Autonomous homing and docking for AUVs using Range-Only Localization and Light Beacons

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Abstract: This paper proposes a method for homing and docking an Autonomous Underwater Vehicle (AUV) to a subsea Docking station (DS) by combining acoustic and optical sensing. The AUV is assumed to be within acoustic ranging distance to the DS, whose location is otherwise unknown *a priori*. The homing and docking procedure comprises two stages. In the first stage, a Sum of Gaussian (SoG) filter is used to estimate the DS location while the AUV is guided along an observable trajectory. Once the DS position becomes known, the vehicle performs a homing maneuver to bring it within visual reach of the DS. In the second stage, a light beacon navigation system is used to estimate the DS pose with respect to the AUV. Visual information is used to update to a Simultaneous Localization And Mapping (SLAM) filter providing an AUV-pose estimate with the accuracy required for the docking maneuver. The feasibility and performance of the method is evaluated through Hardware-in-the-loop (HIL) simulation. The novelty and impact of the proposed approach lies in the complementarity of the two sensing modalities, which have not been yet demonstrated for AUV docking.

Keywords: Autonomous vehicles, Marine systems, Robot navigation, Robot vision, Robot control

1. INTRODUCTION

Modern marine robots (such as ROVs, HROVs, AUVs, gliders and surface vessels) and sensors (profilers, ADCPs, lagrangian buoys, etc. . .) can generate vast amounts of data to help us better understand the oceans and their resources. Nevertheless, with a growing number of deployed systems, some of which operating continuously in permanent ocean observatories, the problem arises of how to make these data accessible to the scientific community. The Underwater Internet of Things (UIoT) concept has the potential to address this issue. Having the deployed systems networked through an UIoT may allow the 'things' themselves to directly provide the data to the internet without any user interaction. This is one of the main concepts behind the SUNRISE FP7 (see Petrioli et al. (2013)) project which provides a federated network of 5 testbeds for research and experimentation. These testbeds include cabled sensors and systems, and provide acoustic modems to interface with mobile systems and robots. Nevertheless, the industrial and/or scientific use of autonomous vehicles for inspection or mapping purposes tend to generate large amounts of data (such as imagery) which are far greater than those used for other applications like oceanography, for instance. In most cases, due to the large computational requirements needed for data analysis and map building, such large amounts of data will need to be transferred to an end-user computer ashore in raw format.

Nowadays, standard operations require the recovery of the vehicle in order to download the data through a wired or wifi connection, it not being possible to rely on low bandwidth acoustic communications for this purpose. Recently, other alternatives have been appearing in the market, providing high-speed communications at short range. This is the case with electromagnetic modems like the WFS S300 (WFS (2014)) providing a speed of 125 Kbps up to 10 m distance, or the BlueComm optical modem (Sonardyne (2014)) providing up to 20 Mbps and a distance up to 200m in deep water. In both cases, data can be downloaded by descending a modem to the respective depth and instructing the Autonomous Underwater Vehicle (AUV) to home-in to its vicinity.

The use of support vessels for AUV operations represents a significant part of the total operation cost. This has motivated researchers in recent years to look for alternatives which bypass the need for such vessels, thus advancing

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towards adopting a persistent deployment. The concept is based on using resident AUVs to pursue systematic inspections of submerged infrastructures on a periodic basis. Between two operations, the AUV homes and docks to a docking station for charging the batteries and uploading the mission data. This method of operation is of particular interest for deep water infrastructures where the cost of surfacing to recover the data is prohibitive. Persistent deployment is on the research agenda of the oil and gas industry (Gilmour et al. (2012)) and it is also of interest for marine science, the renewable energies (wind farms) and defense applications.

A step towards persistent deployment was demonstrated in the SWIMMER EU project by Evans et al. (2001). In this approach an AUV carrying a Remoted Operated Vehicle (ROV), is launched from a support vessel to autonomously navigate and then to dock onto an underwater docking station in an offshore infrastructure. The docking station provides a connection to the AUV and from it to the ROV, allowing a standard ROV operation without the need of a heavy umbilical. The next step towards a fully autonomous intervention system for sub-sea panels was achieved with the ALIVE project by Evans et al. (2003). It demonstrated the capability of autonomously docking into a ROV-friendly panel using hydraulic grabs.

