

# Accurate Geo-Referencing Method for AUVs for Oceanographic Sampling

Rubaina R. Khan  
Singapore-MIT Alliance for  
Research and Technology Centre  
Email: rubaina@smart.mit.edu

Tawfiq Taher  
Singapore-MIT Alliance for  
Research and Technology Centre  
Email: tawfiq@smart.mit.edu

Franz S. Hover  
Massachusetts Institute of Technology  
Email: hover@mit.edu

**Abstract**—The objective of the paper is to understand, characterize and enhance the achievable performance of the system of a state-of-the-art marine observation device, the OceanServer IVER2 Autonomous Underwater Vehicle(AUV), in the Singapore coastal zone and with regard to accurate sampling of oceanographic properties. This paper discusses modifications made to the AUV, in order to make it useful for experiments in this region, which includes shallow water, strong currents, poor visibility, heavy traffic and a poor acoustic environment. These factors strongly influence the choice of navigation method and the system architecture which will enable the AUV to obtain accurate geo-referenced oceanographic properties, and to ensure its safe operation. Our science experiments usually involve sampling at various areas around the coast of Singapore within the same day; this calls for consistent positioning methods that allow ease in deploying and retrieving related equipment. This paper illustrates the use of ultra-short baseline (USBL) tracking system and ranges from an acoustic modem fused by a particle filter to aid the dead reckoning algorithm of the IVER2. The performance of the modified system is shown through simulations and field experiments.

## I. INTRODUCTION

Autonomous under water vehicles (AUVs) make a significant impact in ocean applications such as water sampling and improve quality of forecasts for the region around Singapore [1]. Accomplishing such tasks is a hurdle in dynamic environments such as the Singapore coastal area hence requires AUVs to be localized accurately. In this paper, we discuss modifications made to the state of the art marine observation device, the OceanServer IVER2 AUV. The changes will aid in achieving acceptable positioning of the vehicle in order to gather meaningful, geo-referenced data and ensure safe navigation of the vehicle. For the AUV to recover from drift due to ocean currents or limitations of the navigation method, additional sensors can be utilized to bound the errors. Global positioning system (GPS) radio - frequency signals cannot be received directly by the AUV when underwater, hence we have to rely on acoustic positioning systems. As every sensor or technique has its limitation, it is desired to have a number of sensors whose information can be combined to achieve a better solution. Multisensor data fusion (MSDF) techniques provide significant advantages over using a single sensor. Some benefits include redundancy, better resolution of the observation and accuracy since information resulting from several sources reduces uncertainty [2].

The paper is organized in the following manner. In Section 2, the motivation for this work and a review of related work is discussed. Section 3 explains the enhancements made to the system architecture of the OceanServer IVER2 and the sensors used. In Section 4, we discuss the particle filter algorithm, which is used to fuse ultra-short baseline (USBL) data and ranges from an acoustic modem to aid the navigation system provided by OceanServer. Experimental results from simulations and field experiments in the Singapore coastal area are shown in Section 5. We conclude with Section 6.

## II. MOTIVATION AND PREVIOUS WORK

The primary role of the OceanServer IVER 2 at the Center for Environmental Sensing and Modeling (CENSAM) is to provide water composition information from its YSI in situ chemical sensor payload, of various locations in the Singapore coastal area. It is challenging to conduct experiments in this region due to several factors such as shallow water, strong currents, heavy maritime traffic due to the shipping industry and a poor acoustic environment. The IVER2 runs long lawnmower missions in areas of interest using its default dead reckoning algorithm, which utilizes information from its compass and estimated thruster speed measurements. In a strong ocean environment where currents encountered reach up to 1.6m/s [3], performance of a typical field experiment is shown in Fig 1. Although the AUV surfaced to get a GPS fix to reduce uncertainty, an average error of 30% was recorded at the end of each leg of the lawnmower mission. The drift produces data that are imprecisely geo-referenced which introduces errors to the forecasts that are modeled based on them. Drifts may place the AUV out of the operation area permitted by the Maritime and Port Authority of Singapore (MPA) that can lead to collisions with moving or anchored sea vessels. Therefore, the navigation method and system architecture proposed and implemented, would make the IVER2 useful in this region with ease in deploying and retrieving related equipment.

