Long-Duration Environmentally-Adaptive Autonomous Rigorous Naval Systems

Progress Report for Period: October 1, 2014 – September 30, 2015

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http://mseas.mit.edu/Research/LEARNS/index.html, http://mseas.mit.edu/

Section I: Project Summary

1. OVERVIEW OF PROJECT

Our long-term goal is to *develop and apply new theory, algorithms and computational systems for the sustained coordinated operation of multiple collaborative autonomous vehicles over long time durations in realistic multiscale nonlinear ocean settings, such that the integrated naval system optimally collects observations, rigorously propagates information backward and forward in time, and accurately completes persistent learning, environmental adaptation, machine metacognition and decision making under uncertainty.*

Specific Objectives:

- Derive, implement and evaluate rigorous and efficient Bayesian smoothing theory and schemes that respect nonlinear dynamics and capture non-Gaussian statistics, for robust persistent inference and learning, integrating information backward and forward in time over long durations in large-dimensional multiscale fluid and ocean dynamics.
- Derive and develop adaptive sampling theories and methods that predict the types and locations of the observations to be collected that maximize information about the ocean system studied (e.g. about its model state variables, parameters and/or formulations)
- Merge and refine our reduced-order DO stochastic equations with our path planning methods, to obtain new stochastic schemes for time-, coordination-, energy-, dynamics- and swarm- optimal path planning that efficiently account for ocean forecast uncertainties.
- Develop efficient onboard routing and high-level adaptation schemes that utilize observations collected by vehicles to autonomously adapt optimal plans (e.g. for paths, sampling strategies, collaboration or decision making process).

- Apply these schemes to simulated fluid and ocean dynamics, from idealized to realistic settings, and integrate these schemes for real sea exercises of opportunity involving distributed computations across components of the autonomous naval sensing systems.

2. ACTIVITIES THIS PERIOD

Optimal Path Planning in Dynamic Environments: Our previous path planning results include the development of an exact PDE-based level-set methodology for time-, coordination-, and energy-optimal path planning that rigorously integrate ocean forecasts with optimal control of autonomous vehicles. In this period, we quantitatively assessed the performance of our algorithms and improved runtime by code optimization. Having completed optimal path planning studies in several idealized and complex realistic multiscale ocean flows, we directed our efforts to publish results (Lolla and Lermusiaux 2015, Lolla et. al. 2015, Subramani et. al. 2015a, Subramani and Lermusiaux 2015, Subramani et. al. 2015b).

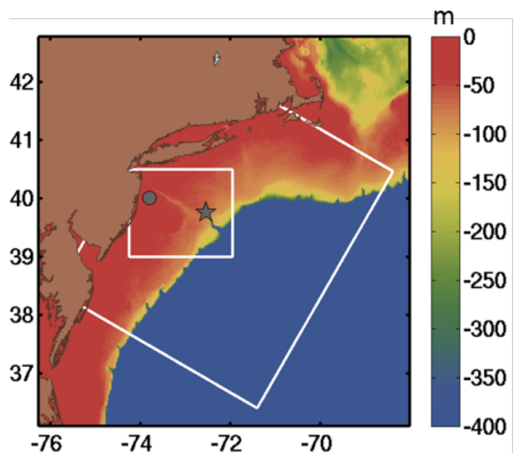

Figure 1: The start point is marked as a circle and the end point is marked as a star, overlaid on bathymetry (colored). The smaller white box is the zoomed part of the domain shown in Fig. 2b

Energy-optimal planning within realistic data-assimilative re-analyses of multiscale coastal ocean flows*:* A stochastic dynamically orthogonal level-set optimization methodology was previously developed for energy-optimal path planning in dynamic flows. To set up the energy optimization, the relative vehicle speed and headings are considered to be stochastic, and new stochastic Dynamically Orthogonal (DO) level-set equations that govern their stochastic time-optimal reachability fronts are derived. Their solution provides the distribution of time-optimal reachability fronts and corresponding distribution of time-optimal paths. An optimization is then performed on the vehicle's energy-time joint distribution to select the energy-optimal paths for each arrival time, among all stochastic time-optimal paths for that arrival time. To objectively analyze and quantify the performance of our methodology, we employed it to perform energy-optimal path planning for vehicles operating in multiscale coastal ocean flows. These flows are realistic data-assimilative re-analyses obtained from multi-resolution 2-way nested primitive-equation simulations of tidal-to-mesoscale dynamics in the Middle Atlantic Bight and Shelf break Front region. We considered a glider released from off the New Jersey coast and travelling to a point in the AWACS region, as shown in Fig. 1. The energy-time joint distribution for the current mission is shown in Fig. 2a, and two paths corresponding to samples marked 1 and 2 are shown in a zoomed part of the domain in Fig. 2b. The effect of tidal currents, strong wind events, coastal jets, and shelfbreak fronts on the energy-optimal paths was quantified. Further figures are available in Subramani et al. (2015) and upon request.

