Bottom Estimation and Following with the MARES AUV

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***Abstract*—It is becoming more and more common to use Autonomous Underwater Vehicles to perform tasks underwater. The use of this vehicles is affordable and its use doesn't raise any significant risk nor does it requires any human intervention. The traditional applications for the use of such vehicles were related with bathymetric tasks. But nowadays AUVs are being more and more used for variety of missions in open water environments, including the inspection of underwater structures and environmental monitoring in diverse oceanographic expeditions.**

Following some previous work, this paper addresses the problem of bottom following by an Autonomous Underwater Vehicle in an environment which is not previously known. In particular, the focus is on integrating a reactive behaviour based on environment sensing, with the on-board navigation software of the MARES AUV. For this, a guidance algorithm will provide the necessary pitch and depth references to the control layer of the vehicle. While the altitude towards the seabed can be measured with an altimeter, the pitch reference values are based on realtime estimation of the slope of the seabed. By doing so, it is possible to control the vehicle in a way that it will always maintain a constant attitude towards the bottom, and the trajectory followed will remain parallel to bottom, regardless of it's profile.

I. Introduction

Traditional applications for the use of Autonomous Underwater Vehicles (AUVs) are mostly related with bathymetric tasks, where the objective of mapping the bottom of the river or sea is achieved by using advanced ultrasound equipment. However, other applications for these vehicles have been envisioned, with a special focus in open waters environments, where the benefits of using them are more dramatic. Nowadays, AUVs are already being used for variety of missions, including the inspection of the bottom, inspection of underwater structures and even remote environmental sensing within oceanographic expeditions.

Performing visual inspection of the bottom with an AUV obviously requires the vehicles to navigate closely to the bottom. With poor lighting conditions and turbid water, the bottom of the sea is usually a quite adverse system for acquiring images. Whenever this is necessary, the vehicle needs to navigate as close to the bottom as possible in order to obtain satisfactory results. Such inspection tasks would also greatly benefit if the trajectories of the vehicle closely resemble the profile of the bottom. In this way, bottom features would be depicted according to their natural size and orientation ratio, decreasing distortion and other disturbances that otherwise may affect the final images.

In known environments navigating close to the bottom doesn't represent a challenging navigation problem, as it is easy to plan ahead a given trajectory. In most cases, however, it is not possible to known in advance the profile of the bottom and the problem of of having an autonomous vehicle navigating close to the bottom becomes non-trivial, and could even put in danger the safety of the vehicle.

Bottom Following, or seabed tracking, has been described as "maintaining a fixed altitude above an arbitrary surface whose characteristics may or may not be known" [1], in one of the initial works on the topic. The problem of bottom following by an AUV has already been widely addressed in the literature. A very interesting and detailed study on the use of high-frequency pencil beam profiling sonars for bottom following problem was proposed in [2]; the solution, further extended in [3] is based on a multi-hypothesis Extended Kalman Filter for motion and environment estimation techniques, and Lyapunov-based guidance system. Also, a description of a survey where bottom-following tasks were extensively done to gather high-precision detailed data from the seabed, with the help of an acoustic rangefinder, can be found in [4]. Some relevant work for the topic can also be found in [5], where the problem of designing high precision bottom following algorithms for Remotely Operated Vehicles, was addressed. In some recent work on the topic [6] a new controller based on the potential field method was presented, to address both the problems of bottom avoidance and bottom following, and in [7] a different controller is proposed, that uses the Nonlinear Output Regulation framework, to address the seabed tracking problem.

The method presented in this article is an extension of previous work by Melo and Matos [8]. There a basic bottom following guidance-based approach, responsible for providing the necessary depth references to the control layer of the vehicle, was introduced. In this article we further expand those results in such way that the vehicle, in addition to follow the bottom at a given distance, also dynamically adjusts its attitude (pitch) to match the slope of the bottom. By doing so, the trajectory performed by the AUV will closely resembles the profile of the bottom. Performing this kind of trajectory is of particular importance for applications where acquiring images of the bottom is needed.

The paper is organized as follows. Section II gives a brief presentation of MARES AUV vehicle and the architecture of the computational system of the MARES AUV, the vehicle we used to validate our results in a open water environment. In section IV different realtime slope estimation algorithms are presented and Section V deals with the transformation of state variables into suitable control variables. The results obtained with the proposed solution, both by simulation and in real missions, are presented in Section VI and finally some conclusions are presented in the last section.

