Expediting recovery of autonomous underwater vehicles in dynamic mission environments: A system-of-systems challenge for underwater warfare

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Abstract
As autonomous underwater vehicle (AUV) adoption increases, operators demand advanced behaviors from commercial off-the-shelf systems. However, new behaviors can often only be deployed operationally once assured. This paper overviews research into expediting recovery to an operator’s vessel through a custom homing behavior, demonstrating technology advancement in conjunction with test and evaluation activities. Advanced docking infrastructure and frameworks are still under development, yet current AUV operations require rapid and reliable recovery when mission factors change. Homing is achieved with a directional acoustic transponder providing range and bearing data to the AUV from the operator’s vessel. A converted measurement Kalman filter processes range and bearing data that generates dynamic waypoints for the AUV through MOOS-IvP as a backseat driver; a universal approach and filtering that is unique from prior AUV research. Results from simulations and field trials were analysed through a modular and experimental Test & Evaluation framework that was adopted specifically to help verify and validate the new AUV behavior, including systematic variations in recovery boat manoeuvres. The process includes documented use for the first time in AUV research of combinatorial screening (high throughput testing) and an average standardized residual metric to focus development early, encourage constructive iteration and build operational and engineering trust. Consistent homing was demonstrated with localization within 0.3 m and homing within 1.8 m of a moving digital acoustic transponder.

KEYWORDS
autonomous underwater vehicles, homing, localization, robotics, test & evaluation
1 | INTRODUCTION

1.1 | Research problem context

Autonomous underwater vehicles (AUVs) represent an increasingly pragmatic technology that can be applied to various maritime endeavors. For example, the defense sector uses AUVs for hydrography, oceanography, antisubmarine, and mine warfare. Costanzi et al. (2020) conducted a significant review of marine robotics in military contexts, and they summarize the potential and interoperability challenges as follows:

Unmanned Maritime Vehicles (UMVs) are increasingly demonstrating their potential for improving existing naval capabilities due to their rapid deployability, easy scalability, and high reconfigurability, offering a reduction in both operational time and cost. In addition, they mitigate the risk to personnel by leaving the man far from the risk but in the loop of decision making. In the long-term, a clear interoperability framework between unmanned systems, human operators, and legacy platforms will be crucial for effective joint operations planning and execution. However, the present multi-vendor multi-protocol solutions in multi-domain UMVs activities are hard to interoperate without common mission control interfaces and communication protocol schemes. Furthermore, the underwater domain presents significant challenges that cannot be satisfied with the solutions developed for terrestrial networks.

Costanzi et al. (2020) document that the application spread of uncrewed maritime vehicles has slowed due to a lack of human confidence. They cite the challenge of interoperability of such vehicles within a system-of-systems context. Similarly, research by Cordle and Cotter (2019) on littoral combat ships finds some of these ships have experienced significant failures in mission accomplishment potentially attributable, at least in part, to under staffing and over scheduling the human component of the integrated human and automation activity in the LCS operational environment. According to a significant structured literature review by Ferreira et al. (2021), systems-of-systems are characterized mainly by operational and managerial independence of constituent systems and they also present distribution, evolutionary development, and emergent behavior. They find that the integration of various heterogeneous and independent software systems on software-intensive systems is a systems-of-systems problem. The general state of interoperability within Defense systems and strategies to mitigate these is compared between the United States and Australian defense departments by Joiner and Tutty (2018), finding key measures to deal with system-of-systems phenomena lags in Australia. Such system-of-system complexity has delayed significant Naval efforts for autonomous mine clearance in many countries, leading them to scale objectives to more realistic human-autonomy teaming approaches (GAO, 2022; Kerr, 2016; Lundquist, 2020).

What causes the lack of confidence to use AUV more broadly? According to Ferreira et al. (2021), when software-intensive system-of-systems are employed in dynamic environments, they require high reliability. Their literature survey provides high-level reliability principles (i.e., their figure 4) specific to such systems-of-systems. Essential to this study, the literature emphasizes the importance of reliability estimation through model-based probabilistic analysis and the need to recover from unexpected disturbances in the operating environment, or put another way, to be resilient (Uday, 2015). Hossain et al. (2019) provide an exemplary case study on resilience modeling of a system-of-system in a maritime context; however, no research could be found on such an approach for AUV system-of-systems. More research is needed like that by Cordle and Cotter (2019) on the littoral combat ship highlighting how to build operator trust for an automated ship and in underwater warfare operations.

In military roles, AUVs are typically preprogrammed before being deployed on subsea data-collection missions. Such missions must be planned from beginning to end, considering factors like bathymetry, currents, salinity, sea state, weather, marine traffic, and enemy threat environment (Keane & Joiner, 2020).

An AUV is unprotected with no autonomy when running on the sea surface and is at its most risk for collision with surface vessels (including the launch and recovery vessel). Conversely, once dived, an AUV is in the environment where it excels. Therefore, from an operational perspective, the sea state and suitability of the recovery vessel are often the limiting factors in AUV deployments. Various recovery methods exist for safely transitioning AUV through this stage of operations (Page & Mahmoudian, 2019; Sarda & Dhanak, 2018); however, many methods are time-consuming, limited by sea state, or require significant additional infrastructure (Yazdani et al., 2020).

