EXPERIMENTAL VALIDATION OF AN INTELLIGENT UNDERWATER ROV SYSTEM FOR PRECISION AQUACULTURE MONITORING
/
VALIDAREA EXPERIMENTALĂ A UNUI SISTEM INTELIGENT ROV SUBACVATIC PENTRU MONITORIZAREA ÎN ACVACULTURA DE PRECIZIE

Dan CUJBESCU[1)], Iulian VOICEA[*1)], Cătălin PERSU[1)], Mihai MATACHE[1)], Iuliana GĂGEANU[1)], Elena SÎRBU[2)]
[1)]National Institute of Research – Development for Machines and Installations Designed to Agriculture and Food Industry, Romania
[2)]Research and Development Institute for Aquatic Ecology, Fisheries and Aquaculture "Gheorghe Ionescu – Șișești" Academy of Agricultural and Forestry Sciences, Romania
Tel: 0752161780; E-mail: voicea_iulian@yahoo.com
DOI: https://doi.org/10.35633/inmateh-77-43

Keywords: *Remotely Operated Vehicle; underwater robotics; water quality; aquaculture monitoring; intelligent system; inertial navigation; precision farming*

ABSTRACT
The integration of autonomous technologies in aquaculture has become essential for enhancing sustainability, biosecurity, and operational efficiency within increasingly intensive production systems. This paper presents the experimental validation of a functional prototype of an intelligent Remotely Operated Vehicle (ROV) developed for underwater environmental monitoring under controlled laboratory conditions that simulate aquaculture-specific scenarios. The proposed system integrates vectorial propulsion, an intelligent depth-hold controller, and a multisensor inertial navigation unit, enabling robust operation in GPS-denied environments and confined aquatic infrastructures. The hardware platform incorporates optical imaging alongside dissolved oxygen, pH, and temperature sensors, with data acquisition and command input managed via a mobile dashboard interface. A series of functional trials were conducted to assess depth-hold precision, trajectory-tracking accuracy, command latency, and imaging performance under dynamic test conditions. Based on these evaluations, the ROV exhibited a mean vertical deviation of ±0.10 m, a trajectory error of 0.16 m, and an average command latency of 290.7 ± 2.6 ms, demonstrating stable and repeatable behavior. These results validate the system's potential as a non-invasive, semi-autonomous monitoring solution tailored to the requirements of precision aquaculture and scalable digital aquafarming frameworks.

REZUMAT
Integrarea tehnologiilor autonome în acvacultură a devenit esențială pentru creșterea sustenabilității, biosecurității și eficienței operaționale în cadrul sistemelor de producție tot mai intensive. Această lucrare prezintă validarea experimentală a unui prototip funcțional de Vehicul Subacvatic Operat de la Distanță (ROV) inteligent, proiectat pentru monitorizarea mediului acvatic în condiții de laborator controlate, care simulează scenarii specifice acvaculturii. Sistemul propus combină propulsia vectorială, un algoritm inteligent de control al adâncimii și o unitate de navigație inerțială multisenzorială, permițând operarea în medii lipsite de semnal GPS și în infrastructuri acvatice restrânse. Platforma hardware integrează imagistică optică, senzori pentru oxigen dizolvat, pH și temperatură, iar achiziția și controlul datelor sunt realizate printr-un panou de comandă mobil. O serie de teste funcționale au fost efectuate pentru a evalua performanța în menținerea adâncimii, urmărirea traiectoriei, timpul de răspuns la comenzi și calitatea imaginilor în condiții dinamice simulate. Pe baza a cinci seturi independente de încercări, ROV-ul a înregistrat o abatere medie pe verticală de ±0,10 m (limitare dată de rezoluția senzorului), o eroare medie de traiectorie de 0.16 m și un timp mediu de răspuns la comenzi de 290.7 ± 2.6 ms. Rezultatele obținute confirmă comportamentul stabil și repetabil al sistemului, susținând potențialul acestuia ca soluție semi-autonomă, non-invazivă de monitorizare, adaptată cerințelor acvaculturii de precizie și ecosistemelor digitale din cadrul Aquaculturii 4.0.