Using only dead reckoning algorithms, yield an accumulation of error and uncertainty, which can be improved significantly by using Doppler Velocity Log (DVL), USBL or Long-Baseline (LBL) acoustic measurements. The current vehicle configuration does not carry a DVL. USBL and LBL systems show stable positioning accuracy but the LBL requires an infrastructure of fixed or moving beacons deployed into the

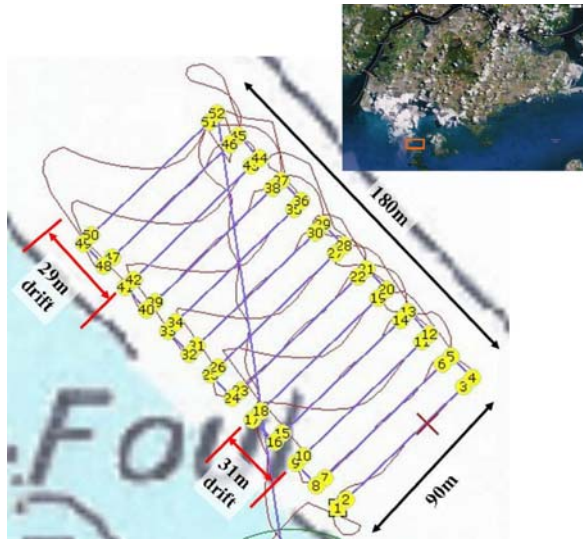


Fig. 1. Dead reckoning data obtained from an AUV lawn-mower mission in the Singapore harbor.

ocean. The setup of a full-up LBL infrastructure in the busy and crowded Singapore harbor is quite a challenge, and could reduce the working area of the vehicle. We prefer a system that involves sensors set up on a specific work platform and on the AUV; hence, we have deployed a USBL system. We augment this with ranging from our acoustic modem, typically mounted on the same work platform as the USBL, shown in Fig 2.

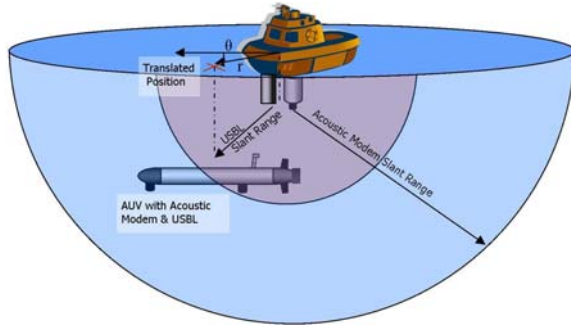


Fig. 2. The setup for correcting dead reckoning position estimation from USBL and range observation from the acoustic modem.

Most accurate positioning algorithms use a MSDF approach. The most related work discussed in this paper is Rigby et al [2], where a particle filter for the navigation system has fused the DVL and USBL data. A navigation method proposed in [4] is similar to aircraft terrain navigation where a digital underwater terrain map and depth measurements from sonar are inputs to a particle filter for state estimation. Successful attempts of using only ranges from acoustic positioning systems for localization have been discussed in [5-7]. For state estimation and data fusion, the Kalman filter and for nonlinear systems the Extended Kalman filter (EKF), are often used [8,9]. Often particle filters are used in lieu of the EKF for nonlinear systems as it does not require Gaussian noise

assumption, which occur due to false returns and multipath of the acoustic signals. They also approach the Bayesian optimal estimate, with sufficient samples, and shows progress in the performance when compared to the EKF [10].

### III. EXPERIMENTAL PLATFORM

The AUV used for the experiment is the Iver2-580-EP Expandable Payload version. The vehicle was purchased of the shelf from Oceanserver Technology, Inc. The basic vehicle comes with GPS, Altimeter, Compass, Pressure Sensor, CPUs and Power system. The diameter of the hull is 14.7 cm and it is about 183 cm long. The sensors and the control system of the AUV are managed by Oceanserver's proprietary software Underwater Vehicle Control (UVC) but it can be accessed by Application Programming Interface (API) provided by Oceanserver. Fig 3 illustrates the AUV in operation.



