Implementation of a Hydrodynamic Model-Based Navigation System for a Low-Cost AUV Fleet

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***Abstract*—This work implements a hydrodynamic model-based localization and navigation system for low-cost autonomous underwater vehicles (AUVs) that are limited to a micro-electro mechanical system (MEMS) inertial measurement unit (IMU). The hydrodynamic model of this work is uniquely developed to directly determine the linear velocities of the vehicle using the measured vehicle angular rates and propeller speed as inputs. The proposed system was tested in the field using a fleet of low-cost *Bluefin SandShark* AUVs. Implementation of the model-based localization system and fusing of the solution into the vehicle navigation loop was conducted using backseat computers of the AUV fleet that run mission orientated operating suite - interval programming (MOOS-IvP). With the model-based navigation system, the maximum localization error (i.e., in comparison to a long baseline (LBL) based ground-truth position) was limited to 15 m and 30 m for two 650-second and 1070-second long missions. Extrapolation of the position drift shows that the model-based localization system is able to limit the position uncertainty to less than 100 m by the end of hour-long mission; whereas, the drift in the default IMU-based localization solution was over 1 km per hour. This is a considerable improvement by only using a MEMS IMU that generally costs less than $100. Furthermore, this work is a step towards generalizing and automating the process of hydrodynamic modeling, model parameter estimation and data fusion (i.e., fusing the localization solution with those from other available aiding sensors and feeding to the navigation loop) so that a model-based localization system can be implemented in any AUV that has backseat computing capability.**

***Index Terms*—Autonomous underwater vehicles, model-based localization, hydrodynamic models, system identification, underwater navigation**

I. Introduction

Low-cost autonomous underwater vehicles (AUVs) are increasingly available to the underwater sensing community for multi-vehicle operations [1] and AUV-based coastal, river and lake surveys. Multiple commercial manufacturers and research groups produce low-cost AUVs, and the majority of them are equipped with basic sensor packages due to budget constraints [2]–[4]. For example, most of these AUVs are limited to a micro-electro mechanical system (MEMS) inertial measurement unit (IMU) for underwater localization with no Doppler velocity logs (DVLs) and no tactical/navigation grade fiber optic gyroscope (FOG) inertial navigation systems (INSs). As a result, underwater positioning accuracy is compromised as the uncertainty from an unaided IMU-based dead reckoning system grows exponentially with time. However, an accurate localization solution is critical for successful AUV operations as well as for vehicle safety.

The localization solution of an AUV is initialized while at surface using the global positioning system (GPS) and it can be reinitialized by resurfacing at regular intervals to avoid large drifts. However, frequent surfacing for GPS fixes compromises the survey time (i.e., especially in deeper waters) and most critically, vehicle safety while on the surface. Ultra short baseline (USBL) and long baseline (LBL) positioning systems are good methods to update ground-truth position regularly while underwater; however, this introduction associates trade-offs in the requirement of additional instruments, manpower, ship time and cost.

Hegrenaes and Hallingstad [5] introduced a hydrodynamic model-aided localization system for AUVs to avoid drifts in the unaided INS solution when a DVL bottom track is unavailable (for example, when the vehicle operates in altitudes larger than its DVL range, when traveling over rough bathymetry, etc.) and to further improve the performance of LBL- and USBL-based positioning. Randeni et al. [6] introduced a model-aided localization technique using a hydrodynamic model that can be field-calibrated for the AUV's cur-

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rent operational environment, and this technique was further improved in [7] with a novel water column velocity estimation technique referred to as the WVAM method. A recent study [8] implemented a model-aided localization system for an AUV with a tactical-grade INS, which limited the positioning uncertainty to around 45 m by the end of a 1000-second mission. By incorporating a water-tracking Acoustic Doppler Current Profiler (ADCP), this solution was further improved to limit the uncertainty to 32 m per 1000 seconds.

Most existing model-aided localization techniques are based on maneuvering equations of motion that determines the linear and angular accelerations, which are fused with acceleration measurements from an accurate INS [5]–[8]. This approach is feasible for AUVs with tactical-grade or navigation-grade INSs or for those with acoustic positioning; however, it is not suitable for low-cost AUVs that are limited to less precise MEMS IMUs since the double integration of the combined acceleration solutions to obtain the position could still result in an exponentially drifting error.