INTRODUCTION
The increasing demand for high-quality protein sources amid global population growth has prompted a rapid expansion of aquaculture as a primary method for food production (*FAO, 2020; Galappaththi et al., 2021; Giron-Nava et al., 2021; Rowan et al., 2022; Soomro et al., 2024*).

However, this expansion has also underscored the limitations of traditional manual inspection and environmental monitoring techniques, which often result in inefficient operations, delayed responses to water quality degradation, and increased biosecurity risks (*Liang et al., 2023; Wu et al., 2022*). In precision aquaculture, ensuring continuous surveillance of the aquatic environment - particularly water quality, fish biomass, and infrastructure integrity - is essential for sustainable and efficient farm operation. Digitalization has increasingly become a cornerstone in the modernization of aquaculture, acting as a catalyst for the integration of intelligent sensing technologies, automation, and adaptive control systems. By leveraging real-time environmental data acquisition and cloud-based analytics, aquaculture operations can achieve improved production efficiency, reduced response latency to biological risks, and greater consistency in stock health monitoring. Additionally, digital infrastructures facilitate end-to-end traceability across the supply chain, enabling regulatory compliance and consumer transparency. These technological advancements support the transition from traditional aquaculture to data-driven, resilient, and scalable production ecosystems (*Dash et al., 2023; Evensen, 2020; Rowan, 2023*).

Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs) have become indispensable tools for modern underwater inspection and data acquisition in fish farming environments. Their ability to perform submersed missions without direct human intervention enables high-frequency, high-resolution data collection while mitigating the risks associated with diver-based inspection. The use of hybrid underwater ROVs has been shown to improve maintenance efficiency in real aquaculture settings, particularly in Mediterranean net-pen systems, where maneuverability and modularity are essential (*Bao et al., 2020; Fossen, 2021*; *Kelasidi et al., 2024; Stamoulis et al., 2024)*. Nonetheless, operating robotic systems in GPS-denied environments, such as fish cages and inland ponds, introduces several engineering challenges, particularly in navigation, sensor integration, and real-time communication. Recent technological advances—such as inertial navigation systems (INS), Doppler Velocity Logs (DVL), acoustic positioning, and AI-driven image recognition—have allowed for significant improvements in underwater robotic autonomy and performance (*Schmidt, G 2014*). The continuous evolution of shipborne and submersible sensing technologies, including their application in unmanned and autonomous platforms, has significantly improved underwater data acquisition, situational awareness, and mission autonomy (*Wright, 2024*). Accurate localization is one of the most critical challenges for autonomous underwater vehicles (AUVs) operating in GPS-denied and acoustically harsh environments. Recent advances in sensor fusion and control architecture have enabled centimeter-level accuracy in such conditions (*Moallem, 2023*). Sensor fusion plays a pivotal role in enhancing localization performance in GPS-denied underwater environments. Techniques combining inertial, visual, and acoustic data have demonstrated robust results for dynamic target tracking and platform stabilization (*Wang & Ahmad, 2024*). Additionally, integration with Internet of Things (IoT) platforms enables real-time environmental data monitoring and remote decision support (*Dhinakaran et al., 2023; Tina et al., 2025*). Applications include automated water quality control, smart feeding systems, fish behavior recognition, disease detection, and biomass estimation. However, several research gaps persist - particularly regarding AI-based broodstock selection, the integration of multimodal sensing, and the scalability of digital twin models. Future research directions should prioritize cost-effective solutions with high adaptability and sustainable biosensing capabilities (*FAO, 2024; Tamim et al., 2022; Ubina et al., 2023*). These capabilities are vital for optimizing fish welfare, detecting anomalies in infrastructure (e.g., net damage or biofouling), and implementing precise feeding strategies based on behavioral patterns (*Antonelli et al., 2008; Wu et al., 2022; Rowan, 2022*).