II. System Architecture

The guidance algorithm proposed in this article is to be integrated in the on-board control software of the MARES AUV. In this context, and for better understanding, this section presents an overview on the architecture of the control system implemented in the vehicle.

The MARES AUV has four thrusters, two vertical and two horizontal, and due to their specific spatial configuration, it is possible to control the horizontal and vertical movements of the vehicle in an almost decoupled way. Because of this, the control layer of MARES is composed by four independent controllers: surge, heading, pitch and depth. The surge and heading controllers are responsible for the horizontal motion of the vehicle, while the pitch and depth controllers are combined to obtain the actuation in the vertical plane. Each one of the four basic controllers can operate in either open or closed loop mode, and a more detailed description of the each of the controllers can be found in [9].

The control layer of MARES also defines a maneuver as a set of coordinated control actions by each of the basic controllers. Four elementary maneuvers - dive, surface, goto, hover - were defined in the core of the control system, but it is also possible to define additional maneuvers, as each of the basic controllers can be controlled externally, accepting inputs from remote processes. This flexibility of the control layer allows to define more entangled maneuvers in a very efficient way. The guidance algorithm to implement will take advantage of this feature, providing the desired depth and pitch references to the respective controllers, controlling in this way the vertical trajectory of the vehicle. A note to the fact that this implementation is entirely guidance-based and independent of the already existing four basic controllers, as opposed to some of the bottom following approaches present int the literature [6], [7].

In the bottom following maneuver, the vehicle should maintain a constant distance towards the seabed, while its pitch should vary in accordance to the slope of the bottom. The altitude of the vehicle off the seabed can be easily measured by using an altimeter - a now very common single beam sonar sensor that provide range distance measurements. However, measuring the slope of the bottom is something that is not so trivial and has to be estimated. Given that the slope of the bottom is closely related with variation of the relief of the bottom, the slope of bottom can be estimated from the altimeter measures. Different techniques for slope estimation are discussed in Section IV. The control variables, pitch and depth, are then computed from these estimates and fed the pitch and depth controllers, respectively.

III. Experimental Setup

The vehicle used to support the work developed is the AUV MARES. This vehicle is a torpedo-shaped, highly modular, small sized AUV, with about 1.5m long, weighting about 32kgs and propelled by 4 thrusters. The configuration of the thrusters - two horizontal thrusters located at the tail to control both forward velocity and heading, and two thrusters in the vertical direction, to control vertical velocity and pitch angle - allow for an decoupled control of the horizontal and vertical motion of the vehicle. Therefore, heave and pitch can both be independently controlled, a feature that is particularly appreciated in this context. A more detailed description of the vehicle can be found in [10].

Fig. 2: The MARES AUV

The most reliable way of assessing the distance to the bottom inside the water is using sonar techniques, mostly due to the unique characteristics of sound propagation in the water. The Imagenex Model 862, was integrated in the MARES hardware to allow to measure the distance of the vehicle to the bottom. This is a completely self-contained altimeter with a narrow conical beam of 10^{o}, range resolutions of 20mm and a maximum range of 30m.

The altimeter, mounted in the vehicle on a downward facing position, is responsible for providing range measurements of the distance towards the bottom, and the different parameters were fine-tuned up to a state on which the altimeter was providing consistent measurements throughout the time. New measurements were being provided at a frequency of 4Hz. Nevertheless, the output of the altimeter needs to be filtered, to prevent the appearance of eventual spurious measurements or outliers, frequent when using underwater sonar. The filtering problem for this configuration was already addressed, and the work in this article will build up on the results presented in [8].