This work implements a hydrodynamic model-based localization system for a fleet of low-cost AUVs that are limited to a MEMS IMU in order to improve their localization and navigation performance without additional hardware. The hydrodynamic model utilized in this work directly produces the linear velocities using the measured vehicle angular rates and propeller speed as inputs; hence, the position can be obtained with a lower drift rate as compared to the general acceleration prediction method. This work was field tested using a fleet of low-cost *Bluefin SandShark* AUVs shown in Fig. 1. The model-based localization system was implemented and fused with the vehicle navigation loop using backseat computers of the AUV fleet that run mission orientated operating suite - interval programming (MOOS-IvP) [9]. The performance of the system was investigated by conducting field trials and comparing the model-based localization solution with LBL-based ground-truth position.

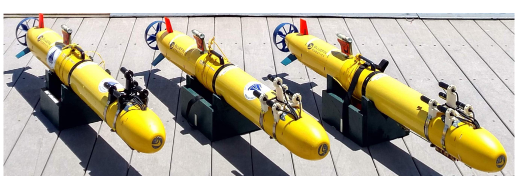

Fig. 1. The fleet of low-cost *Bluefin SandShark* AUVs utilized to test the model-based localization and navigation system. The five-element hydrophone arrays mounted around the nose-cones of the vehicles were configured to be used as LBL systems.

II. METHODOLOGY

A. Hydrodynamic model-based localization system

The hydrodynamic model was developed to predict linear velocities of the AUV using real-time measurements of vehicle's propeller speed, IMU-based vehicle forward speed, roll angle (ϕ), pitch angle (θ) and heading angle (ψ) as inputs. In this work, the model was specifically designed to only utilize the input measurements that are typically available to a backseat computer of an AUV (in a frontseat-backseat paradigm, the frontseat computer provides the navigation information to the backseat computer of the vehicle, which makes decisions and sends desired speed, desired depth and desired heading commands to the frontseat [9]). Therefore, this technique can be implemented in any AUV with backseat computing capability without requiring a change to the manufacturer's proprietary frontseat software or the interface between frontseat-backseat computers (this is further discussed in Section II-B).

The hydrodynamic model given in (1) - (3) was used to determine the linear velocities of the AUV along x, y and z directions respectively.

$$\begin{aligned} u = \alpha_1\dot{q} + \alpha_2\dot{r} + \alpha_3 u_{IMU} + \alpha_4\dot{z}q + \alpha_5 q^2 + \\ \alpha_6 r^2 + \alpha_7 pr + \alpha_8 \sin\theta + \alpha_9 N_{prop} \end{aligned} \tag{1}$$

$$\begin{aligned} v = \beta_1\dot{p} + \beta_2\dot{r} + \beta_3\dot{z}p + \beta_4 u_{IMU} r + \beta_5 qr + \\ \beta_6 pq + \beta_7 r|r| + \beta_8 \cos\theta \sin\phi \end{aligned} \tag{2}$$

$$\begin{aligned} w = \gamma_1\dot{q} + \gamma_2\dot{p} + \gamma_3 u_{IMU} q + \gamma_4 p^2 + \gamma_5 u_{IMU}\dot{z} + \\ \gamma_6 q^2 + \gamma_7 rp + \gamma_8\dot{z}|\dot{z}| + \gamma_9 q|q| + \gamma_{10}\cos\theta\cos\phi \end{aligned} \tag{3}$$

where, u, v, w and p, q, r are the linear and angular velocities around the x, y, z axes of the AUV. The mathematical formulae presented in this paper are based on the SNAME notation [10]. ϕ and θ are the roll and pitch angles of the AUV respectively, measured by the gyroscopes within the IMU. N_{prop} is the vehicle's propeller revolution per minute (RPM) and u_{IMU} is the IMU-based forward speed estimate provided by the vehicle's frontseat. α_1,α_2 ... α_9, β_1,β_2 ... β_8 and γ_1,γ_2 ... γ_{10} are parameters that characterizes the hydrodynamic, hydrostatic, and mass properties of the AUV and are determined using system identification as detailed in Section II-C.