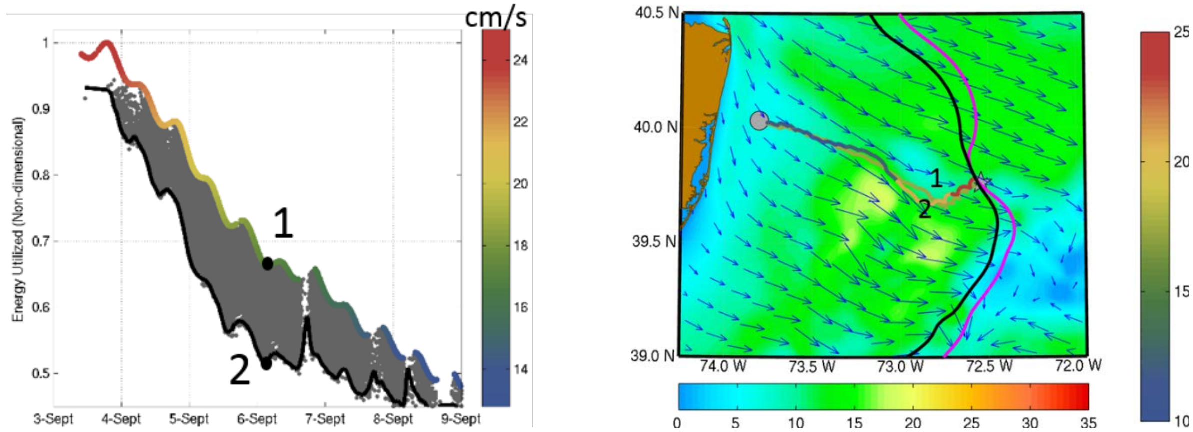

Figure 2 a) Distribution of energy and time for various configurations of vehicle speeds sampled using the switch-sampling algorithm for a mission starting on Aug 28, 2006 00 UTC, in the middle-Atlantic Bight Shelfbreak-front region. The energy-time curve for the constant speed vehicles is colored according to the vehicle speeds. b) The paths traveled by a constant speed vehicle and an energy optimal vehicle, both reaching on 6 Sept. The 24h averaged velocity re-analyses on 6 Sept is colored in the background. The instantaneous vehicle speed (colored) is overlaid on the path. By utilizing the ocean environment intelligently, the energy optimal vehicle expends 26% less energy than the constant speed vehicle.

Time-optimal path planning under uncertainty: Ocean velocity fields in the coastal regions of interest are complex and intermittent, with unstationary heterogeneous statistics. Moreover, due to the limited measurements, there are multiple sources of uncertainties, including the initial conditions, boundary conditions, forcing, parameters and even the model parameterizations and the equations themselves. Therefore, flow forecast uncertainties should be rigorously incorporated in our path planning. We extended the stochastic DO level-set equations to account for uncertainties in the flow field. First, new stochastic DO level set equations with uncertain environmental flows were derived. Next, we implemented these equations and tested them for planning paths in a wind-driven barotropic quasi-geostrophic stochastic double-gyre ocean circulation (these stochastic flow fields are simulated using our DO Navier Stokes equations). The accuracy of the DO level-set equations for solving the governing stochastic level-set reachability fronts was first verified in part by comparing with Monte Carlo solutions. Fig. 3 shows the Frechet distance, which measures the closeness of two closed curves, between the maximum reachable set contours computed by DO and MC. We see that it is less than the spatial resolution used, indicating our DO solutions are accurate. We solved the DO level-set equations and obtained the stochastic distribution of time optimal reachable sets for a constant-speed vehicle operating in the double-gyre. Fig. 4 shows the stochastic reachable sets at four different times. Each level-set realization is colored by its respective optimal arrival time. We note that the reachable sets 'flip-over' due to the flow structures, i.e., for certain endpoints, the optimal path that a vehicle takes for a particular realization of the flow field differs from the path taken for another flow field realization. This means that in long endurance missions where path variability needs to be minimized, certain end points should be avoided. Further figures are available in Wei (2015).

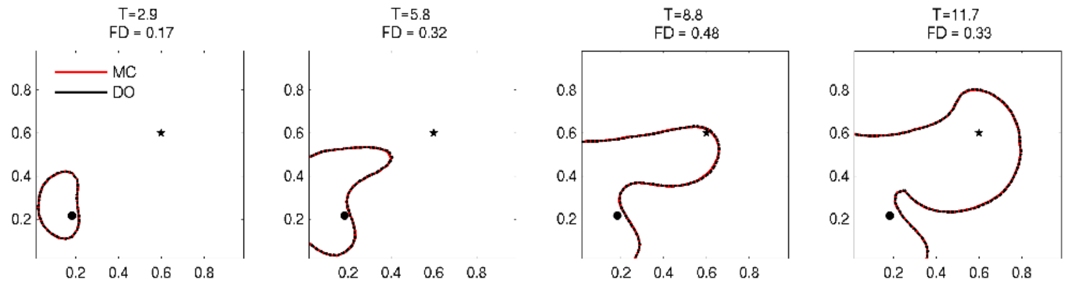

Figure 3 (Top): Comparison of the reachable set computed by DO (black) and MC (red) at 4 non-dimensional times. The frechet distance between the maximum reachable set (i.e. the zero level-set contour) as a ratio of grid spacing is also indicated.

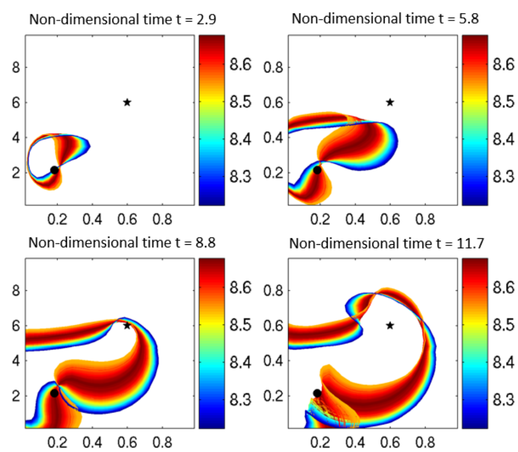

Figure 4 (Right): Distribution of reachable sets shown at 4 non-dimensional time for stochastic time-optimal path planning in stochastic double-gyre flow. Each realization of the reachable set is colored with its respective optimal arrival times

