Behavior Based Adaptive Control for Autonomous Oceanographic Sampling

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Abstract— **This paper describes an investigation into the adaptive control of autonomous mobile sensor platforms for providing oceanographic sampling. Mobile sensor platforms provide an ability to rapidly sample oceanographic data of interest for real-time input into ocean environmental models with the goal of reducing the modeling uncertainty by introducing selected sampled data. The major objective of this paper is to describe the autonomy architecture developed to support adaptive sampling. This architecture consists of an open-source distributed autonomy architecture and and an 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 provided for an adaptive ocean thermal gradient tracking application performed by an autonomous surface craft in Monterey Bay. These results highlight not only the suitability of autonomous sensor platforms for providing adaptive sampling of the ocean environment but, also, the suitability of our behavior-based autonomy approach and distributed autonomy architecture for providing a simple, flexible, and scalable method for autonomous sensor platform control. The paper concludes with an overview of future adaptive sampling experiments planned with autonomous underwater sensor platforms using the same methodology.**

I. Introduction

In the uncertain ocean environment, conventional oceanographic measurement systems can not capture environmental uncertainties on short temporal scales or on very small spatial scales, creating the need for high resolution, in-situ, measurements. Rapidly deployable in-situ measurement systems have long been recognized as an important requirement for capturing environmental uncertainties on scales ranging from 10 to 1000 meters. The Adaptive Rapid Environmental Assessment (AREA) concept was developed to minimize the sonar performance prediction in an area of ocean by adaptively identifying an optimal deployment of in-situ measurement resources and capturing the uncertainty of the most critical and the most uncertain environmental parameters (Fig. 1) [1]. Moreover, the AREA concept can also be applied to minimizing the prediction uncertainty for biologic, chemical, and other oceanic processes of interest.

We are motivated by the following scenario: an oceanographer, having identified a general area of particular uncertainty with regards to an ocean process of interest, remotely deploys an autonomous sensor platform (perhaps on patrol in the area) to gather real-time sensor measurements. Since the optimum

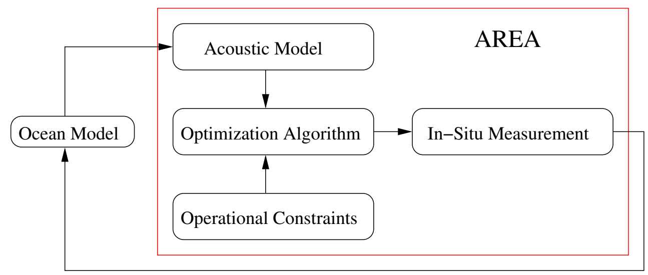


Fig. 1. The Adaptive Rapid Environmental Assessment (AREA) concept was developed to minimize acoustic prediction uncertainty by adaptively identifying an optimal deployment of in-situ measurement resources, capturing the uncertainty of the most critical and uncertain environmental parameters in terms of long term return taking into account existing operational constraints.

sampling path for reducing the model uncertainty is usually not predetermined, the sensor platform must adaptively maneuver itself based on the real-time measurements. Once the sampling is complete, the sensor platform can transmit back the raw or processed data. Feedback from the updated ocean model can then be transmitted back to the sensor platform.

The control requirements for an autonomous sensor platform performing this type of mission are quite severe. Not only must such a platform contend with adaptively altering its motion in response to real-time sensor measurements, it must also contend with a number of harsh environmental conditions that could affect not only the quality of the sampling but, also, the survivability of the platform itself. These conditions include wind, waves, currents, obstacles, and uncertain navigation in the case of underwater platforms. An autonomous control system for such a platform must therefore be capable of reacting to multiple, sometimes complex, environmental conditions in real time in such a way as to maximize the sampling performance. It is also desirable for such a system to be capable of joint control with other cooperating sensor platforms.

In this work we address these challenges by presenting a novel autonomy architecture and a set of sensor platform behaviors and present experimental validation of this work obtained in an adaptive sampling experiment in Monterey Bay by a fully autonomous surface craft equipped with an appropriate oceanographic sensor.

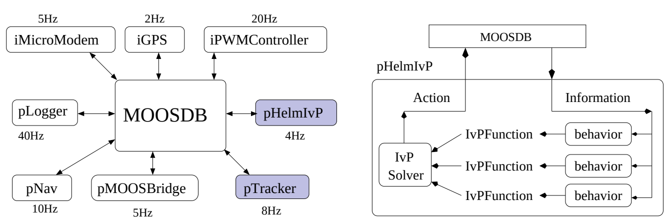
II. Technical Approach

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 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 [2], [3]. See [4] and [5] for other examples of MOOS-IvP on autonomous marine vehicles.

