Learning Identification Models for In-situ Sampling of Ocean features

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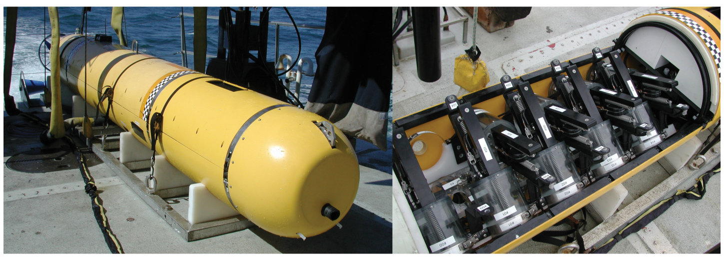

Fig. 1. MBARIs Dorado AUV with its water samplers

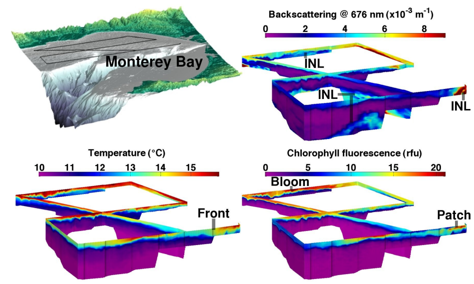

Fig. 2. Coastal ocean phenomena targeted for studies using adaptive control on a robust operational AUV. Along the black surface tracks from a Sept. '07 mission, the AUV executed a vertical Yo-Yo to map the water column in high-resolution for key phenomena such as fronts, intermediate nepheloid layers (INLs), and phytoplankton blooms and patches

I. In-situ Sampling of Ocean Features

The coastal ocean is a rich and dynamic environment with a multitude of features with interacting biogeochemical phenomenon. Land-sea interactions result in processes often interacting with one another over unpredictable spatio-temporal extants. Fig. 2 for example is a representation of three selected phenomena: fronts, Intermediate Nepheloid Layers ([McPhee-Shaw, 2006]), and blooms, each of which can occur over a wide range of spatial scales, from thousands of kilometers (fronts and blooms) down to tens/hundreds of meters.In recent years, robotic platforms such as floats, autonomous profilers, buoys and autonomous underwater vehicles (AUVs) have provided a non-intrusive, and a repeatable and verifiable way of observing the oceans up close, augmenting the data provided by existing methods cost-effectively. Because of the need for sustained observing presence, it has become important to use the platforms to not only measure time-series data routinely [Chavez et al., 1997] and detection of thin phytoplankton layers but for event response situations such as oil-spills and weather events and sampling eddies [Bower, 2007].

While they're often cost-effective and can sustain themselves for increasing duration, their effectiveness has been limited because of a lack of adaptivity given the dynamism of the features in question. To be effective, these platforms need to be able to *sense* their features, and be responsive to what has been sensed and do so in-situ; for example an AUV could alter its navigation or control goals to change direction or its control law to yo-yo through a thin layer when the latter is detected. Or a profiling float while dormant could periodically sample its environment, and be awake to a passing layer in a front and rapidly alter its sampling behavior. Such needs have been prevelant for a while; [Rudnick and Perry, 2003] for example outlines the need for sampling transient and rapidly evolving events with autonomous platforms. A primary problem to meet such needs, has been to deal with in-situ identification of feature of interest, none of which can be modeled deterministically.

Our previous work [Fox et al., 2007] addressed in-situ identification as a standard classification of water-column features. In such cases, identification relied only on the current sensor reading ignoring the past. We present a novel effort in generating a systematic *identification* model based on Hidden Markov Models (HMMs) for environmental state estimation and doing so in-situ embedded in a robotic platform. HMMs [Rabiner, 1989] use the dynamics of classes to exploit sequential information of the sensor readings which provide us with more robust identification than standard classification. Our objectives are to use such HMMs and to dynamically learn ocean features using MBARIs *Dorado* AUV.