GMM-DO Smoother: We derived and developed the GMM–DO smoother, a novel scheme for retrospective Bayesian inference of high–dimensional stochastic fields governed by general nonlinear dynamics (Lolla, 2015, Lolla and Lermusiaux, MWR-2015-sub). The smoother carries out Bayesian inference both forward and backward in time, while retaining the non–Gaussian structure of all the state variables. It uses the stochastic DO PDEs and their time–evolving stochastic subspace to predict the prior probabilities. The forward and backward Bayesian inference is then analytically carried out in the dominant DO subspace, after fitting semi-parametric Gaussian Mixture Models (GMMs) to the DO realizations. We illustrated and assessed the performance of the GMM–DO smoother using several realistic fluid flows governed by nonlinear and noisy dynamics. We demonstrated a superior performance of the GMM–DO smoother when compared to various Gaussian smoothers, such as the ESSE smoother and Ensemble Kalman Smoother. We also validated the GMM–DO smoother using the example of a passive tracer transported by an analytical flow–field, wherein the exact smoothed variables can be determined numerically by reversing the flow starting from the GMM-DO solution at the final simulation time. Fig. 5 compares the mean tracer field of the GMM–DO smoother with the exact smoothed mean at assimilation times. We observe that the mean field of the smoother closely matches the mean field of the exact smoothed solution at all times. The normalized RMS difference between these quantities is plotted in Fig. 6b. At the final time, the error is zero. As we approach time t = 0, the GMM-DO smoother mean begins to only slightly depart from the exact smoothed mean, owing to the approximations in the joint subspace GMM fits. Nonetheless, the GMM–DO smoother mean remains within 1% of the exact smoothed mean throughout the time window of interest. Fig. 6a compares the result of the GMM-DO filter and the GMM-DO smoother, using RMS error as the performance criterion. The filter error, initially as high as 17%, reduces to a final value of 6% after all observations are assimilated. The smoother maintains this error level throughout the window of interest, thereby achieving a significant improvement over the filtered solution.

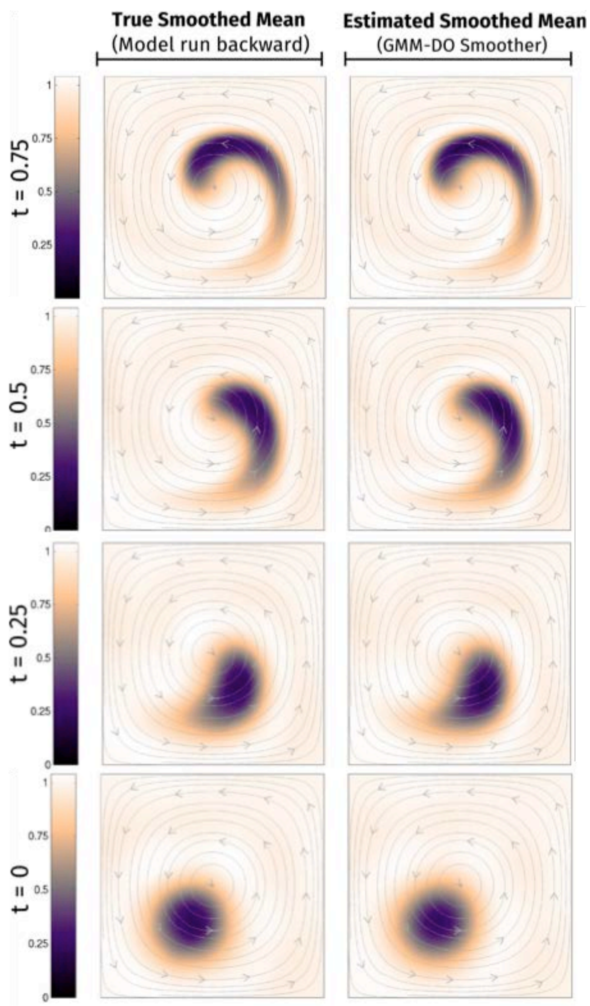

Figure 5: Passive Tracer Advection in Swirl Flow: Time–evolution of the mean tracer field estimated by the GMM–DO smoother plotted alongside the corresponding exact smoothed mean field. The exact smoothed mean is computed by reversing the flow from the final filtered solution.

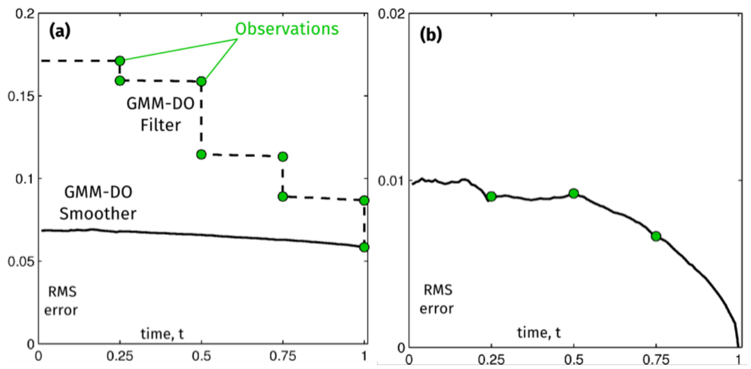

Figure 6: Passive Tracer Advection in Swirl Flow: (a) Normalized RMS difference between the mean estimates of the GMM–DO smoother (solid)/GMM–DO filter (dashed) and the true tracer field. We see that the smoother mean is much closer to the truth than the filter mean at the corresponding time. (b) Normalized RMS error between the smoother mean and the exact smoothed solution, computed by reversing the flow from the final–time filter solution.