Fig. 3. AUV in the Seatrial

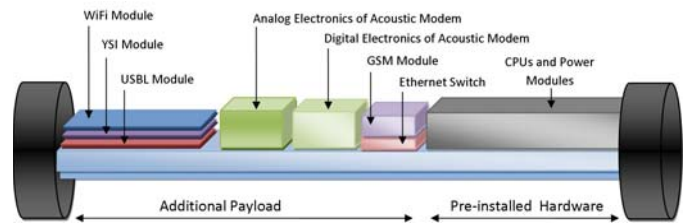


Fig. 4. Center section of the IVER2, populated with payload sensors

The payload section of the AUV, as seen in the Fig 4, was populated with essential modules to suit the experimental requirements which are chemical sensors for oceanographic properties, acoustic modem to communicate under water, USBL system to track the vehicle when it is in the water and other enhancement modules such as high power wireless, cellular modem and Ethernet switch.

Oceanographic sampling is done by the YSI 6600 series sensors. This bulkhead contains conductivity, temperature, depth, salinity, chlorophyll, dissolved oxygen, pH, rhodamine and turbidity sensors. The system under normal conditions is able to actively read data from all the chemical sensors and update the on-land control center of the latest readings via the

acoustic modem. This set-up is useful for adaptive sampling algorithms, data assimilation, and quickly detecting structures and fronts.

The acoustic modem used in the AUV is from the Acoustic Research Laboratory (ARL) of the National University of Singapore (NUS). This modem is optimized for communicating in the shallow warm Singapore harbor water and is able to correct ambient noise such as snapping shrimp and ship turbulence. In a typical Singapore coastal scenario, this modem can achieve up to 1.5 km range with sub-meter accuracy of localization and up to 60 bps of baud rate.

An Easytrak Nexus USBL system is used for the operation which has a slant range accuracy of 10 cm and position accuracy of 0.60 drms. 1.0% of slant range (Acoustic accuracy excluding heading errors). The tracking pattern of the transmitter is hemispherical and the transmission power is typically 190 dB SPL. The position of the USBL is obtained using a Differential GPS (DGPS) sensor to ensure better accuracy. The USBL module used in the AUV uses a spread spectrum transponder. This transponder has wide bandwidth transmissions that reduce its susceptibility to interference and enables more accurate positioning. This is also suitable for this application because spread spectrum transponders are also better at rejecting unwanted reflected signals which improves operations in challenging locations such as ports and harbors.

The AUV has also been enhanced with a redundant Wi-Fi channel and a Global System for Mobile Communications (GSM) modem for cellular communication. The GSM in particular aids the users in communicating with the system when at surface and out of Wi-Fi range. An emergency system is designed to help to locate the AUV in both below and above surface conditions, using USBL tracking, GSM, a secondary GPS unit using an emergency power system. From several experiments, we have observed that the USBL tracking and acoustic communications cause interference to each other, because they work in the same frequency range. A time division multiplexing method is employed to avoid this problem.

#### IV. SENSOR FUSION

Fusion of the ranges acquired from the USBL and acoustic modem has been done using a particle filter. The ranges from the USBL tracking system are noisy but do not degrade with time. On the other hand, the acoustic modem ranges are accurate but the system is less robust than the USBL. This method does not require linearization of state models and assumption of Gaussian distributions for describing sensor errors. The theory of the particle filter is briefly discussed here.

##### A. Motion model

A large number of "particles" are employed that represent possible trajectories of the AUV. These particles remain effective in representation when the motion model of the vehicle is accurately modeled and the errors involved are incorporated. The state of the system is represented by:

$$\mathbf{x}_{t+1} = f(\mathbf{x}_t, u_t, w_t) \quad (1)$$

where  $u_t$  is an input signal, and the  $w_t$  is the process noise at time  $t$ . Here the input signal for the particle filter is the AUV compass reading and estimated velocity derived from its thruster model. Assigning them random location values initializes the particles and the assigned relative weight is the same for each particle. At every iteration, the motion model updates the particles' trajectories. The filter gives a Bayesian solution to:

$$p(\mathbf{x}_{t+1}|Y_t) = \frac{p(\mathbf{y}_t|\mathbf{x}_t)p(\mathbf{x}_t|Y_{t-1})}{p(\mathbf{y}_t|Y_{t-1})} \quad (2)$$

where  $Y_t$  be the set of observations until the present time and  $y_t$  is the observation from a sensor at time  $t$ .