IV. Slope Estimation

The purpose of the work here presented is the development of a environment sensing based reactive behaviour, to be integrated on the on-board navigation software of the MARES AUV. This algorithm should be able to estimate the slope of the bottom, and to adjust the vehicle's pitch and depth accordingly. The estimation of the slope of the bottom is a two step process: first, the range measurements output by the altimeter need to be filtered, and with that data an estimate of the slope needs to computed. From the estimated slope, a time variable pitch and depth references are generated, that take into account a safety distance to the bottom, preventing situations of bottom collision. Due to safety and general efficiency issues

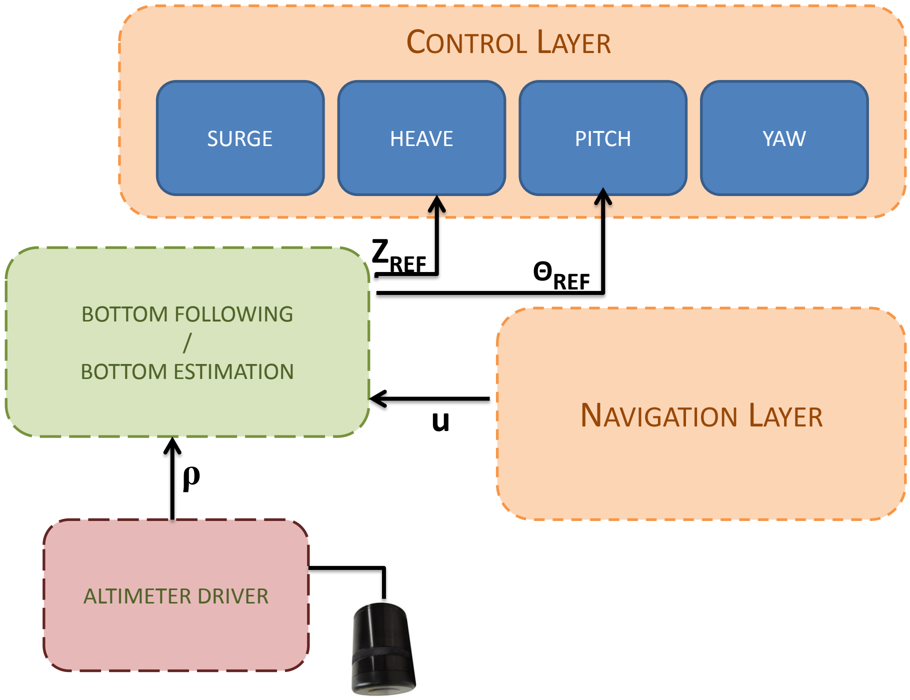

Fig. 1: Output of the altimeter: on the left, a situation when excessive gain and pulse length is depicted, with a lot of noisy measurements; on the right, a situation where the parameters have been correctly set

of the vehicle, the generated depth and pitch control variables are bounded to limits considered reasonable.

Filtering the altimeter measurements has already been partially covered in [8]. There, a uni-dimensional state Kalman Filter was used. Given the filtering requirements, a choice for such filter came naturally, as this filter proved to be not only an efficient smoother but a robust way to discard outliers from the set of measurements. An extension to this, namely the realtime estimation of the slope of the bottom is the subject of this section.

The estimation of the slope of the seabed is an environment sensing based process and. In this case, the environment sensing is made by the altimeter, which is mounted on the vehicle in a down-facing configuration, and provides range measurements to the bottom. Considering that this set of measurements has already been filtered out of outliers, they can be used freely without any major concerns. For the realtime estimation of the slope of the bottom, two different techniques were explored and compared: the first approach, described on Section IV-A, consists on the use of Linear Regression and the second approach, on Section IV-B, consists on extending the Kalman Filter used to filter the measurements of the altimeter, so that the slope of the bottom can also be estimated.

The slope, steepness or inclination of the bottom is usually defined as the rate of change of the bottom relied with the distance traveled in the horizontal direction and between every two points in space. However, we want to define the slope of the bottom as a function of the previous range measurements gathered throughout the time. The altimeter provides measurements of the distance to the bottom over time, and by plotting these data we can have a distorted map of the profile of the bottom over the direction of the movement of the vehicle. This map is distorted because it accounts for the variations of the profile of the seabed over time, and not over the distance traveled. To obtain a correct profile of the bottom, the surge velocity of the vehicle must be taken into account.