Adaptive Sampling and Mutual Information

We derived two theories for adaptive sampling that exploit the nonlinear dynamics of the system and capture the non-Gaussian structures of the stochastic fields. The optimal observation locations are determined by maximizing the *mutual information* between the candidate observations and the future verification variables of interest. Building on the foundations of the GMM-DO smoother, we first developed an efficient technique to quantify the spatially and temporally varying mutual information field in general nonlinear dynamical systems. The panels of Fig. 7 depict the time-evolution of the mutual information field with respect to the starred point of interest at verification time t_v=1, for a passive tracer advected by a reversible swirl flow. It is evident that the region with the largest mutual information is initially localized towards the bottom right of the domain, while the rest of the domain provides comparatively much lesser information about the tracer concentration at the point of interest. As time progresses, the peak of the mutual information approaches the point of interest. Moreover, the entire mutual information field behaves as a tracer field getting advected by the swirl flow. Similar studies were completed for other fluid dynamical systems such as stochastic flows exiting a strait/estuary and stochastic wind-driven double gyre flows. The effects of varying the point of interest and the verification time were also investigated. The results showed that the mutual information field is largely driven by the physics of flow transport (due to advection) and mixing (due to diffusion).

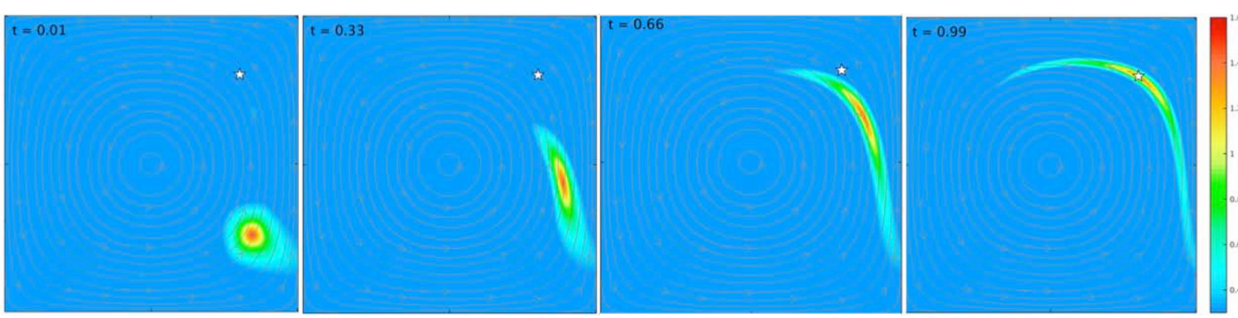

Figure 7: Mutual information field of a passive tracer advected by a reversible swirl flow: Snapshots of the time-varying mutual information field with respect to a given point of interest (depicted as a star). The informative region, initially circular in shape, gets deformed as time progresses and also approaches closer to the point of interest.

(a) Short-term lookahead method for integrated adaptive sampling and path planning: We developed a short–term lookahead approach for adaptive sampling that sequentially identifies the optimal observation sites based on short-term predictions of reachable sets using our level-set methodology for forward reachability. The optimal observation sites at the next assimilation time are identified as the reachable locations at that time, which maximize the mutual information with respect to the future verification variables. Mobile sensors are navigated to their short-term optimal observation sites, and their measurements are assimilated in order to obtain the posterior densities of the state variable.

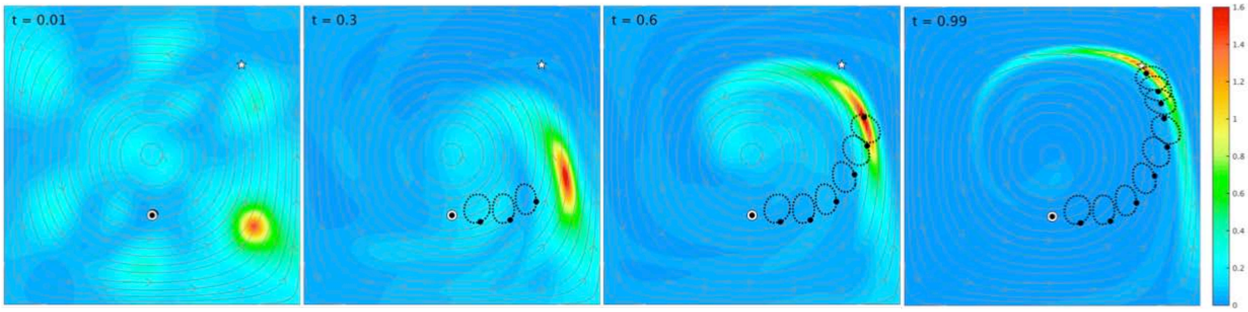

Figure 8: Short–term Lookahead Method (Single Sensor): Time–evolution of the sensors' sampling locations. Various panels depict the short–term reachability fronts of the sensor at the times indicated. The reachability fronts at previous assimilation times are shown as dashed curves. The optimal short–term observation sites are shown as black markers.

Hence, this method for adaptive sampling integrates the computation of mutual information fields with the predictions of the sensors' forward reachable sets. As the search for the most informative sites is restricted to the interior of the sensors' reachable sets, all the physically impossible trajectories are immediately ruled out. However, this approach is myopic and can yield locally optimal solutions, as the search for optimal observation sites is limited to the reachable sets at the next observation time, but not those beyond. Addressing this issue, we developed a globally optimal method for integrated adaptive sampling and path planning, described next.