##### B. Observation model

The observation model uses acceptable observations from the USBL and acoustic modem. The observations determine which particles represent the actual trajectory. The observations  $y_{usbl}$  and  $y_{acom}$  from the USBL and acoustic modem respectively, at time  $t$  is given by:

$$\mathbf{y}_{usbl} = g_1(\mathbf{x}_t) + e_{usbl} \quad (3.1)$$

$$\mathbf{y}_{acom} = g_2(\mathbf{x}_t) + e_{acom} \quad (3.2)$$

The errors  $e_{usbl}$  and  $e_{acom}$  represent measurement noise of the sensors. The location and weight of each particle represents the value of the density in the state space region. The likelihood functions for observations from each sensor is calculated from equation 3 with:

$$p(\mathbf{y}_{usbl}|\mathbf{x}_t) = p_{e_{usbl}}(\mathbf{y}_{usbl} - g_1(\mathbf{x}_t)) \quad (4.1)$$

$$p(\mathbf{y}_{acom}|\mathbf{x}_t) = p_{e_{acom}}(\mathbf{y}_{acom} - g_2(\mathbf{x}_t)) \quad (4.2)$$

The weight of each particle is updated at every iteration by the following:

$$w_{i+1} = w_i (p(\mathbf{y}_{usbl}|\mathbf{x}_t) p(\mathbf{y}_{acom}|\mathbf{x}_t)) \quad (5)$$

These weights have to be normalized so that all weights sum to unity. The output of the filter  $\mathbf{x}_O$ , which is represented by the state of the filter, is calculated by taking the weighted mean of all the particles in the probability distribution function by:

$$\mathbf{x}_O = \sum_{j=1}^M \mathbf{x}_j w_j \quad (6)$$

where  $M$  is the number of particles.

### C. Resampling

The above estimation approach causes divergence, where over time most particles have zero weights. This occurs due to the particles being drifted far enough and their weight is unable to contribute to the probability density function of the vehicle in motion. This requires the algorithm to sample particles with higher weights and discard the ones with lower weights. In this filter, a simple method for resampling was utilized called 'Select with replacement' [11]. Resampling is necessary when the effective number of particles is below a certain threshold level. The effective size of the particle population 'M' is determined by:

$$M_{ES} = \frac{M}{1 + cv_t^2} \quad (7)$$

where coefficient of variation  $cv_t^2$  is given by

$$cv_t^2 = \frac{1}{M} \sum_{i=1}^M (Mw_i - 1)^2 \quad (8)$$

The threshold level was chosen to be  $M_{ES} = \frac{2M}{3}$  [8]. During resampling, when particles with lower weights are discarded, this causes a depletion or sample impoverishment. This is handled by replacing the low weighted particles with ones with higher weights along with some additional noise to make them unique.

## V. EXPERIMENTAL RESULTS

This section shows the performance of the particle filter in simulations based on experimental data followed by actual field results. All of the field experiments were carried out on the surface to record GPS readings, in order to use it as the ground truth. This, of course, hampered the performance of the USBL and acoustic modem due to surface reflections. When no acceptable observations are available, the vehicle runs on its dead reckoning algorithm.

### A. Simulations

The particle filter was tested in MATLAB and was initialized with 1000 particles. Field data was collected for a mission that was run twice in similar sea conditions. First, the performance of the default dead reckoning was recorded using a secondary GPS unit, followed by a GPS corrected mission in order to acquire USBL and acoustic modem ranges for inputs to the simulation. In Fig 5, the mean estimate of the particle filter is shown along with true trajectory paths of the AUV in the field experiments. The error of the particle filter estimates and default dead reckoning path are depicted in Fig 6.

### B. Field Experiments

Experiments to validate the simulations were carried out in Selat Puah, which is located in the southern Singapore coastal area. As computation of 1000 particles every iteration is extensive, a secondary CPU in the AUV handled the updates of the particles. Typically, to receive a fused solution from acceptable observations took nearly 15 seconds. To evaluate

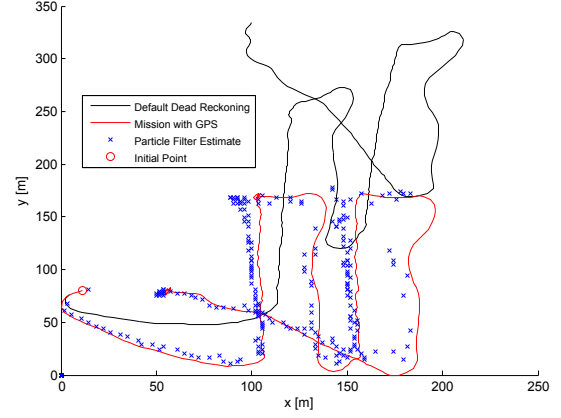


Fig. 5. Simulation of filter performance using actual sensor data.

