Reactive AUV Motion for Thermocline Tracking

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***Abstract*— The thermocline is a vertical transition layer in the water column with a strong impact on marine biology, since it affects phytoplankton concentration and, hence, primary production. AUVs can play an important role in understanding this relationship, by sampling the relevant data, usually describing *yo-yo* patterns spanning the whole water column. In this paper we describe a reactive behavior implemented onboard a small sized AUV, to adapt depth in real time in order to maintain the vehicle in the vicinity of the thermocline and therefore increasing efficiency in the sampling process. Preliminary field tests show that the method is simple, robust and effective.**

I. Introduction

Autonomous Underwater Vehicles (AUVs) are extremely versatile platforms to sample wide regions of underwater environments with minimal setup and operational costs. In most current applications, AUVs are programmed to follow geo-referenced paths while collecting relevant data, which yields more efficient synoptic views of 3D fields as compared to traditional ocean sampling techniques. However, if the mission objective concerns the search for a given underwater feature, then the pre-programmed path has to include all the regions where the feature is likely to be found, resulting in a small percentage of useful data about the specific feature. More, it is common for this data to be post-processed off-line by a human operator to refine the mission plan, which takes valuable time and may even prevent the re-acquisition of a dynamic feature.

A standard AUV navigation system is based on a kinematic or dynamic model that relates the vehicle actuation with the state variables that are used in the feedback loops (position and velocity). All relevant sensors to map the underwater features are carried as independent *payload* sensors, with no direct influence on vehicle control or navigation. Current AUV implementations carry tremendous on-board computational power, which allows for real time, on-line processing of data being collected. As a consequence, it is possible to implement algorithms for AUV guidance that take into account information extracted from a given feature being mapped in order to increase the efficiency in the observation procedure of that same feature, in a process frequently known as *adaptive sampling*. This requires a careful design of the AUV on-board navigation system so that the motion characteristics of the vehicle may be modified in real time without compromising safety and robustness. The main difficulty for this approach is the absence of simple models that relate the mapped features with the vehicle dynamics. Even if feature models are known or assumed, their specific parameters have to be estimated in real time using discrete, possibly noisy measurements.

Our strategy relies on relatively simple feature models for which the AUV can estimate relevant parameters in real time, and then use these parameters to define the motion characteristics (and sampling pattern) of the AUV. This way, the AUV is able to *decide* an adequate trajectory in order to concentrate the measurements in the region of interest, yielding a significant improvement in efficiency as compared to a standard broad survey. Some other forms of reactive behaviors have already been implemented with success in AUVs, particularly for the case of finding the sources of chemical plumes, most of them trying to mimic the real behavior of lobsters or bacterium in odor source localization ([1]–[3]).

In this paper, we show how our *adaptive sampling* approach can be applied to maintain an AUV in the vicinity of a thermocline. We describe the algorithms implemented on board the MARES AUV, developed at the University of Porto, in Portugal (Fig. 1). This AUV weights about 32kg, with a torpedo shaped body of 1.5m of length and 20 cm of diameter [4]. The vehicle has been used in environmental studies off the Portuguese coast since 2007, using a CTD from SeaBird Electronics and an ECO-Puck triplet from WETLabs, measuring fluorescence (CDOM and chlorophyll), and also backscatter at 650nm. For the work described in this paper, the MARES onboard software has been updated to process information from the CTD sensor in real time, so that the vehicle is able to describe a *yo-yo* pattern that adapts dynamically to the characteristics of the thermocline.

Fig. 1. The MARES AUV with an externally mounted CTD.

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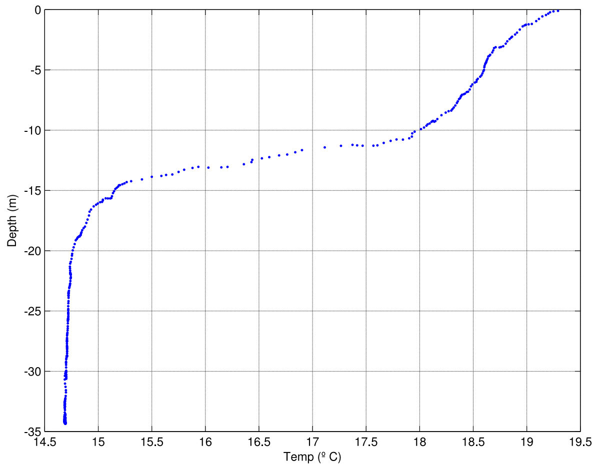

Fig. 2. Temperature profile measured 2 km off the Portuguese coast, June 2009. The thermocline can be easily identified at about 11-14 meters of depth.