Increasing the adaptability and flexibility of AUV missions is critical to mitigating recovery risks while working towards other development goals, such as multiple-platform swarm autonomy. Swarm autonomy is where multiple AUV and unmanned surface vessels (USV) can team together to achieve goal-based outcomes (e.g., Costanzi et al., 2020; González-García, 2020; Li et al., 2019). In addition, mission flexibility can generally be achieved through increasing onboard autonomy. For instance, flexibility increases if the AUV can localize and home to its recovery vessel upon completion of its mission or under changed circumstances. This feature removes the requirement for the operator to wait and recover the AUV in a predetermined location. Hence, the rapid recovery of these million-dollar assets is a resilience feature in dynamic maritime warfare environments critical to building the trust necessary to spread the use of AUV. In researching complex systems governance, Keating and Polinpapilinho’s (2019) research has highlighted that a “clean-sheet” redesign of system-of-systems governance is rarely feasible. Instead, they develop a pathological approach that identifies and treats critical impediments. For the use of AUV in maritime warfare, two key improvements were identified to build resilience and trust: (1) a means of rapid and safe recovery, and (2) for the Australian context, iterative development and assurance involving greater modeling and simulation (Joiner & Tutty, 2018; Keane & Joiner, 2020).
Some AUVs are specifically designed as part of a holistic mission system, including launch and recovery systems and inbuilt homing capability. However, many AUV types are deployed with small teams, often from opportunistic platforms. Hence, recovery is frequently undertaken in less than ideal conditions, including exposed conditions or a rapidly changing threat environment onto platforms often not designed for expedited recovery of AUV. Therefore, the recovery means must be universal to be interoperable among the many AUV types needed to aid complex maritime warfare such as rapid environmental assessment and mine clearance, especially when these are allied operations. By demonstrating that the AUV can localize and home to the recovery vessel, operators can commence longer and more complex missions with the flexibility to determine the optimal location later to recover the AUV and the ability to more rapidly respond to changes in mission objectives (Li et al., 2019; Thomas et al., 2021). According to the survey of homing and docking of AUV by Yazdani et al. (2020), optimal control theory is increasingly being utilized to develop robust and universal guidance systems for complex aerospace problems, however, it still remains a very underdeveloped tool in relation to underwater vehicle guidance applications. Yazdani et al. (2020) propose a universal docking framework arguing that homing and docking should be addressed together.

1.2 Research questions

The primary research question was, can a rapid recovery means for AUV be developed that can be used universally (interoperable) without an inbuilt homing capability or docking station?

A second research question developed on how best to assure the research developments for subsequent use? This assurance challenge arose due to three factors: some aspects experienced internationally and others specific to Australia. First, the degree of autonomy of the capability challenges maritime assurance and regulation (Bolster, 2017; Dean & Clack, 2019; Devitt et al., 2022; Ferreira et al., 2018), similar to other fields. Second, the need for the development to be universal to AUV and not directly from prime system contractors challenges the Australian Navy to develop network integration capabilities and centers similar to the US Defense (Joiner & Tutty, 2018). Third, software-intensive and autonomous systems need agile development, and Australian Defense procurement is predominately “waterfall” and its test and evaluation linear rather than spiral.

1.3 Prior work on AUV recovery problem

AUV localization, tracking, and homing have been comprehensively surveyed by Yazdani et al. (2020). Aspects continue to be researched since then or were not covered by that survey, such as Arunkumar and Vachani (2020), Liu et al. (2019), Bencatel et al. (2017), and Lin et al. (2021). Stanway et al. (2014) and Vallicrosa et al. (2016) are examples of autonomous docking to stationary or moving targets, where much of the research focus has shifted. In many instances, fixed or towed docking stations are either not yet available or may not be appropriate for some missions, meaning a homing-only recovery may be required. Indeed, as established earlier, trusted recovery in warfare today requires this homing-only feature until docking systems are available and universal.

To achieve AUV homing to a moving target, this study leveraged the range and bearing observations communicated between an AUV and the operator’s directional acoustic transponder. Acoustic transponders are generally used to provide the operator with periodic updates of the AUV positions and status to assure the operator that the AUV is on the mission as expected (Borden & DeArruda, 2012). The range-only aspect of Long Baseline (LBL) transponders or the range-and-bearing capability of ultra short baseline (USBL) transponders can be used to increase an AUV’s navigation accuracy (Wolbrecht et al., 2019). Furthermore, inverse navigation has been demonstrated wherein an AUV uses range and bearing between target and transponder to localize the transponder’s position (Jalal & Nasir, 2021; Sarda & Dhanak, 2018). Hence, homing becomes feasible with the existing mission system if acoustic range and bearing observations are available. This data is processed in real-time with the AUV’s navigation data to form position estimates that can be passed to the AUV helm controller as dynamic waypoints, accounting for environmental and system noise.

Homing accurately requires merging sensor data from the AUV navigation and USBL transponder information, with differing errors and reliability depending on the mission. This problem in homing is usually treated with Kalman filtering, such as the research treatment by Krzysztof and Aleksander (2016) for a biomimetic autonomous underwater vehicle (BAUV). They found, Combining the EKF [Extended Kalman Filter] measurement method in the calculations carried out by devices installed on the BAUV (log, INS, hydrostatic pressure sensor) with distance and direction measurements carried out in the USBL system allows for obtaining the position coordinates significantly more accurate. Like most AUV research, research on improving Kalman filtering for AUV homing is focusing on docking (Sans-Muntadas et al., 2015). Another prospect for improving homing is Yan et al. (2019) research to improve homing and docking based on an appreciation that most AUVs are underactuated.