The majority of angular measurements utilized by the hydrodynamic model are angular rate and angular acceleration measurements; hence, the uncertainties due to accumulated gyro biases have minimum adverse effects on the model.

The body-fixed velocities determined using (1) - (3) are converted to the north-east-down (NED) coordinate system using (4) in order to determine the velocity of the AUV in NED coordinate system.

$$\begin{bmatrix} \dot{n} \\ \dot{e} \\ \dot{d} \end{bmatrix} = J_1(\eta_2) \begin{bmatrix} u \\ v \\ w \end{bmatrix} \tag{4}$$

$$J_1(\eta_2) = \begin{bmatrix} c\varphi c\theta & -s\varphi c\phi + c\varphi s\theta s\phi & s\varphi s\phi + c\varphi c\phi s\theta \\ s\varphi c\theta & c\varphi c\phi + s\phi s\theta s\varphi & -c\varphi s\phi + s\theta s\varphi c\phi \\ -s\theta & c\theta s\phi & c\theta c\phi \end{bmatrix}$$

where $\dot{n}$ $\dot{e}$ and $\dot{d}$ are the vehicle velocities along northwards, eastwards and downwards axes. ϕ, θ and ψ represents the roll, pitch and heading angles respectively and *s· = sin(·)* and *c· = cos(·)*.

The velocities of the AUV in northward and eastward axes are numerically integrated, starting from the origin to obtain the displacement of the vehicle from the origin. The origin is considered as the last GPS position fix obtained when the AUV was at the surface.

B. Implementation of the model-based navigation system

In a frontseat-backseat architecture, the frontseat that typically handles vehicle autonomy including mission execution, localization, navigation, control systems, etc. is relieved from majority of these tasks as control over the vehicle autonomy is given to the backseat [9]. That is, the frontseat provides the navigation information such as the current position estimate, speed, depth, vehicle ϕ, θ and ψ angles, last GPS position information etc. to the backseat, and the backseat makes decisions and sends desired speed, desired depth and desired heading commands to the frontseat computer. However, in this typical system, the backseat still relies on the localization solution that is provided by the frontseat.

In this work, the model-based localization and navigation system implementation was generically developed for AUVs with a frontseat-backseat paradigm in which the backseat computer runs MOOS-IvP (see Fig. 2). A new MOOS application referred to as *pModelaid* was developed to compute the model-based localization solution, which follows the procedure given in Section II-A. Typically, AUV frontseat computers are only configured to provide roll, pitch and heading angles to the backseat via the AUV-MOOS interface. Therefore, the angular rates and accelerations required for (1) - (3) were computed by differentiating the roll, pitch and heading angles in order the avoid the requirement to modify the proprietary frontseat software.

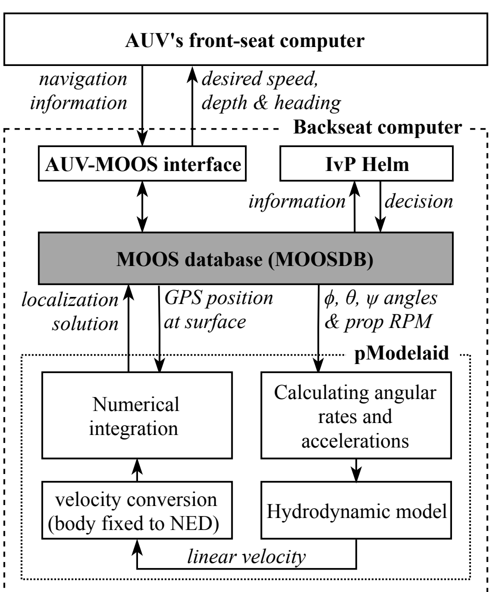

Fig. 2. Hydrodynamic model-based localization solution is calculated in a backseat computer and the estimated position is pushed to the frontseat computer for navigation.

