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Acoustically focused adaptive sampling and on-board routing for marine rapid environmental assessment

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A B S T R A C T

Variabilities in the coastal ocean environment span a wide range of spatial and temporal scales. From an acoustic viewpoint, the limited oceanographic measurements and today's ocean computational capabilities are not always able to provide oceanic-acoustic predictions in high-resolution and with enough accuracy. Adaptive Rapid Environmental Assessment (AREA) is an adaptive sampling concept being developed in connection with the emergence of Autonomous Ocean Sampling Networks and interdisciplinary ensemble predictions and adaptive sampling via Error Subspace Statistical Estimation (ESSE). By adaptively and optimally deploying in situ sampling resources and assimilating these data into coupled nested ocean and acoustic models, AREA can dramatically improve the estimation of ocean fields that matter for acoustic predictions. These concepts are outlined and a methodology is developed and illustrated based on the Focused Acoustic Forecasting-05 (FAF05) exercise in the northern Tyrrhenian sea. The methodology first couples the data-assimilative environmental and acoustic propagation ensemble modeling. An adaptive sampling plan is then predicted, using the uncertainty of the acoustic predictions as input to an optimization scheme which finds the parameter values of autonomous sampling behaviors that optimally reduce this forecast of the acoustic uncertainty. To compute this reduction, the expected statistics of unknown data to be sampled by different candidate sampling behaviors are assimilated. The predicted-optimal parameter values are then fed to the sampling vehicles. A second adaptation of these parameters is ultimately carried out in the water by the sampling vehicles using onboard routing, in response to the real ocean data that they acquire. The autonomy architecture and algorithms used to implement this methodology are also described. Results from a number of real-time AREA simulations using data collected during the Focused Acoustic Forecasting (FAF05) exercise are presented and discussed for the case of a single Autonomous Underwater Vehicle (AUV). For FAF05, the main AREA–ESSE application was the optimal tracking of the ocean thermocline based on ocean-acoustic ensemble prediction, adaptive sampling plans for vertical Yo-Yo behaviors and subsequent onboard Yo-Yo routing.

1. Introduction

In coastal regions, wind driven flows, tidal currents, river outflows, internal waves, solitary waves, fronts, eddies, thermal changes, etc, are some of the commonly dominant oceanographic processes. These processes make the coastal ocean-acoustic environment highly variable in time and space (Schmidt, 2002; Coelho, 2002; Lermusiaux et al., 2002; Lermusiaux and Chiu, 2002; Robinson et al., 2002; Finette et al., 2002; Duda, 2002; Tolstoy et al., 2002; Akal, 2002; Lermusiaux et al., 2006a; Logutov and Lermusiaux, 2008).

In the water column, the temperature, salinity and plankton distribution can vary in complex dynamic ways, driven by these processes and their coupling. Current flows interact with the littoral bottom topography which becomes variable. The properties of the seabed are also variable in space and often not well known, which impacts acoustic predictions.

Conventional oceanographic measurements cannot provide the ability to synoptically observe all those dynamically interlocking, patchy and intermittent processes in the coastal ocean, especially for sub-mesoscales short in time and space (Dickey, 2003). Consequently, the coastal environment is under-sampled at these small and fast scales. Oceanographic forecasting by modeling and data assimilation such as the Harvard Ocean Prediction System with Error Subspace Statistical Estimation (HOPS/ESSE) can produce 4-D oceanographic field estimates and their associated uncertainties (Robinson et al., 1998; Robinson, 1999; Lermusiaux and Robinson, 1999). However, the resolution of the spatial and temporal grids used in computation is limited by the available computational resources. The initial conditions can be relatively unknown due to the environmental synoptic under-sampling (Lermusiaux et al., 2006a). Even if nested or unstructured computational grids are utilized (Deleersnijder and Lermusiaux, 2008), spatial scales smaller than hundred meters in the

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horizontal, and meters in the vertical cannot yet be simulated deterministically over large coastal regions (see Fig. 1).

Modern modeling and assimilation systems (Lermusiaux et al., 2006b) can represent the smaller, sub-grid-scale variability in a statistical or average-of-fluctuations sense (Lermusiaux et al., 2000, 2002; Chen et al., 2005; Lermusiaux et al., 2006a). From an acoustic viewpoint, very small scale variabilities are averaged out by the acoustic wave length; while the sub-mesoscale variabilities of the order of the acoustic wavelength make the speed of sound in the coastal ocean largely unknown. Variabilities and uncertainties in the ocean as well as in the seabed can be responsible for a large part of the acoustic prediction uncertainty (Pace and Jensen, 2002; Lermusiaux et al., 2006a). The uncertainty of the acoustic predictability is critical to the decibel (dB) budget of classical sonar systems by directly affecting detection and false alarm probabilities. It is also one of the major obstacles to adapting new model-based sonar processing frameworks, such as matched field processing (MFP) (Baggeroer et al., 1988), to the coastal environment. Finally, the spatially and temporarily varying sound speed and the random characteristics of the bottom are also of critical influence to acoustic communication systems, which, with the integration of the new Autonomous Ocean Sampling Network (AOSN) (Curtin et al., 1993) concept in the operational Navy, are becoming of increasing tactical significance.

To determine the environmental variability of the critical sub-mesoscales and short temporal scales, a rapid in situ measurement capability is needed (Schmidt et al., 1997, 2002). However, its implementation is being constrained by the limited number of platforms and sensors available. The lack of high-resolution in situ observations for assimilation into modeling systems can limit the usefulness of sound-speed forecasts for acoustic predictions. Acknowledging that the size of a coastal ocean area relevant to an acoustic problem is often as large as tens of kilometers, acoustic-driven coastal environmental assessment is facing the classic conflict between *resolution*, needed to capture the fine scale variability and *coverage*, needed for the larger scale environmental phenomena. Thus, Rapid Environmental Assessment (REA) (Pouliquen et al., 1997; Kirwan and Robinson, 1997; Robinson and Sellschopp, 2002; Coelho and Rixen, 2008; Allard et al., 2008; Ko et al., 2008; Rixen et al., 2008) resources available must focus on the environmental uncertainties critical to the specific acoustic region and application. A quantitative and adaptive sampling approach (Schmidt, 2002,Lermusiaux, 2007; Lermusiaux et al., 2007; Heaney et al., 2007; Yilmaz et al., 2008) is necessary.

Adaptive Rapid Environmental Assessment (AREA) is an adaptive acoustics-environment sampling approach based both on coupled oceanic-acoustic forecasts and on focused localized sampling. In AREA, data-assimilative deterministic ocean forecasts first provide larger scale (0.5 km and larger) coverage and also identify regions and features with strong uncertainty such as fronts and sub-mesoscale features. The limited high-resolution sampling resources are then deployed locally in a manner which is optimal to the acoustic forecasting (Robinson et al., 1998; Wang, 2004). Consequently, once these local data are assimilated, the limit of deterministic characterization is locally shifted towards smaller scales (Fig. 1): the ocean estimate is corrected locally and at high data-based resolution in a way directly relevant to the local acoustic propagation. Such focused adaptive sampling does not sacrifice coverage, and, as a whole, AREA can minimize acoustic forecast uncertainties.

The Focused Acoustic Forecasting-05 (FAF05) real-time at-sea field exercise was held 13–26 July 2005 off Pianosa, Italy (Fig. 2), within the northern Tyrrhenian Sea, on the eastern side of the Corsican channel. This region, around the island of Elba, was the site of a series of real-time prediction exercises in collaboration with the NATO Undersea Research Center (NURC). The first exercise, GOATS-2000 (Sep–Oct 2000), emphasized forecasting, adaptive sampling and a demonstration of inter-model nesting (Onken et al., 2005). During the second, ASCOT-02 (May 2002), the focus was on quantitative forecast skill evaluation (Coelho et al., 2004). The MREA03 experiment (June 2003), was designed to characterize the sub-mesoscale/inertial dynamics north of Elba. This was accomplished using small, high-resolution domains focused on the areas of interest ("Mini-HOPS") (Leslie et al., 2008). FAF05 was part of the Persistent Littoral Undersea Surveillance Network (PLUSNet) program. The emphasis was on AREA methodology development and engineering tests (Wang et al., 2006). In preparation for FAF05, virtual experiments were conducted in which ocean and acoustic predictions were used to optimize the AUV path along a set of pre-selected sections. Acoustic computations were carried out using the Range-dependent Acoustic Model (RAM, Collins, 1989; Jensen et al., 1994), with sound-speed field inputs from the HOPS/ESSE predictions. RAM is a popular wave-theory parabolic-equation scheme for solving range-dependent propagation problems in the coastal ocean. Subsequent ocean-acoustic exercises in this Tyrrhenian region include Lam et al. (2009-this volume) who carry out coupled four-dimensional oceanographic and acoustic forecasts at sea, for the Battlespace Preparation 2007 exercise. Within BP07, Rixen et al. (2009-this volume) investigated the use of dynamic super-ensemble prediction techniques for acoustic inversion and tomography, and Carriere et al. (2009-this volume) investigated full-field tomography and tracking.

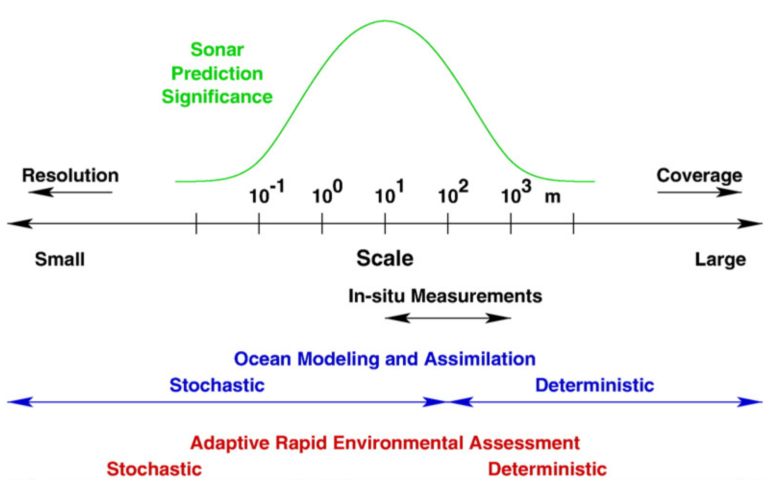

Fig. 1. Multi-scale environmental assessment. Typical sonar system performance is dependent on the acoustic environment variability over a wide range of scales (horizontal scales are shown in the diagram). Optimal environmental assessment is thus a compromise between conflicting requirements of coverage and resolution. By targeting areas of high sensitivity to the sonar system through in situ measurements, the deterministic assessment range will be shifted towards smaller scales.