A MOOS community contains processes that communicate through a database process called the MOOSDB, as shown in Fig. 2(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. 2(b)). Each iteration of 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 control in the oceanographic sampling platform used in this work are discussed in Section IV.



(a) A MOOS Community

(b) The pHelmIvP process

Fig. 2. 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.

B. Autonomous Sampling

In many applications, MOOS processes are used to process and abstract sensor data for use by the vehicle behaviors. This is especially true when computations can take longer than the individual vehicle control cycle. In this work, the MOOS process iCTDSBE49 provides the driver for interfacing with the physical sensor (described in more detail in Section V). iCTDSBE49 posts sensor data to the MOOSDB at a frequency of one Hertz. MOOS process pTwoD is the MOOS process responsible for coordinating the sampling. At each sampling station, pTwoD lowers the sensor to the proper depth and records the ocean temperature at that depth for later use by the gradient calculation algorithm described in Section III. After subsequently raising the sensor, pTwoD posts a flag to the MOOSDB indicating that sampling is finished. At the conclusion of each sampling segment (see Fig. 5) pTwoD computes the 2D thermal gradient direction from the sampled data and dynamically sets the mean bearing for the next sampling segment. When the maximum number of segments have been sampled, pTwoD posts a flag to the MOOSDB which deactivates the sampling behaviors and activates the behavior to return the surface craft to a predetermined location.

C. Validation with Experimental Data

Experimental validation of this work is presented using an autonomous surface craft specially developed to be a mobile oceanographic sampling platform. The use of surface craft for this type of oceanographic sampling has both advantages and disadvantages versus using autonomous underwater vehicles (AUVs). The surface craft are able to maintain much better navigation and communications than an AUV could. However, the surface craft are at a disadvantage with respect to sampling due to the time and power requirements needed to raise and lower the sensor at each sampling station. The AUV, able to sample continuously (on the order of a sample per second) in 3D space, can provide a much higher sampling density.

III. Thermal Gradient Computation

The thermal gradient can be defined in Cartesian 2D coordinates as

$$\nabla T(x, y) = \frac{\partial T}{\partial x}\hat{x} + \frac{\partial T}{\partial y}\hat{y} \tag{1}$$

where T is the ocean temperature at a point (x, y) with z fixed. Of course, ∇T is also a function of x, y and z but, we will only concern ourselves with the 2D gradient due to the fact that the sensor for this demonstration is not easily towed from a surface craft. Future planned experiments with autonomous underwater platforms will use the full 3D gradient. In this work, the direction of ∇T is estimated using a linear least squares fitting method based on in-situ measurements on each sampling segment. The method for collecting measurements for the gradient direction estimation is explained in detail in Section

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 ([2], [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 and this work validates that such search is feasible in a vehicle control loop of 4Hz on a 600MHz computer.

To enhance search speed, the initial decision provided to the branch and bound algorithm is the output of the previous cycle, since typically the optimal prior action remains an excellent candidate in the present, until something changes in the world. Indeed when something *does* change dramatically in the world, such as hitting a way-point, the solve time has been observed to be up to 50% longer, but still comfortably under practical constraints.

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 designed for transiting to a set of specified waypoints. The objective function produced by this behavior is defined over the 2D action space given by possible heading and speed choices and produces objective functions that favorably rank actions with smaller detour distances along the shortest path to the next waypoint. Once the last waypoint in the set has been reached, the behavior will set its *completed* flag to *true*. Several predefined regular waypoint patterns have been defined including orbits and the "zigzag" pattern that was used during the experimental run shown in Fig. 5. For the zigzag pattern, the mean direction, amplitude, period and length of the pattern are specified. For the adaptive sampling run shown in Fig. 5, the parameters for the zigzag pattern were dynamically generated by the *pTwoD* MOOS process described in Section II-B.