The LOON-DOCK Experiment of the SUNRISE-FP7 project targets the demonstration of the persistent deployment of an AUV for survey/inspection in the LOON cable submerged infrastructure connected to the surface world through the UIoT. In future development, a Docking Station (DS) will be integrated within the LOON testbed, see Alves et al. (2014). A DS, to be designed and implemented, will be equipped with an Evologics acoustic modem acting as a transponder for homing purposes and also providing on-line monitoring of the AUV operation (Fig. 1). It will also be equipped with visual light beacons (see Bosch et al. (2016)) to allow for a robust autonomous visual based docking. A contact-less high bandwidth communication link will be used to download the vast amounts of data required for mapping purposes. The complete system will be integrated with the GATE architecture using the SUNSET framework (Petrioli et al. (2014)) and will be tested by remotely launching persistent survey operations that will be carried out by SPARUS II AUV (see Carreras et al. (2013)) at La Spezia (Italy).

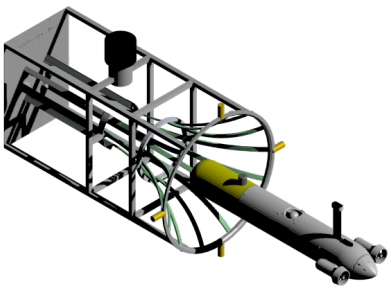

Fig. 1. Docking station concept with Sparus II AUV. An acoustic modem on top (black) and 4 light beacons (yellow) at the front.

In this paper, a method is proposed using range-only acoustic measurements for homing and light-beacon localization for docking, and demonstrated using Hardware-in-the-loop (HIL) simulation. A distinctive feature of this proposal with respect to the current state of the art is the fact that it combines the two complementary modalities. Acoustic ranging can provide reliable distance measurements over large distances, but cannot provide pose information for all the degrees of freedom that are required for docking. Optical sensing is limited in range due to visibility constraints, but can provide very fast and accurate updates on the pose, which are needed for fine position control during the final stage of dock entry. Another important aspect of this approach is the fact that acoustic ranging and optical sensing are capabilities that either already exist, or can be easily added to most AUVs, due to their low cost. The same reasoning applies to the DS, since the light beacon system is relatively inexpensive to manufacture.

The paper is divided into sections as follows: Section 2 describes the mission strategy for homing and docking. Section 3 describes the range-only localization as well as the light-beacon detection and navigation. Following these descriptions, Section 4 reports the HIL simulation results before concluding in Section 5.

2. HOMING AND DOCKING

The DS localization for homing and docking is obtained in 2 steps. First the AUV localizes the DS with range-only measurements obtained by the acoustic modem (if the DS position is unknown) and uses this approximate position for homing. Then, once the AUV is in the vicinity of the DS, the light beacon detection system provides feedback through the Simultaneous Localization and Mapping (SLAM) navigation filter for a precise docking.

A state machine has been developed to control the various stages of the autonomous homing and docking. First of all, it is worth noting that there are two different scenarios to the problem of docking.

In the first, the vehicle starts at the DS and it is requested to execute an autonomous mission. It uses the range updates in the navigation filter to reduce position uncertainty and when the mission is finished returns to the DS.

In the second, the vehicle doesn't know the exact position of the DS because of loss of communication or because its position was *a priori* unknown. In this case, the vehicle must use the range-only localization (Section 3.1) to estimate the DS location and then home towards it.

In both cases the final docking maneuver is aided by detection of light beacons (see Section 3.2) which drastically reduce the uncertainty of the DS position. Their higher update rate compared to the range-only allow for a precise control for the final docking maneuver.

For the sake of simplicity, only the second scenario is detailed next (see Fig. 2), which includes the following sequential phases:

(1) Create a waypoint far from the approximate DS position.
(2) Navigate towards this waypoint.
(3) Use SOG filter to detect the DS following a star like trajectory.

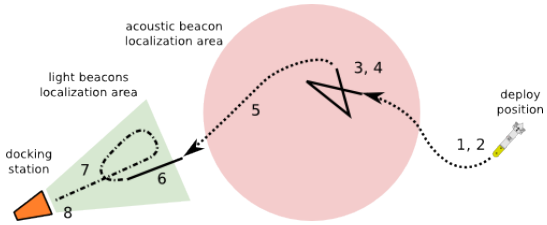

Fig. 2. Schematic of the mission steps to localize and dock to the DS.