Calculating the slope of the profile using measurements from an altimeter has the potential risk of associating variations of the depth of the vehicle with possible changes in the slope of the bottom: if a vehicle is moving on a given location where the bottom is flat but changes its depth - e.g. when submerging to a given bottom following distance. The variations on the altitude measurements from the altimeter will in fact be perceived as a change in the slope of the bottom. This situation will likely lead to a situation where the pitch of the vehicle keeps oscilating. To overcome this, the slope estimation algorithms must only consider actual differences in the slope of the bottom - between every altimeter measurement differences in the depth of the vehicle, calculated by the navigation layer, must be subtracted.

By differentiating these set of data with respect to time, we arrive to a figure of merit which is simply the rate of change of the distance to the bottom, for a given time period. To arrive to an actual slope we need to simply multiply it by the surge velocity, usually provided by the navigation layer of the on-board software. However, this figure of merit - a "slope over time" - by itself is enough to access the performance of the algorithms.

A. Linear Regression

The only available information regarding how far from the bottom is the vehicle navigating is provided by the altimeter, with a constant stream of data containing a time series of ranges to the bottom. As previously described, estimating the slope of the can be accomplished by merely differentiating this time series with respect to time, and scale it afterwards according to the surge velocity of the vehicle.

The idea behind using a linear regression to estimate the slope of the bottom arises naturally: as differenciating a time-series can be tricky at times, being extremely sensitive to noise, the alternative is to find a curve that best fits to this time series. Having the analytical expression for this curve, it is straightforward to calculate it's derivative, and from there inferring the "slope over time" of the bottom. From there, and just by multiplying it by surge velocity of the vehicle, we have an estimate of the actual slope of the bottom.

$$W^T X = w_0 + w_1 x + w_2 x^2 + \dots \tag{1}$$

The Linear Regression algorithm tries to find the polynomial, which order has to be defined in advance, that best fits a set of existing data points. Usually this fit is made in the least-squares sense. The polynomial that best fits the data can be written as in (1). It can be shown that W, the vector of coefficients of the polynomial, can be obtained by simple algebraic manipulation, as in (2), where X, the design matrix, is built using the input variables, and Y is the matrix of the independent variables. To apply the linear regression to the specific problem of estimating the slope of the bottom, there are two main design choices to be made: the order of the the approximating polynomial, and the size of data set to use.

$$W = (X^T X)^{-1} X^T Y \tag{2}$$

The order of polynomial is directly related to how the seabed is to be modeled. The assumptions about the bottom are that it should be smooth, without sudden variations of the profile - more than 1 meter. Given this, the bottom could be modeed whether by a first or a second order model. Whilst a second order model might seem a good option, due to the fact that it is curvy and smoother than a linear one, it has a tendency to overfit - it adapts too closely to the set of data points - and has a poor performance, specially when in presence of a very noisy data set.

The second design choice, the size of the data set, has an important role on the overall performance of the fit: while increasing the size of the data set makes the fit smoother, on the other hand, it also increases the delay introduced and, therefore, the reaction time to significant changes in the slope of the bottom. The number of measurements to include in the regression must be a compromise between delay of the algorithm and performance.

B. Kalman Filter

The slope estimation described in the previous subsection, by means of a Linear Regression, is a two-step approach: it requires first a filter, to remove outliers from the measures, and then a Linear Regression estimator, that predicts the slope of the bottom. An alternative to this is to try to integrate both features onto the same algorithm, thus eliminating the extra delay introduced by the different estimators.

Having in mind the good performance on removing outliers of the Kalman Filter described in [8], and the bottom follower presented by Caccia et al in [3], we also developed an Kalman Filter integrating both the outliers removal and the bottom estimation features.

The bottom estimator state and measurements equations can be represented by equations (3) and (4), which represent a linear systems with a linear measurement, both affected by random white noise, w_k and v_k.

$$d_{k+1} = d_t + \dot{d}_k \Delta_t \tag{3a}$$

$$\dot{d}_{k+1} = \dot{d}_k + w_k \tag{3b}$$

The distance from the AUV to the bottom at time instante k is represented by d_k, and $\dot{d}_k$ is the derivative of this distance, previously refered as the "slope per time" figure of merit. The state of the system is continuously estimated by applying the usual Kalman Filter recursive prediction and update equations. (3a) expresses the fact that changes in the distance to the bottom are only affected by the "slope per time" of the bottom plus a normally distributed noise factor. The rate of change ot $\dot{d}_k$ is adjusted by the value of w_k, in (3b). In the measurement update equation (4), ρ_k refers to the raw measurement of the altimeter at time instant k.