II. THE THERMOCLINE

The thermocline is a vertical transition layer in the water column, separating the warm surface layer, or *mixed layer*, from the cold deep water bellow it. The mixed layer, closer to the surface, is the most easily influenced by atmospheric conditions (wind, rain and solar heat), which naturally results in a wide range of values throughout the year. However, the dynamic of the surface waters, due to the wind and wave action, mix the water in such a way that the gradient is small. In the thermocline, typically a relatively thin layer of the water column, the water temperature drops nearly linearly as the depth increases, with a significant gradient as compared to the rest of the profile. Finally, the deep-water layer is the bottommost and less dynamic zone. Water temperature in this layer decreases slowly as depth increases. Figure 2 shows an example of a temperature profile measured 2km off the Portuguese coast, in about 40m of water.

The characterization of the thermocline is particularly important in marine biology, since the presence, location and variability (both spatial and temporal) of the thermocline can provide valuable information about phytoplankton concentration and primary production [5]. As far as underwater acoustics are concerned, the thermocline can also be associated with a strong stratification, which greatly affects the propagation of sound waves. This means that the identification and characterization of the thermocline can also play an important role in underwater communications and military strategic planning. Even though the thermocline is most usually associated to the ocean [6], including both the seasonal occurrences in shallow waters and the *permanent thermocline*, it is also possible to find seasonal thermoclines in fresh water, particularly in dam reservoirs [7].

Temperature profiles have been collected and systematically stored in databases for the last decades. Typical data sets include position information together with temperature, with a much higher resolution and accuracy in the vertical position than in the horizontal. Given the huge amount of data that exists about the world oceans, there have been several attempts to represent these temperature profiles by simple sets of coefficients. Furthermore, this effort has been helped by the relatively regular *shape* of the profiles, that suggests a parametric representation. It is obvious that any accurate parametric representation of such profiles would allow for a dramatic reduction in data warehousing requirements.

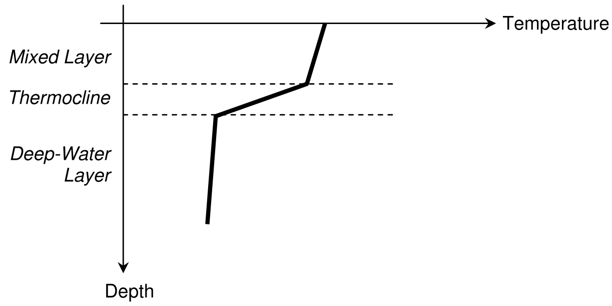

Fig. 3. Simplified temperature profile.

Although there are several models represented by a reduced set of parameters (for example [8]–[11]), they require the availability of the full temperature profile, and need a significant computational power, to determine the parameters. It should be stressed that our idea is not to provide a very accurate model that approximates the true vertical profiles, minimizing some optimization criteria. Instead, our main concern is that the model is simple enough to be iteratively estimated in real time. Even with only a partial vertical profile, the AUV has to be able to determine its main characteristics and maintain a *yo-yo* trajectory in the vicinity of the thermocline. In order to achieve this, we assume a 3-layer piecewise linear model, similar to the one proposed by Haeger [8], with a high gradient at the thermocline, and low gradients both above and below. Figure 3 shows such a representation, where the three vertical zones can be easily identified.