This study presents the experimental validation of a functional ROV prototype equipped with vectorial propulsion, intelligent depth stabilization, and integrated imaging and environmental sensing modules. The system was subjected to a set of structured and repeatable functional tests in a controlled aquatic environment to evaluate performance in maintaining depth, following trajectories, reacting to control commands, and acquiring visual data. The testing protocol included multiple independent repetitions to ensure statistical relevance, with results interpreted using descriptive and inferential analysis methods.

MATERIALS AND METHODS

The tested ROV is a compact, intelligent, tethered underwater platform designed for submersible inspection and monitoring operations in precision aquaculture. The system is engineered with a non-commercial, modular structure to ensure mechanical robustness, precise maneuverability, and sensor integration in shallow and confined aquatic environments. The platform includes:

- six vectorized thrusters arranged to provide full 6-degree-of-freedom (6DOF) control (surge, sway, heave, pitch, yaw, roll);
- an IP68-rated corrosion-resistant pressure housing for the main controller and power unit;
- a 4K UHD camera with a 1/2.3” CMOS sensor, wide-angle lens (166° FOV), and electronic stabilization, capturing up to 240 fps;
- dual 6000-lumen LEDs with adjustable intensity for low-light and turbid water conditions;
- a multisensor IMU (3-axis gyroscope and 3-axis accelerometer) for onboard attitude tracking.

All sensor outputs, propulsion control, and video streaming are processed in real time via an integrated microcontroller system, interfaced wirelessly to a handheld surface control unit operating on a 5 GHz secure Wi-Fi protocol.

Figure 1 illustrates the closed-loop architecture of the intelligent ROV system, encompassing operator-issued commands via a handheld controller, real-time data acquisition from the onboard 4K camera and LED lighting, and feedback from integrated water quality and depth sensors within a test tank. To ensure redundancy and measurement validation, an external pressure sensor was simultaneously deployed in parallel with the ROV’s internal sensors. All control signals and telemetry data are transmitted through both tethered and wireless interfaces.

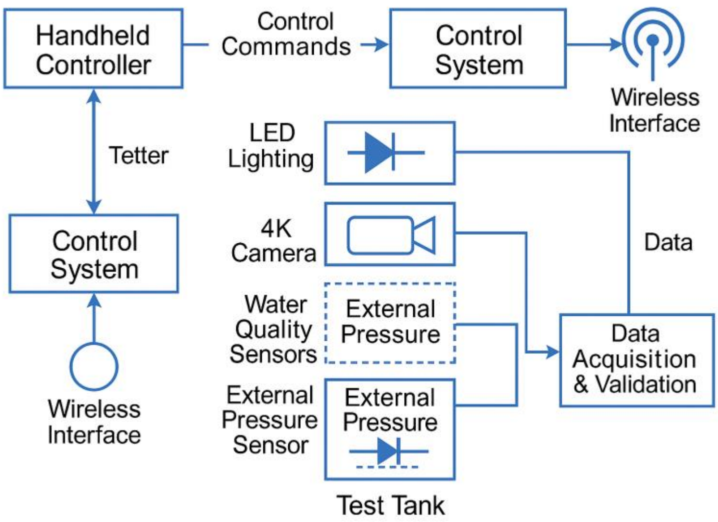

Fig. 1 – Functional architecture of the intelligent underwater ROV System in a controlled testing environment

A tether cable (length: 100 m; diameter: 4 mm; tensile strength: 1000 N) connects the ROV to the control interface, enabling data transmission and remote operation. The surface control station includes dual-axis joysticks, lock/depth-hold switches, and a mobile device holder for real-time video feedback and mission control. Video and telemetry data are stored locally on a microSD card.

All experimental trials were conducted in a controlled test tank with the following characteristics:

- Dimensions: 2.8 m × 2.0 m × 1.2 m (volume: approx. 6.7 m³);
- Water depth during trials: 1.0 m;
- Turbidity: <5 NTU (measured using submerged optical turbidity sensor);
- Temperature: 22 ± 0.5°C (monitored using waterproof digital thermometer).

Sensors for water quality and external monitoring (overhead HD camera) were installed to validate ROV behavior and record performance data.