C. The StationKeep Behavior

The StationKeep behavior is designed to keep the vehicle at a given position by varying the speed to the station keeping point as a linear function of its distance to the point. The parameters allow one to choose the two distances between which the speed varies linearly, the range of linear speeds, and a default speed if the vehicle is outside the outer radius. This station keeping behavior conserves energy and aims to minimize propulsor use. The objective function produced by this behavior is defined over the 2D action space given by possible heading and speed choices and produces objective functions that favorably rank actions that result in smaller distances from the station point. An example of the objective function for this behavior is shown in Fig. 3. For the adaptive sampling run shown in Fig. 5, the desired station keeping point is dynamically generated by the *pTwoD* MOOS process described in Section II-B.

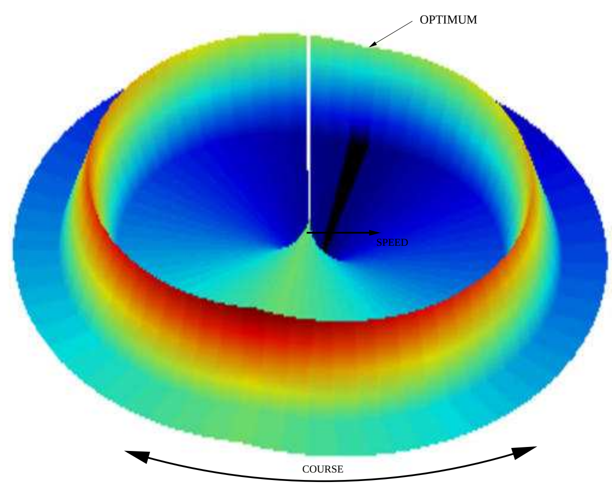


Fig. 3. Objective function for the StationKeep behavior. This plot shows an example objective function for the StationKeep behavior with the station point being at a course of 10 $degrees$ from the current vehicle position. The function is plotted in polar form with the theta direction being course and the radial direction being speed with darker colors indicationg higher values.

D. The ConstantSpeed Behavior

The ConstantSpeed behavior is designed to keep the vehicle moving at a constant speed. The objective function produced by this behavior is defined over the 1D action space given by possible speed choices and produces objective functions that favorably rank actions with the smallest deviation from the desired speed.

E. The Timer Behavior

The Timer behavior is designed to be active for a fixed number of seconds after activation after which it completes and posts its endflags. This behavior produces no objective function.

V. Experiment Setup

Experimental validation of the architecture and algorithms for autonomous adaptive sampling was conducted using an autonomous surface craft carrying a conductivity-temperature-depth (CTD) sensor which could be autonomously raised and lowered to take measurements of the ocean temperature profile. The experiment was conducted off of the R.V. Point Sur operating in Monterey Bay, California on August 29, 2006. The scenario called for the CTD-equipped surface craft to sample the water temperature at a constant depth of 20 m in a regular interval in a zigzag spatial pattern for a predetermined distance. Once this distance was reached, the compute the direction of the thermal gradient and would then sample another zigzag pattern in that direction. The plan called for this sampling to continue until the surface craft was low on power. Since wind, waves, and current can all act to push a surface craft off of its intended station, a special station keeping behavior was implemented that was designed to keep the surface craft close to its intended sampling location.

A. Marine Vehicle Platforms

The autonomous surface crafts used in this experiment are based on a kayak platform (Fig. 4). Each is equipped with a Garmin 18 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

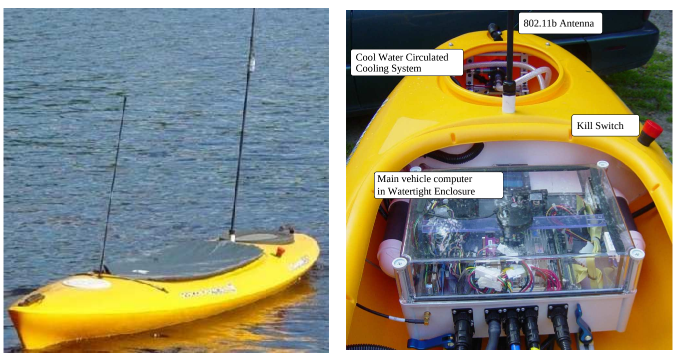


Fig. 4. The kayak-based autonomous surface craft. These lightweight and portable platforms are not only suitable proxies for the much larger autonomous underwater vehicles but also show the suitability of autonomous surface craft for oceanographic sampling. The autonomous kayak used in this work was equipped with a Seabird Electronics SBE 49 FastCAT CTD sensor which was raised an lowered on an autonomously controlled winch.