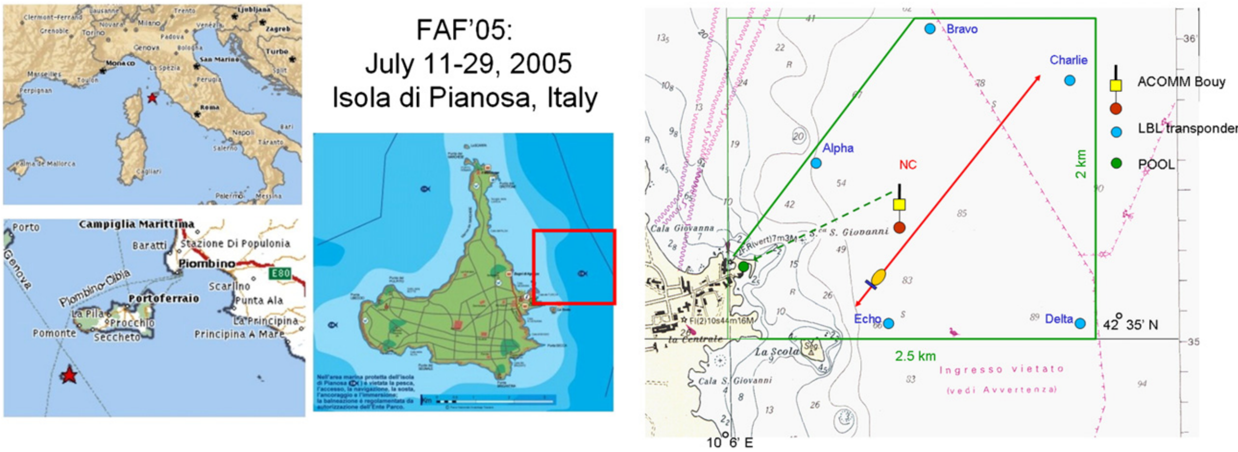

Fig. 2. Left: geographic location of the experiment, south of the island of Elba, Italy. Right: general schematic of the FAF05 experiment site, Pianosa, Italy. The AUV domain covered an area of about 2.5 km by 2.5 km, with a preference for southwest to northeast sections (green and red lines). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The intent of the FAF05 exercise was a real-time at-sea proof of concept but not a validation of schemes and approaches. The specific objectives were to: (1) Develop new algorithms and software for initiating the coupling of real-time ocean environmental modeling, uncertainty prediction and adaptive sampling with the adaptive rapid environmental assessment and acoustic predictions schemes; (2) Test and improve these algorithms and software in real-time; and (3) Issue physical–acoustical adaptive sampling recommendations every day, aiming to capture the vertical variability of the thermocline (due to fronts, eddies, internal waves, etc) and to minimize the corresponding uncertainties. These adaptive sampling plans were computed based on 1-to-2 day long forecasts of fields and uncertainties. The statistical impacts of the data for these plans were forecast, using an ESSE adaptive sampling approach (Lermusiaux, 2007). In classic path planning schemes (e.g. Popa et al., 2004; Lermusiaux et al., 2007; Heaney et al., 2007), these statistical impacts are usually not computed and not used. With ESSE adaptive sampling, ensembles of data assimilation steps are carried out in the future and the uncertainty reduction for each candidate sampling plan is nonlinearly forecast beyond these assimilation times. A novelty here is to accomplish this in real-time for coupled acoustic–oceanographic fields.

In what follows, Section 2 introduces the principles and methodologies of AREA. Section 3 describes the autonomy architecture for implementing AREA in an AOSN framework, including the autonomous platforms, vehicle behaviors, and onboard routing and control. Section 4 presents the results obtained for the FAF05 exercise, which were obtained in real-time, based on simulations. They include: the coupled high-resolution physical–acoustical ocean simulations; the new online Adaptive Yo-Yo control scheme for onboard vertical routing of AUVs; the novel prior optimization of these Yo-Yo parameters based on the ocean-acoustic predictions and AREA–ESSE optimization; the procedures and daily protocol; a selected sub-set of the real-time findings; and, finally, an evaluation of real-time modeling estimates via independent observations. A summary and conclusions are provided in Section 5.

2. AREA

Fig. 3 shows the architecture of the AREA–ESSE concept and its connection with ocean environmental models. Via data assimilation, the HOPS/ESSE and the geoacoustic modeling produce an ensemble of environmental realizations for the water column and the seabed respectively (Lermusiaux et al., 2006a). These ensembles are used to represent the probability density of the predicted ocean and seabed fields. They are used as inputs to the acoustic model, which for this exercise was RAM.

By coupling the ocean, seabed and acoustic models, the dominant acoustic prediction uncertainties can be generated via Monte Carlo ESSE simulations. The result is a probability density for the acoustic fields, which is input to the optimization schemes for selecting the ideal future measurements. Finally, acoustic measurements and inversion methods can be utilized to improve the environmental predictions and uncertainties.

The quantitative uncertainty maps, e.g. obtained from the standard deviation of the ensemble, provide guidance for optimally reducing the uncertainties and so guide the sampling plans.

Compared with sound velocity in the water column, the variabilities in bathymetry are less rapid and can be captured by a side-scan/sub-bottom profiling AUV, water depth detection etc. Thus, AREA presently focuses on the water column and treats bathymetry deterministically.

In general, the objective function in the AREA–ESSE optimization algorithm is a weighted sum of the ocean-acoustic-seabed prediction uncertainties which is to be reduced optimally by the ideal sampling plan. Specific applications lead to specific weight balances in this sum. The aim is to select the sampling plan, e.g. an optimal AUV path, that reduces these integrated predicted uncertainties the most. Thereafter, REA resources are deployed according to this optimal plan and in situ measurements collected and passed back to the ocean and seabed models. Those new local data are rapidly assimilated (Robinson et al., 1998; Lermusiaux and Chiu, 2002; Xu et al, 2008), and ocean and acoustic predictions for the next day are generated. This is a daily AREA–ESSE optimal resources allocation.

The daily AREA–ESSE constitutes a first level of adaptivity. The AREA optimization problem can also be treated as a *Sequential Decision Making* Problem and modeled in the *Dynamic Programming* (*DP*) framework (Bertsekas, 2001), in which the REA resources allocation pattern is not predetermined but generated on-board. An optimal adaptive routing strategy is then produced, as a function of the data sampled by the autonomous data-collecting platforms. The dynamic optimization algorithm then only computes the optimal sampling path for the next step; after the local data in this "next step" is collected and rapidly objective analyzed or assimilated in real-time, a new ocean estimate is computed to optimize the subsequent step. The whole optimal REA resources allocation is adaptively generated step by step on-board. This is the second level of adaptivity. In general, it would involve DP. However, it is known that a DP problem is usually at least [NP]—hard (Bertsekas, 2001). Determining an optimization approach for an adaptive routing strategy that can be computed on-

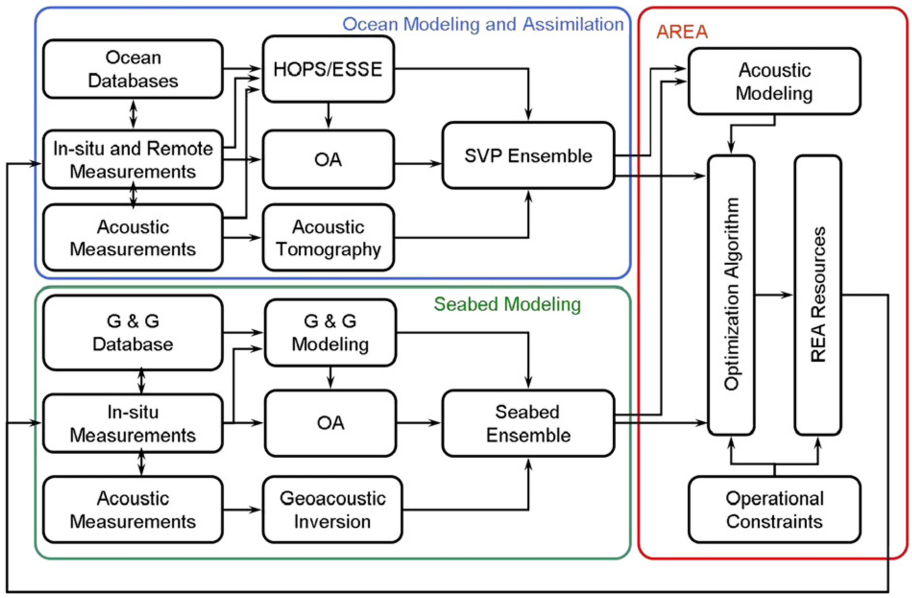

Fig. 3. Wiring diagram of the AREA–ESSE concept. Deterministic–stochastic forecasts and nowcasts of the ocean and seabed provide spatial and temporal environmental statistics in the form of realization ensembles. These ensembles are then used as input to acoustic models to provide realizations for the sonar performance, e.g. in the form of probability of detection and false alarms. To minimize the uncertainty of the acoustic prediction and therefore improve the probability of detection to false alarm ratio, the realizations of ocean-acoustic fields and the operational constraints are used as input to an adaptive sampling optimization scheme that determines an optimal deployment strategy for the REA resources. The collected REA data are then assimilated. The resulting reduced uncertainty fields are ultimately used for the acoustic prediction.

board can be extremely difficult. However in some particular cases, this difficult problem can be solved by indirect methods (see Section 4).

