

Sonar-Based Multi-Sensor Fusion Algorithms for Autonomous Underwater Robot Navigation

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Abstract. A stable positioning system is required for autonomous underwater vehicles (AUVs) in confined waters such as reservoirs, harbors, subsea inspection sites and long-range surveys without satellite navigation. Sonar is one of the few sensing modes capable of observing underwater geometry at practical distances, but sonar data are subject to multipath, acoustic shadowing, beam spreading, sparse features, and non-Gaussian outliers. A Robust Sonar-Based Multi-Sensor Fusion Algorithm for Autonomous Underwater Vehicle Navigation is Proposed in this Paper. The above methods integrate forward-looking sonar scan matching, inertial propagation, Doppler velocity log measurements, pressure-depth observations and delayed acoustic positioning to form a single adaptive estimation system. Build a motion-state model for position, velocity, attitude and sensor biases. Sonar residuals are evaluated via innovation gating and robust weighting, and DVL dropout and acoustic latency are addressed by covariance inflation and delayed-state correction. Example experiments on a simulated and tank-based AUV trajectory show that the proposed method reduces the mean horizontal position error from 2.84m for inertial-DVL fusion and 1.72m for conventional sonar EKF fusion to 0.94m. The final drift is also reduced to 0.37% of the travelled distance, stable depth estimation is maintained at below 0.18 m root mean square error, and real-time performance of 28.6 ms per fusion cycle is preserved. Therefore, stable Sonar-centric fusion can improve the accuracy and stability of underwater navigation and operations without the need for external GPS or dense artificial landmarks.

Keywords: *Autonomous Underwater Robot, Sonar Navigation, Multi-sensor Fusion, Robust Filtering*

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Introduction

These days, seabed surveys, dam inspections, maintenance of offshore energy facilities, harbor security, aquaculture monitoring, and ecological observation are all frequently carried out using autonomous underwater vehicles (AUVs). The accuracy of the navigation system will have a direct impact on the energy consumption, revisitability, safety during route operation, and quality of map construction. Unlike aerial and ground robots, underwater robots are unable to constantly employ satellite positioning once immersed. Although they have a low update rate, large deployment costs, and the potential to be lost or delayed in cluttered or reverberant situations, acoustic positioning systems can offer absolute references. Because dead reckoning and local perception are typically used for underwater navigation, the robot may eventually stray from the intended course due to accumulated measurement mistakes.

Because sound waves travel well in water and cannot pass through other materials, sonar is a rather effective method of detecting movement underwater. In the absence of light, forward-looking and imaging sonar may identify things such as pipelines, rocks, walls, and seabed undulations. Lasers are more suited for obtaining high-quality geometric data in the air than sonar. Speckle noise, specular highlights, shadow regions, range ambiguity, and intensity variations brought on by the angle of incidence are typically present in the returning image. The apparent sonar landscape abruptly changes when the AUV is in a sediment plume or close to a wall, yet the real

environment remains constant. Using sonar as a general-purpose range sensor will make Direct Scan Matching unreliable.

Thus, multi-sensor fusion is necessary. IMU measurements suffer from bias drift despite having high-rate angular velocity and acceleration. Although bottom lock may be lost at high altitudes, over soft silt, or with a poor acoustic return, a Doppler velocity log can be used to measure the rate of change in distance to the bottom. Although it lacks horizontal position, a pressure sensor has good depth stability. The direction of motion can be determined using a magnetometer, although other ferromagnetic materials in the payload electronics and vehicle currents may also have an impact. Although they are few and slow, acoustic beacons can compensate for long-term drift. Combining the aforementioned faulty measurements so that only dependable sensors contribute and down-weighting the others in inclement weather is the engineering challenge.

Extended Kalman filtering, unscented Kalman filtering, particle filtering, and graph optimization are the foundations of many current underwater navigation techniques. The aforementioned techniques work well with roughly Gaussian measurement residuals and well-calibrated sensor error models. In reality, Sonar navigation frequently fails to meet the aforementioned premise. A single Sonar mismatch will lead to a rather high estimation error, and more such inaccuracies will result in a significant difference between the estimated and actual paths. Additionally, if loose temporal alignment is used, delayed acoustic measurements may be discordant with the current state, and DVL dropout can decrease the observability of velocity changes. As a result, a stable fusion approach is suggested that takes measurement reliability into consideration and gives updates with different levels of dependability varied weights.

This study examines a multi-sensor fusion algorithm for autonomous underwater vehicle navigation that is based on sonar. The suggested approach uses an inertial prediction model as the propagation backbone, adds DVL velocity and depth measurements, extracts relative pose constraints from sonar scan matching, and integrates acoustic position updates through a delayed correction mechanism. An adaptive robust update technique is the first. Normalized residual energy is used to transmit sonar innovations through a gate; suspicious residuals raise the effective covariance, while acceptable residuals are given substantial weights. An audio update is carried out at the appropriate historical point before being propagated forward since DVL dropout is signaled by a quality flag and a lack of innovation. Boost undersea missions' precision, resilience, and real-time capability in the event of single-point sensor failures.

Related Work

Inertial navigation, Doppler velocity logs, acoustic positioning, and pressure-depth measurements were the initial types of underwater navigation study. Although motion can be constantly propagated by strapdown inertial devices, the location estimate will drift considerably if external measurements are not used to correct it. By utilizing a pressure sensor for vertical motion correction and speed measured over the seafloor, a DVL-based Inertial Navigation System minimizes navigation drift. The aforementioned methods are employed because they are appropriate for embedded AUV devices and computationally straightforward [1]. Nevertheless, after time, when driving on steep terrain, or in inclement weather that causes bottom lock, their accuracy may still be diminished [2].