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. The kayak used in this experiment was equipped with a Seabird Electronics SBE 49 FastCAT CTD sensor, a DC powered, pumped, CTD sensor commonly used on small ROVs and AUVs. The SBE 49 provides data to the vehicle via a serial line.

B. Behavior Configurations

A total of six behaviors were used for the adaptive sampling experiment shown in Fig. 5. Upon startup, a Waypoint behavior is active in order to get the vehicle to the proper starting location for the experiment. Upon reaching the desired location, the Waypoint behavior completes and activates another Waypoint behavior which controls the zigzag motion pattern. For this run, an amplitude and period of $150\ m$ and a distance of $300\ m$ were used for the zigzag pattern. An initial bearing of $270\ degrees$ was chosen a priori for the first leg. A ConstantSpeed behavior was used to provide a desired speed of $3.0\ m/s$.

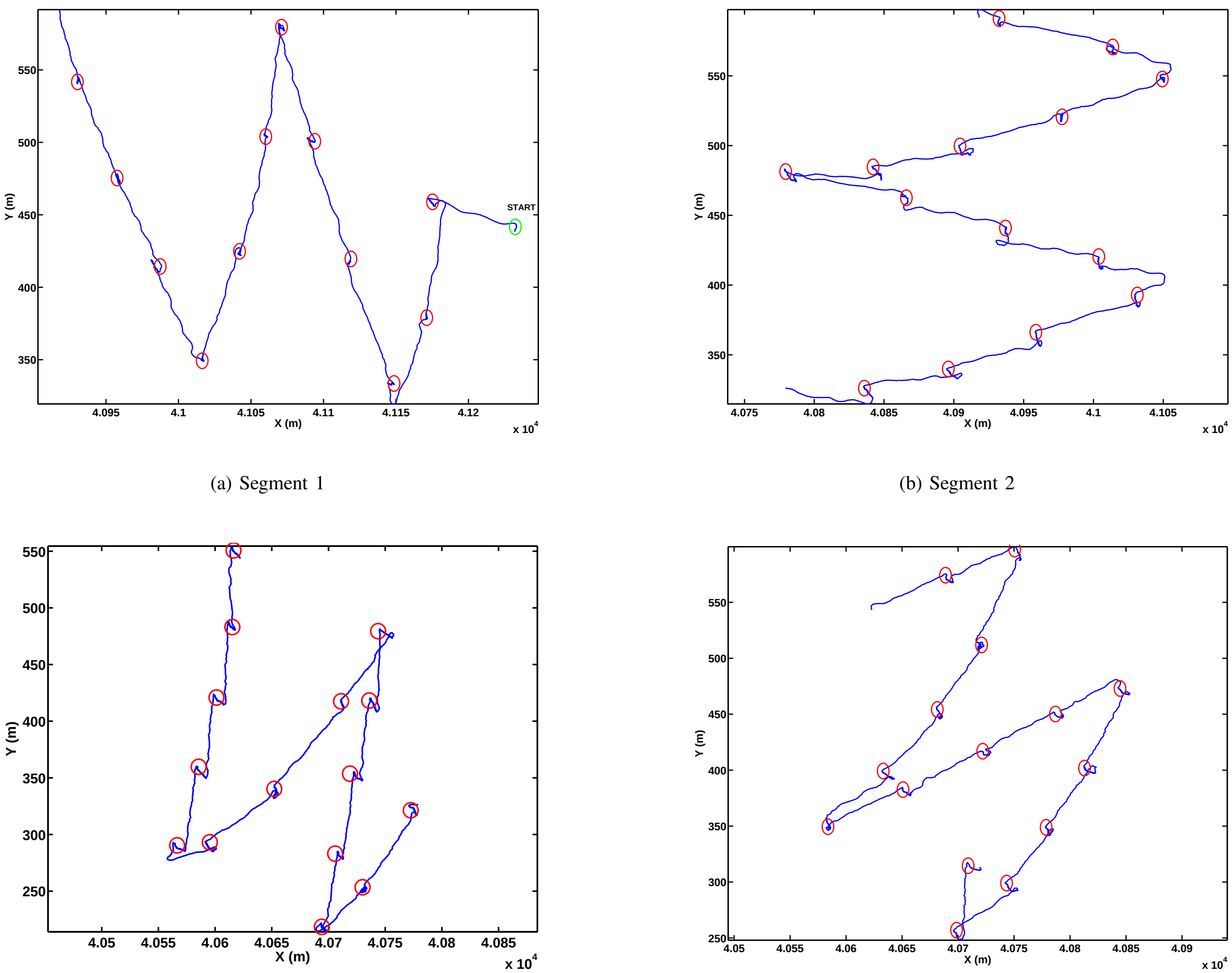
Simultaneously active with the Waypoint and ConstantSpeed behaviors is the Timer behavior. This behavior is used to time the interval between CTD casts and was set for a duration of $60\ s$. When the timer completes, the Waypoint and ConstantSpeed behaviors are deactivated and the StationKeep behavior is activated. During this period, the MOOS process *pTwoD* lowers the CTD, takes its measurement, and then raises the CTD. When the CTD is fully raised, *pTwoD* sets the ON_STATION flag to FALSE which deactivates the StationKeep behavior and again activates the Waypoint and ConstantSpeed behaviors to continue to the next sampling station. When sampling is complete for the current segment, *pTwoD* computes the bearing for the next sampling segment and dynamically updates the Waypoint behavior. When a maximum number of segments are completed, the ON_STATION flag is set to DONE by *pTwoD*. This activates another Waypoint behavior programmed to return the kayak to a pickup location.