A computationally efficient type of Kalman Filtering not previously used in AUV homing and localization is the converted measurement Kalman filter, which according to Bordonaro et al. (2014):

\[\text{(CMKF)} \text{ is commonly employed to address the problem of target tracking when the measurements are in polar or spherical coordinates. The technique involves conversion of the raw measurement into Cartesian coordinates prior to tracking, allowing for the use of a linear Kalman filter. This avoids the pitfalls of the extended Kalman filter (EKF), which include the potential for divergence and inconsistency between the filter-calculated estimation error covariance and the true estimation error.}\]

The converted measurement Kalman filter (CMKF) differs from the EKF used by AUV researchers such as Krzysztof and Aleksander
1.4 Significance of rapid recovery approach

This study is unique in researching dynamic recovery through homing-only with range and bearing, using a universal software-only approach for those occasions where complex docking infrastructure is not available or appropriate. Further, it is the first research to apply a computationally efficient unbiased Kalman filtering (CMKF) method to improve the resilience to nonlinearities and uncertainties in AUV homing. Finally, this is the first AUV research to trial average standardized residual as a foundational metric for trust to demonstrate localization consistency for the recovery phase.

1.5 Literature on AUV assurance and trust

Earlier, it was established that the degree of autonomy of AUV challenges maritime assurance and regulation (Bolster, 2017; Dean & Clack, 2019; Devitt et al., 2022; Ferreira et al., 2018). Enhancing an AUV with adaptive behavior changes the nature of the human-autonomy team (Yaxley et al., 2021), as the operators are no longer in control of the mission waypoints. Instead, the AUV is tasked with and thus trusted to generate its waypoints to achieve the outcome. Given that AUVs have endurance of many hours, top speeds greater than five knots, and maximum depth of thousands of meters, there is a risk that poor behavior could cause total vehicle loss. Therefore, before a new and untested behavior can be used on the AUV, the research and testing must first build confidence in the performance of the new programming. For instance, by demonstrating that the new programming can be integrated into the existing system without causing the fault and that the new behavior will perform as expected within representative environmental and mission conditions (Kass, 2015), including, as noted earlier, at a systems-of-systems level (Ferreira et al., 2021). We require a testable, repeatable, and auditable assurance framework to prove confidence in the system under test (SUT) (Freeman, 2020). One that deals more adaptively with the complex nature of the system but adheres to the core assurance principles (Joiner et al., 2019). Weiss et al. (2009) further insist that test and evaluation must evolve to be integrated into the development itself, as “...waiting for the results of developmental and operational testing will only exacerbate the delay in rapidly fielding advanced capabilities. Therefore, the assurance method used must be tightly integrated with development while building trust for introduction into service. These factors required the research team to adopt an appropriately agile test and evaluation framework (Keane & Joiner, 2020) similar to that adopted in US Naval ship support (Castelle et al., 2019). The capabilities to do virtual simulations, bench-level partial simulation and field validations enable design iteration to extend beyond the AUV developer to the Navy’s systems-of-systems level with all the benefits for optimizing, building trust and resilience (Joiner & Tutty, 2018; Wynn & Eckert, 2017).

Localization and homing are challenging to achieve and assure subsea when compared to surface or in air, primarily due to multipath sonar systems, low speed and low bandwidth. Challenges extend to include the inherently noisy and unpredictable environment, low real-time observability, lack of test infrastructure, and hence no objective ground truth from which to evaluate robot performance (Costanzi et al., 2020; Paull et al., 2014). Therefore, repeatability is challenging to achieve in dynamic subsea environments, and test opportunities are often limited by the same changing surface conditions that drive the need for expedited recovery.

There is currently no accepted standard for AUV assurance (test and evaluation) (Legashev et al., 2019). However, established test design fields like the design of experiments (Antony, 2014) and modern, efficient high throughput screening test designs (Baker, 2010; Hagar et al., 2015; Kuhn et al., 2016) can execute a test framework. Such a framework is more likely to achieve statistical significance in test results by combining simulation screening and testing with subsea field trials (Johnson et al., 2012; Simpson et al., 2013). This approach has further benefits, as by using high throughput testing for screening, we can identify any significant factors impeding performance and then put mitigations in place to improve the results of algorithms in real-world deployments (Keane & Joiner, 2020). The framework proposed combines simulations and real-world trials, quantifies results in a manner suitable for verifying this capability for deployment within existing and future systems engineering and regulatory requirements, and could be applied to many maritime autonomous systems.

1.6 Significance of AUV assurance work

The use of advances in test design underpinned by spiraled modeling and simulation is not unique (Joiner & Tutty, 2018) but was applied for the first time in this study for Australian underwater warfare systems. Many small to medium militaries are still to adopt such fundamental assurance practices for autonomous robotic systems, significantly beyond their prime contractors’ ability to facilitate the necessary interoperability of multiplatform operations. Applying combinatorial screening (i.e., high-throughput test) to focus the simulations and improve development efficiency appears to be the first documented use in the AUV research reviewed earlier. Further, the screening process to systematically account for variability from recovery boat manoeuvres appears to be a first in the AUV research reviewed, where prior work has focused on environmental variability.
2 | MATERIALS AND METHODOLOGY

2.1 | Mission system

AUV homing research was focused on a Teledyne Gavia AUV, a Teledyne Benthos Directional Acoustic Transponder, and custom software running on the Gavia AUV control computer. Operations were conducted using only the mission system typically deployed for Gavia AUV operations (AUV, DAT and Topside Box, Laptop, and Iridium phone), as seen in Figure 1. Operations were conducted from a 4.7 m rigid hull inflatable boat (RHIB), which performed dual roles as homing target and recovery vessel. The details of the AUV, acoustic transponder, homing and localization programming, and filtering are now covered.