A two-level AREA simulation software has been assembled to search for (sub)-optimal sampling patterns and/or sampling strategies and to test the optimization in virtual settings before in situ experiments (Wang, 2004). This software can also be used to estimate the feasibility of real-time adaptive sampling for a given situation. Once a sampling strategy is successful in simulation, the real-time sampling algorithm can be implemented in the MOOS-IvP autonomy architecture described in Section 3. The MOOS-IvP architecture enables real-time adaptive routing onboard autonomous marine vehicles using a variety of oceanographic sensors and allows the sensor platform to optimize its path based on multiple competing goals such as the need for reducing the sampling uncertainty while simultaneously providing robust communications and safe navigation (e.g. avoiding obstacles).

3. Integrating AREA with AOSN

AREA via onboard routing is made possible with the use of mobile marine sensor platforms that are able to adapt their motion based on sensor readings gathered in real-time. These platforms are able to carry a wide variety of oceanographic sensors that can monitor ocean environmental variables including conductivity, temperature, dissolved oxygen, pH, and turbidity (Dickey, 2003). In general, the AOSN concept envisions networks of cooperating marine sensor platforms. This enables the capability to use distributed, simultaneous measurements to gain additional information about the ocean environment as

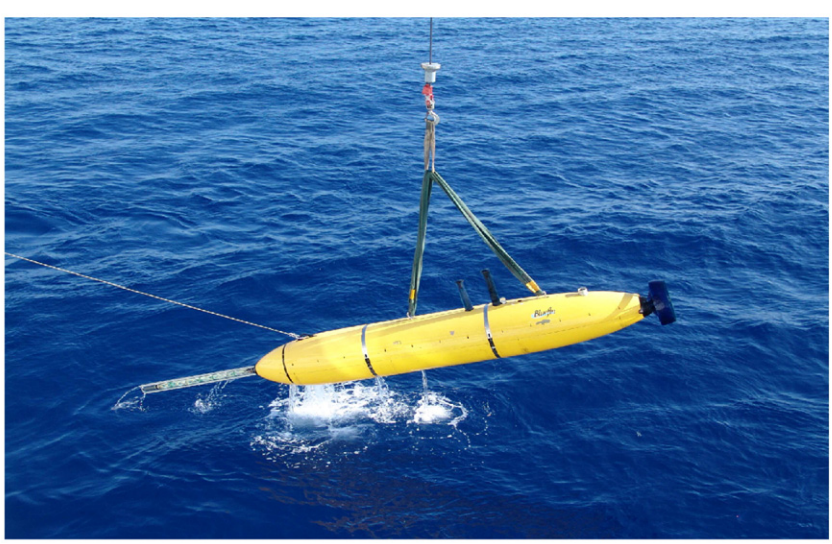

Fig. 4. An Odyssey-III AUV equipped with a sonar payload, CTD, and acoustic line array used for acoustic sensing.

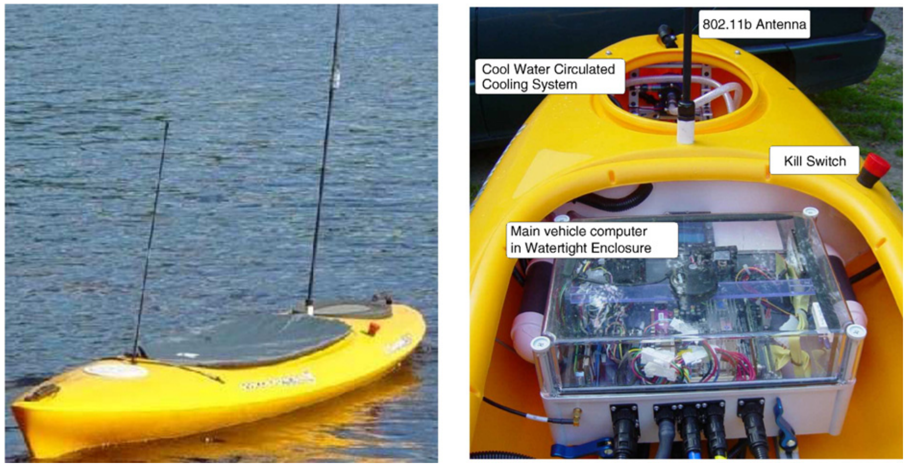

Fig. 5. The kayak-based autonomous surface craft. These small, lightweight platforms are ideal proxies for the much larger, more resource intensive AUVs for autonomy experiments as well as well as being capable sensor platforms in their own right.

well as the capability to cover broad areas. This section describes the autonomous sensor platforms used in our AOSN implementation, the autonomy architecture that enables these platforms to perform adaptive sampling, and a number of specific path planning and on-board routing applications.

3.1. Autonomous sensor platforms

Two types of autonomous sensor platforms are used in our prototype AOSN, autonomous underwater vehicles (AUVs) and autonomous surface craft (ASCs). Both are capable of carrying a variety of oceanographic sensors. In our AOSN configuration, the ASCs are able to communicate with the AUVs, allowing oceanographic measurements to be transmitted worldwide in real-time.

3.1.1. Autonomous underwater vehicles

The AUVs used in MIT's adaptive sampling architecture are based on the Odyssey-III platform built by Bluefin Robotics Corporation (Fig. 4). These underwater vehicles are capable of carrying a wide variety of oceanographic sensors including sonars, CTDs, chemical and biological sensors, and cameras (Benjamin et al., 2007). Data processing can be carried out in real time and/or archived for offline processing. Each AUV is also equipped with an acoustic modem for networked communications with other AUVs, communications buoys, ships, and ASCs. Shown in Fig 4 is an AUV equipped with a sonar payload, CTD, and acoustic line array used for acoustic sensing.

3.1.2. Autonomous surface craft

The autonomous surface craft are based on a lightweight kayak platform (Fig. 5). 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 is powered by 5 lead-acid batteries and a Minn Kota motor providing both propulsion and steering. The vehicles have a top speed of roughly 2.5 m/s. Each kayak is equipped with an acoustic modem for communications with other kayaks and AUVs and can carry a variety of sensors including CTDs, sidescan sonars and optical cameras. See (Curcio et al., 2005) for more details on this platform.

3.2. The MOOS-IvP autonomy architecture

The sensor platforms described in this work use the MOOS-IvP architecture for autonomous control. An autonomy architecture coordinates the gathering of sensory data from multiple environmental, navigation, and communications sensors, the processing of this data into an understanding of the state of the world, and the translation of this world state into a set of actions. MOOS-IvP is composed of the Mission Oriented Operating Suite (MOOS), an open source software project for coordinating distributed software processes running on autonomous platforms, 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 function optimization with the Interval Programming (IvP) model (see next Section 3.3.1 for behavior coordination (Benjamin, 2002; Benjamin and Curcio, 2004; Benjamin et al., 2006a,b).

A MOOS community consists of processes that communicate through a database process called the MOOSDB in a publish and subscribe manner as shown in Fig. 6(a). Each MOOS process has two key methods which are called at a user specified frequency. The OnNewMail() method is used to check for new mail (i.e. variables to which this process has subscribed to and that have changed during the

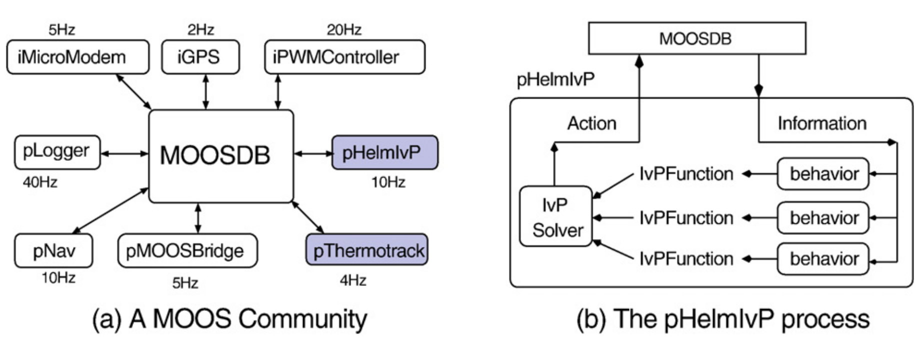

Fig. 6. The IvP helm runs as a process pHelm called in a MOOS community. MOOS may be composed of processes for data logging (pLogger), data fusion (pThermotrack), actuation (iPWMController), navigation (iGPS, pNav), communication (pMOOSBridge, iMicroModem), and much more. They can all be run at different frequencies as shown.

last iteration) from the MOOSDB. The Iterate() method is called to allow the process to handle any newly received mail. Results are published back to the MOOSDB during the call to the Iterate method. The IvP helm runs as the MOOS process pHelm (Fig. 6(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.

3.3. The IvP helm and vehicle behaviors

A helm is a process responsible for producing desired actions for the vehicle actuators controlling the vehicle motion. Classically, there have been two major approaches to this problem. The first approach, which we'll term the world-model approach, is the classical control theory method whereby sensor states are directly mapped to actuator outputs. A major weakness of this approach for controlling marine vehicles is the combinatorial explosion of states needed for any reasonably complex world model in which a sensor platform may not only have to deal with sensing but also with duties such as communications, obstacle avoidance, energy usage minimization, etc. An alternative approach introduced by Brooks (Brooks, 1986) is termed the behavior-based approach in which multiple modules (termed behaviors), each operating in parallel, post their desired course of action on each control cycle (see Fig. 6(b)). Each behavior is responsible for suggesting actions based on its particular function such as vehicle safety or other application-specific duties like adaptive sensing and communications. The key to any behavior-based approach is in the action selection mechanism that is employed to arbitrate between behaviors with conflicting desired actions. Brooks' original approach was to give each behavior a priority and then choose the output of the behavior with the highest priority, thereby creating a hierarchy of behaviors with behaviors such as vehicle safety behaviors having the highest priority. This selection mechanism fails to address situations in which compromise between behaviors is both possible and desired. Section 3.3.1 describes an alternative method of action selection using multiple objective functions which allows compromise between competing behavior goals. Section 3.3.2 describes the specific behaviors developed to implement adaptive sampling and routing in our FAF05 exercises.

3.3.1. Behavior-based control with interval programming

By using multi-objective optimization in action selection, behaviors produce an *objective function* over the vehicle control parameters such as course, speed, and depth rather than a single preferred action (Rosenblatt, 1997; Pirjanian, 1998; Benjamin, 2002). 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 assumed locally piecewise linear (see also (Yilmaz et al., 2008), hence approximating the true underlying utility function. The search is over the weighted sum of individual functions and uses branch and bound (Bertsekas, 2001; Deb, 2001) 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 than errors due to a restriction of the function form of behavior output, for example to linear or quadratic functions. Furthermore, the search is faster than brute force evaluation of the decision space, as done in (Rosenblatt, 1997).