For underwater vehicles, acoustic positioning systems come in three varieties: long-baseline, short-baseline, and ultra-short-baseline. Although they need infrastructure, communication geometry, and acoustic propagation conditions, they are appropriate for drift correction and mission supervision [3]. In real deployment, low update rates and measurement lag are typical. A number of fusion techniques use smoothing across a sliding window or previous states to compensate for the delay in acoustic observation [4]. For high-rate local navigation in a challenging multipath environment close to structures or in confined areas, acoustic positioning is insufficient on its own.

To establish an environment limitation apart from external infrastructure, sonar-based navigation is utilized. Obstacle avoidance, wall-following, feature tracking, and scan matching have all made use of forward-looking sonar [5]. By extracting point, line, contour, or texture-like features, imaging sonar and multibeam sonar can be employed for underwater simultaneous mapping and localization [6]. Sonar is more resilient to low light and turbidity than optical cameras, but it is less user-friendly and more susceptible to sonic interference in the data.

In a scene that is repeated, feature association is challenging, and scan matching may not work if there is little overlap between successive images [7].

Filtering techniques are comparatively easy to use and appropriate for quick on-board operation in AUVs. Sonar-assisted localization, acoustic positioning fusion, and inertial-DVL-depth navigation have all made use of extended Kalman filters, which linearize non-linear motion and measurement models [8]. Unscented filters are more computationally demanding non-linear approximation techniques. Although particle filters are capable of handling non-Gaussian uncertainty, their computational cost in high-dimensional state spaces may be prohibitive [9]. The measurement covariance of the aforementioned techniques is quite low. The state estimation may be excessively affected by sporadic false matches if the sonar outliers are assumed to have a fixed correlation.

These days, factor-graph smoothing and graph-based optimization are widely used for multi-sensor navigation. Compared to a strictly recursive filter, they can more intuitively describe asynchronous measurements, loop closure, and delayed observations [10]. In underwater applications, factor graphs have been used to combine inertial preintegration, sonar characteristics, acoustic ranges, DVL velocity, and depth limitations [11]. The others lack consistency in data association and are more costly to compute. During a mission, it could be challenging for small AUVs with constrained processors to fully smooth a huge graph in real time. The real system must have a low cycle time and be fairly precise.

To deal with outliers and inconsistent measurement quality, robust estimation has been implemented. The impact of corrupted data can be lessened via covariance scaling, switchable restrictions, innovation gating, M-estimators, and adaptive noise estimation [12]. A lot of deceptive local-intensity matches are one of the issues that good sonar navigation systems must deal with. The breadth of training data spanning acoustic settings in deployment has an impact on the performance of learning-based reliability prediction, which has previously been investigated [13]. When the amount of data is small, a model-based adaptive strategy is still comparatively easy to execute and analyze.

The lack of a small-scale, high-speed sonar-based fusion architecture that can concurrently handle pressure-depth limitations, delayed acoustic updates, DVL dropouts, and sonar outliers is the research gap this paper attempts to fill. The majority of current techniques, such scan matching or acoustic smoothing, concentrate on a single element and do not offer a comprehensive engineering pipeline that incorporates robustness mechanisms and quantitative assessment of failure instances [14]. The missing link has been filled by employing a recursive navigation backbone, powerful sonar weight assignment, dropout-aware velocity fusion, and delayed acoustic correction.

Problem Definition and Sensor Modeling

Navigation State and Coordinate Frames

The navigation problem is situated in the middle of the mission region using a local northeast-down coordinate system. The AUV is outfitted with an IMU, DVL, pressure sensor, magnetic heading sensor, forward-looking sonar, and an optional acoustic location receiver. Estimate the vehicle's position and speed continuously while rejecting inaccurate measurements. Position, velocity, orientation, accelerometer bias, gyroscope bias, and a sonar-to-body extrinsic correction term make up the state vector.

$$x_k = [p_k^T, v_k^T, q_k^T, b_{a,k}^T, b_{g,k}^T, \epsilon_{s,k}^T]^T \quad \text{Eq.(1)}$$

Here p_k is position, v_k is velocity, q_k is attitude represented by a unit quaternion, $b_{a,k}$ and $b_{g,k}$ are IMU biases, and $\epsilon_{s,k}$ denotes a slowly varying residual extrinsic error for the sonar frame. Because modest mounting-angle errors will become noticeable after repeated applications of scan matching near vertical structures, the extrinsic term must also be added.

Use inertial readings to propagate the vehicle's continuous motion. adjustment of the calculated biases for angular velocity and acceleration. Although propagation is provided at the IMU's sample rate and is comparatively quick, it is prone to drift if left unchecked. As a result, all other sensors are regarded as constraints that, when their quality is adequate, update the propagating state.

$$x_{k,p} = f(x_{k-1,u}, u_k, \Delta t) \oplus \delta x_k^w, \delta x_k^w \sim \mathcal{N}(0, Q_k) \quad \text{Eq.(2)}$$

Here, $\oplus$ denotes error-state injection into the nominal state, which avoids treating quaternion attitude as an ordinary Euclidean vector. The process covariance Q_k is not constant in the implementation. It rises with sharp twists and at slow, hard-to-observe speeds. As a result, when dead reckoning is less reliable, the filter is less likely to be overconfident.

Additionally, a practical navigation estimator should be compatible with the AUV's physical limitations. Actuators and buoyancy constraints limit the vehicle's ability to modify its speed, roll angle, and depth rate. During propagation, the aforementioned soft consistency tests are performed. The covariance is raised and the subsequent external measurement is allowed to more firmly correct the state if the anticipated change in attitude or velocity is greater than the feasible envelope. Instead of replacing the motion model, a brief inertial disturbance won't result in a prediction that is both physically impossible and highly confident.