(b) Globally optimal method for integrated adaptive sampling and path planning: Building on the short–term lookahead approach, we developed a novel, globally optimal method for integrated adaptive sampling and path planning. To determine the sampling strategy, this method considers the impact of informative zones beyond the next observation time. It first predicts the set of reachable locations at all subsequent observation times, thereby implicitly populating an exhaustive set of candidate sampling trajectories. The globally optimal sampling sequence is rigorously and efficiently computed using a Dynamic Programming (DP) formulation of the governing optimization. The results are exemplified and the performance of the method was quantitatively assessed using a variety of realistic test cases.

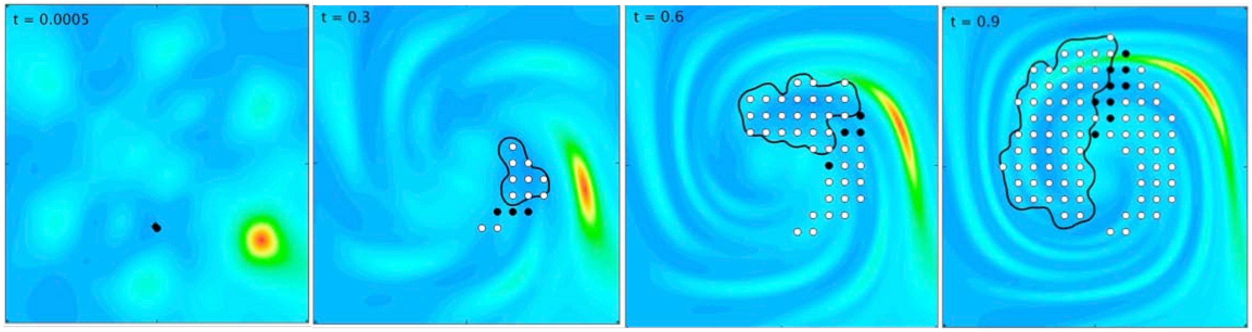

Figure 9: Globally optimal method for adaptive sampling: Various panels depict the reachable observation sites (both present and past) computed using our level set method for forward reachability. These discrete locations form the search space for the globally optimal sequence of future observation locations.

The panels of Fig. 9 depict the set of reachable observation sites at different observation times, computed using our level-set method for reachability. The set of reachable sites naturally grows with time-it starts off as a singleton at the time of deployment, and eventually expands to cover a large portion of the domain at the final observation time. The optimal sequence of future sampling locations is determined from within this set of reachable observation sites by carrying out a DP recursion backward in time. Fig. 10 shows the result of this optimization at the deployment time. The optimal sequence of future observation sites is marked in black. As the mobile sensor performs measurements, the underlying state fields and the sampling strategies are recomputed by accounting for the new information. The above two methods for integrated adaptive sampling and path planning were also extended to the case of swarms of mobile sensors operating simultaneously.

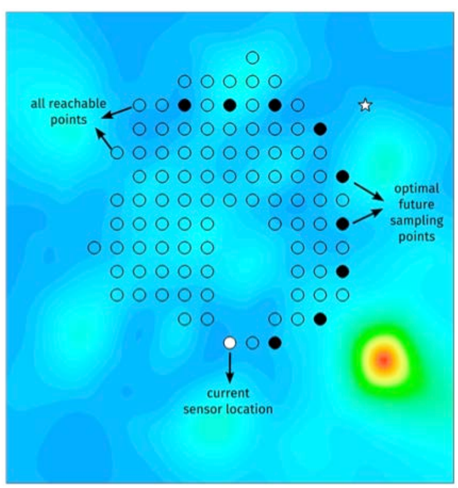

Figure 10: The globally optimal sequence of future sampling locations (marked in black), selected from within the reachable observation sites (not shaded).

Pursuit-Evasion Games in Dynamic Flow Fields.
In collaboration with Prof. P. Tsiotras and his student W. Sun (Sun et al., ACC-2015-sub), we utilized our reachability set analysis equations and software to deal with the pursuit-evasion differential game between two players in the presence of dynamic environmental disturbances (e.g., winds, sea currents). We give conditions for the game to be terminated in terms of reachable set inclusions. Level set

equations are defined and solved to generate the reachable sets of the pursuer and the evader. The corresponding time-optimal trajectories and optimal strategies can be retrieved immediately afterwards. We validated the method by applying it to pursuit-evasion games in both simple and more realistic flow fields.

3. SIGNIFICANCE OF RESULTS

Our energy optimal path planning results showcase the energy saving opportunities for longer-duration missions that intelligently utilize the ocean environment, rigorously integrating ocean forecasting with optimal control of autonomous vehicles. Such an integration has been completed for the first time and may lead to a paradigm shift in the science of autonomy. The extension of the new stochastic DO level-set equations to account for uncertain flow environments allows us to perform decision making under uncertainty efficiently and rigorously.

Our results on optimal Bayesian inference in high dimensional nonlinear stochastic dynamical systems, both forward and backward in time have important applications in geophysical systems, ocean modeling and prediction, meteorology and numerical weather prediction. In particular, smoothing has a critical role to play in reanalysis, target tracking, identification of sources of environmental pollutants, adjustment of ocean forcings in numerical simulations, estimation of numerical boundary conditions etc. By addressing how to accurately propagate information from observations backward in time, we provide a significant advance over traditional inference schemes based on the classic Kalman smoother.

Our results on optimal integrated adaptive sampling provide real-time computational intelligence for collaborative swarms of autonomous sensing vehicles. The integrated system can guide groups of vehicles along predicted optimal trajectories and continuously improve field estimates as they collect the most informative observations. The optimal sampling locations and optimal trajectories are continuously forecast, all in an autonomous and coordinated fashion.