$$z_k = \rho_k + v_k \tag{4}$$

As usual, the performance of the filter can be tuned by adjusting the matrix Q and R, respectively the process noise and measurement noise covariance. While R was set to be equal to 2.5 times the quantum of the altimeter, values for Q were empirically set for the best performance having in consideration both the delay introduced, and the quality of the tracking of the seabed. As in [8], validation of new measurements and, hence, outliers removal, can be performed by evaluating the covariance of the innovation. Recall that S_k is obtained through (5), where H_k is the observation model, and the validation of new measurements is done according to (6). The parameter γ can be adjusted to fine tune the whole process.

$$S_{k+1} = H_k P_k H_k^T + R \tag{5}$$

$$\| z_k - H x_k \| \, S_k^{-1} \leq \gamma \tag{6}$$

V. Control Variables

The control layer of the MARES AUV is composed out of four different controllers, namely surge, heading, pitch and heave. For the bottom following behaviour, both heave and pitch need to be properly actuated. This section deals with the process of converting the estimated state variables, depth and slope of the bottom, into proper control references, as both the controllers need to be provided with relative, and not absolute, reference values.

The heave controller is responsible for the controlling the depth of the vehicle and, therefore, the distance from which the vehicle is from the bottom.

The depth reference for this controller, Z^*_{REF}, in (7), uses the estimated distance to the bottom, d_k, to generate the proper reference, but also compensates for the relative position between the location of the altimeter and the vehicle's center of gravity, x_{ALT}, and for the actual pitch of the vehicle θ. D_f is the parameter that sets bottom following distance - the distance to the bottom that the vehicle should always maintain.

$$Z^*_{REF} = -d_k + D_f + x_{ALT} sin(\theta) \tag{7}$$

We also want to prevent situations of possible trap or loss of the vehicle. Therefore, the reference sent to the controllers, Z_{REF} should be bounded, as in (8). By bounding the calculated reference, Z^*_{REF}, the vehicle is not allowed to follow sudden discontinuities in the slope, as this is not considered a safe behaviour, nor is under the assumptions for the model of the bottom. The value on which we wish to bound will obviously vary according to the environment and the missions being executed.

$$Z_{REF} = \begin{cases} Z^*_{REF} & \text{if } Z^*_{REF} < Z_{MAX} \\ Z_{MAX} & \text{otherwise} \end{cases} \tag{8}$$

As for the pitch controller, a suitable pitch reference must be derived from the previously estimated slope of the bottom, $\dot{d}_k$. A "slope per time" has already been estimated and, by multiplying this value by the surge velocity, u, estimated on the navigation layer of the vehicle, we get the actual the slope of the bottom.

$$\theta^* = \theta + atan(\dot{d}_k u) \tag{9}$$

In (9) we neglect the effect of water currents might have on the direction of the vehicle, and assume that u accurately describes the velocity of the vehicle in the forward direction. As $\dot{d}_k u$ is a slope, or a ratio, to get the equivalent angle it is enough to simply compute its arc tangent.

VI. Results

In this section we will present results both for the proposed bottom estimation and bottom following approach. These results are both simulated and experimentally validated, during several missions performed during the Summer 2012 in a location in the Douro river, close to Porto, in Portugal.

A. Simulated Results

The results presented in this section were obtained through extensive simulation, using for that previously gathered data from the altimeter on an open-waters environment. Using this data allowed to recreate an actual profile of the bottom and compare and tune the different slope-estimation algorithms.

For this simulation tests, we were mainly focused on both the accuracy and the delay introduced while estimating the distance to the bottom: this estimate must be accurately estimated and evolve smoothly through time; on the other hand, the realtime estimation step shouldn't introduce a significant delay, otherwise the ability to avoid collisions with the ocean floor could be compromised. The simulations also allowed to find the best tradeoff for a number of design parameters: for the Linear Regression algorithm we were able to establish the most appropriate number of samples to use in the regression, while for the Kalman Filter we determined the parameter γ and the covariance matrix values that best improved the results obtained.