The solver guarantees an piecewise globally optimal solution and this work validates that such search is feasible in a vehicle control loop of 4 Hz on a 600 MHz computer.

To enhance the 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.

3.3.2. Adaptive sampling behaviors and processes

For FAF05, the key sampling behavior for efficiently capturing the vertical variability of the thermocline was the Adaptive Yo-Yo behavior. This behavior was simulated and used in real-time (Section 4.2). Onboard, in the IvP helm, it is responsible for adaptively tracking and sampling the thermocline using vertical sound speed gradient estimates provided by the pThermoTrack MOOS process which uses raw CTD data provided by the vehicles onboard instrument. These sound-speed gradient estimates are published to the MOOSDB for use by the Adaptive Yo-Yo behavior in the IvP helm. While the Adaptive Yo-Yo behavior is controlling the vertical motion of the vehicle, the Waypoint behavior controls the horizontal motion of the vehicle between two 2D waypoints which are determined a priori according to region to be sampled. These are described next. Other behaviors for adaptive thermal gradient tracking and front detection have also been integrated and tested in the PLUSNet MB06 exercise (Wang, 2007; Haley et al., 2009).

3.3.2.1. pThermotrack. pThermotrack is a process which runs in the MOOS-IvP architecture (Fig. 6(a)) that is responsible for onboard monitoring of the real-time CTD data and for interacting with the Adaptive Yo-Yo behavior described below. pThermotrack uses p samples of the sound velocity (obtained from the CTD at approximately 1 Hz) to compute the vertical gradient of the sound speed (see Section 4.3) $|\frac{\partial c}{\partial z}|$ and then compares this value to a threshold γ (the values of p and γ being determined a priori). Once $|\frac{\partial c}{\partial z}|$ exceeds the threshold γ and then goes back below the threshold, pThermotrack signals to the Adaptive Yo-Yo behavior to toggle the vertical direction of the AUV. The AUV then samples through the thermocline in both directions. pThermotrack also monitors the depth of the AUV. If the depth is greater than the lower limit or shallower than the upper limit (determined a priori), the Adaptive Yo-Yo behavior will be given the signal to toggle the AUV's vertical direction. This occurs when a thermocline has not been detected.

3.3.2.2. Adaptive Yo-Yo behavior. The Adaptive Yo-Yo behavior controls the vertical direction of the AUV. The AUV is assumed to begin the adaptive thermocline sampling mission at shallow depth. At startup, the behavior orders the AUV to dive. After this, the behavior looks for signals from pThermotrack with regard to toggling the state of the vertical motion of the AUV. The objective function for the Adaptive Yo-Yo behavior is one-dimensional over depth. This vertical motion of the AUV can be controlled independently of the horizontal motions, controlled by the Waypoint behavior.

3.3.2.3. 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. 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. In our FAF05 exercises, this behavior aims for a constant velocity motion. It is used to move the AUV between two fixed horizontal points while the Adaptive Yo-Yo behavior is simultaneously controlling the vertical behavior of the AUV.

4. Results of the FAF05 exercise: methods, schemes and simulations

The Focused Acoustic Forecasting-05 (FAF05) real-time at-sea field exercise was held 13–26 July 2005 off Pianosa, Italy (Fig. 2). The

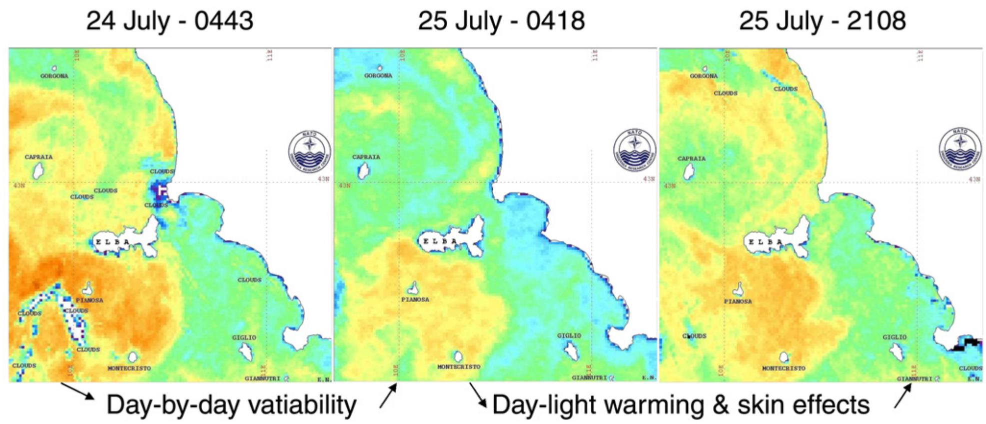

Fig. 7. AVHRR measurements of sea surface temperature for July 24 (0443Z) and July 25 (0418Z and 2108Z) demonstrating day-to-day and daily variability.

objectives of FAF05 were given in Section 1. In what follows, sub-section 4.1 describes the coupled physical–acoustical ocean forecasting carried out during FAF05 and its main results. The new online Adaptive Yo-Yo control scheme which is run onboard the AUV (onboard routing) is presented in sub-section 4.2. The novel prior optimization of these Yo-Yo parameters which are computed on-the-ground based on the ocean-acoustic predictions and the AREA–ESSE adaptive sampling are presented in sub-section 4.3. The procedures and daily protocol that explain how the latter adaptive sampling predictions are used as inputs to the former onboard routing are given in sub-section 4.4. Selected interesting results of the real-time applications of these schemes and procedures during FAF05 are discussed in sub-section 4.5. Finally, a brief forecast evaluation is presented in sub-section 4.6.

4.1. Real-time coupled oceanographic and acoustic simulations

4.1.1. Ocean modeling

During the FAF05 experiment, ocean environmental fields and uncertainties were predicted daily by the Harvard Ocean Prediction System and the Error Subspace Statistical Estimation approach. The data used for initialization and assimilation via Optimal Interpolation (Lermusiaux, 1999) were satellite sea surface temperature (SST) snapshots (Fig. 7) and historical synoptic profiles of ocean temperature and salinity. To estimate environmental uncertainties, various scenarios were computed daily as a function of different initial condition estimates, assimilation procedures, modeling domains, numerical/physical model parameters and time of day. Fig. 7 exemplifies some of the SST conditions measured by AVHRR. The left and central panels illustrate the day-to-day variability as conditions cool from one day to the next. The central and right panels illustrate variability encountered during a single day as skin temperatures warm during the daily heating cycle. The variability pictured in this figure helps to illustrate some of the varying conditions included within the scenarios designed for the ocean forecasts on a daily basis. As seen later, this variability is captured in the forecast sound speed sections. The synoptic CTD sound speed profiles were used on a daily basis for tuning and evaluation.

HOPS was run daily for 13 days, set-up in stand-alone, one-way- and two-way-nested modeling configurations, in 2 domains: (i) a high-resolution mini-HOPS domain along the eastern coast of Pianosa (the region of FAF05 operations) and (ii) a coarser resolution domain south of Elba and east of Pianosa (see Fig. 8). The model resolutions and domain sizes are given in Table 1. The fine 100 m resolution of the “Mini-HOPS domain” is designed to capture some sub-mesoscale dynamics relevant to acoustic propagation. At the time of FAF05, this was the highest resolution modeling that we had ever run in real-time. Importantly, the other two larger HOPS domains within which this small high-resolution domain is nested are required to provide adequate boundary conditions to the small domain. This is because the boundary values in the about 10 km wide Mini-HOPS domain are advected through the domain in less than one day. Without inputs from the larger domains, the Mini-HOPS domain would thus be completely uncertain after one day.

To initialize, HOPS utilized historical data from the May–June 2003 MREA03/BP03 real-time mini-HOPS modeling in the Ligurian Sea/

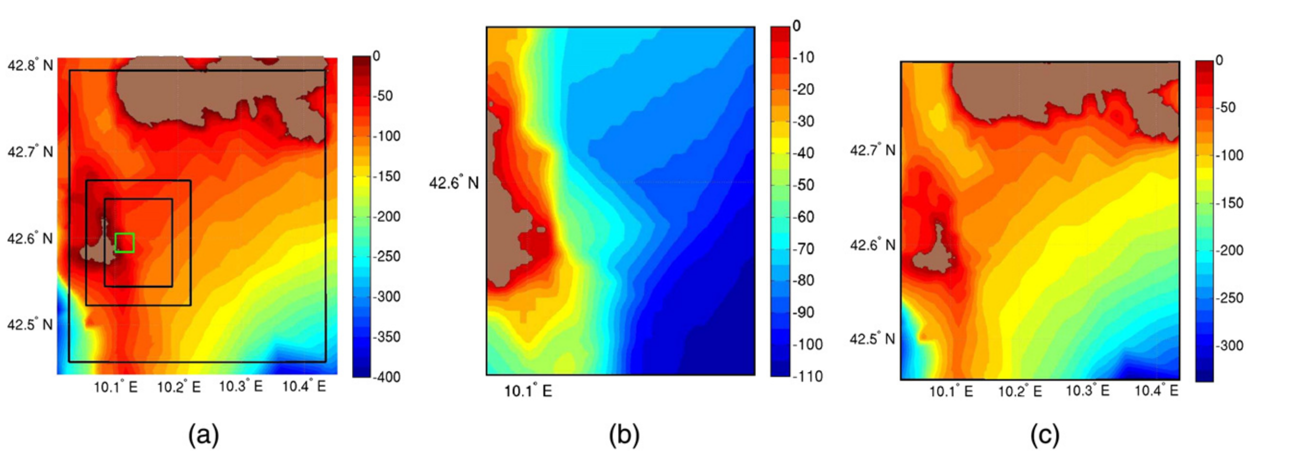

Fig. 8. HOPS 2-way nested domains: (a) overall schematic overlaid on bathymetry (in m), (b) Pianosa domain, (c) Elba domain.

Table 1
Two-way nested ocean domain resolution and sizes.