C. Experimental Results

Fig. 5(a) through 5(d) show the four segments of the autonomous surface craft experiment launched from the R.V. Point Sur with the goal of adaptively following the ocean thermal gradient. The first segment was run in a pre-determined mean direction of $270 degrees$ while the directions for the other three segmentss were chosen adaptively. Each segment is shown separately for clarity due to overlap in the vehicle track. Each red circle indicates a point where a CTD cast was performed. As can be seen, the vehicle exhibits a small amount of drift at each sampling station. The amount of drift can be seen to steadily increase as the weather worsened during this run, eventually reaching sea state three by the final segment where the station-keeping behavior is having a more difficult time keeping the kayak within the $20m$ outer station keeping radius. Only four segments of this experimental run were accomplished due to limitations on the amount of power available on the surface craft. In roughly two days of experimentation, over 300 CTD casts were performed with this platform, showing the robustness and suitability of this type of craft for oceanographic sampling.

Fig. 7 shows the thermal profile of the ocean obtained from one of the $20m$ autonomous CTD casts performed during the adaptive surface craft run shown in Fig. 5. A well-mixed layer of nearly constant temperature can be seen in the first $8m$ of depth with a major thermocline occurring between $8m$ and $10m$. The thermocline is an area of relatively rapid temperature change and is an important feature for analyzing the sound velocity profile of the ocean in a given area.

Fig. 6 shows the mean direction of each of the four segments of the adaptive sampling mission. The bearings for segments 2 through 4 were the estimated direction of the thermal gradient as computed by the MOOS process *pTwoD*. The changing bearings for the last three segments show that the sparse sampling provided by the surface craft's winch-lowered sensor is inadequate. As the number of samples increases, the thermal gradient direction is generally computed to be to the southwest, in agreement with other sampling runs. AUV simulations using real ocean data and a sensor which can sample about every second (about $1.5m$ at the AUV's typical



(a) Segment 1

(b) Segment 2

(c) Segment 3

(d) Segment 4

Fig. 5. Autonomous thermal gradient following experiment on 29 August, 2006 in Monterey Bay, California. Fig. 5(a) through 5(d) show the four segments of the autonomous surface craft experiment launched from the R.V. Point Sur with the goal of adaptively following the ocean thermal gradient. The first segment was run in a pre-programmed mean direction while the directions for the other three segments were chosen adaptively. Each red circle indicates a point where a CTD cast was performed. The thermal profile from a representative CTD cast from this run is shown in Fig. 7.

speed) do not show the same problem.

Segment	Bearing
1	270.0
2	181.6
3	296.6
4	142.4

Fig. 6. Segment bearings. This figure shows the mean direction for the four segments of the autonomous gradient following experiment depicted in Fig. 5. The bearing of the first segment was determined a priori and the bearings of the final three segments were determined adaptively using the sampled data.