4. PLANS AND UPCOMING EVENTS FOR NEXT FISCAL YEAR

We first plan to further analyze the GMM-DO smoother in high dimensional systems, including comparison with other smoothers, both Gaussian and non-Gaussian. We will start implementing and improving such schemes in realistic codes for physical, biological and acoustic ocean dynamics. We expect to further develop, optimize and implement our adaptive sampling schemes based on dynamic mutual information fields. We intend to further develop theory and schemes on “adaptive sampling swarms” and “artificial intelligence for collaborative swarms”. We plan to study the effect of uncertain stochastic ocean predictions on the optimal path planning, both for single paths and for coordinated paths maintaining vehicle formations. We also plan to continue working on onboard routing using data assimilation updates and to initiate research towards other optimality criteria such as dynamics-optimal and swarm-optimal. We plan to further integrate our Bayesian smoothing, adaptive sampling and path planning to enable long-duration environmentally-adaptive autonomous rigorous naval systems. We plan to continue transferring the methods and algorithms to NRL. We expect to continue to apply our work to realistic ocean fields and/or participate to sea exercises, aiming to couple ocean-acoustic predictions, uncertainty prediction, autonomous strategies for learning and swarming, with all feedbacks. We will continue to report our findings and enable knowledge transfer through publications and participation in technical conferences.

5. RECOMMENDED READING

Lermusiaux P.F.J, T. Lolla, P.J. Haley. Jr., K. Yigit, M.P. Ueckermann, T. Sondergaard and W.G. Leslie, 2015. *Science of Autonomy: Time-Optimal Path Planning and Adaptive Sampling for Swarms of Ocean Vehicles*. Chapter 11, Springer Handbook of Ocean Engineering: Autonomous Ocean Vehicles, Subsystems and Control, Tom Curtin (Ed.), In press.

Lolla, T., Lermusiaux, P. F. J., Ueckermann, M. P. and Haley Jr, P. J. (2014a). *Time-optimal path planning in dynamic flows using level set equations: theory and schemes*. Ocean Dynamics, 64(10), 1373-1397. DOI: 10.1007/s10236-014-0757-y

Lolla, T., Haley Jr, P. J. and Lermusiaux, P. F. J. (2014b). *Time-optimal path planning in dynamic flows using level set equations: realistic applications*. Ocean Dynamics, 64(10), 1399-1417. DOI: 10.1007/s10236-014-0760-3

Subramani, D.N., T. Lolla, P.J. Haley and P.F.J Lermusiaux, 2015. A stochastic optimization method for energy-based path planning. In: Ravela, S., Sandu, A. (Eds.), DyDESS 2014. Vol. 8964 of LNCS. Springer, pp. 1–12.

Sondergaard, T. and P.F.J. Lermusiaux, 2013a. *Data Assimilation with Gaussian Mixture Models using the Dynamically Orthogonal Field Equations. Part I. Theory and Scheme*. Monthly Weather Review, 141, 6, 1737-1760, doi:10.1175/MWR-D-11-00295.1.

6. TRANSITIONS/IMPACT

We met with (and provided theory and software to) different NRL researchers. We transfer results to ONR-supported PIs. Mr. Matt Swezey - LT USN is working on his SM with our group on coupled ocean physics and acoustics uncertainty forecasts for subsurface counter-detection. We continue to work with NRL-Stennis for transition possibilities. We maintain a software web-page for the distribution of our results. MIT undergraduates are involved in this research. They are sponsored by MIT's Undergraduate Research Opportunities Program (UROP). Undergraduates completed research and their senior thesis with us on the science of autonomy. Material from this project is used in MIT courses. Companies (e.g. air transports, shipping) and research labs (e.g. MIT Lincoln Lab) contact us for our methods, software and ongoing collaborations.

7. COLLABORATIONS

We collaborate with several ONR-supported PIs and had meetings with other PIs in the Science of Autonomy program. We completed and submitted a joint publication (with Prof. P. Tsiotras and his student W. Sun) because of the Science of Autonomy meetings. Collaborations occurred with our related ONR project "Stochastic Forcing for Ocean Uncertainty Prediction" (N00014-12-1-0944) and Naval Research Laboratory – Stennis project (N00173-13-2-C009). Visitors from the NATO CMRE research center and Pisa/Bologna Universities were also given methods and software.

8. PERSONNEL SUPPORTED

Principal Investigator: Dr. Pierre F.J. Lermusiaux

Graduate Students: Tapovan Lolla, Deepak Subramani

Research staff: Dr. Patrick Haley Jr.

Undergraduate Students: Quantum Wei, Sina Booeshaghi (both for free to this grant and ONR)

List of any students previously supported by the program who have taken positions performing DoD relevant research and where they have gone

9. PUBLICATIONS

Publications resulting from this project (some of these publications started as part of N00014-09-1-0676):

Journal Articles

Lermusiaux P.F.J, T. Lolla, P.J. Haley. Jr., K. Yigit, M.P. Ueckermann, T. Sondergaard and W.G. Leslie, 2015. *Science of Autonomy: Time-Optimal Path Planning and Adaptive Sampling for Swarms of Ocean Vehicles*. Chapter 11, Springer Handbook of Ocean Engineering: Autonomous Ocean Vehicles, Subsystems and Control, Tom Curtin (Ed.). In press.

Lolla, T. and P.F.J. Lermusiaux, 2015. *A Forward Reachability Equation for Minimum-Time Path Planning in Strong Dynamic Flows*. SIAM Journal on Control and Optimization, sub-judice.