The results obtained with the Linear Regression and with the Kalman Filter can both be seen, respectively, of figures 3 and 4, an both of them correspond to the same altimeter data set, that simulates a given profile of the bottom. The plots contain points for the raw altimeter data, in blue, estimates of the depth of the vehicle, in red, and the estimated slope of the bottom, in green. It can be noted that the estimates for the slope of the bottom are more smooth when estimated with the Kalman Filter. Also the Linear Regression estimated slope is more sensitive to small oscillations in the bottom, which in this case were caused by the normal overshoot in the heave controller. This sensitiveness, however, can lead to a behaviour which is not the desired one.

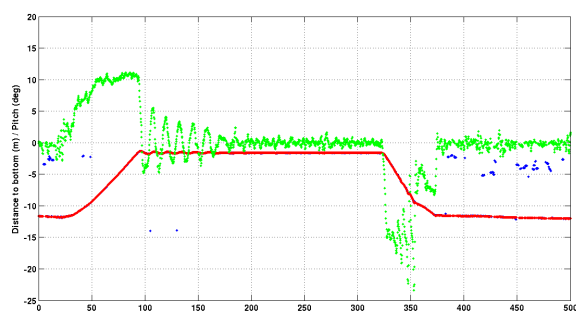

Fig. 3: Simulation of the Linear Regression algorithm: output of the altimeter (blue), estimated distance to the bottom (red) and pitch of the vehicle (green)

On both approaches, the points that correspond to the estimated distances to the bottom overlap almost entirely the points corresponding to altimeter measurements, with the exception of the removed outliers, which are the only points clearly visible. This is, in fact, a proof of the good behaviour of two algorithms, in terms of the delay introduced by the estimators. Both the approaches have a similar and negligible

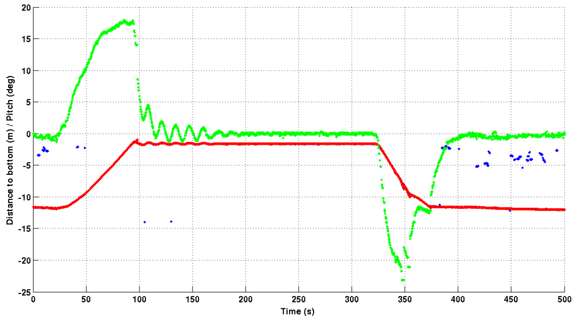

Fig. 4: Simulation of the Kalman Filter algorithm: output of the altimeter (blue), estimated distance to the bottom (red) and pitch of the vehicle (green)

impact, introducing a very small delay, as this is depicted in figure 5. There, it can be seen a detailed view of the steepest region of our simulated altimeter data produced by the Kalman Filter. Steep regions of the bottom are likely to be the ones where the delay would have a more visible effect but, as the plot demonstrates, this delay is small enough to be neglected.

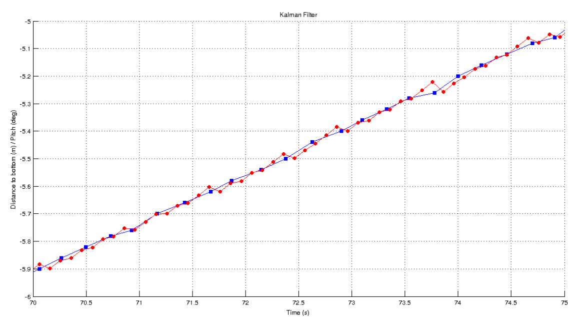

Fig. 5: The delay introduced by both estimators is negligible: altimeter measurements (blue) and depth estimates (red) are almost overlapping in the steepest region of the simulation

These simulations results showed that the Kalman Filter has a better performance, as the Linear Regression estimator induces noisy estimates for the slope of the bottom. This is in fact a key reason for the choice of the Kalman Filter as the algorithm to be actually implemented. The final step of the simulation results consisted on integrating the Kalman Filter approach together with the vehicle simulator, in order to access the behaviour of the controllers and of the trajectory performed by the the vehicle. Figures 6 and 7 depict, respectively, a simulation of the depth and pitch of the vehicle while doing a bottom following task on which the vehicle should follow the bottom with a distance of 2 meters.