II. Learning Identification Models

We have designed a general purpose two-step machine learning process that automatically builds the identification model of a specific feature of interest. Fig. 3 shows an overview of this process. The input is a collection of raw sensor data; the output is the identification model for the corresponding feature. This model presents the form of a Hidden Markov Model. Unlike identification models based on traditional classifiers, HMMs can use the dynamics of classes to exploit sequential information of the sensor readings which provide us with more robust identification. The states of the HMM represent the states of the feature to identify and the HMM observations represent values of the platforms sensors. Therefore, the learned HMMs capture the relationship between

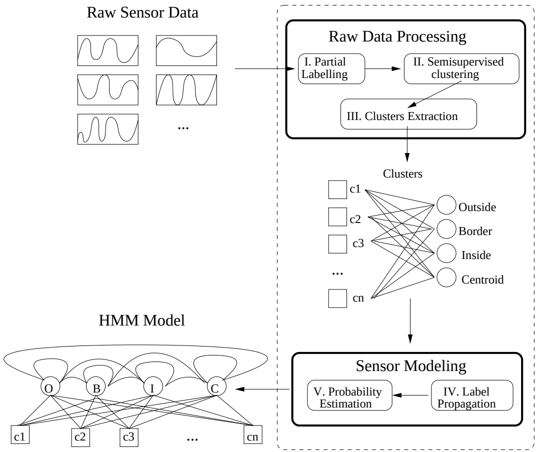

Fig. 3. Two-step proccess for the automated building of identification models

the possible sensor readings and the states of a given feature of interest, as well as the transitions of the feature states as the platform transitions thru the feature in the coastal ocean. As an example, the HMM generated in Fig. 3 is built for the identification of four different locations of the feature of interest: **O***utside* the feature, at the **B***oundary*, **I***nside* the feature or at the **C***entroid* of the feature driven by our studies of Intermediate Nepheloid Layers (INLs) [McPhee-Shaw, 2006, Ryan et al., 2010] and their science requirements.

First we perform a semi-supervised clustering in this two-step machine learning process, that discretizes the raw sensor data. Second, we include the found clusters as observations of the HMM and adjusts the parameters of the HMM to the historical data we have. The most effective algorithms for learning the probabilities of an HMM (step V of Fig. 3) are based on Expectation Maximization (EM) techniques that require input data completely labeled [Rabiner, 1989]. However, completely labelling sensor data is usually not viable. An AUV water-column survey of few hours with sensors sampling at 4 to 5 Hz will generate a substantial volume of raw sensor data with a corresponding amount of effort in labelling. Our aim then, is to make our approach viable; in the process we introduce a preliminary step of automatic label propagation (step IV of Fig. 3) that allows experts to only label a small fraction of the data. Label propagation relies on a set of prototypes (clusters) of the different sensor readings. This set of clusters is found completing a semi-supervised generalization (steps II and III in Fig. 3) over sensor readings partially labelled by a scientific expert (step I in Fig. 3).

III. Usage of Identification Models

Our approach exploits the resulting HMM for in-situ event response as follows. The HMM is executed on-board a platform like an AUV, to identify the diverse states of a given feature of interest as the platform transits through it. This identification is based on feature state predictions computed with the built HMM and the observed sensor values. In particular, we are interested in the probability of being in a given state s_j (for purposes of robotic actuation) at the current step t, i.e., $fwd(1:t, s_j)$. This probability is computed using the *Markov property*, i.e., that the state at the current time depends *only* on the state at the previous step.

$$fwd(1:t, s_j) = \alpha_t P(Y_t = o_k | X_t = s_j) \sum_i P(X_t = s_j | X_{t-1} = s_i) P(X_{t-1} = s_i)$$

where $alpha_t$ is a normalization factor and $\sum Prob(X_t = s_i) = 1$. The initial state of the HMM is **O**`utside`, therefore $Prob(X_0 = \texttt{Outside}) = 1$ and $Prob(X_0 = \texttt{Inside}) = 0$, $Prob(X_0 = \texttt{Boundary}) = 0$ and $Prob(X_0 = \texttt{Centroid}) = 0$. When continuous sensor data triggers an HMM state transition which has been marked as being of interest, the HMM can track the continuous state till an appropriate threshold can trigger a response on a robotic platform leading to adaptation in its control strategy. This is a promising a new approach to efficient measurement and sample collection with an initial demonstration for capturing water samples within INLs in the Monterey Bay.