(4) If the DS is detected, create a waypoint 10m in front of the DS. Otherwise, return to (1).
(5) Navigate towards the waypoint.
(6) Follow a trajectory towards the DS until light beacons are detected. Otherwise, return to (4).
(7) Execute the docking maneuver.
(8) If correctly docked inform the DS to latch the AUV. Otherwise, undock and return to (4).

The docking maneuver consists of several waypoints placed in front of the DS entrance that the AUV must follow in a straight line. At the end of this line, docking is finalized by an extra command which requests the vehicle to exert a constant force along the x axis of the AUV while keeping its heading and depth constant for a specific period of time.

Similarly, the undocking maneuver requests the AUV to move backwards exerting a constant force along the x axis of the AUV while keeping the heading and depth constant for a specific period of time.

2.1 Navigation filter

The navigation filter of the AUV is based on the well known Extended Kalman Filter (EKF). It combines the information on depth returned by the Pressure sensor, velocities from the Doppler Velocity Log (DVL) and attitude from the Attitude and Heading Reference System (AHRS) to provide a Dead Reckoning (DR) navigation. This navigation drifts over time and needs absolute measurements to correct it. Those measurements can come from either Global Positioning System (GPS) when on the surface, Ultra-Short Baseline (USBL) with a support vessel, ranges to a known position, or visual detections (Fig. 3).

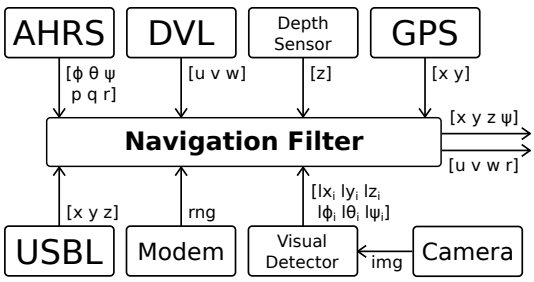

Fig. 3. Set of sensors that take part in the navigation algorithm of the AUV software architecture.

When the position of the DS is known with certain precision, its position is used to setup a landmark in the feature-based EKF-SLAM navigation filter with the following state vector:

$$\boldsymbol{x} = \begin{bmatrix} x & y & z & u & v & w & l_1 & \dots & l_N \end{bmatrix} \tag{1}$$

where $[x\ y\ z]$ and $[u\ v\ w]$ are the position and linear velocity vectors, and l_i is the landmark i pose vector defined as:

$$l_i = \begin{bmatrix} lx_i & ly_i & lz_i & l\phi_i & l\theta_i & l\psi_i \end{bmatrix} \tag{2}$$

those landmarks can come either from visual detection, where they are fully defined or from range-only measurements, where orientation cannot be estimated.

The navigation filter uses a constant velocity model with attitude input:

$$\hat{\boldsymbol{x}}_k = \begin{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ z_{k-1} \end{bmatrix} + \mathcal{R}(\phi_k \theta_k \psi_k) \left(\begin{bmatrix} u_{k-1} \\ v_{k-1} \\ w_{k-1} \end{bmatrix} t + \begin{bmatrix} n_{u_{k-1}} \\ n_{v_{k-1}} \\ n_{w_{k-1}} \end{bmatrix} \frac{t^2}{2} \right) \\ u_{k-1} + n_{u_{k-1}} \\ v_{k-1} + n_{v_{k-1}} \\ w_{k-1} + n_{w_{k-1}} \\ l_{1_{k-1}} \\ \dots \\ l_{N_{k-1}} \end{bmatrix} \tag{3}$$

where t is the sample time, $[n_u\ n_v\ n_w]$ is the noise vector and $[\phi_k\ \theta_k\ \psi_k]$ are the Euler angles used as the filter input u_k.

In the case of range-only measurements, the observation equation provides the expected range measurement $h(\boldsymbol{x}_k)$ which is given by the norm of the difference between the vehicle and beacon positions at time k.

$$h(\boldsymbol{x}_k) = ||(x, y, z) - (lx_i, ly_i, lz_i)|| \tag{4}$$

The standard EKF update equations are used with $R = \sigma^2_{range}$.

In the case of visual detection update, refer to Palomeras et al. (2015) for details on its implementation.