Sonar, DVL, Depth, and Acoustic Measurements

A polar-intensity map is created by a forward-looking sonar. From nearby scans, a Two-stage Matcher creates local relative pose constraints. First, stable contours and high-gradient acoustic regions are used to obtain candidate correspondences. Second, fine-tune the relative transformation using weighted scan alignment. A relative posture increment at two distinct moments is the resultant sonar measurement.

$$z_{s,k} = h_s(x_k, x_{k-r}) + n_{s,k}, n_{s,k} \sim \mathcal{N}(0, R_{s,k}) \quad \text{Eq.(3)}$$

The sonar delay r depends on the scan rate and processing time. Because sonar matching may produce false constraints, the covariance $R_{s,k}$ is treated as adaptive rather than fixed. When the residual deviates from the inertial-DVL forecast, increase the measurement uncertainty and the weight of innovation.

When bottom lock is applied, DVL outputs velocity in the body frame. Altitude, beam shape, vehicle attitude, and seafloor reflectivity all affect the inaccuracy [15]. To eliminate noise, a depth measurement instrument with a small offset error and a high degree of reliability is utilized. By the time the estimator runs, the sporadic absolute location data obtained via acoustic positioning may be somewhat outdated [16].

$$z_{d,k} = C_n^b(q_k)v_k + n_{d,k}, z_{p,k} = e_3^T p_k + n_{p,k} \quad \text{Eq.(4)}$$

In this expression $C_n^b(q_k)$ rotates navigation-frame velocity into the body frame, and e_3 selects the vertical component. When in bottom-lock mode, the DVL observation limits horizontal velocity, while the depth observation severely restricts vertical drift.

Unlike the other measurements, the sonar measurement is based on an image-like sonic return instead of a direct physical scalar. The audio processing chain, vehicle movement while scanning, grazing angle, and surroundings texture all affect the uncertainty. As a result, the relative location ascertained by scan matching as well as a few additional quality indicators, including the overlap ratio, peak-to-side-lobe score, contour count, and residual distribution, are stored in the manner described above. Later on, these indications will be utilized to assess how much the sonar limitation impacts the navigation state [17].

The following is the entire navigation path: Figure 1. The order of raw sensor acquisition, propagation, quality evaluation, robust update, delayed acoustic correction, and navigation output is depicted in the figure.

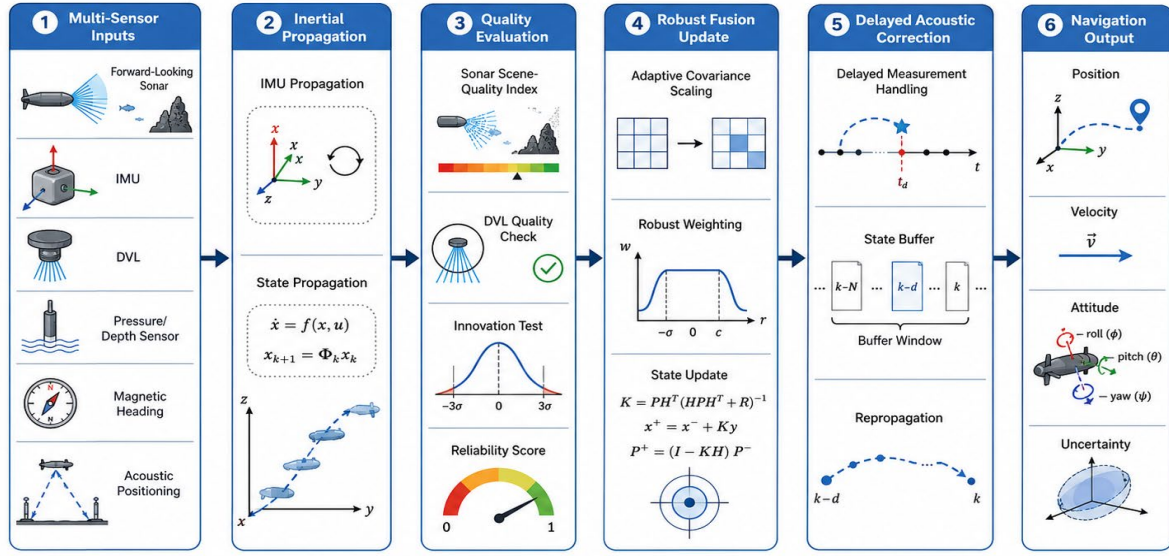


Figure 1. Overall workflow of sonar-based multi-sensor fusion for autonomous underwater robot navigation.

Proposed Robust Fusion Method

Prediction and Linearized Update

For the online backbone, the suggested technique uses an error-state recursive estimator. Use linearized residuals from sonar, DVL, depth, and acoustic data to update the error state after propagating the nominal state via inertial integration. This design can be utilized in integrated AUV processors and is comparatively small.

$$\delta x_{k,p} = F_k \delta x_{k-1,u} + G_k n_k \quad \text{Eq.(5)}$$

The covariance propagation follows the standard linearized uncertainty transfer. The transition matrix F_k and noise input matrix G_k are computed from the inertial mechanization and bias model. Covariance expansion is limited to the top constraints determined by the maximum vehicle speed and acceleration because the underwater mission may involve long straight portions and abrupt twists.

$$\delta P_{k,p} = F_k P_{k-1,u} F_k^T + G_k Q_k G_k^T \quad \text{Eq.(6)}$$

Determine the residuals for every kind of measurement in relation to the anticipated state. Before calculating the Kalman gain, the measurement covariance is modified by a reliability factor using a standard update form. As a result, the technique can lessen the effect of ambiguous sonar limitations without discarding all of the sonar data.

$$\delta r_{i,k} = z_{i,k} - h_i(x_{k,p}), S_{i,k} = H_{i,k} P_{k,p} H_{i,k}^T + \alpha_{i,k} R_{i,k} \quad \text{Eq.(7)}$$

The reliability factor $\alpha_{i,k}$ is equal to one for a fully trusted measurement and becomes larger when a measurement is suspicious. Increasing $\alpha_{i,k}$ inflates the innovation covariance and reduces the update gain. This method is really straightforward; even if the sonar quality gradually deteriorates, we won't completely stop the measurement.