Lolla, T., P.J. Haley. Jr. and P.F.J. Lermusiaux, 2015. *Path Planning in Multi-scale Ocean Flows: Coordination and Dynamic Obstacles. Ocean Modelling*, 94, 46-66.

Lolla, T. and P.F.J. Lermusiaux, 2015. *Gaussian-Mixture Model – Dynamically Orthogonal Smoothing for Continuous Stochastic Dynamical Systems*. Monthly Weather Review. To be submitted.

Subramani, D.N. and P.F.J. Lermusiaux, 2015. *Energy-Optimal Path Planning by Stochastic Dynamically Orthogonal Level-Set Optimization*. Ocean Modeling, sub-judice.

Subramani, D.N., P.J. Haley. Jr. and P.F.J. Lermusiaux, 2015b. *Energy-Optimal Path Planning in Coastal Oceans: Integrating Re-analyses with Stochastic DO Level-Set Optimization*. Ocean Dynamics. To be submitted.

Conference Papers

Cococcioni M., B. Lazzerini and P.F.J. Lermusiaux, 2015. *Adaptive Sampling Using Fleets of Underwater Gliders in the Presence of Fixed Buoys using a Constrained Clustering Algorithm*. Proceedings of IEEE OCEANS'15 Conference, Genoa, Italy, 18-21 May, 2015.

Petillo, S., H. Schmidt, P.F.J. Lermusiaux, D. Yoerger and A. Balasuriya, 2015. *Autonomous & Adaptive Oceanographic Front Tracking On Board Autonomous Underwater Vehicles*. Proceedings of IEEE OCEANS'15 Conference, Genoa, Italy, 18-21 May, 2015.

Subramani, D.N., T. Lolla, P.J. Haley and P.F.J Lermusiaux, 2015a. *A stochastic optimization method for energy-based path planning*. In: Ravela, S., Sandu, A. (Eds.), DyDESS 2014. Vol. 8964 of LNCS. Springer, pp. 1–12.

Sun, W., P. Tsiotras, T. Lolla, D.N. Subramani, and P.F.J. Lermusiaux, 2016. *Pursuit-Evasion Games in Dynamic Flow Fields via Reachability Set Analysis*. American Control Conference 2016. Sub-judice.

Other Publications

Lolla, T., 2015. Path Planning and Adaptive Sampling in the Coastal Ocean. Ph.D. Thesis, Massachusetts Institute of Technology, Dept. of Mechanical Engineering, Feb. 2016.

Wei, Q.J., 2015. Time-Optimal Path Planning in Uncertain Flow Fields Using Stochastic Dynamically Orthogonal Level Set Equations, B.S. Thesis, Massachusetts Institute of Technology, Dept. of Mechanical Engineering, June 2015.

Cumulative List of Journal Articles

Lolla, T., Lermusiaux, P. F. J., Ueckermann, M. P. and Haley Jr, P. J. (2014a). *Time-optimal path planning in dynamic flows using level set equations: theory and schemes*. Ocean Dynamics, 64(10), 1373-1397. DOI: 10.1007/s10236-014-0757-y

Lolla, T., Haley Jr, P. J. and Lermusiaux, P. F. J. (2014b). *Time-optimal path planning in dynamic flows using level set equations: realistic applications*. Ocean Dynamics, 64(10), 1399-1417. DOI: 10.1007/s10236-014-0760-3

Lermusiaux P.F.J, T. Lolla, P.J. Haley. Jr., K. Yigit, M.P. Ueckermann, T. Sondergaard and W.G. Leslie, 2015. *Science of Autonomy: Time-Optimal Path Planning and Adaptive Sampling for Swarms of Ocean Vehicles*. Chapter 11, Springer Handbook of Ocean Engineering: Autonomous Ocean Vehicles, Subsystems and Control, Tom Curtin (Ed.). In press.

Lolla, T. and P.F.J. Lermusiaux, 2015. *A Forward Reachability Equation for Minimum-Time Path Planning in Strong Dynamic Flows*. SIAM Journal on Control and Optimization, sub-judice.

Lolla, T., P.J. Haley. Jr. and P.F.J. Lermusiaux, 2015. *Path Planning in Multi-scale Ocean Flows: Coordination and Dynamic Obstacles*. Ocean Modelling, 94, 46-66.

Lolla, T. and P.F.J. Lermusiaux, 2015. *Gaussian-Mixture Model – Dynamically Orthogonal Smoothing for Continuous Stochastic Dynamical Systems*. Monthly Weather Review. To be submitted.

Subramani, D.N. and P.F.J. Lermusiaux, 2015. *Energy-based Path Planning by Stochastic Dynamically Orthogonal Level-Set Optimization*. Ocean Modeling, sub-judice.

Subramani, D.N., P.J. Haley. Jr. and P.F.J. Lermusiaux, 2015b. *Energy-Optimal Path Planning in Coastal Oceans: Integrating Re-analyses with Stochastic DO Level-Set Optimization*. Ocean Dynamics, To be submitted.

Sun, W., P. Tsiotras, T. Lolla, D.N. Subramani, and P.F.J. Lermusiaux, 2016. *Pursuit-Evasion Games in Dynamic Flow Fields via Reachability Set Analysis*. American Control Conference 2016. Sub-judice.