3. DS LOCALIZATION

As explained in previous sections when the position of the DS is unknown, the range-only localization method is needed to obtain an approximate location. Once the vehicle homes to the vicinity of the DS the light beacon detection provides updates to the navigation filter for a precise docking maneuver.

3.1 Range-Only Localization

Range-only localization is a highly non-linear problem. Given 1D measurements (range), the vehicle must be localized in a higher dimensional space (3D). With an unknown position of the beacon, a simple EKF approach is not enough to solve the localization problem. A particularly interesting feature is the symmetries of the possible localizations when the AUV follows a straight trajectory.

Several range-only localization methods have been applied in the literature, see Vaganay et al. (2000); Newman and Leonard (2003); Olson et al. (2006); Webster et al. (2009); Wang et al. (2013); Blanco et al. (2008). However,

those methods are demonstrated offline after the vehicle is recovered and no online localization is performed.

In this paper we assume that the beacon depth is known *a priori*, since it is easy to measure during the DS deployment. This simplifies the problem from 3D to 2D (Fig. 4). Depth information provided by the AUV pressure sensors is very precise, only having to take into account the tide, for which appropriate models are already available.

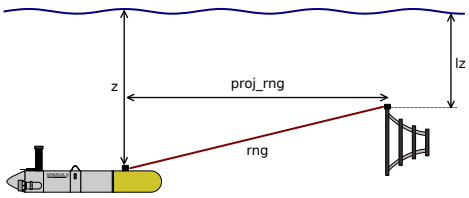

Fig. 4. Projection of the range measurement.

During the estimation of the beacon position, we rely on the on-board DR navigation filter based on the DVL/AHRS/Pressure. The drift is not taken into account because the time needed to localize the DS is small enough, as demonstrated in Vallicrosa et al. (2014) where a 3D Sum of Gaussian (SoG) filter with Active Localization (AL) was used to successfully localize an acoustic beacon in a real scenario.

At known depth, a range measurement describes a beacon as being in any position on a circumference around the AUV with a radius equal to the projected range and thickness equal to the uncertainty of the measurement. To cover this big space of possibilities one might use a Particle Filter (PF) to represent the static beacon position, however, the PF solution will leave empty space without coverage. To avoid that, a much larger number of particles could be used, but then the problem will become intractable. Another more elaborate option is the SoG filter, see Blanco et al. (2008). The SoG filter is similar to the PF, but instead of using weighted particles, it uses weighted Gaussians. It represents the believed beacon position $\mathcal{B}$ according to the odometry $\boldsymbol{x}_k$ and the measurements z_k:

$$p(\mathcal{B}|\boldsymbol{x}_k, z_k) \approx \sum_{i=1}^{N} \upsilon_k^i \mathcal{N}\left(z_k; \mu_k^i, \Sigma_k^i\right) \tag{5}$$

where υ_k^i is the weight associated with each Gaussian, and μ_k^i and Σ_k^i its mean and covariance matrix.

The Gaussians in the SoG can cover all the probability space if they are well distributed. Moreover, an EKF is used to correct their position according to the measurements, thus improving its performance.

The SoG is initialized with the first range measurement (Fig. 5). The filtering is carried out in two main steps. First, the range measurement is used to update each of the Gaussians (μ_k^i, Σ_k^i) with an EKF. Second, the weights are updated with the innovation $y_k^i = z_k - h(\mu_k^i)$:

$$\upsilon_k^i = \upsilon_{k-1}^i \cdot \exp\left(-\left(y_k^i\right)^2\right). \tag{6}$$

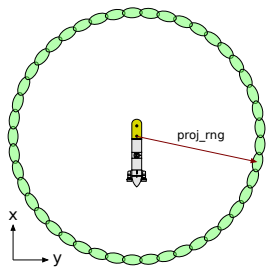

Fig. 5. Initialization of the SoG filter (2σ bounds).

i being the index of the Gaussian and υ_{k-1} the previous weight. This computed weight is always in the $[0, 1]$ range. The weights of the Gaussians with a small innovation are significantly greater than those having a greater innovation. With time, the Gaussians which are not consistent with the observed ranges become negligible while those consistently compatible will influence the estimated pose of the beacon.