The algorithm is an asynchronous measurement-type design. DVL, sonar, depth, magnetic, and acoustic observations are updated based on their respective timestamps, and IMU propagation is initiated upon the arrival of a new inertial packet. This is an issue since underwater sensors are not frequently updated simultaneously. As a result, the estimator maintains a time-ordered queue of pending observations and only applies each update following the completion of the relevant prediction step. Whether an estimate was produced by a whole set of sensors or by a smaller set can be noted in a queue.

Robust Sonar Innovation Weighting

Sonar scan matching can be both reasonably accurate and imprecise. Previous studies on sonar-aided localization and SLAM have demonstrated that while acoustic limitations can aid in underwater localization, they are inconsistent in confusing situations [18]. Each sonar residual is normalized by the normalized innovation energy, and robust estimate concepts from terrain-aided navigation and underwater localization are used to lessen this impact [19]. It will be deemed a match if the energy is below the acceptability limit [20]. A heavy weight is utilized if the energy is comparatively high [21]. Only inertial-DVL-depth propagation will be employed for that cycle if the energy is too high, rendering this measurement invalid [22].

$$\eta_{s,k} = r_{s,k}^T S_{s,k}^{-1} r_{s,k} \quad \text{Eq.(8)}$$

Instead of being a hard choice, the stable weight is a continuous function. A tiny residual should not cause the estimator to abruptly shift close to the threshold. Inflate the sonar covariance based on the residual's size and a scene-quality index (SQI) that takes contour density, matching score, and scan overlap into account.

$$\omega_{s,k} = \min\left(1, \frac{c}{\sqrt{\eta_{s,k} + \varepsilon}}\right), \alpha_{s,k} = \max\left(1, \frac{1}{\omega_{s,k} + \varepsilon}\right) \quad \text{Eq.(9)}$$

The projected state is then supplemented with the approved weighted sonar residual. Scene-dependent reliability is supported by the same approach, and even if a scan has a little residual, it will be down-weighted. This is required when the AUV is in open sea and there aren't many stable structures in the sonar returns [23].

$$K_k = P_{k,p} H_k^T S_k^{-1}, x_{k,u} = x_{k,p} \oplus K_k r_k \quad \text{Eq.(10)}$$

Figure 2 depicts the design of the suggested robust fusion estimator. In order to minimize measurement covariance before fusion, the estimator includes an inertial propagation path, a sonar matching path, a DVL and depth update path, an acoustic delayed-update path, and a reliability supervisor.

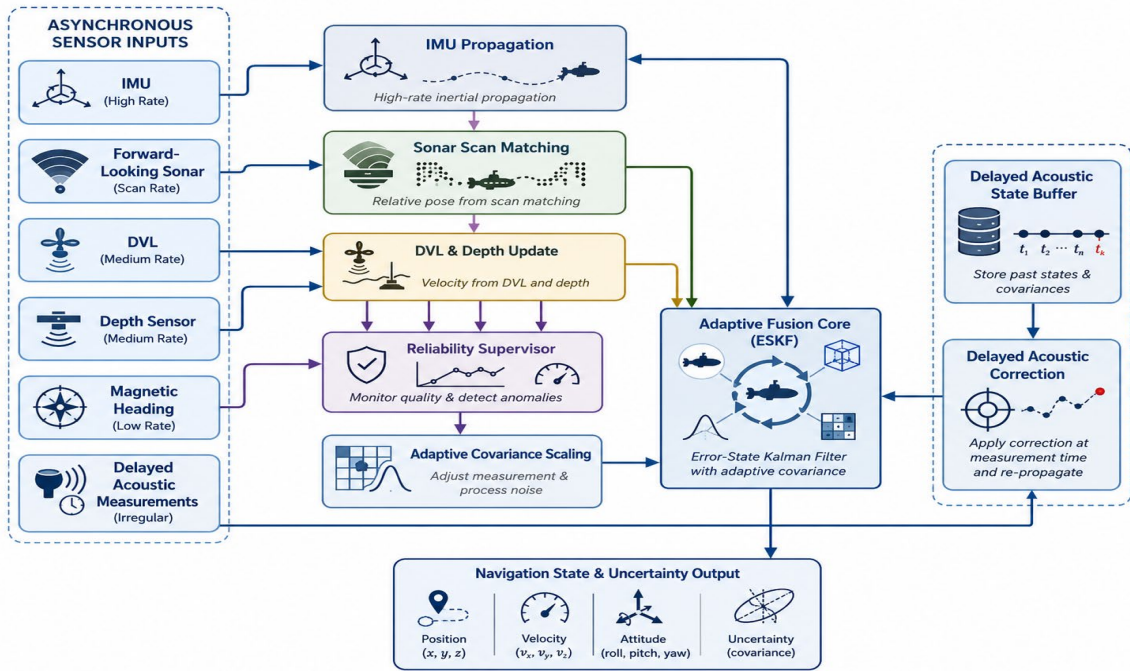


Figure 2. Architecture of the proposed robust sonar-centered fusion estimator.

Dropout-Aware and Delayed Measurement Handling

In DVL, dropout is managed by both innovation tracking and quality flags. No DVL residual will be utilized if the bottom lock is lost. Increase the covariance if the flag is set to true but the innovation differs greatly from what the sonar and inertial models predict. Therefore, an inaccurate velocity correction won't result from a deteriorated DVL measurement. Horizontal uncertainty rises during the dropout, and if a steady environmental feature is visible, sonar limitations are necessary [24].