III. ON-BOARD SOFTWARE ARCHITECTURE

In standard data gathering operations, AUVs move along trajectories that cover the area of interest. These trajectories, which are geo-referenced and defined a priori, are then decomposed in sequences of elementary maneuvers together with conditions that determine transitions between consecutive maneuvers, constituting the so called *mission plan*. To execute the mission plan, the on-board software schedules the real time controllers required to the execution of each maneuver, and provides them with the proper references and also with the real time data given by the AVU navigation system (position, velocity, attitude). Assuming that all on-board systems are fully operational and that no unexpected event occurs, the standard operation of an AUV is almost deterministic and depends only on the mission plan. This determinism relies on the proper design of the real time controllers and is of major importance since large deviations of the vehicle behavior from the mission plan can be used to detect the malfunctioning of on-board systems and to trigger emergency behaviors.

On the other hand, in adaptive sampling operations, AUV trajectories are defined in real time and the vehicle motion directly depends on mapped features that cannot be easily related with the vehicle dynamics. It is, therefore, difficult to predict the vehicle motion and also to devise simple mechanisms to detect malfunctions and ensure the safe operation of the AUV.

The MARES onboard software architecture [4] was adapted to include the capability of performing real time adaptive sampling operations. In order to maintain the system as robust as possible it was decided that adaptive sampling maneuvers simply define reference inputs for the already existing real time controllers. In this way, when an adaptive sampling maneuver is activated, the reference inputs for the control system are computed in real time by dedicated modules of software (that implement the adaptive sampling behaviors) and are fed to the controllers. In the particular case of thermocline tracking, the depth reference for the vertical controller is no longer defined a priori in a *yo-yo* pattern with fixed bounds, but is continuously updated based on the acquired CTD data, as explained later. Nonetheless, the control system imposes bounds on the reference values provided by the external modules in order to ensure safety of operation, preventing the vehicle to enter unwanted regions.

IV. The Thermocline Tracking Maneuver

Overview

The thermocline tracking maneuver only acts on the vertical reference for the AUV controllers, and it can be seen as a special case of a *yo-yo*, for which the limits may be redefined in real time. In fact, in parallel with the standard *yo-yo* pattern, a separate process is identifying the thermocline, filtering temperature data and fitting a gradient search algorithm implemented in real time. The thermocline is detected when the vertical temperature gradient exceeds a given threshold. The vehicle will proceed the vertical motion until the algorithm detects a *significant decrease* in the gradient, as compared to the current *maximum*. At this position, the vertical profile is reversed and the algorithm restarts on the other direction. In the absence of a positive identification of the thermocline in either direction, then the vehicle will continue the vertical motion until the pre-specified limit is reached (either the surface or the maximum depth), as in a standard *yo-yo* motion. All thresholds are dynamic and depend on the gradient information acquired on previous profiles, so that the AUV can be used to track a time- or space-varying thermocline while moving along a pre-defined *lat-lon* trajectory.

During the thermocline tracking maneuver, the model parameters can be passed on to other AUV processes, if necessary. This allows, for example, the AUV to switch on any special sensor or to trigger an underwater sampler at the right instant, in order to capture a relevant sample of water for later laboratory analysis, such as suggested in [12].

The MARES AUV has 4 independent controllers for 4 degrees of freedom, and the vehicle is able to control the