When the vehicle follows an observable path, see Vaganay et al. (2000), the beacon is localized in a few seconds (see Section 4). In this work, a simple approach using a star shaped trajectory is used to avoid symmetries and locate the beacon (Fig. 6). This trajectory is scaled proportionally to the first measured range and it is aborted as soon as the beacon is localized.

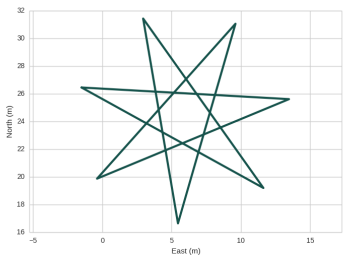

Fig. 6. Star shaped trajectory used for beacon localization.

3.2 Pose Estimation using Light Beacons

Acoustic localization can be very effective from medium to long distances, but it is not so advantageous at short distances when high precision operation is required for successfully completing the docking maneuver. To achieve a level of performance capable of ensuring the vehicle's safety during docking, visual sensing is used to provide updates with small uncertainty and high update rate.

The proposed solution consists in placing a set of active light beacons in distinct and known positions of the DS (Fig. 1). Using a standard camera it is possible to detect the lights in the images and estimate the pose between the DS and the camera. It is worth noting that differently from range-only localization, this method is able to provide information on the relative orientation of the DS, with the full 6 DOFs (3 relative translations and 3 rotations).

With the aim of facilitating the detection of the light markers (beacons) and avoiding wrong identifications, the markers follow a known pattern, turning off simultaneously for 0.1 seconds every second. This blinking pattern allows the actual markers to be discerned in the presence of

any reflection or permanent shiny spot in the scene being viewed.

The detection technique used for field experiments is similar to the one detailed in Bosch et al. (2016), where it was used to track multiple AUVs for cooperative navigation in real sea conditions, and proved to be both effective and robust.

For simulation purposes the visual tracking module has been simplified to avoid the use of synthetic images, which differ significantly from real images. During simulation, the ground truth poses of both the AUV and the DS are known, thus, the light markers can be projected into the image-plane. In order to achieve a more realistic simulation the light markers are considered visible only when the distance camera-marker is smaller than 10 m, which is a conservative value in normal visibility conditions. Furthermore, Gaussian noise has been added to the location of the lights in the image-plane, to simulate the uncertainty of the estimate of the center of a light in a real image.

When at least three markers have been detected, the relative landmark pose $\hat{l}$ of the DS that best fits the observation of the markers in the image, u, is found using non-linear least squares minimization. This is done by searching for the values of the variable l that minimize the re-projection error of the markers; that is, the difference between the real observation and the projection of the marker derived from the variable l and the calibration parameters of the camera.

$$\hat{l} = \arg\min_{l} \sum_{i}^{n} (f_l(q_i) - u_i)^2 \tag{7}$$

The variable x contains the complete pose of the DS with respect to the camera $l = \left[l_x^c \; l_y^c \; l_z^c \; l_\phi^c \; l_\theta^c \; l_\psi^c\right]^T$. The function f computes the image projection of a marker given l, and the position of the marker in the DS reference frame, q_i. This function uses the pinhole camera model (Zhang (2000); Hartley and Zisserman (2004)), and assumes known intrinsic calibration parameters. Although an approximate linear solution can be found for 4 or more light markers using a different pose parametrization, we are interested in the above parametrization since it can be directly used in the docking problem. The problem is solved with the Levenberg-Marquardt algorithm available in the Ceres library (Agarwal et al. (2012)). As with all iterative methods, it needs an initial guess of the variables, which can be approximated from the range measurements between acoustic modems. Further details on the pose estimation problem and its performance with a varying number of light markers can be found in Gracias et al. (2015).

For the proper operation of the navigation filter it is essential to have an estimate of the pose uncertainty. A first-order approximation of the pose covariance $\Sigma_{\hat{l}}$ can be computed from the assumed covariance Σ_u of the pixel location of the beacons in the image and the Jacobian $J(\hat{l}) = \frac{\partial u}{\partial l}(\hat{l})$ that relates small changes in the pose parameter with small changes in the observations. The Levenberg–Marquardt implementation provides this Jacobian at the end of the minimization. The pose covariance estimate is given by:

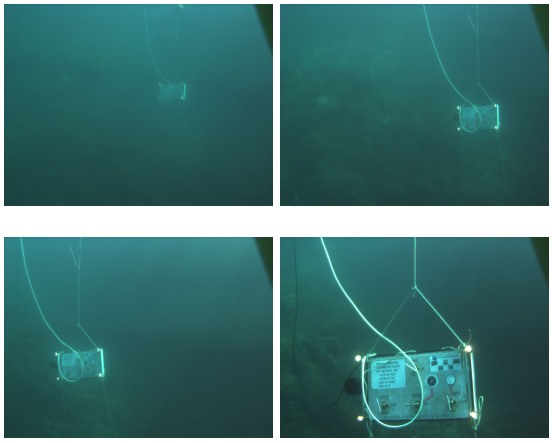

Fig. 7. Light markers located during preliminary experiments at 10m , 6.5m, 5m and 3m from the camera.

$$\Sigma_{\hat{l}} = (J(\hat{l})^T \Sigma_u^{-1} J(\hat{l}))^{-1} \tag{8}$$

The uncertainty in the localization of a light in the image is inversely dependent on the distance of the beacon from the camera. The closer the beacon is to the camera, the larger the projected light will be in the image, thus leading to higher uncertainty than for far away beacons, which appear in the image as small disks (Fig. 7).

In order to have an approximate value of this uncertainty, the size of the lights was analyzed using a set of selected real images from one preliminary experiment. The beacons in the images were fitted to a 2D Gaussian distribution centered at u, with standard deviation σ, amplitude A and an offset c_0: $f(u, \sigma, A, c_0)$. The results of this experiment (Figure 8) show that the variation of σ can be considered constant without significantly affecting the final uncertainty computed. A conservative mean value of $\sigma = 2$ pixels was chosen for the standard deviation of both horizontal and vertical pixel uncertainties.

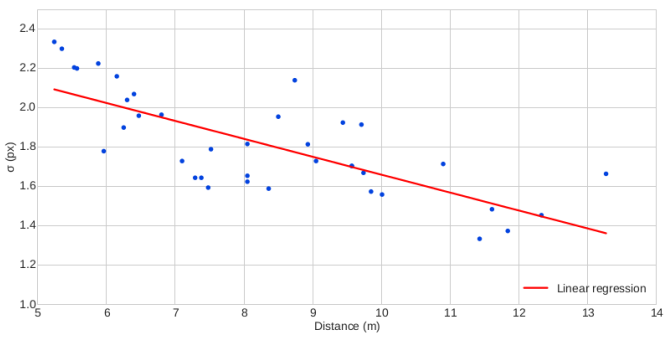

Fig. 8. Evolution of the standard deviation of the Gaussian distributions fitted to the lights as a function of distance.

4. RESULTS

Experiments were carried out in a HIL simulation. The light beacon measurements were simulated as explained in

Section 3.2. Range measurements were simulated by using the modulus of the difference between the position of the AUV and the DS every 3 seconds with added Gaussian noise, and a probability of success of measurement of 80% to take into account communication loss.

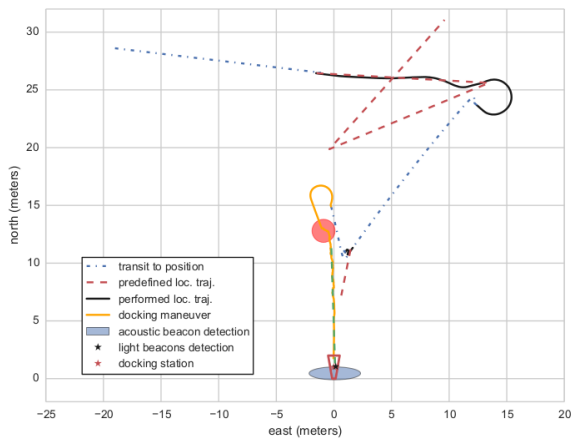

Fig. 9. Autonomous trajectory performed by the AUV while homing and docking.

Figure 9 shows a trajectory performed by the AUV in one of these simulations while locating the DS and docking to it. The AUV follows the steps previously described. Note that both the acoustic beacon and the light beacons' localization trajectories are aborted as soon as they are detected.

The SoG filter detects the DS at position $(0.46, 0.08, 4.0)$ with an uncertainty of $2\sigma = (1.12, 4.47, -)$. The visual landmark detector places the DS at $(0.15, 0.16, 3.98)$ with and uncertainty of $2\sigma = (0.12, 0.12, 0.04)$.