Our at sea experiments this Fall, are based on the continum of work with oceanographers using AUVs outfitted with the Gulper water sampling instrument [McGann et al., 2008a]. We have designed, built, tested and deployed and onboard hybrid planning and execution system called TREX (the Teleo-Reactive Executive) [McGann et al., 2008b, McGann et al., 2008a, McGann et al., 2009, Py et al., 2010] which is built around the paradigm of sense-plan-act. While previous versions of the HMM have been manually generated using statistical clustering methods such as Self Organizing Maps (SOM) and labelled, our current approach will synthesize more complex HMMs as a way to finely tune when and where water samples should be taken in dynamic environments such as Monterey Bay.

References

[Bower, 2007] Bower, A. (2007). Irminger rings project: Impact of irminger rings on deep convection in the labrador sea.

[Chavez et al., 1997] Chavez, F., Pennington, J., Herlien, R., Jannasch, H., Thurmond, G., and Friederich, G. (1997). Moorings and drifters for real-time interdisciplinary oceanography. *Journal of Atmospheric and Oceanic Technology*, 14:1199–1211.

[Fox et al., 2007] Fox, M., Long, D., Py, F., Rajan, K., and Ryan, J. P. (2007). In-Situ Analysis for Intelligent Control. In *Proc. of IEEE/OES OCEANS Conference*.

[McGann et al., 2009] McGann, C., Py, F., Rajan, K., and Olaya, A. (2009). Integrated Planning and Execution for Robotic Exploration. In *Intnl. Workshop on Hybrid Control of Autonomous Systems, in IJCAI09*, Pasadena, California.

[McGann et al., 2008a] McGann, C., Py, F., Rajan, K., Ryan, J. P., and Henthorn, R. (2008a). Adaptive Control for Autonomous Underwater Vehicles. In *Assoc. for the Advancement of Artificial Intelligence, National Conference (AAAI)*, Chicago, IL.

[McGann et al., 2008b] McGann, C., Py, F., Rajan, K., Thomas, H., Henthorn, R., and McEwen, R. (2008b). A Deliberative Architecture for AUV Control. In *IEEE International Conference on Robotics and Automation (ICRA)*, Pasadena, CA.

[McPhee-Shaw, 2006] McPhee-Shaw, E. (2006). Boundary-interior exchange. reviewing the idea that internal-wave mixing enhances lateral dispersal near continental margins. *Deep-Sea Research II*, 53:45–49.

[Py et al., 2010] Py, F., Rajan, K., and McGann, C. (2010). A Systematic Agent Framework for Situated Autonomous Systems. In *9th International Conf. on Autonomous Agents and Multiagent Systems*, Toronto, Canada.

[Rabiner, 1989] Rabiner, L. R. (1989). A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition. In *Proceedings of the IEEE*, pages 257–286.

[Rudnick and Perry, 2003] Rudnick, D. and Perry, M. (2003). ALPS: Autonomous and Lagrangian Platforms and Sensors, Workshop Report. Technical report, www.geo-prose.com/ALPS.

[Ryan et al., 2010] Ryan, J. P., Johnson, S., Sherman, A., Rajan, K., Py, F., Paduan, J., and Vrijenhoek, R. (2010). Intermediate nepheloid layers as conduits of larval transport. *Limnology & Oceanograhy Methods*. To Appear.