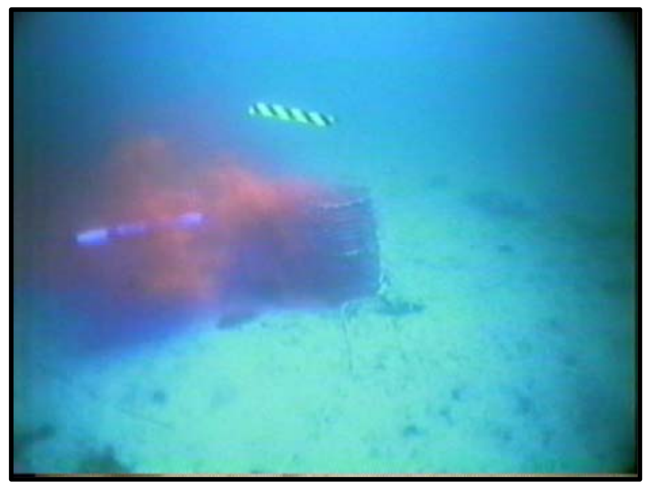

Figure 8. Image of REMUS vehicle performing CPT near the chemical source.