2.1.1 | Autonomous underwater vehicle

The Teledyne Gavia AUV is a modular system capable of missions over 8 h and depths of up to 1000 m. The Gavia AUV has homed and docked with stationary targets (i.e., Keane & Joiner, 2018); however, this was the first known instance researching a Gavia AUV homing to a moving target. Subsea AUV positioning is achieved using the inertial navigation system and doppler velocity log (González-García et al., 2020). Once deployed subsea, the AUV control system performs trajectory planning to achieve the next waypoint. Each waypoint is given a closing radius, where, once the AUV deems itself to be within that radius, it updates its mission profile to continue to the next waypoint until the mission is complete. The Gavia AUV default closing radius of 15 m was maintained for operations and trials. This precaution meant that attempting to demonstrate homing within 15 m was subject to control limitations, and hence localization and homing accuracy of 15 m was deemed successful under the current approach. Navigational drift was not accounted for in assessing the results of this field trial.

2.1.2 | Directional acoustic transponder

The Teledyne Benthos ATM915 directional acoustic transponder is an acoustic modem used for mission monitoring while the AUV is subsea. Directional acoustic transponders, or USBL, are also often used as navigation aides by providing range and bearing data to the AUV from a known point of reference (Hegrenaes et al., 2009). The AUV queries the transponder, which returns range and bearing data to estimate the transponder’s position, speed, and heading aboard the recovery vessel in an absolute frame of reference (Masmitja et al., 2016). No calibration was conducted on the transponder, although an offset correction was needed to account for local magnetic declination. Table 1 shows the technical parameters of the Benthos modem.

2.1.3 | Localization and homing software

The programming component of the localization and tracking system is Python modules running on top of the MOOS-IvP middleware with PyMoos bindings (Benjamin et al., 2013). In addition, MOOS-IvP provides a backseat driver interface allowing independent programming to take control of the AUV to perform customized and advanced behaviors (Keane et al., 2020). MOOS-IvP-GAVIA (iGavia) is a Teledyne-developed interface between MOOS-IvP and the Gavia (frontseat driver) control system that publishes the AUV position and navigation data, and subscribes to navigation commands such as desired heading, depth, and speed. Our programming subscribes to this data, processed using a CMKF to form position estimates of the AUV (Bar-Shalom et al., 2011). Finally, waypoints are created from the estimates and broadcast to IvP Helm, generating desired heading commands to be forwarded to the Gavia control system. The data flow is shown in Figure 2.

2.1.4 | Converted measurement Kalman filter

The advantages and uniqueness of this study in using a CMKF to estimate range and bearing were outlined earlier (Bar-Shalom et al., 2011; Bordonaro et al., 2014). The recovery vessel (target) is assumed to travel in a nearly constant velocity motion in the X.Y.plane. Let

\[ x_t = [x_t, y_t, \dot{x}_t, \dot{y}_t] \]

denote the target state vector at the time \( t \). where \( (x_t, y_t) \) and \( \dot{x}_t, \dot{y}_t \) are its position and velocity, respectively, and \( (\cdot)^T \) denotes matrix transpose. The observer state is similarly defined as

| Table 1 | Directional acoustic transponder Parameters. |
|---|---|
| **Parameter** | **Value** |
| Data rate | 140–15,360 bps |
| Range and bearing updates to Gavia | Once every 15 s |
| Transmission frequency | Band C 22–27kHz |
| Range | 2–6 km |
| Weight | 11 kg dry, 5 kg wet |
and is assumed to be known via the information supplied by an onboard inertial navigation system. Then, the state dynamics for the target evolution can be written as

\[ x_{k+1} = F_k x_k + v_k \]

with the transition matrix \( F_k \) defined as

\[
F_k = \begin{bmatrix}
1 & T_k & 0 \\
0 & 1 & T_k \\
0 & 0 & 1 \\
0 & 0 & 0
\end{bmatrix}
\]

\( T_k = t_k - t_{k-1} \) is the sampling interval for processing the measurement at \( t_k \) and \( v_k \) is a zero-mean Gaussian process noise sequence with covariance \( Q_k \) given by:

\[
Q_k = \begin{bmatrix}
\frac{T_k^2}{3} & 0 & \frac{T_k^2}{2} & 0 \\
0 & \frac{T_k^2}{3} & 0 & \frac{T_k^2}{2} \\
\frac{T_k^2}{2} & 0 & \frac{T_k^2}{2} & 0 \\
0 & \frac{T_k^2}{2} & 0 & \frac{T_k^2}{2}
\end{bmatrix} \tilde{q}.
\]

Here \( \tilde{q} \) is the process noise intensity parameter. Noise-corrupted measurements of the target range \( r_k \) and azimuth \( \theta_k \) are available at times \( t_k, k = 1, 2, \ldots \); the measurement vector \( z_k = [r_k, \theta_k] \) is modeled as

\[ z_k = h(x_k) + w_k \]

where

\[
h(x_k) = \begin{bmatrix}
\sqrt{(x_k - x_0)^2 + (y_k - y_0)^2} \\
\tan^{-1}\left(\frac{y_k - y_0}{x_k - x_0}\right)
\end{bmatrix}
\]

and \( w_k \) is an independently and identically distributed zero-mean Gaussian measurement noise sequence with covariance:

\[
R = \begin{bmatrix}
\sigma_r^2 & 0 \\
0 & \sigma_\theta^2
\end{bmatrix}
\]