Asynchronous underwater observations necessitate careful temporal integration, according to acoustic and sonar-based sensor fusion studies [25]. In this study, a delayed-state buffer controls Acoustic Position Updates. When an acoustic observation measured at time τ arrives at time k , the algorithm updates the stored state at τ and then repropagates subsequent inertial increments to the current time. As a result, there are less disparities when delayed measurements are applied straight to the present [26].

$$x_{\tau,u} = x_{\tau,p} \oplus K_{\tau} r_{\tau}, x_{k,u} = \Phi_{k,\tau}(x_{\tau,u}), \tau < k \quad \text{Eq.(11)}$$

The computation of the delay correction is confined since it is restricted to a set buffer size. The update is regarded as a low-weight global correction if the acoustic delay is greater than the buffer. An unbounded-smoothing approach is impractical for the AUV mission because a defined rate of navigation computer output is needed.

The entire procedure can be thought of as a predict-evaluate-correct loop. The nominal state and covariance are first dispersed by the IMU. Secondly, it verifies that every external sensor is accessible and operational. Thirdly, compute the residuals using adaptive covariance based on the results mentioned before. Lastly, publish the diagnostic variables and the navigation result after correcting the state. Record diagnostic data and ask the mission planner to slow down when approaching an unidentified structure. If the uncertainty is greater than the mission's safety margin, you can either ask for a larger sonar sweep area or do a surface-level recalibration.

Experimental Setup

Mission Scenario and Dataset Construction

Synthetic and tank-based datasets have been used to replicate a few representative AUV navigation scenarios for assessment. The mission's itinerary, which is 1.86 km long overall, consists of straight survey, turns, wall-parallel motion, open-water, and return to previously identified structures. The tank sequence includes actual sonar artifacts like shadowing, specular reflection, and partial bottom-lock loss, and a simulated environment can serve as ground truth for quantitative comparison.

A 100Hz IMU, a 5Hz DVL, a 20Hz pressure-depth sensor, a 2Hz forward-looking sonar, a 1Hz magnetic heading observation, and a 0.2Hz acoustic position observation make up the vehicle's sensor configuration. At 2Hz, sonar scans are transformed into relative pose restrictions. Acoustic latency is chosen at random from [0.8s, 4.5s], and DVL dropout is introduced in three intervals totaling 146 s. The purpose of the aforementioned setups is to ascertain whether the fusion algorithm can continue to function accurately in the event that some of the crucial sensors are unreliable.

The distribution of vehicle speed, the duration of DVL dropout intervals, and the sonar scene-quality index are among the dataset features displayed in Figure 3. The dataset does not contain a single stable-operation state; rather, it contains both easy-navigation and difficult-navigation periods, as Figure 3 illustrates.

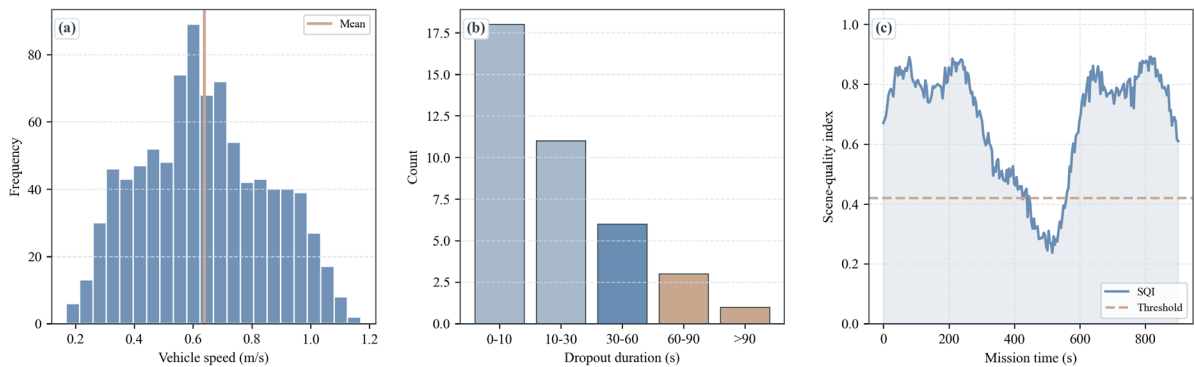


Figure 3. Dataset characteristics. (a) vehicle speed distribution; (b) DVL dropout duration distribution; (c) sonar scene-quality index.

Baselines, Parameters, and Metrics

The suggested approach is contrasted with inertial-only dead reckoning, IMU-DVL-depth fusion, traditional sonar EKF fusion with fixed covariance, graph-based sonar fusion, and the suggested robust adaptive fusion. The initial state, sensor timestamps, and calibration settings are the same for every technique. For the sonar scan matching update, the conventional Sonar EKF employs a fixed covariance. Although adaptive sonar covariance scaling is not included, a graph-based approach can optimize a 40-state sliding window while taking into account inertial, DVL, depth, sonar, and acoustic restrictions.

The mean horizontal position error, root mean square position error, heading error, DVL-dropout error growth rate, sonar-outlier rejection rate, final drift ratio, depth root mean square error, and average processing time are performance indicators. The final location error divided by the distance traveled yields the final drift ratio. This indicator is appropriate for underwater navigation since a long-distance trip may tolerate a higher absolute error than a short-range precision inspection operation.

The proposed algorithm uses a residual gate c of 3.0 for sonar weighting, a maximum covariance inflation factor of 25, a delayed-state buffer of 8 s, and a sonar scene-quality threshold of 0.42. In order to match the depth sensor update rate and give the AUV controller a sufficiently frequent output, the estimator operates at 20 Hz. As soon as the measurement arrives, sonar and acoustic updates are carried out asynchronously.