The body-fixed linear velocities from the hydrodynamic model are converted into northward and eastward velocities and numerically integrated to determine the localization solution. The numerical integration is initialized when a GPS fix is available. The final model-based localization solution is published to the MOOSDB, and is utilized by *IvP Helm*, instead of using those given by the vehicle frontseat when making decisions for desired speed, depth and heading. This approach provided the ability to fuse the model-based localization solution into the vehicle navigation loop without changing any frontseat proprietary software or the AUV-MOOS interface.

C. Hydrodynamic model parameter identification

The parameters within the hydrodynamic model are dependent on the physical properties and shape of the vehicle. They generally remain the same for similarly configured and ballasted AUVs of the same class [6]. The prediction error method (PEM) estimation function of MATLAB System Identification toolbox was utilized to identify the parameters of the AUVs used in this work (i.e., *Bluefin SandSharks*) [11]. Equations (1) - (3) are modified to the format given in (5):

$$y_t = H_t \Theta_t \tag{5}$$

where, y_t, H_t and Θ_t are vectors as defined in Table I.

TABLE I
Y_T, H_T AND Θ_T VECTORS OF (5) FOR x, y AND z DIRECTIONS

***x* direction**	***y* direction**	***z* direction**
$y_t = u$	$y_t = v$	$y_t = w$
$H_t = [\dot{q}\ \dot{r}\ u_{IMU}\ \dot{z}q\ q^2\ r^2\ pr\ \sin(\theta)\ N_{prop}]$	$H_t = [\dot{p}\ \dot{r}\ \dot{z}p\ ru_{IMU}\ qr\ pq\ r\|r\|\ \cos(\theta)\sin(\phi)]$	$H_t = [\dot{q}\ \dot{p}\ qu_{IMU}\ p^2\ \dot{z}u_{IMU}\ q^2\ rp\ \dot{z}\|\dot{z}\|\ q\|q\|\ \cos\theta\cos\phi]$
$\Theta_t = [\alpha_1\ \alpha_2\ \alpha_3\ \alpha_4\ \alpha_5\ \alpha_6\ \alpha_7\ \alpha_8\ \alpha_9]$	$\Theta_t = [\beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_5\ \beta_6\ \beta_7\ \beta_8]$	$\Theta_t = [\gamma_1\ \gamma_2\ \gamma_3\ \gamma_4\ \gamma_5\ \gamma_6\ \gamma_7\ \gamma_8\ \gamma_9\ \gamma_{10}]$

A dataset with accurate measurements of vehicle linear velocities (y_t) for corresponding model input values (H_t) is required to estimate the model parameters (Θ_t) using system identification. In this case study, the identification dataset was obtained by converting the LBL position measurements into body fixed linear velocities. In PEM, the parameters are identified by minimizing the difference between the predicted output according to the parameters that are being estimated recursively and measured outputs.

$$\Theta_t = \underset{\Theta}{argmin} V(\Theta_t) \tag{6}$$

$$V(\Theta_t) = \frac{1}{2N} \sum_{t=1}^{N} \left\| y_t - \hat{y}_{t|t\text{-}1\ (\Theta_{(t\text{-}1)})} \right\|^2 \tag{7}$$

where, $\hat{y}_{t|t\text{-}1\ (\Theta_{(t\text{-}1)})}$ is the predicted output at t, using parameters estimated using data until t - 1. The initial parameter values were set to 1. A thorough explanation regarding the computation of the minimizing argument can be found in [12].

III. Case study: *Bluefin SandShark* AUV fleet and field experimental setup

A. Bluefin SandShark AUVs

A fleet of *Bluefin SandShark* AUVs were used to test the proposed system in the field. *Bluefin SandShark* is a low-cost micro AUV fleet mainly developed for vehicle autonomy research and multi-vehicle operation [2]. The utilized *SandShark* vehicles were equipped with a depth sensor, GPS unit and a MEMS IMU that contains accelerometers, gyroscopes and a magnetometer. The overall vehicle length was 1.15 m, the body diameter was around 0.124 m, and the dry weight in air was approximately 10 kg. The propulsion module consisted of a three-bladed ducted propeller with three individually-functioning control surfaces arranged as shown in Fig. 1.