Here \( \sigma_r^2 \) and \( \sigma_\theta^2 \) are the variances of the range and azimuth measurements, respectively. Given a set of range measurements \( Z_k = [z_1, \ldots, z_k] \), the objective is to estimate the target state vector recursively \( x_k \). We use the CMKF with unbiased measurement conversion (Longbin et al., 1998) to solve this problem. In particular, denoting:

\[ Z_k \triangleq \Xi[\cos(w_{k,2})] = e^{-\sigma_\theta^2/2} \]

where \( w_{k,2} \) is the azimuth noise component of the measurement noise \( w_k \), and the unbiased measurement conversion from polar to Cartesian coordinates is:

\[
z_k' = \begin{bmatrix}
\lambda_k^{-1} r_k \sin \theta_k \\
\lambda_k^{-1} r_k \cos \theta_k
\end{bmatrix}
\]

with an associated Cartesian measurement error covariance matrix \( R_k' \). The interested reader is referred to Longbin et al. (1998) for details on the computation of \( R_k' \). The filter is initialized with a two-point differencing technique using the first two measurements from the data set. Note that this CMKF uses the two-dimensional version of the unbiased conversion (in polar coordinates of range & bearing), not the complete spherical coordinate system or the direction cosine coordinates approach (Cho & Thak, 2022).

### 2.2 Design of experiments

Experimental design for autonomy is better enabled through experimental test and evaluation concepts (Kass et al., 2015, Keane et al., 2020), where high throughput test design was leveraged to provide an efficient and robust test regime for AUV.

A design of experiments diagram (Antony, 2014) forms a sound basis for the test design. The diagram shows controlled variables (left), constants (top), noise (bottom) and measured outputs (right), as seen in Figure 3 below.
2.2.1 | Screening with simulation

The test plan was executed in simulation as part of a screening process to identify significant factors (which informed algorithm refinement) before validation in the real-world (Bartolomei et al., 2006). Software simulations using MOOS-IvP AUV simulators were executed according to a high-throughput test plan developed on QuantumXL® in the “D-Optimal” feature and using script-driven testing, which configured, executed and analysed results (Thrasher & Pippard, 2018). High Throughput Test allows us to reduce the number of runs required while retaining statistical significance across testing for a large number of variables by finding common factors across each possible combination or permutation of controlled variables (Hagar et al., 2015; Kuhn et al., 2016; Simpson et al., 2013). For example, a general factorial design test plan would require 648 runs (with 10 repetitions for each run) to cover six factors. A high throughput test plan for these simulations required 57 runs and 10 repetitions for each run that was sufficiently orthogonal in quadratics and two-way interactions (Variance inflation factor <1.4; which measures the extent of orthogonality using the determinant, compared to a perfect 1.0).

This screening test design is critical to ensure that: the test plan is feasible with finite time and resources, the effects can, where applicable, be attributed to the primary factors and their interactions, and that statistical significance of results can be achieved. Perhaps counter-intuitively, the screening runs are intended to test conditions where the homing behavior had the highest chance of failure rather than demonstrate the best performance. Table 2 gives the variables and factors used to generate the simulation test plan used for screening.

Starting range refers to the distance between the AUV and boat at the beginning of a mission. First, two common AUV survey behaviors (lawnmower and reacquire missions) were simulated. Next, different AUV and boat speeds were simulated, with the boat following different loiter patterns (Figure 4). Finally, a simulation was ended if a logic script confirmed homing was achieved, else if, a timeout was reached. The metrics of success are defined ahead in Section 2.2.3.

2.2.2 | Field trial validation

Field trials were conducted in Jervis Bay, ACT, Australia (May 17–25, 2021) to verify and validate the homing behavior. Field trials used the Gavia AUV mission system and were deployed across the range of conditions in Table 3.

A subset of the high throughput test plan was executed for field trials, with less complexity in boat behavior as the vessel used lacked navigational and seakeeping abilities needed to execute many of the boat behaviors simulated. The Gavia AUV began each trial with a short (5–30 min) sonar-survey mission. The AUV would begin to localize the target during the survey mission. At the end of the survey mission, the AUV would begin the homing action. Actual AUV position data was obtained from the AUV’s navigation software. Actual vessel position data was obtained from a handheld GPS unit. The vessel loiter was limited to drifting at low speeds while the transponder was deployed. The simulation suite was rerun with field conditions to check for correlation, albeit the number of field runs was understandably limited. The range commander determined the mission end for field trials after visual or acoustic reports confirmed the AUV was close to the recovery vessel, ensuring the AUV was suitably positioned to avoid collision with the recovery vessel.

![Figure 3: DoE diagram (black box trust diagram) for AUV homing. AUV, autonomous underwater vehicle](image-url)
2.3 Metrics of success to build trust and resilience

Three metrics were chosen to measure success related to accuracy, consistency and confidence of the homing behavior: localization accuracy, homing accuracy, and average standardized residual (ASR). Localization accuracy is deemed as the distance between estimated and actual vessel position. Homing accuracy is the actual Euclidean distance between AUV and vessel position at mission end. Finally, the Average Standardized Residual is used as a foundational metric for trust (through demonstrating localization consistency for the recovery phase) and is given by:

\[

d = \frac{\sum_{i=0}^{j} (\text{Actual USV position} - \text{Estimated USV position})}{3 \times \text{predicted standard deviation}}.
\]

Consistently quantifying test outcomes through the above metrics means we can compare results from simulations and field trials to analyse success in a way that is testable, repeatable and auditable through an agile approach to analysis (Antony, 2014; Freeman, 2020).

The AUV homing behavior was first tested in simulations and then validated in field trials. Following field trial validation, the real-world observations were replayed through simulation to verify the suitability of simulation results as a predictor of future field trial performance. Localization accuracy and standard average residual are expected to be comparable between simulation and field trials; however, homing accuracy is not as comparable (as the simulation control and physics are for a generic AUV; not tuned specifically for the Gavia AUV).