VI. Conclusions

In this work we have demonstrated a method for sensor-adaptive control of autonomous marine vehicles in an autonomous oceanographic sampling scenario and shown its suitability for controlling autonomous sensor platforms in complex conditions where environmental conditions can impact sampling performance. The results show that our proposed method combining a behavior-based, multiple objective function control model with a distributed autonomy architecture is a viable and robust method for adaptive sampling of ocean phenomena. In complex environments where such vehicles may have to contend with unknown situations like obstacle avoidance, waves, current, uncertain communications, and uncertain navigation while still maintaining sensing performance, the state space for the vehicle control is much too large for

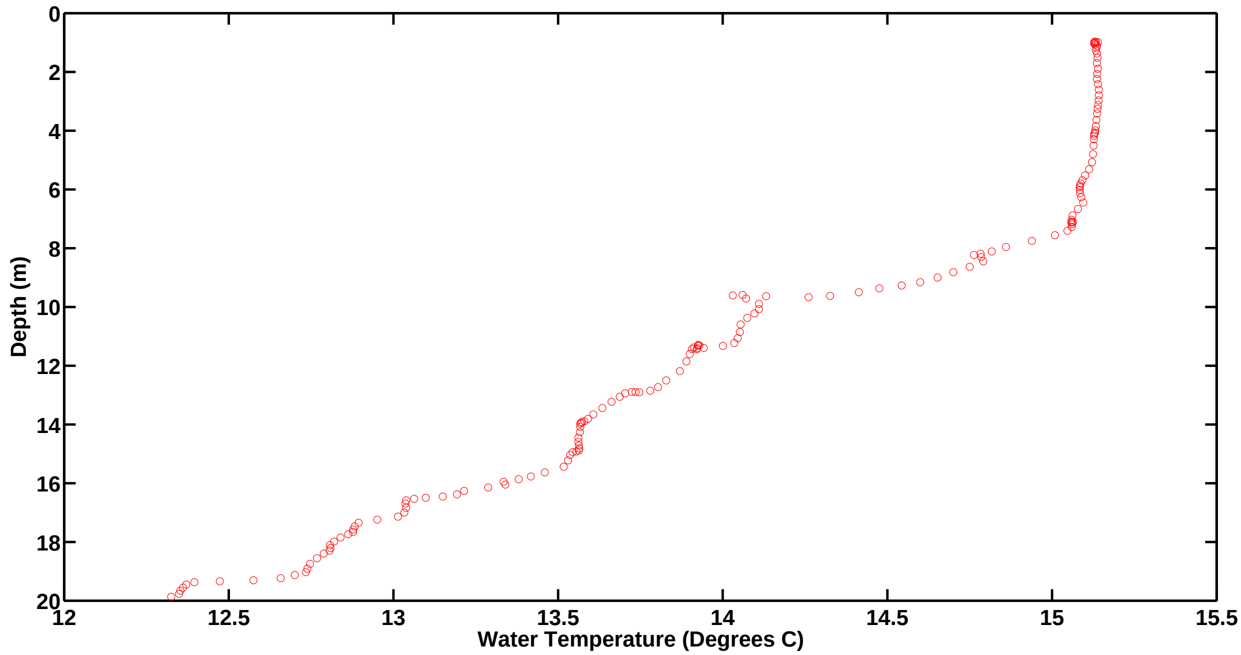


Fig. 7. Representative 20m CTD cast on 29 August, 2006. This figure shows the thermal profile of the ocean obtained from one of the 20m autonomous CTD casts performed during the adaptive surface craft run shown in Fig. 5.A well-mixed layer of nearly constant temperature can be seen in the first $8m$ of depth with a major thermocline occurring between $8m$ and $10m$.

a world-model approach and a behavior-based approach such as described in the paper is indicated. This approach has also been applied to the problem of target tracking with single and multiple marine platforms with success [10]. Current plans call for using both autonomous surface craft and AUVs for adaptive thermal gradient following, thermocline tracking, and front detection using both single sensor platforms and multiple, cooperating platforms. A system for an email-activated remote sampling capability is also in the design stage which will allow an oceanographer the capability to remotely deploy the surface craft via email to an area of interest and have a file of either raw or processed data sent back in real time.

ACKNOWLEDGMENTS

This work was supported by the Office of Naval Research, under Contract N00014-05-G-0106 Delivery Order 008, "PLUSNET: Persistent Littoral Undersea Surveillance Network", Grant N00014-05-1-0255, "Integrated, Adaptive Autonomous Acoustic Sensing Systems", and Grant N00014-04-1-534, "Adaptive Sampling and Prediction MURI". Special thanks go to the personnel of the R.V. Point Sur whose help contributed greatly to a successful experiment. The authors also wish to thank Joe Curcio, designer and builder of the kayak platforms and chief scientist on the R.V. Point Sur when this work was accomplished.

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