Vehicles had an in-house designed general autonomy payload module containing an acoustic receiver system and a backseat computer that was configured as an LBL system [13]. The acoustic receiver consists of a five-element hydrophone array. Two custom acoustic beacons, time synchronized with the vehicle's acoustic receiver system, were spaced approximately 135 m apart, each at a depth of approximately 1 m. Each beacon transmitted a user-specified acoustic signal, and the ranges to each beacon from the vehicle were determined using matched filtering during post-processing. The intersection of these ranges from the two beacons (i.e., trilateration) allows to determine the ground-truth position of the AUV in order to analyze the performance of the default IMU-based and model-based navigation. Although trilateration provides with two position solutions every second, the vehicles are restricted to operate in one of the half-spaces defined by the line joining the two beacons, enabling to determine which of these two solutions is correct. For further details of the LBL system, refer to [1] and [14]

B. Experimental setup for model parameter estimation

A set of race-track pattern AUV maneuvers were conducted to estimate the parameters of the hydrodynamic model for the *SandShark* AUV platform. Parameter identification maneuvers should stimulate all motion modes (i.e. surge, sway, heave, roll, pitch and yaw motions) of the vehicle during the runs. Under-actuated AUVs, such as *SandSharks*, move in heave, roll and pitch motion modes while changing heading angle. Therefore, the race-track runs was suitable for identification.

The parameter identification maneuvers were conducted on 2018-08-28 in Charles river, Massachusetts, USA, adjacent to the MIT Sailing Pavilion around 7 km upriver from Boston harbor. The water depth of this portion of Charles river varies from 3 - 5 m and water currents are in the order of 0.1 - 0.3 m s^{-1}. The AUV maneuvers were conducted at a depth between 1.5 - 2.5 m to avoid surface wave formation and boundary interaction from the riverbed.

The vehicle position measured by the LBL system described in Section III-A was used to obtain the body-fixed linear velocity of the AUV for system identification. The LBL measurements were first treated with an outlier removal filter and a moving average filter with a window size of 5 samples, and differentiated to determine body-fixed linear velocities. The outlier removal filter removes position measurements if the difference between two consecutive position samples is larger than 15 m. This is a reasonable selection of the threshold value since the AUV is unable to move 15 m within an LBL sampling interval of 1 second. The calculated body-fixed linear velocity data in response to model input commands were post-processed as described in Section II-C to determine the model parameters. The estimated parameters are most accurate for the vehicle speed and turning rate ranges of the identification maneuvers [6]; therefore, it is important to conducted identification maneuvers that covers the nominal operational range of an AUV.

C. Experimental runs for validation

A second set of AUV missions were conducted for validation and performance analysis of the model-based localization and navigation system. Two identical 100 × 100 m square patterns missions were conducted on 2018-09-21 at Charles river test site with each square mission including two square loops. The specified depth for the missions was 2.4 m. The wind speed and direction during the mission time was around 15 knots from North-East.

During the first mission, the default localization solution from the vehicle frontseat (i.e., unaided IMU-based solution) was fused into the navigation loop and during the second mission, the model-based localization solution was fused according to the procedure explained in Section II-B. The IMU-based, model-based and LBL-based position solution were logged during all missions for performance analysis.

IV. Performance analysis and discussion

In this study, the position of the AUV obtained from the LBL system is considered as the ground-truth solution for performance analysis. This is a reasonable assumption since the uncertainty of LBL measurements is less than 3 m. Fig. 3 illustrates the vehicle tracks for the first square pattern mission from the default IMU-based localization, model-based localization and LBL position measurements. The solid black line shows the planned square pattern mission with stars representing the four waypoints.

During this mission, the default IMU-based localization solution (i.e., solid red line in Fig. 3) was fused to the vehicle navigation loop. The vehicle navigation system assumes that the fused localization solution is correct and therefore, navigates the AUV according to the planned mission. As seen from Fig. 3, the ground-truth vehicle position from the LBL system (i.e., dotted black line) shows that vehicle's actual position is far from the planned mission track.

In comparison to the IMU-based solution, the model-based localization solution closely resembles the ground-truth LBL vehicle track; however, it does not resemble the sliding box pattern seen in the LBL track. The sliding box pattern seen in the dotted line is most likely due to the drift of the AUV due to underwater currents. The model-based solution presented in this study does not include a water current estimation technique; therefore, it is unable to predict the position drift due to currents and external forces.