Resolution		Mini-HOPS	Elba
		100 m	300 m
Size	$nx \times ny \times nz$	$89 \times 114 \times 21$	$106 \times 126 \times 21$
	Extent	8.8×11.3 km	31.5×37.5 km

Elba. However, as we have repeatedly observed, (e.g. Onken et al., 2008; Lam et al., 2009-this volume), historical and climatological data have limited use in the Mediterranean, due to interannual variability and human activities. In fact, it is the in situ synoptic data acquired at sea during FAF05 that allowed us to set adequate properties of the thermocline (see Section 4.6).

This synoptic data included: (i) Sound-speed profiles east of Pianosa from the R/V Leonardo and AUVs, (ii) meteorological data from the R/V Alliance, (iii) Satellite Sea Surface Temperature (SST) from NURC. The decay scales of the OA varied from 2 km to 5 km in the small Pianosa domain and 5 km to 15 km in the larger Elba domain.

Atmospheric forcing (ocean–atmosphere fluxes) for HOPS was generated as a combination of: (i) Aladin forecasts and analyses (~8 km resolution) from the Croatian Meteorological Service (DHMZ), (ii) NOGAPS coarse resolution forecasts and analyses from the Fleet Numerical Meteorology and Oceanography Command (FNMOC), and, (iii) Coupled Ocean/Atmosphere Mesoscale Prediction System (COAMPS) forecasts and analyses from NURC. The criterion to select the atmospheric forcing was to use the forcing with the highest resolution when it was available.

Fig. 9 illustrates the HOPS daily simulations and forecasts of the ocean environment. The 1-day forecasts of the temperature and current fields at 20 m depth (near the main depth of the thermocline) from July 24 to July 25 are shown in the Pianosa (Fig. 9(a) and (b)) and Elba (Fig. 9(a) and (d)) domains. These figures show the warm areas to the east of Pianosa and south of Elba. There is a sharp temperature contrast between the northern and southern coasts of Pianosa. In the largest domain, an anti-cyclonic circulation is visible, bounded by Elba, Pianosa and the cyclonic circulation of the northern Tyrrhenian sea. This circulation creates an on-shore (east to west) flow at the eastern coast of Pianosa. In the operational area this circulation is intensified and flows from southeast to northwest. Larger surface currents in the northwestern corner appear to be due to unrealistic atmospheric forcing and boundary conditions.

4.1.2. Acoustic modeling coupled to ocean-seabed modeling

Based on the nominal at-sea configurations of the R/V Leonardo and AUVs, we chose a 100 Hz continuous-wave (single-frequency) sound source located at $r = 1950$ m, $z = 35$ m and the transmission loss (TL) at 5 m depth was chosen as the acoustic signal which mattered in the AREA–ESSE objective (see Fig. 10 next).

To implement acoustic simulations and optimization in real-time, the RAM code was carefully configured so that TLs could be computed as fast as possible with sufficient precision. This was done in the virtual experiments, prior to the real-time work. For coupled ocean-acoustic computations, a preliminary data-transfer interface was created to connect the HOPS/ESSE output with RAM, and so allow rapid and RAM-compatible extraction of the acoustic-related data from the HOPS/ESSE output. Once the HOPS/ESSE ocean, seabed and RAM codes were set-up and coupled together, a software-human system was created such that ensembles of sound velocity profiles (SVPs) and SST data were the inputs, and ensemble of TLs at the receiver's depth were the outputs.

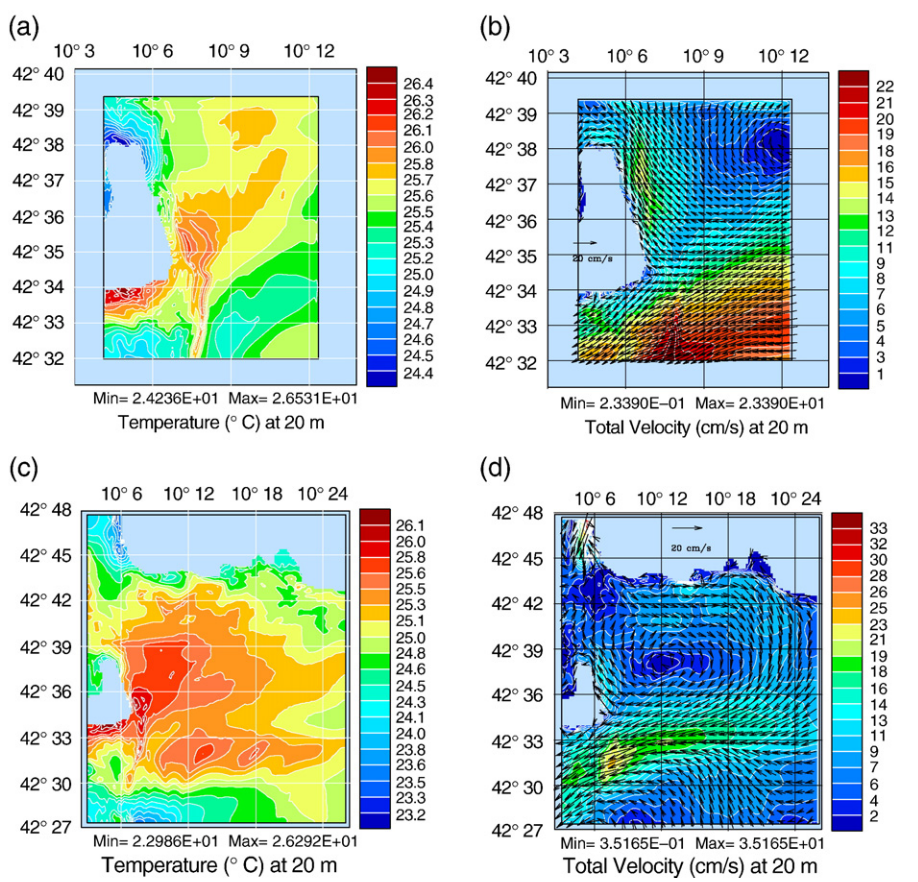

Fig. 9. HOPS 2-way nested forecasts for the morning of July 25, 2005 (local time), issued on July 24. (a) and (b): Temperature and total velocity overlaid with current vectors at 20 m depth in the Pianosa domain; (c) and (d): as (a) and (b) for the Elba domain.

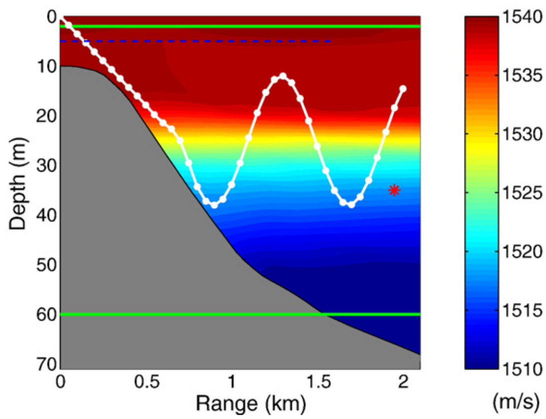

Fig. 10. Illustration of the ocean-acoustic configuration and of the thermocline-oriented AUV Yo-Yo track along a vertical section in the FAF05 experiment domain, overlaid on sound-speed (m/s). Pianosa is to the left, the source a red star and the target TL depth a blue dashed line. The green lines are the minimum and maximum depths allowed. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Onboard Adaptive Yo-Yo control scheme

At the small 2.5-by-2.5 km site of the FAF05 experiment (see Fig. 2), the depth and slope of the thermocline is the key ocean property which sets the sound-speed field. Therefore, the adaptive sampling strategy that aims to capture the vertical variability of the thermocline due to fronts, eddies, internal waves, etc. can capture the dominant sound-speed feature and so also minimize the TL uncertainty. To track the vertical variability of the thermocline, a new thermocline-oriented AUV path control was researched. The aim was to guide the AUV so that it finds the depth of the thermocline and crosses this depth back and forth. Since the thermocline is where the sound speed changes rapidly with depth, a simple criterion to find the position of the AUV relative to the thermocline is to compare the absolute value of local vertical gradient of sound speed $\left|\frac{\partial c}{\partial z}\right|$ with a threshold. By doing so, the AUV can estimate whether it is above, inside of or below the thermocline (Fig. 10).

It is assumed that at the beginning of the mission, the AUV stays on the surface. While it is diving, its CTD collects data every second. The $\left|\frac{\partial c}{\partial z}\right|$ is estimated onboard the AUV via *Linear Least Squares Fitting* method based on every p CTD data. If at the beginning, $\left|\frac{\partial c}{\partial z}\right| \leq \gamma$, where γ is the threshold, and then $\left|\frac{\partial c}{\partial z}\right|$ becomes greater than γ, and after that $\left|\frac{\partial c}{\partial z}\right|$ becomes lower than γ again, then the criterion will indicate that the AUV is now below the thermocline and it will turn around upwards. Thereafter, while the AUV is going up, if $\left|\frac{\partial c}{\partial z}\right|$ becomes greater than and then lower than γ again, the criterion indicates that the AUV is now above the thermocline and it will turn around downwards. An upper bound and a lower bound on the depth range of the AUV are also set up. Should the AUV have crossed the thermocline or not, once the lower bound or upper bound is reached, the AUV has to turn around to avoid reaching too deep depths or the surface. This path control will lead the AUV to carry an up-and-down Yo-Yo track (Fig. 10).