It is clear from figure 6 that the AUV follows the bottom at the desired 2 meters. The points in blue are relative to a simulated bottom profile, and the points in red are relative to depth data given from the navigation layer of the vehicle simulator. The distance between bottom and the vehicle is always around 2 meters, as desired, even when there are

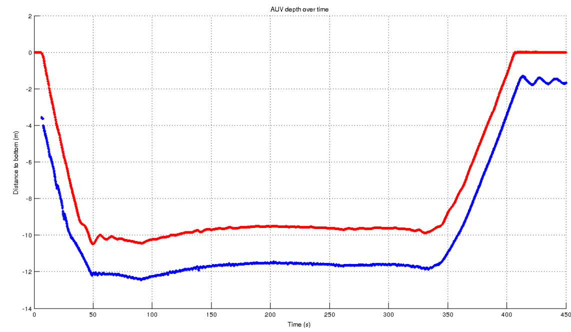

Fig. 6: Simulation of a typical Bottom Following mission: profile of the bottom (blue) and AUV depth (red)

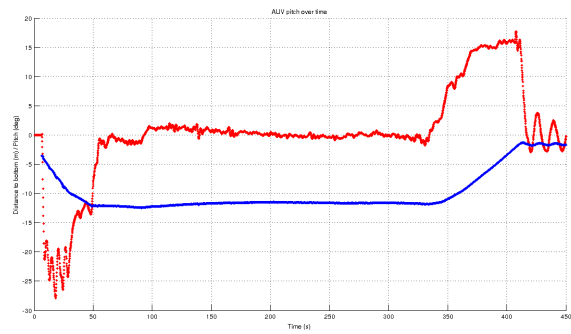

Fig. 7: Simulation of a typical Bottom Following mission: profile of the bottom (blue) and AUV pitch (red)

significant changes in depth of the bottom, as shown in the begginning and end of mission. The only exception to this occurs in the end of the mission, when the vehicle is only at 1.5 meters of the bottom, but already at surface level.

In figure 7, on the other hand, there is a plot of the same profile of the bottom, in blue, against the pitch of the vehicle given from the navigation layer of the vehicle simulator. Again, the blue points are relative to the profile of the bottom, while the red ones are relative to the pitch of the vehicle. In this plot it is visible the change of pitch over time, in accordance to the profile of the bottom: when the depth of the bottom starts increasing the pitch of the AUV is negative, when the bottom is flat the pitch of the AUV is around zero, and the depth of the bottom starts decreasing the pitch of the AUV is positive.

B. *Experimental Results*

The experimental tests presented in this section are the result of a series of trials that were carried away in the Summer of 2012 in the Douro river, in a location close by Porto, in Portugal. Simulations are never able to entirely model the dynamics and behaviour of the vehicle, and the complexity of an open-waters scenario. The challenge with these trials is to assess if the proposed algorithm is robust enough to be used in a real mission.

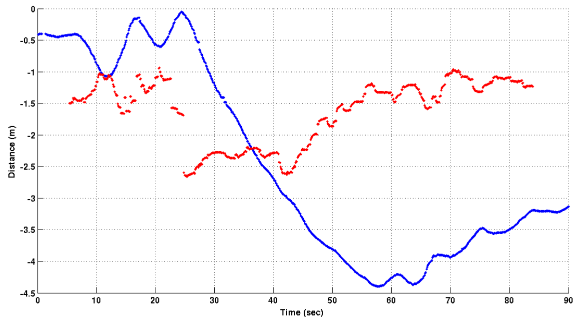

Fig. 8: Bottom Following mission: depth of the vehicle (blue) and distance to the bottom (red) over time

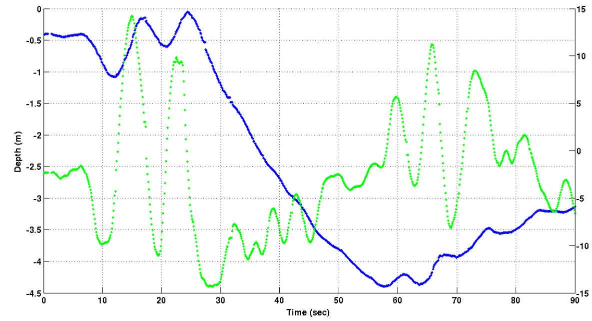

Fig. 9: Bottom Following mission: depth (blue) and pitch of the vehicle (green) over time

The AUV MARES was programmed to perform a number of different bottom following missions, and the plots depicting the behaviour of the vehicle during them can be seen in figures 8 to 10. A typical mission consists on sending the AUV performing a straight line, maintaining a specified heading while controlling heave and pitch to do the bottom following at 1.5 meters above the bottom. The selected missions for the plots here presented correspond to the data that more clearly demonstrates the performance of our approach in typical mission scenarios.