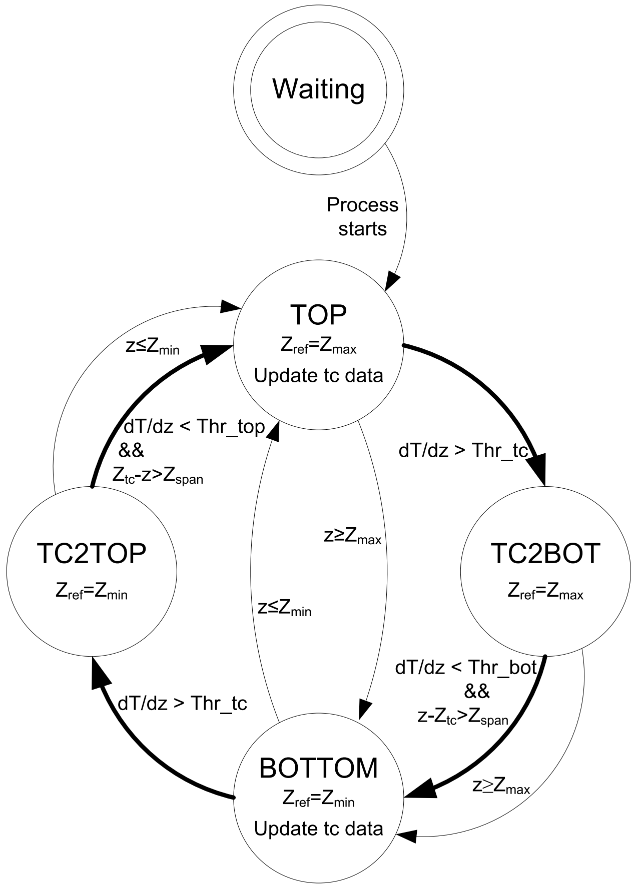

Fig. 4. State machine and transitions representing the thermocline tracking maneuver. The bold arrows represent the expected cyclic transitions during normal tracking.

vertical velocity, from zero (*i.e. hovering*) to a maximum value around 40cm/s. This means that the vehicle can implement this algorithm to track the vertical thermocline at a single *lat-lon* location, or while following a completely independent *horizontal* trajectory. In most other AUVs, however, the vertical motion is obtained using horizontal fins or deflectors, in which case the vertical motion requires a minimum value for the horizontal velocity. In any case, the same principles described here can be implemented as a particular case of the *yo-yo* maneuver.

Tracking the thermocline

The algorithm developed for thermocline tracking can be described by the state machine represented in fig. 4. Note that the darker arrows represent the transitions that are expected during a normal tracking maneuver. These transitions will cycle the state machine through the most relevant states:

- TOP - The vehicle is located above the thermocline.
- TC2BOT - The AUV is within the region of the thermocline, on a downward vertical motion.
- BOTTOM - The vehicle is located below the thermocline.
- TC2TOP - The AUV is within the region of the thermocline, on an upward vertical motion.

The process usually starts when the vehicle is at the surface, so the first state is set to TOP. On entering this state, the depth reference is set to Z_{max}, which means the AUV will try to dive in the water column. The vehicle will then evaluate the vertical temperature gradient and compare it with a given threshold, Thr_tc. When this threshold is exceeded, the vehicle will assume the thermocline has been detected on the downward motion, entering the TC2BOT state. This can be seen as the *upper limit* of the thermocline region and then the vehicle will try to detect the *lower limit* of this region, by diving deeper. Therefore, the vertical direction will remain the same as before, with $Z_{ref} = Z_{max}$. At this state (TC2BOT), the gradient search algorithm will try to find if the level decreases below another threshold, Thr_bot. Note that this low gradient level has to be searched only for depths greater than the depth of the maximum gradient. In order to confirm the *lower limit* of the thermocline and avoid (early) false detections, an additional test is performed, verifying that the vertical span is large enough, *i.e.* if $z - Z_{tc} > Z_{span}$, where z is the current depth, Z_{tc} is the depth of the maximum gradient and Z_{span} his an optional parameter set by the user. When both these conditions are met, the vehicle enters the BOTTOM state.

Note from the state machine of fig. 4 that the BOTTOM state is also reached if $z \geq Z_{max}$. This is a safety mechanism to ensure that the maximum depth the AUV will be limited to Z_{max}, even if the algorithm is not able to positively *find* the thermocline. More, this condition contributes to a performance index, since it signals a failure in the algorithm.

When the vehicle enters the BOTTOM state, the thermocline characteristics are extracted from the previous vertical profile (in particular, the maximum gradient and the thermocline limits) and this information is used to adapt the thresholds for the thermocline detection during the next vertical profile. At this state, the depth reference changes to Z_{min}, which means the AUV will now move towards the surface. The temperature and depth values arriving from the CTD sensor will be used to determine when the vertical gradient exceeds the new thermocline threshold, Thr_tc. This will change de state machine into the TC2TOP state, signaling the *lower limit* of the thermocline. In order to find the *upper limit*, the algorithm will proceed in much the same way as in the downward motion, but with a natural symmetry: the reference for the vertical controllers will be maintained at Z_{min} and the gradient search will be done for depths lower than the depth of the maximum gradient. Once again, the TOP state is only confirmed if a minimum vertical span has been covered.