Comparing against the ground truth given by the simulator, the position estimated using the light beacons has an error below 0.06m in the X-Y plane, and below 0.03m in depth which means that the funnel shaped DS is big enough to dock the vehicle.

The DS position is added as a new landmark in the EKF once the light beacons are detected. From this moment, every time they are detected, the AUV/Docking positions are corrected. This can be seen in the trajectory performed by the AUV in Fig. 9 around position $(13, -1)$, marked with a red circle, where it seems that the vehicle slides to the east. In fact, new beacon detections were introduced in the EKF updating the AUV/docking position.

If the vehicle starts the mission from the DS, the acoustic modem position is already defined in the EKF as a landmark and therefore, range updates can be done during the whole mission without waiting for the light beacon to detect the DS. Figure 10 shows how the uncertainty, along the east axis, grows at a reduced rate in the presence of range updates.

Looking at the range-only localization using a SoG filter, a strong symmetry can be observed while the AUV is following the first straight line of the star-shaped trajectory (Fig. 11). When the second line starts, the small turn of the AUV brings a discrepancy to the symmetry. This discrepancy ensures that the correct localization is the

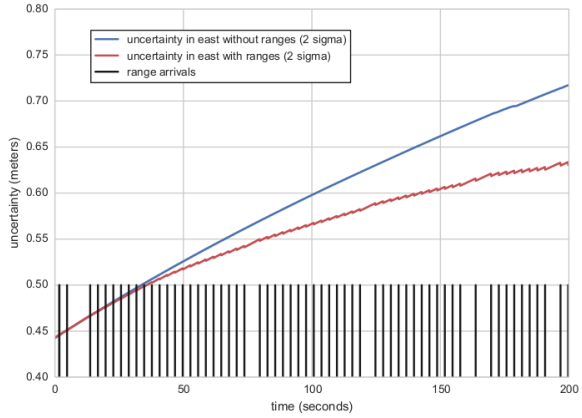

Fig. 10. Uncertainty of the navigation filter without and with range updates.

bottom one. The filter correctly localizes the beacon and quickly aborts the remaining trajectory.

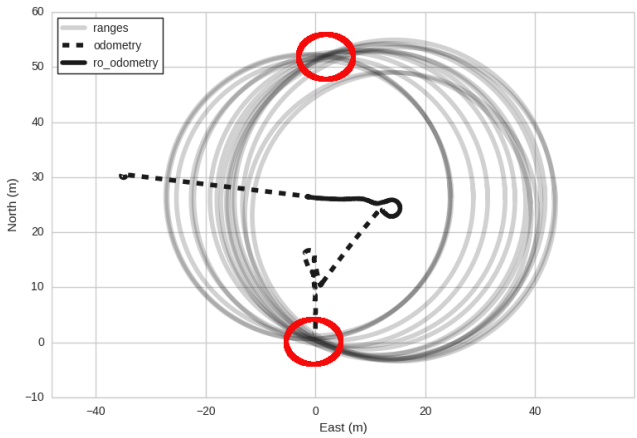

Fig. 11. Odometry of the AUV with circles representing the ranges obtained while range-only localization was running. Observe the symmetry (red) in localization between top and bottom.

The module for pose estimation using light beacons showed very good results in uncertainty for both position and orientation. As shown in Table 1 the uncertainty drastically reduces as the distance between the camera and the DS decreases. The values of the uncertainty were calculated assuming a constant value for the noise in the detection of the center of the lights of $\sigma = 2$ pixels as detailed in section 3.2.

Table 1. Volume of the ellipsoid that contains the position of the DS with a probability of 95% at different distances according to the optical tracking.

Distance (m)	10	7.5	5	3.5
Volume (dm^3)	45	27.3	16.5	4.3

5. CONCLUSIONS

This paper has presented the design and implementation of a homing and docking algorithm for AUVs. The main

innovation of the proposed method is the combination of a single beacon range-only localization system at large distances, with a light beacon localization module over short distances. This combination allows localization of the DS from afar, while maintaining enough accuracy to successfully perform a docking maneuver. Both systems are conveniently combined by a state machine used for mission control. HIL simulated results show that the homing and docking algorithm is successful with acceptable error on both localization systems.

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