Figures 8 and 9 are complementary and correspond to the same bottom following mission: on figure 8 we can see the plot of the depth of the vehicle, given by the navigation layer of the vehicle, and the estimated distance to the bottom, and on figure 9 we can see the same depth of the vehicle, plotted against the measured pitch of the vehicle. Initially, the vehicle is performing a hover maneuver, at 0.5 meters deep and then, after approximately 5 seconds, the bottom following maneuver is initiated. The AUV was initially on a location with very shallow waters, of less than 2 meters. As this is really close to the desired 1.5 meters, there were some oscillations on both depth and pitch. These oscillations can also be explained by the small overshoot that affects the heave controller. As the vehicle progresses, it can be seen that the measured distance to the bottom has a rough change, from around 1 meter to 2.5 meters. After this, the AUV starts behaving more smoothly, first steadily increasing it's depth for some seconds and, after second 60, it decreasing again the depth. The distance to the bottom, however, clearly approaches the 1.5 meters bottom-following distance. At the same time, the pitch of the vehicle changes accordingly to the evolution of the profile of the bottom, as can be seen on figure 9.

In figure 9 some oscillations on the pitch of the vehicle can be seen, while the vehicle is following some ascending or descending bottom profiles. These oscillations are quite small, usually less than 5 degrees, and they result from small changes in the topography bottom. However, if it is not desired that the vehicle reacts to such small changes, it is likely that this can be achieved by tuning the filter accordingly.

Figure 10 depicts a different bottom following mission, and represents the profile of the bottom and the trajectory followed by the AUV. This was done by combining data from the depth and distance to the bottom of the vehicle. The plot also contains data representing the pitch of the vehicle, which can be easily related with the steepness of the bottom. In this figure it is clear that the AUV trajectory is clearly following the bottom.

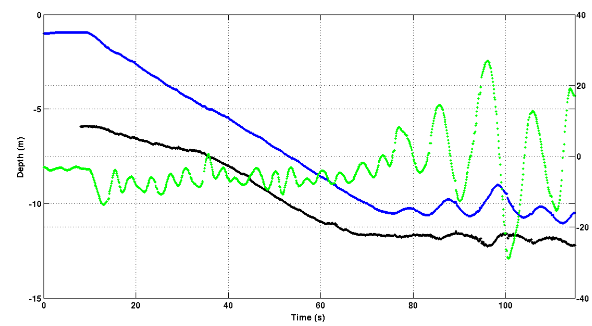

Fig. 10: Bottom Following mission: bottom of the river (black), trajectory performed by the AUV (blue), and pitch of the vehicle(green)

VII. Conclusion

When AUVs need to do tasks where the visual inspection of the bottom is required, they need to navigate as close to the bottom as possible, in order to maximize the quality of the final images. Moreover, they should maintain a parallel attitude towards the bottom in order to decrease the level of distortion of the images. Therefore, a bottom-following behaviour, where the vehicle follows a trajectory always parallel to the bottom, is of critical importance. In this article we propose a Bottom Estimation and Bottom Following guidance-based approach, that uses only an altimeter that continuously provides ranges to the bottom of the seabed.

Two different estimation algorithms were initially proposed: one based on a Linear Regression, and one based on a Kalman Filter. Both the approaches consist on feeding the pitch and heave controllers of the vehicle with the desired control variables. These control variables are generated according to the real-time estimates of both the distance of the AUV to the bottom, and the slope of the bottom. After some simulation tests, it was concluded that the Kalman Filter performance to be more adequated to this problem. The subsequent sintegration of this Kalman Filter algorithm with the onboard software of the MARES AUV, allowed to experimentally verify the robustness of the solution in a real-world scenario. In the field tests, the AUV performed a trajectory closely resembling the profile of the bottom, something that can be very useful for missions requiring the visual inspection of the bottom.

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