As long as this process is active, the above cycle will be maintained, resulting in a *yo-yo* pattern around the thermocline. In case the thermocline is not detected in one of the vertical profiles, the vehicle will extend the vertical span up to Z_{min} or Z_{max}. It should be noted than on the very first time the algorithm runs (usually during the first descend), it is possible either to use *a priori* data to define the detection thresholds, or to use no information at all and let the AUV acquire a full vertical profile to determine those values.

V. Practical Implementation Issues

Iterative gradient estimation

When looking at a full temperature profile such as the example of fig. 2, one can clearly visualize a thermocline and imagine an online algorithm to extract 3 regions from that profile. However, this seemingly simple task is visually facilitated by the *long* low gradient regions, both above and below the thermocline. In a practical implementation, the challenge is to maintain the AUV in the region of the thermocline, detecting as early as possible a significant decrease in the temperature gradient and avoiding as much as possible to navigate within those *flat* regions. A difficult problem in detecting the thermocline is then to estimate de derivatives $\frac{dT}{dz}$ for a limited number of previous values of depth and decide if those derivatives are sufficient to conclude that the thermocline has already been passed and there is no need to proceed further. More, this data is updated several times per second (16, in our case), it may show small scale variations, it is not uniformly distributed and, surely, may have errors.

In order to estimate the gradient, we start by clustering the depth and temperature values into bins, as soon as they are available. For each new data point, only the derivatives (or differences, to be more accurate) affected by this data are updated. The derivatives are then estimated by the differences of the averaged bin values. In order to prevent biases in the average values of depth, we consider the average of both temperature values and depth values within a bin, as compared to considering an average temperature in the middle of the depth bin. This is particularly relevant if we increase the size of the bins, because as the vehicle ascends/descends in the water column, the first few samples within a depth bin are biased towards the bin boundary.

Robustness and performance

Even with the clustering of data into bins, there may exist some false detections of gradients if we only consider a single bin at a time. In order to avoid these false detections, we need a consecutive number of differences, above or below a threshold, to confirm the change of state. Note that if we increase the number of confirmations required to validate a low gradient, the main consequence will be for the AUV to dive further into the *flat* regions of the profile, with a minor impact on performance. On the contrary, if we increase the number of confirmations for the high gradients, we may not be able to detect a very thin thermocline.

The described algorithm provides information to monitor the performance in real time, by counting the times the thermocline boundaries are detected (the state machine of fig. 4 passes in the dark transitions) and the times the limits of depth are reached (both Z_{max} and Z_{min}). The percentage of detections is then a good performance metric and if it gets too low, a proper action may be triggered, according to instructions given by the user when preparing the mission. For example, the user can define that if the AUV doesn't detect a proper temperature variation, then the mission is aborted or, alternatively, the vehicle just reverts to a broader survey to try to reacquire the feature – a standard *yo-yo* pattern with user-defined vertical limits.

Magic numbers

The size of the depth bins is an important design parameter for the algorithm, since it acts as a low pass filter which may affect the ability to detect gradients. If the bins are too small, only few data points will fall into that bin, resulting in large errors in gradient estimation. If the bins are too large, then they will smooth the temperature variations and the algorithm will have difficulty in separating significant variations. After several tests with both real and simulated vertical temperature profiles, we've found that we should have at least 5 to 8 bins spanning the depths of the thermocline to have significant changes in the gradients. Currently, the bin size is a fixed number chosen when the algorithm runs, so, as a rule of thumb, we usually set this value so that the first estimated thermocline spans about 10 bins.

The number of consecutive detections required to confirm a given threshold also depends on the size of the bins. For the size of our bins, we've considered a minimum number of 3 consecutive detections to confirm the gradient thresholds. We've also implemented a mechanism of validating a bin, depending on the quantity of data points used. For our experiments, we've considered a minimum number of 5 data points in a bin for its data to be used for gradient detection.