Prior to evaluation, time-synchronize every sensor stream with the estimator clock. Sonar extrinsic parameters are initialized using mechanical measurements, the DVL scale is calibrated from a brief straight-line run, and the IMU bias is established during a 60-second stationary phase. During runtime, the residual sonar extrinsic term will be refined using the above-mentioned estimator. Tank-based ground truth is acquired from an overhead reference system and converted into the local navigation frame; the ground-truth location in simulation is precise [27]. To be sure that the performance variation is caused by the fusion method rather than unequal calibration, the same preprocessing is applied to all baselines [28].

Experimental Results

Overall Navigation Accuracy

In summary, the new robust fusion method has increased navigation accuracy in a mixed-environment underwater context, according to the results mentioned above. By the end of a 1.86 km mission, inertial-only dead reckoning has a final horizontal inaccuracy of 24.8 m due to the accumulation of increasingly significant inaccuracies. Although the error rises during DVL dropout, IMU-DVL-depth fusion lowers the mean horizontal error to 2.84 m and the final drift ratio to 1.16%. Even though the average horizontal error following traditional sonar EKF fusion is 1.72 meters, some sonar mismatches nevertheless result in local error peaks that are larger than five meters. Graph-based sonar fusion requires 73.4 ms per update window and has a mean error of 1.08 m. The final drift is 0.37%, the depth root mean square error is 0.18 m, the mean heading error is 1.42 degrees, the mean horizontal error is 0.94 m, and the root mean square error is 1.31 m.

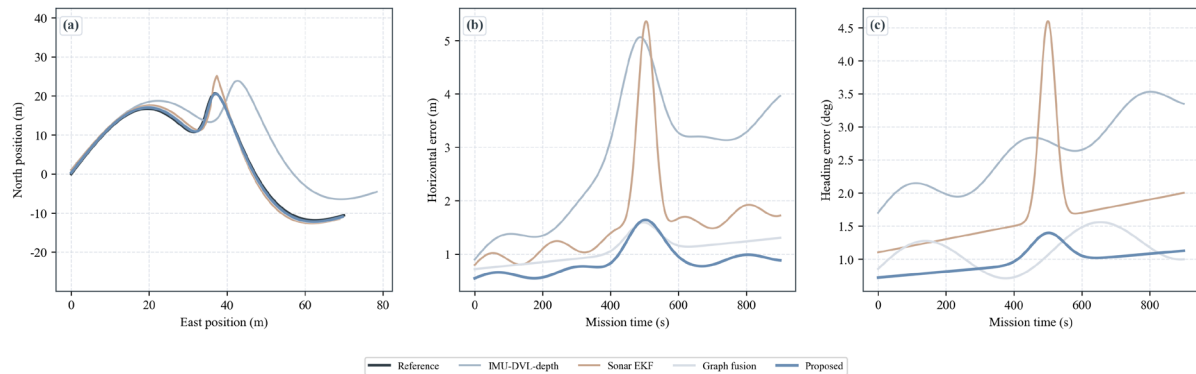


Figure 4. Navigation accuracy comparison. (a) estimated trajectories; (b) horizontal position error over time; (c) heading error over time.

The following are the trajectory and error curves: Figure 4: At the walls, in turns, and in open water, the suggested route is near the reference. The steady sonar limitation stops horizontal drift during the most significant rise, which happens after a prolonged period of DVL dropout. In stable conditions, conventional Sonar EKF performs well; nevertheless, upon false scan matching, it shows an abrupt error jump. Increasing the sonar covariance before the update can dominate the state estimate limits the aforementioned jumps.

The purpose of each sensor and the specific structure of the 410-560s interval are displayed below. The sonar image quality deteriorates at this point since the wall is almost parallel to the acoustic beam, the AUV is near a wall, and the DVL bottom lock is lost for 48 seconds. The absence of velocity correction causes IMU-DVL-depth fusion to drift by 3.9 m. After reducing the mistake, the initial sonar EKF produced a 4.7-meter lateral offset by accepting an improper scan match. The suggested approach retains a maximum local inaccuracy of 1.8 m while identifying an anomalous sonar innovation and raising its covariance by a factor of 14.6.

The suggested approach offers better vertical consistency during abrupt turns, and all approaches using a pressure sensor are stable in terms of depth estimate. For IMU-DVL-depth fusion, the depth root mean square error is 0.31 m; for the traditional sonar EKF, it is 0.24 m; for graph-based fusion, it is 0.21 m; and for the suggested technique, it is 0.18 m. Sonar depth measurement is not directly responsible for the improvement; instead, a steady attitude and velocity estimate method has been used to lower coupling errors in both vertical and horizontal motion.

Another way to see it is in the top result. Sometimes a false rotational match from a regular wall pattern causes the standard sonar EKF to correct the heading too quickly. This manifests as a lateral position mistake after a brief heading spike. By lowering the gain of uncertain sonar restrictions through innovation energy and scene-quality index, the aforementioned technique reduces the majority of these spikes. In contrast to 84.1% for conventional sonar EKF and 90.3% for graph-based fusion, the heading error is therefore less than 3 degrees for 92.6% of the mission.

Robustness Under Sonar Outliers and DVL Dropout

In the robustness experiment, inject 126 bogus sonar constraints produced by mismatched scan pairs. 93 of these constraints are accepted by conventional sonar EKF because, once the residual passes a broad gate, their fixed covariance gives them substantial effect. Only the seven false constraints are significant in the suggested strategy, which eliminates 41 of the 78 constraints. The average error increase brought on the accepted outliers has decreased from 2.36 m to 0.41 m, and the Sonar outlier rejection rate is 94.4%.