3 RESULTS

3.1 Screening simulation results

Running the CMKF in simulations demonstrated an ability to localize to within 10 m of the target and home within 35 m for all simulated runs. Figure 5 shows histograms of the localization and homing simulation results.

A multiple logistics regression was calculated to predict the average standardized residual of the actual target position from the predicted target position (Equation 6) and the variance of that average standardized residual based on the six independent variables in Table 2. A regression equation for average standardized residual was found \( F(13, 556) = 22.575, p < 0.000, R^2 = 0.3455 \). A significant regression equation for the variance of the average standardized residual was also found \( F(10, 34) = 7.015, p < 0.000, R^2 = 0.6735 \) (Cronk, 2020). An uncoded (i.e., with units) significant regression equation for average standardized residual \( \delta \), can thus be predicted (Equation 9) and its standard deviation \( \sigma_\delta \) (Equation 10). Where \( R \) is the starting range, \( v_A \) and \( v_B \) are the velocity of the AUV and boat, respectively, \( b_\delta \) are the behavior coefficients (Table 4) and \( p_\delta \) are the pattern coefficients (Table 5).

\[
\delta = 0.9414 - 0.000329R + b_0 + p_0 + 0.01366v_A - 0.9334v_B + p_1R + 0.0003774Rv_B + b_1v_A + p_2v_B + 0.2463v_B^2.
\]
Regression analysis identified boat speed as a significant factor for homing accuracy. Localization accuracy and average standard residual were most impacted by the relationship between boat speed and boat behavior. Figure 6 shows Pareto reports for $\hat{Y}$ and $\hat{S}$ of average standard residual across each factor for each controlled variable. The interaction between Boat loiter pattern (C) and Boat speed (E) strongly influences the average standardized residual (Figure 7).

Interaction plots for loiter pattern and boat speed show that polygon pattern at higher speeds gave the worst average standardized residual.

### 3.2 Field test validation results

Twelve field trials were conducted across 3 days, starting at short ranges of 180 m, keeping the AUV speed at four knots, boat speed at 0.5 knots and drifting (i.e., approximately straight line) and graduating to a maximum range 1260 m. Ten runs were with lawnmower mode and two with reacquire mode. The AUV was visually sighted in 10 of the 12 runs from the target vessel. A summary of the results is given in Table 6, showing the best localization accuracy of 0.3 m and the best homing accuracy of 1.8 m. The worst localization accuracy reported was 10.0 m, with the worst homing accuracy of 17.8 m. Except for the homing test mission (mission 12), all field missions were deemed successful (passing within 15 m of the transponder). Average standardized residual in the field trials, as a measure of CMKF estimation performance across each run, had a mean of less than 0.87 m and a standard deviation of 0.61 m indicating the AUV could localize the drifting boats consistently. When the ASR was compared to the prediction equations at Equations (9) and (10), the field trials were within an average of 0.98 of the predicted standard deviations (i.e., $<1\sigma$) (Antony, 2014). Generally, short-range ($<500$ m) had a slightly less ASR than predicted (absolute $<0.4\sigma$), whereas longer ranges had an actual ASR greater than predicted, with two instances exceeding $3\sigma$. To check the veracity simulations were run with 10 repetitions of each field condition. The ASR from the field trials correlated significantly with the ASR from simulated field conditions with a Pearson's correlation coefficient of 0.671 ($p = 0.0169$).

Figure 8 shows homing from an example test run conducted during field trials. This run began with the AUV conducting a sonar survey (single lawnmower survey leg) before homing to the boat (which was drifting at 0.6 m/s away from the AUV). Localization accuracy initially decreases as the AUV conducts its survey away from the target vessel and increases as it turns toward the vessel. As the AUV converged on target, it completed five passes underneath the recovery vessel before it was called to the surface for recovery.

Localization accuracy (distance between CMKF estimate and actual boat location) from all field trials is shown converging in Figure 9. Error spikes seen are the result of noise and outliers. The CMKF shows robustness in recovering from these errors.

![Figure 5](image_url)  
**FIGURE 5** Results from 570 real-time simulation runs showing localization accuracy (left) and homing accuracy (right). Note that batch-processed simulations in the screening phase were programmed only to demonstrate the ability to home rather than seek the best accuracy of homing results. However, this was a limitation of the unsupervised automated test scripting approach at the time, and the results were still deemed appropriate for screening.

### Table 4 Coefficients for AUV survey behavior used in predicting the average standard residual (Equation 9) and its standard deviation (Equation 10)

| Behavior     | $b_0$  | $b_1$  |
|--------------|--------|--------|
| Reacquire    | 0.8341 | -0.1805|
| Lawnmower    | -0.8341| 0.1805 |

$$d_\delta = 0.9685 + 0.0004403 R + p_2 - 0.0533 \nu_s - 0.2920 \nu_b + p_4 R + 0.0003843 R \nu_s + p_5 \nu_b.$$  

(10)
Homing accuracy (distance between AUV and boat) from all field trials is shown converging in Figure 10. The distance between AUV and recovery vessel is often seen to increase before converging as distance to the target is shown while the AUV is conducting survey mission and in the recovery phase. Once the AUV reaches the target, it manoeuvres and reacquires the vessel’s estimated position (distance to target can be seen increasing and decreasing) until given an acoustic command to return to the surface.