VI. Field tests and results

In order to test the algorithm described in this work, we chose a dam reservoir in the Douro river, close to Porto, in the north of Portugal. This location was selected both to facilitate logistics and also because it is known to develop a seasonal thermocline from late spring to early autumn. We started by running a vertical profile in the operation area, in order to confirm the thermocline and also to extract some initial data for the algorithm. This profile can be seen in fig. 5. Comparing this profile with a typical ocean profile (see for example, fig. 2), it is clear that the reservoir thermocline has much more small-scale variations, particularly in the mixed layer, above the thermocline. For the thermocline tracking algorithm, this provides a much harder scenario than a smooth variation and, therefore, it is a good way of demonstrating its effectiveness. From the vertical profile, we estimate a maximum temperature gradient of around 1^{o}C/m, with a very thin thermocline between about 6.1 and 7.3 meters of depth. As described earlier, taking these numbers, we chose a bin size of 12cm so that we would have a thermocline spanning around 10 bins. For a vertical velocity of about 10cm/s and a 16Hz sampling rate, this results in about 18 samples per bin.

The MARES AUV was then programmed to perform a *yo-yo* pattern from a minimum depth of 2 meters up to a depth of 12 meters, while the thermocline tracking algorithm was running in parallel. Fig. 6 shows the details of the depth during the *yo-yo* motion, the temperature readings and the corresponding state of the algorithm state machine, as described earlier: TOP

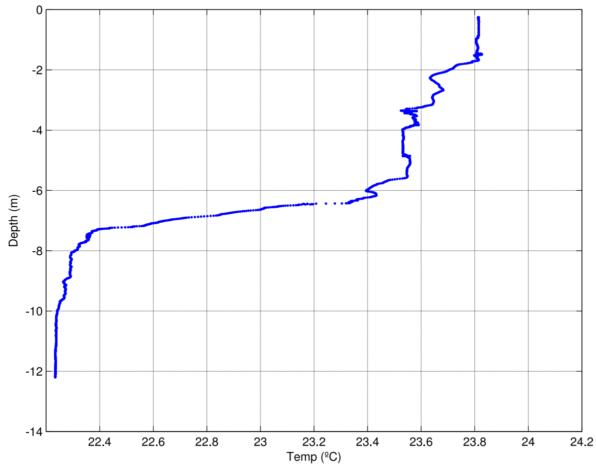

Fig. 5. Temperature profile measured by the MARES AUV in the Crestuma reservoir, July 2008. Note the small scale variations above the thermocline.

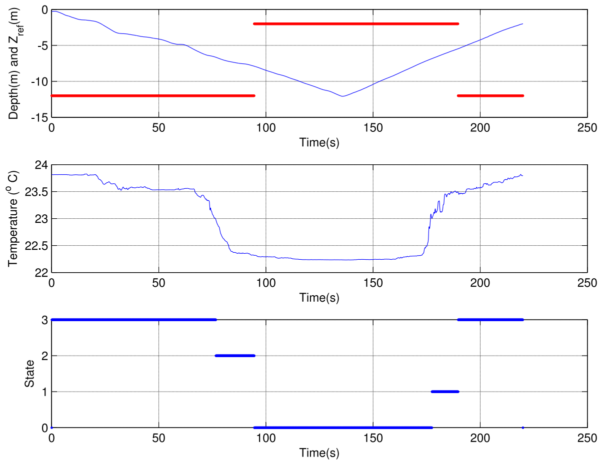

Fig. 6. *Yo-yo* profile by the MARES AUV in the Crestuma reservoir, July 2008. Plots in bold show the outputs of the thermocline tracking algorithm.

(3), TC2BOT (2), BOTTOM (0), and TC2TOP (1). Note in the first graph the solid red line indicating the depth reference suggested by the thermocline tracking algorithm. It can be seen that the algorithm suggests an inversion in the direction of the vertical motion around $t = 95$ seconds, when the vehicle was at 7.9 meters of depth. On the upward motion, the algorithm also indicates the *upper limit* of the thermocline to be around 5.5 meters of depth.

Although the AUV was not directly controlled by the thermocline tracking algorithm, it is possible to simulate the behavior of the vehicle if the depth reference suggested by the algorithm were transmitted to the vehicle controllers. We assume a simple kinematic model for the vehicle, which is a reasonable assumption since the vertical velocity is very slow. We also assume that the temperature profile is constant, which is also reasonable for such a short duration. Figure 7 shows the resulting profile if the vehicle were to use the information provided by the algorithm, superimposed to the original *yo-yo*.