4.3. Adaptive sampling scheme: prior optimization of Yo-Yo parameters

In the AUV Yo-Yo control, there are two parameters to be optimized: p, the number of sampling CTD values used to compute $\left|\frac{\partial c}{\partial z}\right|$, and γ, the threshold used to compare with $\left|\frac{\partial c}{\partial z}\right|$. Note that p is defined over the space of time-averaged raw CTD values (one raw CTD data is obtained about every second. This CTD data is here boxed-averaged over a grid of horizontal and vertical resolutions that are a function of the scales of interest). The γ parameter defines how rapidly the sound speed changes with depth can be linked to the thermocline. The optimal values of these parameters were predicted daily, using the forecast ocean and acoustic fields and their uncertainties. This novel optimization is an adaptive sampling scheme: it is based on predicted (unknown) data properties and computed on-the-ground, prior to sending the AUV at sea. The optimization problem can be formulated as finding:

$$\min f(p, \gamma) \tag{1}$$

$$\text{s.t. } \gamma \geq 0,\ p \text{ is a positive integer,} \tag{2}$$

where the objective function is

$$f(p,\ \gamma) = E\left\{tr\left(covar\left(TL^{OA}\right)\right)\right\}. \tag{3}$$

TL^{OA} is the stochastic-deterministic TL vector corresponding to the posterior ocean estimate and its error field, after applying the Yo-Yo control in the forecast ocean estimate (the predicted ensemble mean or the ocean state the closest to it) and rapidly assimilating the most recent in situ measurements (e.g. last 10 to 30 min of data) via objective analysis. *covar* (TL^{OA}) is the error covariance matrix of TL^{OA} and *tr* the trace operator. Since the CTD noise may influence the estimation of the thermocline depth and thus change the AUV track, an expectation over all possible CTD noise is needed, $E\{std(TL^{OA})\}$.

This optimization problem is essentially a mixed-integer non-linear programming problem. The objective function here only contains one term, the forecast error standard deviation of the TL field, after statistical assimilation of the Yo-Yo data. It is only defined on integer-valued p, so it can't be solved by relaxation. Additional real-time challenges arise because of the time required to compute the objective function via Monte Carlo simulations prior to resolving this optimization problem. Of course, other objective functions, including multiple (non-dimensionalized) terms or different objectives could be used. For example, one could aim to optimize the source depth so as to maximize the detection range, accounting for the forecast TL and its uncertainties.

In FAF05, a small size enumeration method was implemented. The objective function was computed every day for 7 potential Yo-Yo control parameter pairs listed below. These pairs are a subset of representative values carefully selected for real-time computations. This selection was based on a large number of simulations and virtual experiments prior to FAF05. During FAF05, the optimization was to predict the pair among the 7 possibilities that is associated with the minimum objective function value and to use this optimal Yo-Yo control parameter pair for the forecast (next) day. This information was sent to the at-sea team and ultimately to the AUVs as the prior (i.e. forecast) optimal adaptive sampling parameters which are used to start the onboard routing control.

4.4. Procedures and daily protocol for adaptive sampling and onboard routing

The real-time data-driven simulations were implemented from 7/17/2005 to 7/26/2005. Each day, the ocean-acoustic environmental fields were predicted by HOPS/ESSE with the associated uncertainties. The data used for initialization and assimilation were satellite sea surface temperature snapshots and historical profiles of ocean temperature and salinity. To estimate ocean uncertainties (Lermusiaux, 2006; Lermusiaux et al., 2006a), various scenarios were computed daily as a function of different initial condition estimates, assimilation procedures, modeling domains, numerical/physical model parameters and time of day. This scenario procedure was used instead of a more classic ESSE initialization (Lermusiaux et al., 2000, 2002) because of the lack of initial data for constraining these initial conditions and parameters. Each resulting sound speed field (in time and 3D space) of this ensemble of predictions was interpolated along several characteristic vertical sections and used for acoustic

Table 2
Enumeration table for the p and γ parameters.

	1	2	3	4	5	6	7
P	20	20	20	30	30	30	30
γ	0.1	0.5	1	0.1	0.5	1	1000

predictions with RAM. The ensemble of sound-speed sections and the corresponding ensemble of acoustic transmission loss fields were utilized as input to the optimizationalgorithm that forecast the optimal parameters of the AUV sampling pattern's for the next day(s), as described in Section 4.3. These prior optimal sampling parameter estimates for optimal reduction of the predicted acoustical uncertainties and the corresponding ocean and acoustic predictions were emailed daily to the FAF05-MIT team at-sea aboard the R/V Leonardo. They provided the basis for onboard optimal routing the MIT AUVs.

The daily operational adaptive sampling tasks were to solve the optimization problem (Section 4.3) and so forecast the optimal sampling parameters. The specific steps in the procedure included:

1. Generate environmental forecasts of fields and uncertainties of 1-to-2 days of duration using HOPS and the ESSE approach.

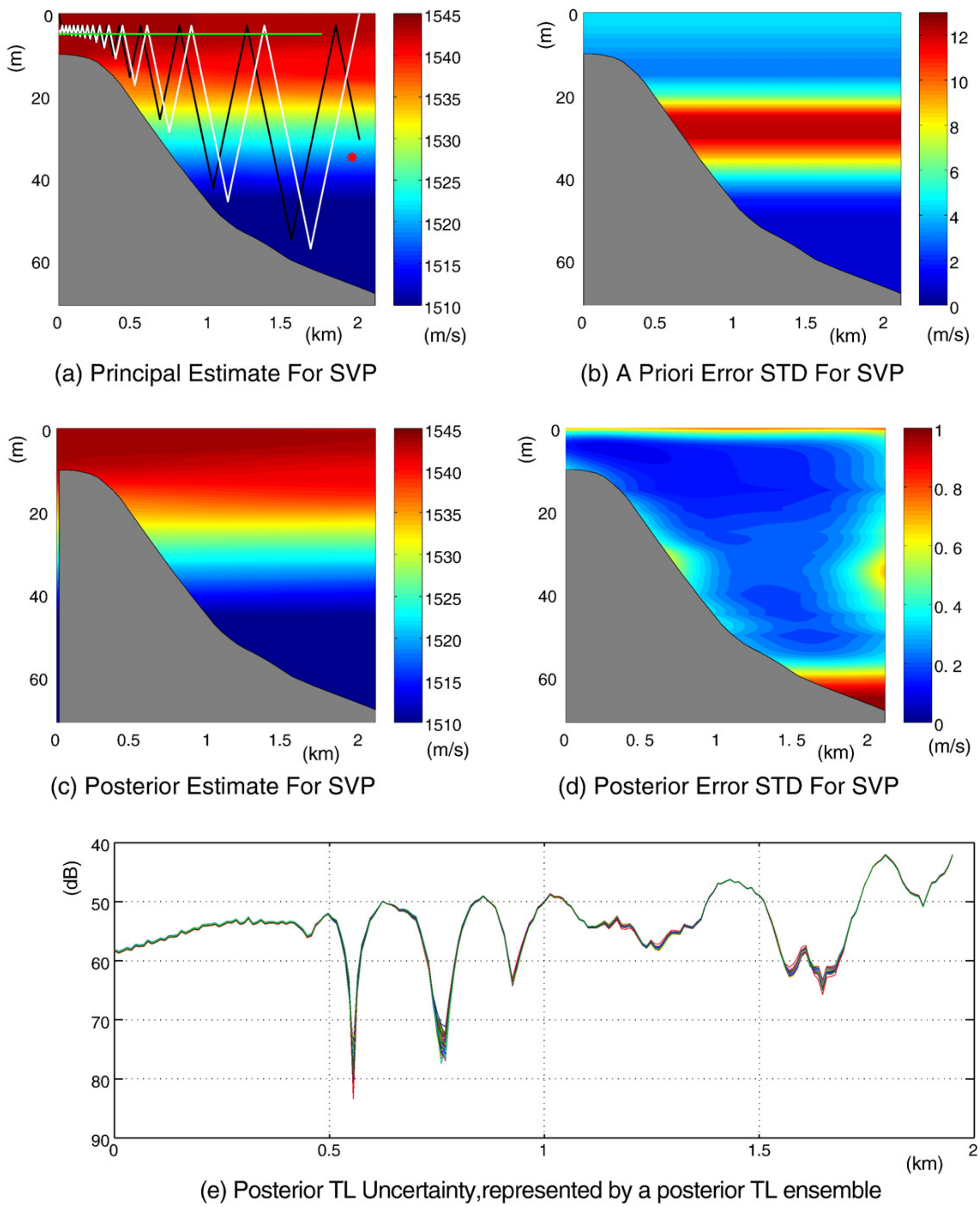

Fig. 11. AREA–HOPS–ESSE simulations for 7/23/2005. (a) Estimate of SVP output from HOPS/ESSE. Black line: forward AUV Yo-Yo track. White line: backward track. A 100 Hz CW sound source is located at the red point $r = 1950$ m, $z = 35$ m. Green line: TL depth which is 5 m. (b) Associated error standard deviation. (c) Posterior SVP estimate after objective analysis (predicted data assimilation). (d) Associated posterior error standard deviation. (e) TL realizations associated with the environment shown in (c) and (d), where in the seabed, the sound speed is $c = 1700$ m/s, the density is $\rho = 1700$ kg/m^3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2. Couple these forecasts with the seabed and acoustic modeling, running an ensemble of acoustic propagation forecasts.
3. Implement the AUV Yo-Yo control with the ith parameters pair in the enumeration Table 2. Output its objective function value.
4. Repeat step 3 for m times ($m=10$), so as to account for the modeled uncertainties in the expected CTD data of the AUV. Calculate the average objective function value.
5. If $i<7$, then $i=i+1$ and go to step 3; otherwise, find the parameters pair associated with the minimum average objective function value and plot AUV track.

4.5. Real-time coupled ocean physics–acoustic AREA–ESSE

The real-time results of the application of the above schemes (Sections 4.2 and 4.3) and procedures (Section 4.4), which utilize the forecast inputs from Section 4.1, are now illustrated. A typical daily result is shown in Fig. 11, which corresponds to forecasts for the morning of 7/23/2005. In this case, $p=30$, $\gamma=1000$ were the optimal parameters, as forecast in real-time by the AREA–ESSE adaptive sampling and routing schemes for FAF05 (Section 4.4).

Analysis on the AUV Yo-Yo control shows that when p becomes larger, the thermocline-oriented criterion is less sensitive to the CTD noise. When γ becomes larger, the thermocline is estimated to be weaker by the criterion. If γ is very large such as $\gamma=1000$, no thermocline is measured to be strong enough (for the AUV, no thermocline is present) and the AUV simply goes up-and-down between the upper and lower bound. In contrast, if p and γ become smaller, the criterion is more sensitive and thus the AUV's track is a more complex zigzag in the vertical plane.