### Table 5

| Pattern          | \( p_0 \)   | \( p_1 \)   | \( p_2 \)   | \( p_3 \)   | \( p_4 \)   | \( p_5 \)   |
|------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Circle           | -0.6340     | 0.000258    | 0.3281      | -0.9731     | 0.0005169   | 0.3099      |
| Tracks           | 0.2110      | -4.183\(^{-5}\) | -0.1495     | 0.5794      | -0.0003468  | -0.2202     |
| Box              | 0.4230      | -0.0002164  | -0.1785     | 0.3937      | -0.001701   | -0.08976    |

**Figure 6**  Pareto reports of \( \hat{Y} \) (top) and \( \hat{S} \) (bottom) for average standard residual showing test factors against influence coefficients (how factors influence homing performance).

**Figure 7**  Interaction plots showing the interaction of boat speed and loiter pattern as it impacts average standardized residual. Polygon pattern at higher speeds gives the worst average standardized residual.
TABLE 6 Summary of results from field trials

| Measured outputs            | Averages         | Max (worst) | Min (best) |
|-----------------------------|------------------|-------------|------------|
| Homing accuracy             | $\mu = 7.8 \text{ m}, \sigma = 4.6 \text{ m}$ | 17.8 m      | 1.8 m      |
| Localization accuracy       | $\mu = 2.9 \text{ m}, \sigma = 3.0 \text{ m}$ | 10.0 m      | 0.3 m      |
| Average standardized residual | $\mu = 0.87 \text{ m}, \sigma = 0.61 \text{ m}$ | 2.25 m      | 0.32 m     |

FIGURE 8 Autonomous underwater vehicle (green) homing to a drifting vessel (blue dashes) with converted measurement Kalman filter estimates (purple) shown converging on vessel track for mission 6. Zoom decreases from left to right.

4 | DISCUSSION

4.1 | Can universal rapid recovery be achieved

This study has demonstrated the suitability of a universal software-only CMKF to localize a moving target and achieve AUV homing to a moving target with range and bearing observability. Simulations and field trials showed consistent localization within expected error margins. The localization and homing accuracy demonstrated is suitable for expediting AUV recovery in dynamic mission environments or pre-positioning the AUV for docking with moving targets. However, it is acknowledged that homing for docking would require additional infrastructure and increased observability (e.g., higher update rates of range and bearing to the target) (Hien et al., 2020; Sans-Muntadas et al., 2015; Yazdani et al., 2020).
By adopting screening through simulation as part of the development process, we began to understand system performance under the test framework while simultaneously identifying potential algorithmic improvements for more accurate and reliable results (Bartolomei et al., 2006). Screening is not intended to demonstrate optimal system performance. Instead, it aims to understand early the factors that cause worst performance so that any issues can be addressed or understood before operational deployment by the human autonomy team. Screening demonstrated the ability to localize and home and identified boat loiter patterns and boat speed as the significant factors that would affect performance and the consistency of localization.

Multiple linear regression of screening simulation results reasonably predicted the ASR ($\hat{Y}$) and its variance ($\hat{S}$) based upon the six controlled variables. This finding is crucial as it indicates we can predict some of the error and its variance and correct for these factors, or at least those known to the AUV (i.e., onboard) ($\hat{Y}$, $R^2 = 0.3455$; $\hat{S}$, $R^2 = 0.6735$), which can guide operations to procedures or conditions where recovery is more assured. By measuring the variance of ASR (where ASR variance is an indicator of consistency), we can quantify system improvements or degradation over algorithm iterations. Predictable results can be calibrated or compensated for, and hence we anticipate being able to refine performance, confidence and trust further. An example of excellent guidance for operators is Figure 11, which infers ASR from significant factors (start range and boat speed). At the same time, loiter
pattern (Box), AUV survey behavior (Lawnmower) and AUV speed (4.5 knots) are fixed.

Figure 11 suggests that ASR will increase for ranges greater than 1300 m and boat speeds greater than 2.5 knots for the above starting conditions. Hence for long-range operational implementation, the recovery team would be advised to maintain a low boat speed to increase the likelihood of recovery. Conversely, the recovery team could be advised to maintain boat speed of two knots for shorter-range missions when they conduct box loiter patterns.

4.1.2 | Field trials

The accuracy and consistency of homing were better than the mean homing accuracy seen in simulations. This outcome is likely a result of the simplified boat behavior in real-world trials compared to the complex behaviors (i.e., significant changes in direction) tested in screening. Aside from the final homing mission (which was terminated early due to surface traffic entering the area of operations), all runs were successful (within 15 m), and 10 of 12 runs were seen visually from the recovery vessel.

Results demonstrated algorithm robustness with real-world noise (range and bearing errors) significantly greater than expected and greater than had been modeled in simulations. Range errors experienced had error $\mu = 15.7$ m, $\sigma = 47$ m, compared to expected errors ($\mu = 1$ m, $\sigma = 1$ m). Bearing errors of $\mu = 7.8^\circ$, $\sigma = 12.6^\circ$ compared to the expected errors ($\mu = 1^\circ$, $\sigma = 1^\circ$). It is noted that occasional outliers skew these averages. Figures 12 and 13 show the range and bearing errors (respectively) for a demonstrated homing run. Range error can increase with distance to the target in Figure 12.

Figure 13 shows increased bearing errors closer to the target. This outcome likely indicates a timing offset issue in the software, which was outside the scope of this study. However, field results are more encouraging in the presence of such errors as this shows the adaptive behavior can perform as required despite system noise (as will likely be common when AUV are modified for custom behaviors).

Homing accuracy could be visually confirmed as AUV passed the transponder. Visual results suggested homing accuracy would be better than has been reported. However, the transponder was
moving up to 2 m from the boat (due to drift), which means that the actual boat position does not accurately represent the transponder position. Hence, localization and homing results are likely affected by the recording process itself. This result highlights the need for dedicated underwater tracking infrastructure for autonomous maritime systems to accurately characterize system performance (i.e., shallow water tracking range). Figure 14 shows the AUV passing the transponder in two of the trials.