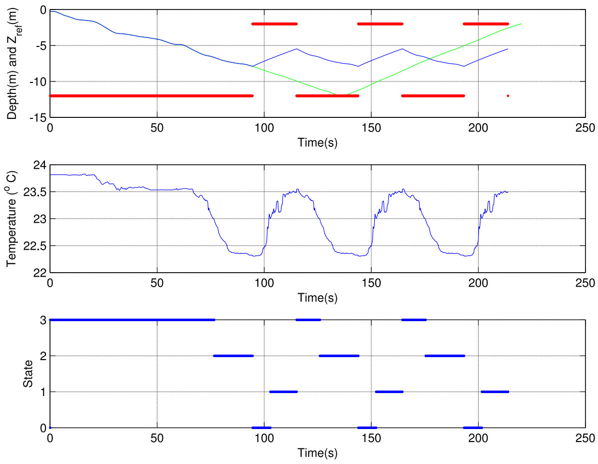

Fig. 7. Simulation of a *yo-yo* profile using the thermocline tracking maneuver for the same data set shown in fig. 6. Note the differences between the new profiles (shown in blue on the first plot) with the original (in light green).

With the new algorithm, the initial 10 meters of vertical span are reduced to about 2.5 meters, resulting in a corresponding 4-fold increase in the sampling frequency of the thermocline (from the original 200 seconds period of the *yo-yo* down to 50 seconds). It is obvious that this increase can be much more significant when the ratio between the full water depth and the thickness of the thermocline layer increases, such as the case of deeper water scenarios.

VII. Conclusions and Future Work

In this work, we have implemented a new approach to AUV surveys that is to replace the standard predefined *mission* by an adaptive sampling strategy. Such an approach exploits the on-board computational power to infer some characteristics of the oceanographic environment and react to this environment by making decisions about the best sampling strategy to use. By continuously interpreting collected data, this decision can be made in real time so that the vehicle can use most of the available resources (mainly power) in sampling the ocean in regions of interest. Naturally, this will contribute to faster and more efficient surveys.

In our implementation, we assume that the thermocline can be coarsely approximated by a very simple model with time varying parameters. We've described how a small size AUV can change the sampling pattern in order to maintain tracking of a thermocline and therefore contribute to a more efficient characterization of a space- and time-varying thermocline. We've developed a very low complexity algorithm that may be implemented in real time, with minor impact on CPU load and memory usage. Using an illustrative example, we've shown that the new maneuver allows the AUV to gather much more information about the thermocline than a standard *yo-yo*. This improvement may be accentuated in scenarios with a thin thermocline layer, particularly in deeper waters. We estimate that a similar approach can be followed to increase the efficiency in the sampling process of other ocean processes.

Even though the acquired data affects the vehicle motion pattern, the algorithm was implemented on the MARES AUV in such a way as to ensure safety of operation – in case the algorithm is not able to positively detect the thermocline, then the AUV will revert to a standard *yo-yo* pattern. This has been extensively tested with both real and simulated vertical temperature profiles, in order to make sure that the inclusion in the library of maneuvers will result in a safe operation. During the summer of 2010, the MARES AUV will be using this new maneuver to follow *lat-lon* transects while tracking the thermocline. At the same time, the vehicle will gather data from the optical sensors, in order to evaluate the correlation between thermocline characteristics and chlorophyll concentration. If required, the algorithm may be adapted for different sampling requirements, for example, the AUV may extend the bottommost part of the *yo-yo* to evaluate a phytoplankton layer trapped below the thermocline.

As far as the thermocline tracking is concerned, we expect to improve on the mechanism of initializing the algorithm, by calculating the size of the depth bins automatically. This will be done using information gathered on the first vertical profile and adjusting the bin size to maximize detectability. We also plan to improve the real time filtering of the parameters of the algorithm, so that the tracking mechanism may benefit more from the results of previous profiles, such as thermocline depth limits, detection thresholds, and temperature levels both above and below the thermocline.

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