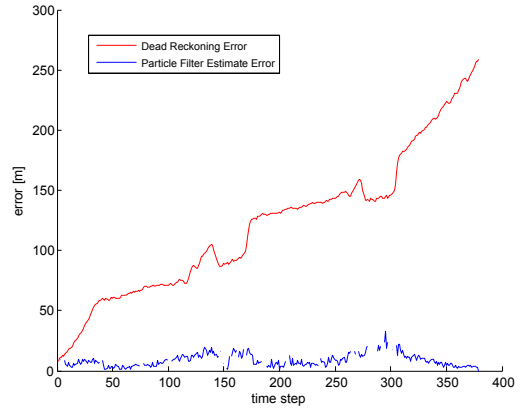


Fig. 6. Error of default Dead Reckoning and simulated particle filter estimates.

only the performance of the filter in the field, USBL and acoustic modem ranges were transmitted via the WI-FI link to rule out loss of packets during acoustic communication. The results are shown in Fig 7 with respect to the true trajectory of the AUV. The AUV ground truth was recorded using a secondary GPS unit as the vehicle was planned to follow only its dead reckoning estimates corrected by the particle filter. The USBL exhibits an acceptable range up to 500m when the AUV is at the surface. Hence, when the AUV is at depth and within optimal range of the USBL transceivers, the range in shallow waters of 20m reaches almost a kilometer. The same condition is also true for robust acoustic communication and range measurements. When the acoustic modems are deployed in the mid channel of shallow waters, ranges up to 1.5km can be established. Hence, to have a record of the ground truth, we experienced an 80 percent and 65 percent throughput of the USBL and the acoustic modem respectively. The mean error between the fused solution and the true trajectory is shown in Fig 8.

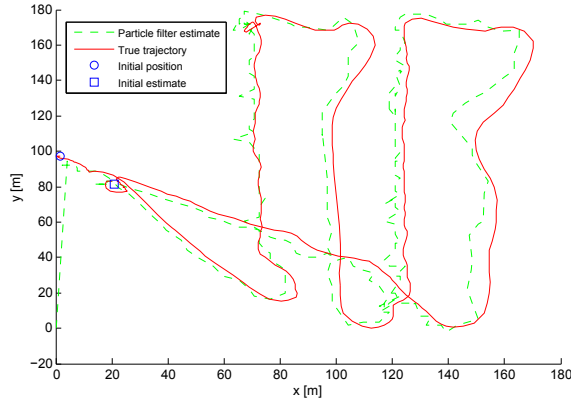


Fig. 7. Mission trajectory using Particle Filter Estimates.

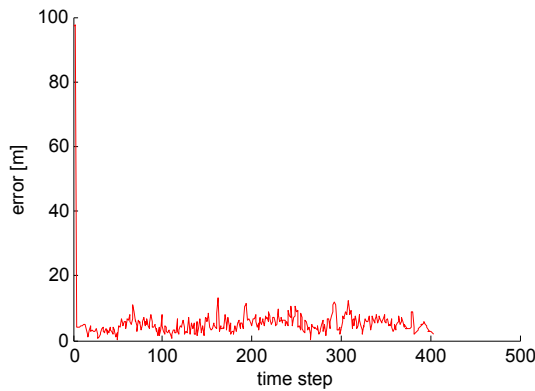


Fig. 8. Error of fused estimates against GPS data.

## VI. CONCLUSION

In this paper, we have shown the usage of USBL and acoustic modem ranges to help localize the OceanServer IVER2 in order to improve its dead reckoning algorithm. The results were acceptable in terms of better geo-referenced water sampling data that would be used as inputs to forecast modeling of the Singapore coastal area. The localization helps the vehicle to operate longer as GPS fixes are less required to reduce uncertainty when performing missions underwater. The technique is practical in terms of logistics and ease of deployment of related equipment.

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