In the AREA–ESSE procedure, the simulated data sampled by the AUV (not the raw data but the box-averaged data over the vertical and horizontal scales of interest, see Section 4.3) in the ensemble of ocean forecasts is rapidly objectively analyzed to update the central forecast (selected from the ensemble of forecasts), see Section 1. For FAF05, the parameters utilized in this vertical objective analysis were scales set based on experience, data and model outputs in the region, specifically the horizontal oceanic correlation length set to $Lr=1$ or 2 km and the vertical correlation length set to $Lz=5$ m. Since the Lr can be almost as long as the total horizontal span of experiment area, a few sampling points per depth can dramatically reduce the SVP uncertainties at that depth for a relatively large range. If the AUV can explore the deepest depths, it can very likely capture most of the SVP and TL uncertainties. On several of the days of the experiment, the choice of bounding values for p and γ, i.e. $p=30$, $\gamma=1000$ (which makes the AUV go up-and-down between the upper and lower depth bounds) was forecast to give the optimal results. However, if the experiment area had spanned an area larger than three times Lr, the choice $p=30$, $\gamma=1000$ would not often have been the optimal solution (as confirmed in our simulations for larger sections). The small FAF05 region was selected here for easier engineering tests with the AUVs.

Fig. 12 shows an interesting phenomena and result obtained on 7/21. For both the morning and afternoon forecasts, $p=30$, $\gamma=0.1$ was the optimal parameter pair for the outbound–inbound sampling path. With these parameters, the AUV did not go from the upper to the lower depth bound, but focused on tracking internal vertical variabilities of the sound velocity. In the morning, the optimized inbound–outbound AUV path captured the main thermocline along its path, both back and forth. However, in the afternoon, the optimized Yo-Yo first samples the full thermocline in the outbound path but in its return inbound path, the optimized AUV automatically captures the so-called “afternoon effect” on the surface thermocline, i.e. the warming of the upper ocean layers due to the strong day-light sun.

4.6. Evaluation of real-time modeling estimates via independent observations

The FAF05 experiment was a demonstration of concept that was not designed to include independent observations for validation of the ocean-acoustic models and of the adaptive sampling approach. However, as the sound speed profiles acquired during the experiment were not assimilated into the model forecasts, they were available for use in evaluating and validating the model outputs.

During the real-time experiment, the information regarding oceanic structures gleaned from the sound speed profiles was utilized to improve the model representation (Fig. 13). As described previously, HOPS was initialized with historical synoptic CTD profiles. These profiles were from a prior experiment in this region which took place in late May 2003. Fig. 13(a)–(c) illustrates the initial mismatch of the model with synoptic sound velocity observations. The vertical section of sound speed has a mixed layer depth which is roughly similar to that of the observations but the value of the sound speeds in the model fields is significantly lower than that of the observations. Post-experiment estimates of the bias between the profile data in Fig. 6 and the model sound speed values in Fig. 6 show that overall the model underestimates the sound speed by ~10 m/s. The historical profiles were cooler than the synoptic conditions of mid-July 2005. To alleviate this mismatch, the initial temperature fields were first modified in real-time by melding the historical data with 15 July 2005 satellite SST extended down to the estimated mixed layer depth. Fig. 13(d)–(f) shows an improved match with the 2005 conditions as the field is closer in value to the sound velocity profiles. The model bias in the upper layers is reduced to around −2 m/s. However, while this first correction was made and the updated model simulations were run, the ocean mixed layer in the observations had deepened further. This dynamical evolution was not yet reflected in the model forecasts. The resulting incorrect vertical structure exacerbated the

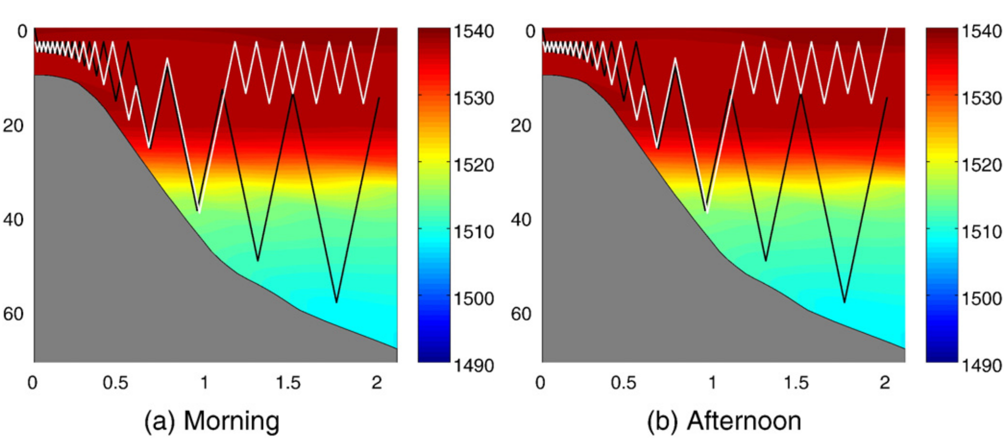

Fig. 12. AREA–ESSE simulations for 7/21/2005. In the afternoon, when the AUV came back, it tried to capture the “afternoon effect”.

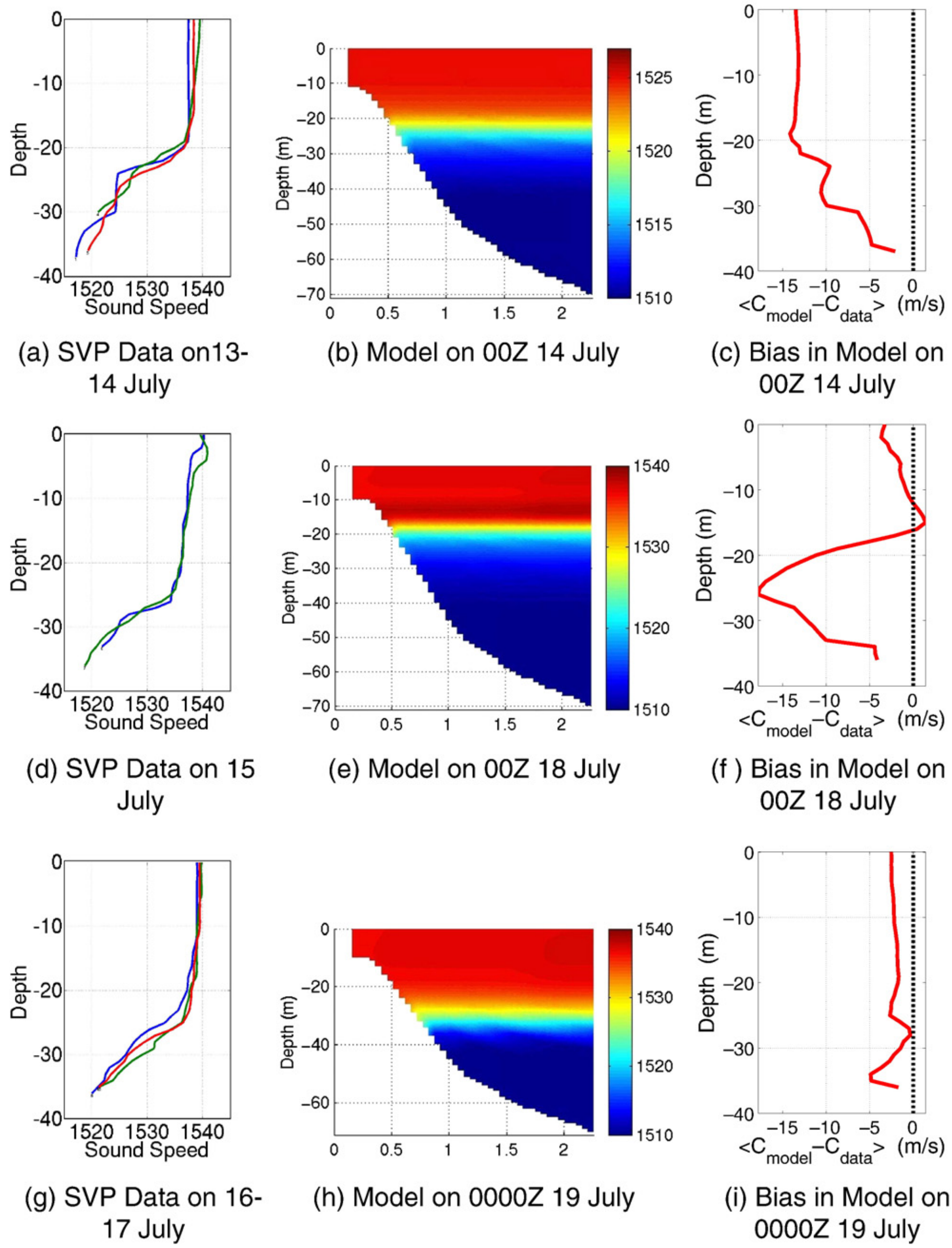

Fig. 13. Tuning the model initialization based on comparison of in situ sound speed profiles with sound speed sections from the numerical model field forecasts. The three model sections are all from (42.586N, 10.105E) to (42.602N, 10.122E). (a) Sound speed profiles acquired 13−14 July. (b) Sound speed model section on 0000Z 14 July. (c) Estimated bias in (b) when compared to (a). (d) Sound speed profiles acquired 15 July. (e) Sound speed model section on 00Z 18 July. (f) Estimated bias in (e) when compared to (d). (g) Sound speed profiles acquired 16-17 July. (h) Sound speed model section on 0000Z 19 July. (i) Estimated bias in (h) when compared to (g).

model bias in the deeper layers, which reached a peak value around −17 m/s. A third initialization was then created by (i) further increasing the estimated mixed layer in the SST melding procedure and (ii) modifying the extension procedure to allow deeper penetration of SST within the mixed layer. Fig. 13(g)–(i) demonstrates that the updated real-time model fields have both the appropriate vertical structure and values, the overall model bias being reduced to ~2 m/s. A conclusion of our real-time adaptation (see Lermusiaux, 2007) of the model initialization and assimilation procedures is that our focus on the depth of thermocline is certainly a key property in the region.