Fig. 4 shows the vehicle track solutions for the second square pattern mission in which the model-based localization

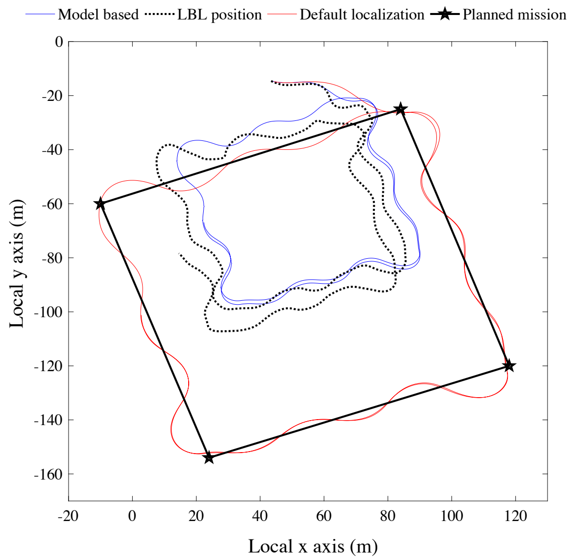

Fig. 3. Comparison of vehicle tracks from the model-based and default IMU-based localization solutions with LBL-based ground-truth position and planned mission for the first square pattern mission. During this run, the default IMU-based localization solution was fused to the AUV navigation loop.

solution was fused to the vehicle navigation loop. In comparison to the previous mission, the ground-truth LBL solution closely follows the planned mission track. However, similar to the first square mission, the AUV has drifted in a sliding box pattern due to underwater currents that are not accounted for. This drift should be expected since a ground-relative vehicle position update or a water column estimation is not fed back to the navigation loop. Again, the default IMU-based localization solution has deviated significantly from ground truth LBL, while the model-based localization solution is in better agreement with LBL.

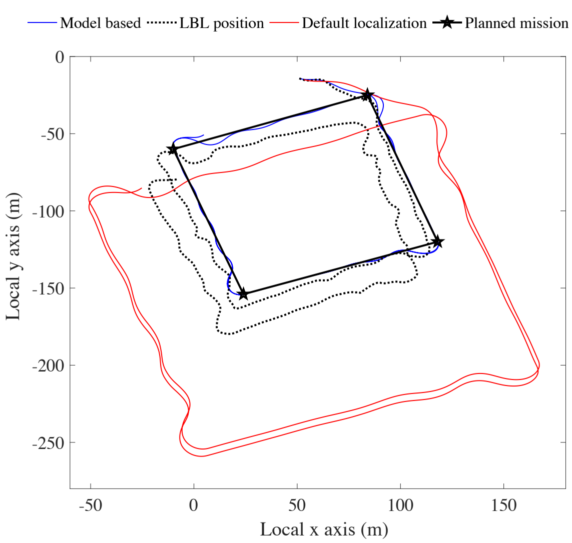

Fig. 4. Vehicle tracks of the second square pattern mission. The model-based localization solution was fused to the AUV navigation loop.

Fig. 5a and 5b compare the variations of localization error of model-based and default IMU-based solutions with time, with respect to the LBL position for the two square pattern missions respectively. The mission duration of the second square mission was 1070 seconds while the first square mission was limited to 650 seconds since the vehicle did not perform the planned mission due to inaccurate position feedback during the first mission.

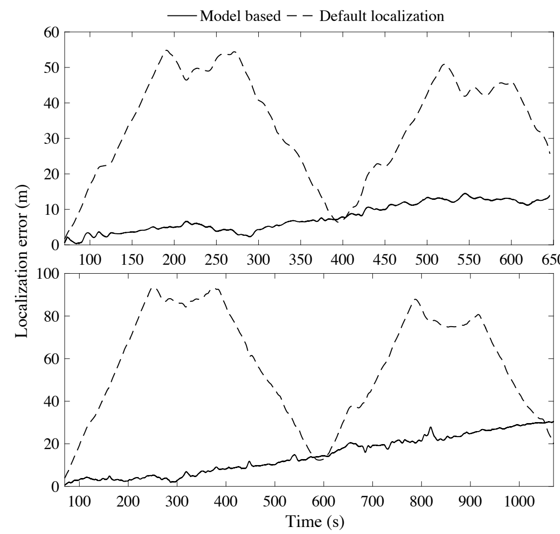

Fig. 5. Variations of the localization error of model-based and default IMU-based localization solutions with time in comparison to the LBL position for the (a) first and (b) second square pattern missions.