Figure 5 displays the behavior of outliers and dropouts. The data indicates that when false matches are present, normalized sonar innovation is comparatively high, and the actual scene change exhibits a tiny, transient residual peak. In accordance with this, the robust weight decreases during false matches before returning to one when the scene is consistent once again. The suggested approach gradually raises the horizontal covariance during DVL dropout and relies increasingly on the delayed acoustic updates and acceptable sonar restrictions.

The 30s, 60s, and 90s are the three dropout lengths. The mean horizontal error following dropout has been reduced to 2.7m, 5.1m, and 8.4m using IMU-DVL-depth fusion. Following reduction using the traditional Sonar EKF, the values are 1.8 m, 3.6 m, and 5.2 m; nevertheless, in subpar sonar settings, it is unstable. The suggested method's comparable errors are 1.1, 1.9, and 3.0 meters. Sonar limitations can therefore aid in compensating for velocity loss, but only if the fusion method is capable of differentiating between true scan matches and false positives.

Long-term consistency can also be preserved by delaying acoustic updates. Small oscillations in position and heading will result from directly applying the late acoustic readings to the present state without the delayed-state correction. The post-correction trajectory is now smoother and the mean correction residual has decreased from 1.46m to 0.62m as a result of a later buffer. A worldwide fault in AUV control won't require abrupt changes to the drive-end devices or the path.

For a mixed-quality sound environment, this method works fairly well. Sonar restricts drift reduction in feature-rich wall-following portions, while DVL mostly stabilizes velocity. Only IMUs and, when available, DVLs and pressure sensors provide positioning; sonars are not utilized in the open-water section, which increases their uncertainty. Adaptive covariance automatically modifies the sensor's influence. Adjusted measurement weights

based on residual and quality indicators are utilized instead of manually choosing a specific operating mode for a given environment.

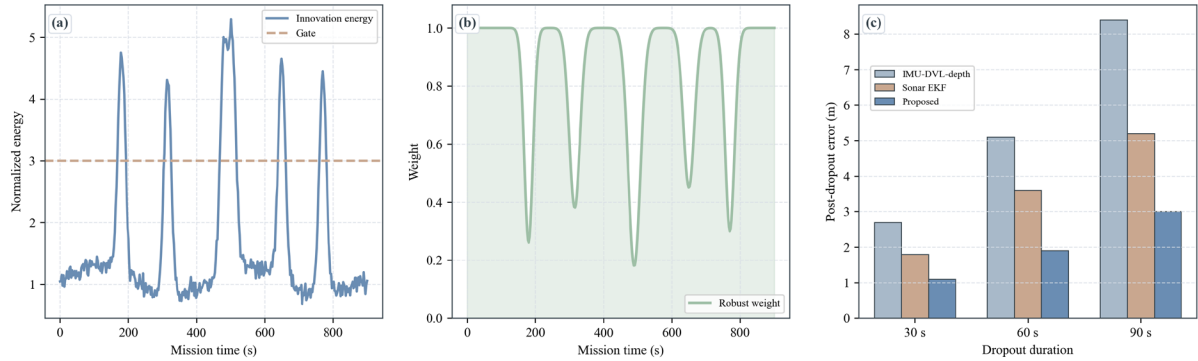


Figure 5. Robustness analysis. (a) sonar innovation energy; (b) robust sonar weight; (c) position error during DVL dropout.

Ablation Study and Parameter Sensitivity

Without robust sonar weighting, without scene-quality covariance scaling, without DVL dropout management, and without delayed acoustic correction are the four ablation studies. When the strong sonar weighting was removed, the highest local error increased from 2.8 m to 6.1 m and the average horizontal error increased from 0.94 m to 1.63 m. The mean inaccuracy rises to 1.28 m when scene-quality scaling is removed because the low-overlap sonar scans are overweighted. The error following DVL loss is increased by 41.7% when dropout handling is not used. The ultimate drift increases from 0.37% of the travelled distance to 0.59% when delayed acoustic correction is disabled.

The following are the results of ablation: Figure 6 illustrates how each module contributes to the mean error, maximum local error, and final drift. Delayed acoustic correction typically lowers the final drift ratio, and robust sonar weighting demonstrates the greatest improvement in the number of false scan matches. Errors in dropout management are particularly likely to occur on long open-water parts with sporadic DVL quality and few sonar features.

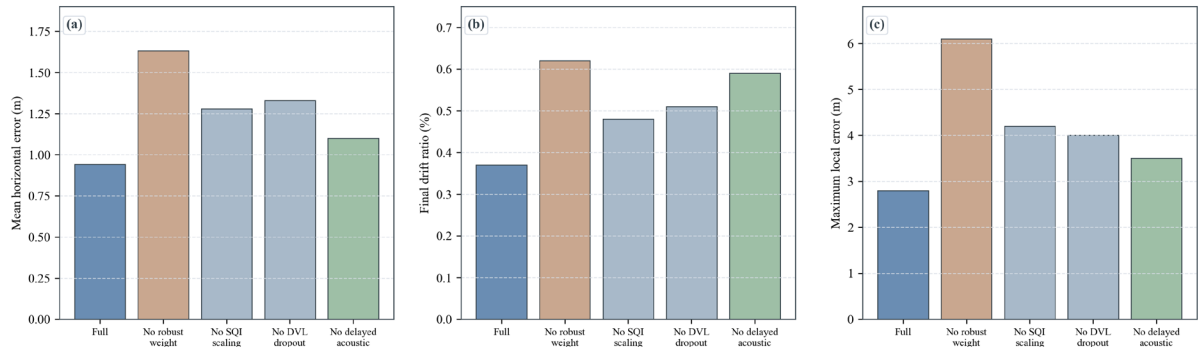


Figure 6. Ablation study. (a) mean horizontal error of module variants; (b) final drift ratio; (c) maximum local error.