Once the initialization and SST assimilation were satisfactory, further qualitative assessments of the model estimates were made. Fig. 14 illustrates a model forecast that evolves the vertical structure of sound speed in a fashion that is consistent with the evolution of the independent observed sound speed profiles. As the model moves forward in time, 13-13-13, the mixed layer deepens and spreads, becoming less well-defined. Similar behavior can be seen in the observed profiles. In particular profile 15 (red), shows the most deepening/broadening. The mean biases between the forecasts and profile 15 (red curves in 13-13-13) show a clear reduction in the deep bias as time progresses. Conversely, profiles 13 and 14 (blue and green, respectively) show an increase in bias around 30 m as the mixed layer deepens, followed by a slight decrease again as the broadening erodes the bottom of the mixed layer. Fig. 13 also shows that the model captures the surface heating effect, as there is a ribbon of high sound speed at the surface which is also found in Profile 15 (red). This afternoon effect was also captured by the adaptive sampling and onboard routing (see Fig. 12).

5. Summary and conclusions

The principles of Adaptive Rapid Environmental Assessment were developed, using ideas from ensemble ESSE adaptive sampling and

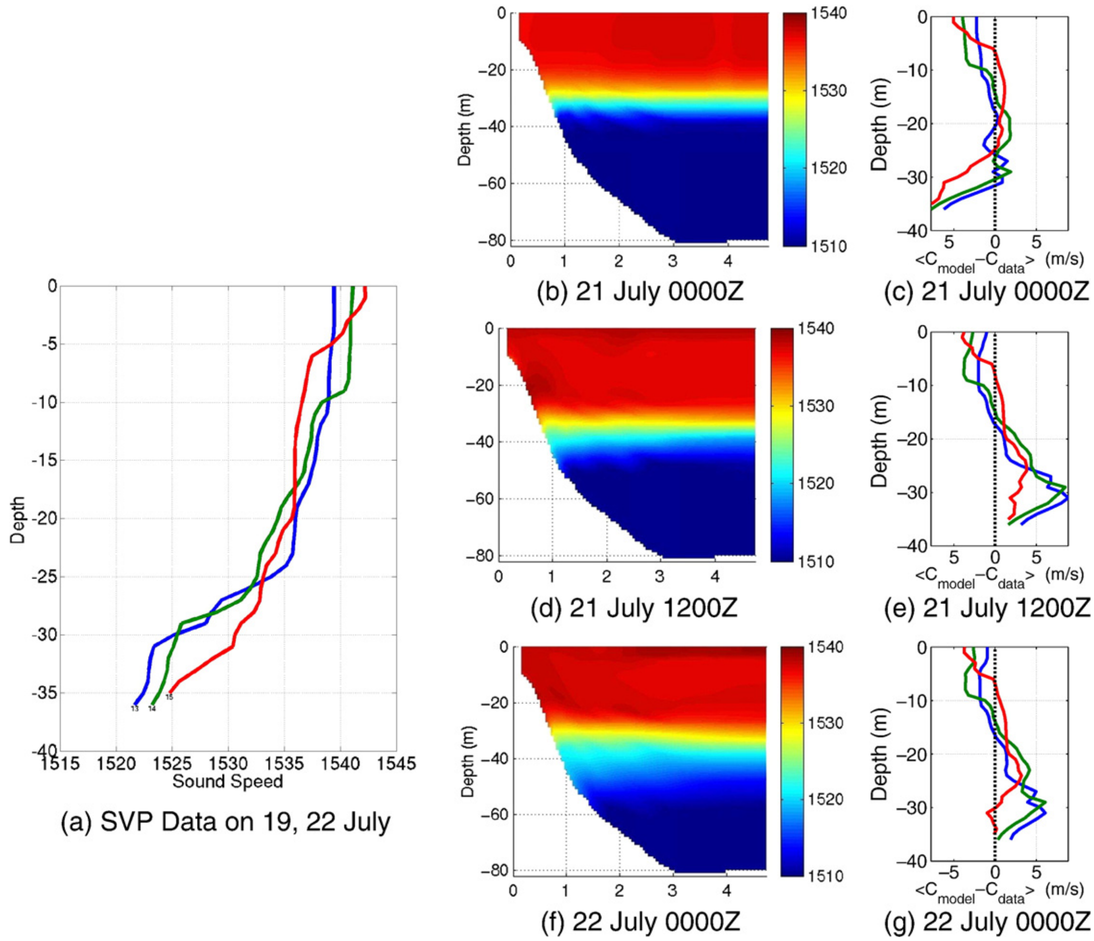

Fig. 14. Comparison of in situ sound speed profiles with forecast sound speed sections from the numerical model field forecast. The model section here is longer than in Fig. 13, extending from (42.586N, 10.105E) to (42.62N, 10.14E). (a) Sound speed profiles acquired 19 July (blue) and 22 July (green and red). Sound speed section forecasts for (b) 21 July 0000Z, (d) 21 July 1200Z and (f) 22 July 0000Z. Mean bias estimates between each profile and the sound speed section forecasts for (c) 21 July 0000Z, (e) 21 July 1200Z and (g) 22 July 0000Z. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

smart onboard routing. The corresponding algorithms and schemes were derived, a preliminary computational structure was implemented, and a demonstration of concept was simulated in real-time during FAF05. In summary, the first components of AREA–ESSE are algorithms and software for the coupling of scenario- or ensemble-based ocean predictions with acoustic predictions. These predictions are then used as inputs to an optimization scheme which seeks the parameter values of sampling behaviors that optimally reduce the predicted acoustic uncertainties. This uncertainty reduction is computed as an ESSE-based adaptive sampling problem (Lermusiaux, 2007): a set of future sampling plans is drawn from the possible sampling behaviors, a data assimilation is carried out for each member of the set and the parameters of the sampling plan which leads to the optimum uncertainty reduction is selected as the best forecast plan. These optimal parameters are then fed to the sampling vehicles as priors. A second adaptation of parameters is finally carried out underwater by the autonomous sampling vehicles using onboard routing. This onboard routing is a simple controlled response to the real ocean data that the vehicle acquires. The algorithms and software to carry out this adaptive sampling strategy and onboard routing algorithm were implemented and utilized in real-time during the two weeks of the FAF05 exercise in the northern Tyrrhenian sea. To coordinate the on-the-ground ocean-acoustic field and adaptive sampling predictions with the onboard routing, a preliminary system integration was completed and tested. For the AUV, this included setting-up and testing at sea the physical CTD sensor hardware, MOOS-IvP autonomy architecture and platform navigation systems. For the autonomous surface craft, this mainly involved the MOOS-IvP architecture and communication tests.

The main accomplishments for the FAF05 exercise simulations included first an initial coupling of ocean-acoustic ensemble methodologies and software so that: (i) ocean environmental fields and uncertainties were predicted daily by the HOPS ocean model and ESSE approach; (ii) various (10 to 20) scenarios of 0.5–2 days predictions of sound-speed sections were computed and transferred for acoustic forecasts; (iii) corresponding ensembles of acoustic TLs were computed using RAM; and, (iv) sound-speed sections and TL curves were input to an adaptive sampling scheme which uses an optimization algorithm to forecast the optimal prior parameters for Yo-Yo sampling during the next 1–2 day(s). Second, physical–acoustical adaptive sampling recommendations were issued in real-time every day (on the internet and by email), aiming to: (i) capture the vertical variability of the thermocline, due to the daily solar cycle, atmospheric-driven vertical mixing and mesoscale features (eddies, etc); and (ii) minimize the corresponding uncertainties. Finally, all these advances were coordinated with the hardware and autonomous software of the AUV.

The results of the FAF05 simulations are encouraging. First, the applications of our scenario-based adaptive sampling and onboard routing schemes were found computationally feasible on-the-ground and underwater, respectively. An interesting result was the impact of the “afternoon effect” on the optimal sampling in this summer period in the Pianosa island area. In the morning, the result of the optimization of the Yo-Yo sampling based on scenarios of ocean-acoustic predictions and assimilation was to sample the whole water column. However, in the afternoon, the optimized result was to sample the whole water column in the first trip but to sample the secondary thermocline (due to stratified afternoon warming of the ocean surface) in the return trip. It was also shown that wind-forced coastal ocean modeling predictions can have forecast skill over small regions, even if the amount of in situ data is very limited. This ocean forecast skill was achieved by assimilation of SST and by adaptively tuning the vertical extension of the SST based on a few sound speed profiles. The adaptive sampling focus on the thermocline opmitized the data collected for this purpose.

The sensitivity of the AUV Yo-Yo behavior to its onboard control parameters was studied in simulations. For the small (2.5 km or less) FAF05 ranges in the Pianosa area, the optimum Yo-Yo parameters were every so often found to be those that make the AUV go up-and-down over the full allowed depth range. This is because over the 2.5 km, the depth of the thermocline was often forecast to be relatively uniform in range: even though it varied from day to day, due to the advection of different ocean features through the small FAF05 operational area, it often remained constant with range. If the experiment area had spanned larger ranges (e.g. 7 to 10 km or more), these upper and lower depth bounds were non-optimal. In that case, the optimal bounds varied with range, as a function of the specific ocean features. The “afternoon effect” was another situation for which variable bounds were found optimal.

In the longer term, our combination of adaptive sampling priors and onboard routing for coupled physics–acoustics aims for optimal autonomous coastal ocean surveillance. Much work remains in this field of research, including the optimal underwater vehicle-to-vehicle and cluster-to-cluster communications as well as optimal ocean sampling for these communications. Adaptive sampling schemes (Lermusiaux, 2007; Heaney et al., 2007; Yilmaz et al., 2008) can also be further researched. Other objectives could also be used for the AREA–ESSE approach, including: minimize oceanic uncertainties (Lermusiaux et al., 2006a) and biological uncertainties (Wang, 2004; Lermusiaux, 2006; Makris et al., 2006), or to objectively evaluate the performance of new REA concepts, such as Acoustically Focused Ocean Sampling (AFOS) (Schmidt et al., 1997) and Acoustic Data Assimilation (ADA) (Elisseeff et al., 2002; Lermusiaux and Chiu, 2002).

The implementation of multi-vehicle AOSNs with robust at-sea hardware and software also requires further research. Underwater behavior modeling is still in its infancy. For example, in the behavior-based control we implemented, although the use of objective functions is designed to coordinate multiple simultaneously-active behaviors, helm behaviors could also be 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 (Brooks, 1986). Examples of this approach, although with different missions and behaviors, are given in (Benjamin et al., 2006a,b).

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