As seen from Fig. 5a, during the first mission, the default IMU-based solution reached its maximum error of 54 m within a mission time of 190 seconds. By extrapolating the variation of error using the averaged error growth rate, the default IMU-based localization solution of the AUV can be estimated to drift up to 1024 m in an hour. During the second mission, the maximum error of 94 m was reached within 251 seconds; i.e., an extrapolated position drift of 1334 m in an hours time. Therefore, the position uncertainty of the IMU-based localization solution is more than 1 km after an hour of operation.

On the other hand, the maximum error of the model-based localization solution was 15 m and 30 m for the first and seconds missions respectively. These maximum errors were reached after respective mission times of 545 seconds and 1072 seconds. Therefore, error extrapolation shows that the proposed model-based localization system limits the position uncertainty drift to less than 100m per hour. In comparison, a DVL bottom-track aided tactical grade INS (i.e. $>$ \$50K) can have a position drift up to around 22 m per hour and that of a navigation grade INS (i.e. $>$ \$100K) is around 8 m per hour. However, the positioning uncertainties of unaided tactical and navigation grade INSs can be approximately up to 10 km and 1 km per hour respectively [8]. Therefore, the proposed model-based localization system is able to considerably improve the performance of low-cost AUVs that are limited to a MEMS

IMU.

V. Limitations

A major limitation of this work is the inability to estimate the velocity of the water column without more cost intensive additional hardware such as a tactical/navigational grade INS, an acoustic positioning system or an acoustic Doppler current profiler (ADCP). Although [5], [15] and [8] proposed techniques to accurately estimate underwater currents, such techniques require the above mentioned sensors, and cannot be applied to low-cost AUVs that are only packaged with a MEMS IMU. Martinez et al. [16] proposed a method to estimate the magnitude and direction of surface currents by running the AUV in circles on the surface when the AUV has GPS fix and computing the drift due to currents. This technique can be utilized by low-cost AUVs; however, the water column velocity often varies with the depth. Therefore, only utilizing surface currents may not entirely solve this problem.

VI. Future directions

Model-based localization has been shown to be a useful tool for many situations including deep water diving, mid-water column operations, surveillance operations, as a potential solution for under-ice operations, and as an enhancement for acoustic positioning [5]. Therefore, possession of a model-based localization system is beneficial for any AUV; however, developing an accurate hydrodynamic model and identification of model parameters require specific knowledge and can be time consuming.

Our goal is to generalize and automate the process of hydrodynamic model optimization, parameter estimation and data fusion. That is, a universal model-based localization toolbox that can be implemented on any AUV with backseat computing capability. The toolbox will autonomously optimize the hydrodynamic model and identify model parameters during operations with accurate position information and, the model-aid when the default localization solution is compromised or unreliable.

VII. Conclusions

This work implements a hydrodynamic model-based localization system for a fleet of low-cost AUVs to improve their localization and navigation performance without adding any additional hardware. The hydrodynamic model is uniquely developed to directly produce the linear vehicle velocities as opposed to existing modeling techniques, which usually determine the acceleration and integrating to obtain the vehicle velocity. Therefore, this method can predict the position with a lower drift rate compared to acceleration prediction method without requiring a tactical or navigation grade INS.

The model-based localization and navigation system was field tested using *Bluefin SandShark* AUVs and their performance was considerably improved. The maximum localization error in comparison to an LBL-based ground-truth position was 15 m and 30 m for two 650-second and 1070-second long missions respectively. That is, the model-based localization system limits the position uncertainty drift to less than 100 m by the end of an hour long mission; whereas, the drift in the default IMU-based localization solution was over 1 km per hour. Therefore, this technique considerably improves the performance of low-cost AUVs that are limited to a MEMS IMU.

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