The significant factors identified through screening (boat speed and boat loiter pattern) were not tested in field trials. However, the localization and homing accuracies that simulations indicated would be possible were achieved and verified in field trials for the factors tested (Table 3). Localization and homing accuracy, and ASR, are expected to give better results if system noise can be reduced.

4.2 | How to best assure universal rapid recovery of an AUV

The constructed experimental test framework proved suitable for guiding development and verifying and validating system performance for deployment in an operational context. The assurance process is illustrated in Figure 15. It is focused on adapting a commercial off-the-shelf (COTS) AUV to operate reliably through universal interoperability features within an operational systems-of-systems context. The natural
progression from virtual simulation to bench-level partial simulation, then to field trials, each uses screening and iteration, as illustrated and referenced in this case study. We established a modular framework that allowed comparison between simulation and field trial results using contemporary test design techniques. Furthermore, the framework captured performance metrics in a way that can be used to simultaneously shape future developmental iteration and satisfy requirements for operational deployment. The development of the ASR metric for AUV development was key to success. This experimental assurance approach shows that such a framework can help shift test and evaluation to manage autonomous robotic systems, as called for by Joiner et al. (2019) and Weiss et al. (2009). This shift was achieved by enabling rapid discovery and flexible assessment of new adaptive behaviors needed for resilience in maritime warfare.

Subjectively the process used helped develop and sustain trust in participants, which, as discussed earlier, is needed for sustained AUV development and assurance. Many test events occur organically as part of any software design spiral, including the development of new robotic behaviors. By providing additional rigor to the test design process, we can use contemporary test design techniques to screen and refine algorithms (for instance, by requiring less time on the water) and guide development to ensure it fits within any specific software requirements. Such systematic screening focused on factors that would detract from the trust, giving the development team a focus on what worked and what would inhibit confidence for operational use. Furthermore, by considering this new AUV homing behavior in a testable, repeatable, and auditable framework, we can begin to measure the level of confidence (or trust) in the human autonomy team. The level of trust should increase through meaningful interactions (e.g., instances of expedited recovery) (Yaxley et al., 2021) and is expected to form a critical component of achieving user adoption while satisfying likely new regulatory requirements for AUV (Devitt et al., 2022).

4.3 | Future work

The priority for future work is to field-test the complete high throughput test design, focusing on verifying whether homing at higher speeds is achievable with different boat loiter patterns. Screening has indicated this should be achievable, although we anticipate avoiding polygon or circular loiter patterns as simulations have shown these boat patterns degrade the consistency of localization accuracy. Further development work for the simulation
manager is also required for automating analytics to compare simulation and field trial results at scale.

Screening with simulation still set some expectations for testing that could not be achieved in the real world (e.g., executing target patterns from a 4.7 m RHIB while towing the DAT was not feasible with weather encountered). Screening with simulation should be combined with real-world screening to ensure experiment designs are fully executed to enable the best comparison between simulation and field results. This addition will be critical for building models to predict performance in the field. Time taken to localize and conduct homing should also be factored into the success metrics.

Some algorithmic and path-planning enhancements should be implemented before localization and homing at higher speeds. For example, an outlier rejection algorithm could be implemented to improve the accuracy of CMKF estimates. We further note that the transponder used in this experiment required a particular calibration of sensor bias, estimated off-line before processing. Future work will investigate online calibration methods that will eliminate the need for precalibrating the data before processing by the CMKF. In particular, we will develop joint state and parameter estimation techniques for this problem to enable simultaneous estimation of target state and sensor bias.

The AUV currently homes directly to the estimated target position before rising to the surface; future work will also introduce other homing patterns and behaviors, such as trajectory planning for the final stages of homing or docking (Stanway et al., 2014; Yazdani et al., 2020).

5 | CONCLUSION

Custom adaptive behaviors for autonomous maritime systems to be universal are likely to become more common as user groups seek to increase the efficiency and effectiveness of human autonomy teams within systems-of-systems contexts like mine clearance. Integrating new programming onto robotics in existing systems engineering or regulatory frameworks introduces additional challenges for developers and regulators.

Homing AUV to moving targets was researched with a universal software-only approach and Kalman filtering, different from previous AUV research. The approach was developed to demonstrate an expedited recovery in dynamic mission environments and as an example of how such a new adaptive behavior can be verified and validated through a modular experimental test and evaluation framework. In addition, the metric of average standardized residual was found to be effective to span from simulations through to the field trials, focusing iterations and thus building trust in the recovery of AUV: this metric was also unique from prior AUV research.

AUV homing to a moving target is achievable with a digital acoustic transponder providing range and bearing between AUV and target, even with significant non-Gaussian noise. Using a converted measurement Kalman filtering unique to prior AUV research, consistent homing was demonstrated in 12 field trials. A Gavia AUV demonstrated localization within 0.3 m and homing within 1.8 m of a moving digital acoustic transponder. Consistency was measured using average standardized residuals to quantify performance to increase operator understanding and confidence.

Developing within a testable, repeatable, and auditable experimental test or assurance framework facilitates algorithm refinement while simultaneously generating data required to verify and validate the AUV homing behavior. This AUV research was likely the first to document using high throughput test design and simulations to screen the impact of significant factors on performance and to systematically explore operational factors other than the environment, such as boat recovery manoeuvres. Such approaches efficiently focus development early while relating results to systems engineering or regulatory requirements to build and sustain operational trust in AUV.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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