10. Point of Contact in Navy

Jen Landry - LCDR U.S. Navy, 08/26/2014
Matt Swezey - LT US Navy, 10/06/2015
Ruth Preller (NRL Stennis), 09/01/2015
Gregg Jacobs (NRL Stennis), 02/01/2015
Charlie Barron (NRL Stennis), 09/20/2015
Ira Schwartz (NRL - DC), 08/11/2015
Steve Rutherford (OPNAV N2/N6E), 11/01/2012

11. Acknowledgement/Disclaimer

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Section II: Project Metrics

Long-Duration Environmentally-Adaptive Autonomous Rigorous Naval Systems

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http://mseas.mit.edu/Research/LEARNS/index.html, http://mseas.mit.edu/

12. Metrics

[Please include each of the following metrics. If none, please indicate N/A.]

Number of faculty supported under this project during this reporting period: 0.7 month

Number of post-doctoral researchers supported under this project during this period: 0

Number of graduate students supported under this project during this reporting period: 1.5

Number of undergraduate students supported under this project during this period: 0 (2 for free)

Number of refereed publications during this reporting period for which at least 1/3 of the work was done under this effort: 8

Number of publications (all) during this reporting period: 8

Number of patents during this reporting period: 0

Number of M.S. students graduated during this reporting period: 0

Number of Ph.D. students graduated during this reporting period: 1

Awards received during this reporting period: 2

D. Subramani, Best poster award, "A Stochastic Optimization Method for Energy-based Path Planning" at the Computations for Design and Optimization / Computational Eng. Symposium 2015

D. Subramani and T. Lolla, "2015 de Florez Design Competition", Honorable Mention award

D. Subramani, PhD Student, Esteemed Presenter award in the Best Theoretical or Computational Category at the Mechanical Engineering Research Exhibition (MERE) 2015.

13. 1-2 paragraph summary of all accomplishments for the entire grant

Nine refereed publications on our time-optimal and energy-optimal path planning were published or completed and submitted. We developed an exact PDE-based level-set methodology for time-, coordination-, and energy- optimal path planning that rigorously integrate ocean forecasts with optimal control of autonomous vehicles. We employed the stochastic dynamically orthogonal level-set optimization methodology to compute energy-optimal paths (vehicle speeds and headings) of gliders missions operating in the New Jersey shelf/Middle-Atlantic Bight Shelfbreak front region. The energy-optimal planning is performed with realistic multiscale ocean re-analyses obtained from multi-resolution 2-way nested primitive-equation simulations of the tidal-to-mesoscale dynamics in this region. We analyzed the effects of tidal currents, strong wind events, coastal jets, and shelfbreak fronts on energy-optimal paths for these missions. Results showcase the opportunities for longer-duration missions that intelligently utilize the ocean environment to save energy, rigorously integrating ocean forecasting with optimal control of autonomous vehicles. Stochastic DO level-sets were extended to incorporate uncertainty in the environmental flows and used to analyze time-optimal path planning in stochastic wind driven barotropic quasi-geostrophic ocean circulation. Results predicted the stochastic reachable sets and minimum uncertainty paths for missions operating in such probabilistic flows.

We also developed two novel theories for adaptive sampling that accurately capture the non-Gaussian structures of the stochastic fields, and exploit the nonlinear dynamics of the system. They facilitate an efficient usage of observational platforms by accounting for the predicted effects of their measurement and the current distribution of uncertainty in the system. Optimal observation sites are determined by maximizing the mutual information between the candidate observations and the variables of interest. We also developed a novel Bayesian smoother for high-dimensional continuous stochastic fields governed by general nonlinear dynamics. This smoother combines the adaptive reduced-order Dynamically-Orthogonal equations with Gaussian Mixture Models, extending linearized Gaussian backward pass updates to a nonlinear, non-Gaussian setting. The Bayesian information transfer, both forward and backward in time, is efficiently carried out in the evolving dominant stochastic subspace. Building on the foundations of the smoother, we then derived an efficient technique to quantify the spatially and temporally varying mutual information field in general nonlinear dynamical systems. The globally optimal sequence of future sampling locations is rigorously determined by a novel dynamic programming approach that combines this computation of mutual information fields with the predictions of the forward reachable set. All the results were exemplified and their performance was quantitatively assessed using a variety of simulated fluid and ocean flows.

14. A list of which items on the SOW will be worked on during FY16 (Oct 2015 to Sept 30 2016). Please give this to me as narrative text and not just as a list of numbers from your proposal. Please divide by base and potential option if you have both.

We will further analyze the GMM-DO smoother in high dimensional systems, including comparison with other smoothers, both Gaussian and non-Gaussian. We will start implementing and improving such schemes in realistic codes for physical, biological and acoustic ocean dynamics. We expect to further develop, optimize and implement our adaptive sampling schemes based on dynamic mutual information fields. We plan to develop theories and schemes on adaptive sampling swarms and artificial intelligence for collaborative swarms, accounting for uncertain stochastic ocean predictions in our planning schemes, both for single paths and for coordinated paths maintaining vehicle formations. We also plan to investigate other optimality criteria such as dynamics-optimal and swarm-optimal. We plan to start integrating our novel smoothing, adaptive sampling and path planning to enable long-duration environmentally-adaptive autonomous rigorous naval systems. We plan to continue to transfer the methods and algorithms to NRL. We expect to continue to apply our work to four-dimensional realistic ocean fields and/or participate to sea exercises, aiming to couple ocean-acoustic predictions, uncertainty prediction, autonomous strategies for learning and swarming, with all feedbacks. We will continue to report our findings and enable knowledge transfer through publications and participation in technical conferences.

15. If you are in your final year, will you require a no-cost extension to your period of performance? If so, until when?

- N/A

16. 1 summary PowerPoint slide of your entire project in any format. This should be something I can use to brief your effort to an external audience at a professional society meeting or to explain the significance of your work to my management in a few minutes when I am overviewing my entire program.

See attached