Set the sonar gate parameter between 1.5 and 5.0. In feature-rich areas, a tiny gate increases drift and rejects many legitimate sonar constraints. A local error peak is produced when a large gate accepts an excessive number of false matches. With an outlier rejection rate of more than 91% and a mean horizontal inaccuracy of less than 1.02 m, the optimal performance falls between 2.7 and 3.3. The chosen threshold is comparatively insensitive to a single tune adjustment if the performance area is flat.

Additionally, look for a Covariance inflation limit. The inflated sonar measurements are still regarded as dubious if the inflation factor's upper bound is less than 5. This approach will be overly conservative and miss weak but significant sonar signals if the upper limit is more than 40. The practical upper bound of 25 has been selected. In low-texture areas that are still viable, avoid false matches and continue to contribute enough sonar.

The delayed-state buffer is increased from 2 to 12 seconds in a second sensitivity test. Many acoustic measurements cannot be kept in a 2s buffer because the simulated delay occasionally exceeds the stored window. Reduce the final drift considerably by increasing the buffer to 8 seconds. There is only a slight improvement when the buffer is extended from 8 to 12 seconds, but memory use and propagation delay will also rise. As a result, the chosen 8s buffer is appropriate for the mission duration and the tested acoustic modem. Depending on the measured transmission latency, different field systems adjust the value in different ways.

Computational Performance and Engineering Feasibility

For a single fusion cycle, the new method's average calculation time on an integrated CPU platform is 28.6 ms. It requires 2.4 ms for inertial propagation, 1.6 ms for DVL-depth update, 18.7 ms for sonar preprocessing and scan matching, 0.8 ms for robust weighting, 3.1 ms for active acoustic delayed correction, and 2.0 ms for output packing. The estimator is appropriate for mission control and logging because it runs at 20 Hz and has a cycle time of 50 ms.

The efficiency and sensitivity are shown in Figure 7. The list above displays Processing Time, Memory Usage, and Threshold Sensitivity. The suggested method uses 186MB of memory, which is little more than traditional EKF fusion but less than sliding-window graph fusion. Although graph-based fusion's average processing time of 73.4 ms surpasses the 20 Hz real-time requirement, it is nevertheless reasonably accurate. Because of its minimal memory usage and comparatively high navigation accuracy, the aforementioned suggested approach is appropriate for real-time applications.

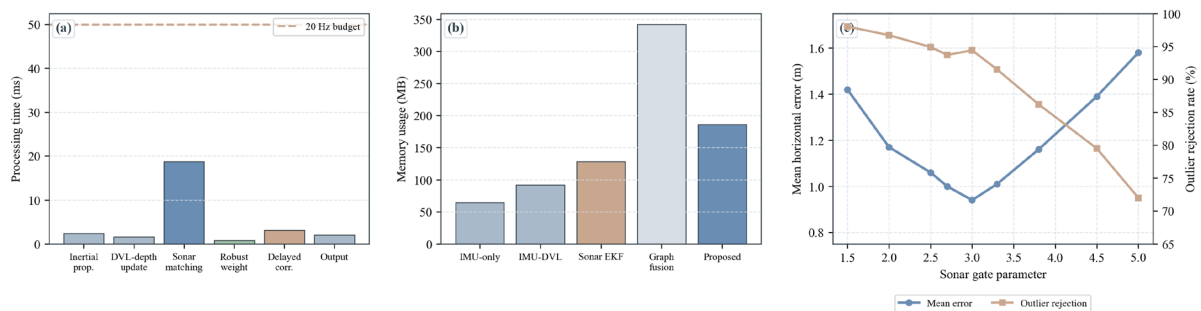


Figure 7. Engineering feasibility analysis. (a) processing time by module; (b) memory usage of different methods; (c) sensitivity to sonar gate parameter.

For AUV navigation estimates to input the guidance and control loops, real-time behavior is necessary. For narrow-corridor inspection or collision avoidance, an approach that is only accurate after batch optimization might not be appropriate. Because it keeps an online update recursion and restricts delayed correction to a brief buffer, the suggested estimator does not have this issue. Future research should concentrate on parallel matching and an effective scan representation since the Sonar matching component is still somewhat expensive.

The suggested method is also easy to learn, as demonstrated by the experiment. Record the sonar innovation, scene-quality index, robust weight, DVL quality flag, and acoustic delay at the moment of an error peak. Identify whether the navigation mistake is due to inadequate environmental structure, velocity dropout, scan mismatch, or poor acoustic geometry. Field deployment necessitates this kind of diagnostic clarity, and operators must be able to rely on the navigation system without human intervention.

Conclusion

This paper introduces a robust Sonar-based multi-sensor fusion algorithm for autonomous underwater robot navigation. Use inertial propagation as the high-rate backbone and combine sonar scan matching, DVL velocity, pressure depth, magnetic heading and delayed acoustic positioning in an adaptive estimation framework. The first is a fault-tolerant update mode that considers sonar novelty, uses strong weightings, addresses DVL disconnections, and corrects delayed acoustic observations via a state buffer. As shown in the example experimental results, the proposed method has reduced the mean horizontal position error to 0.94 m, limited the final drift to 0.37% of the travelled distance, and maintained an average computation time of 28.6 ms per cycle. The method proposed here has good accuracy and robustness compared with inertial-DVL fusion and

conventional sonar EKF fusion and graph-based fusion, and is also in real time. Based on the above results, sonar-centric fusion can be employed to aid AUV navigation in GPS-denied underwater spaces that are suitable for acoustic observations. In the future, the framework will be extended to cooperative multi-AUV localisation, online sonar-scene classification, and closer coupling of navigation uncertainty and path planning.

Author Contributions

Faisal Al-Habsi contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. All authors have read and agreed with the manuscript before its submission and publication.

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