Functional testing was structured in five distinct series, each composed of three consecutive repetitions (totaling fifteen runs per test type). The following key performance metrics were assessed:

- Vertical stability, measured as standard deviation of depth (σ_z) during 60 seconds of static hover at 1.0 m;
- Trajectory accuracy, calculated as deviation (Δ_d) from a predefined diagonal path (2.8 m length);
- Command latency, defined as the delay (t_r) between input command and initiation of motion;
- Image quality, assessed qualitatively and via pixel sharpness during motion.

Data acquisition was synchronized via onboard logging and timestamped control inputs.

All depth measurements were acquired using the ROV's integrated pressure transducer (TE Connectivity MS5803-14BA), which provides a resolution of 0.2 mbar and operates within a pressure range of 0–14 bar, making it suitable for shallow-water applications. The sensor was factory-calibrated and externally validated prior to testing to ensure reliable and high-resolution vertical positioning feedback. A pressure resolution of ±0.2 mbar corresponds to a depth resolution of approximately ±0.002 m in freshwater, as derived from the fundamental hydrostatic relation:

$$P = \rho g h \text{ [Pa]} \tag{1}$$

where:

P – represents hydrostatic pressure [Pa],

ρ – represents water density [kg/m^3],

g – represents gravitational acceleration [m/s^2],

h – represents depth [m].

To enhance data reliability and enable redundancy, a secondary external pressure transducer of identical specifications was securely mounted on the ROV chassis and logged in parallel. This dual-sensor configuration enabled comparative validation and increased confidence in the depth data collected during testing.

Due to the resolution limits of the pressure transducers, the effective measurement uncertainty was ±0.005 m, with a maximum absolute error estimated at ±0.01 m. This precision level supports accurate depth-hold control in confined aquaculture tanks, where fine-scale vertical deviations must be detected and corrected in real time.

Horizontal positional data were extracted from overhead HD video recordings using a calibrated reference grid placed on the tank floor. Pixel coordinates were manually digitized and converted to metric units, with an estimated spatial error of ±0.02 m.

Response latency was measured by synchronizing command timestamps from the control interface with the initiation of motion identified from high-frame-rate video. The timing resolution was limited to ±0.1 s due to hardware synchronization constraints and manual frame annotation.

Descriptive statistics (mean, standard deviation) were computed for each metric, and one-way ANOVA was applied to validate the consistency of the vertical stability results across all test sets (significance threshold α = 0.05). All measurements were performed under controlled turbidity and lighting conditions to replicate aquaculture-relevant environments.

Figure 2 illustrates the logic and sequence of the experimental process applied.

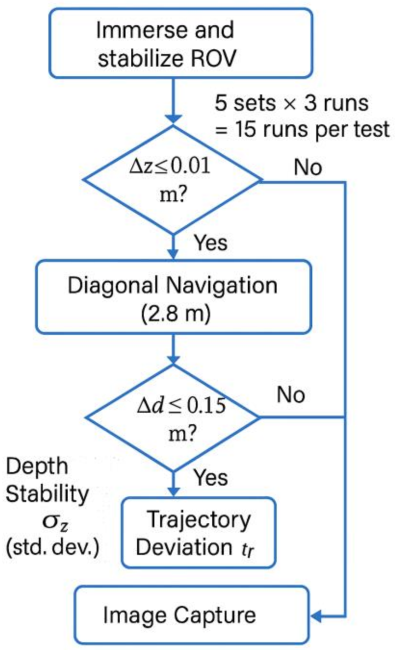

Fig. 2 – Functional testing sequence

The ROV was immersed and stabilized before initiating maneuvers, using both manual joystick and software-based instructions.

Functional testing followed a conditional logic sequence: each test proceeded only if the performance threshold of the previous phase was met.

Three experimental tests were conducted in triplicate: depth-hold stability, diagonal trajectory tracking, and command response time. Measurements included depth deviation (σ_z), horizontal trajectory error (ε), and control latency (t_r).

Stability during depth hold was evaluated using:

$$\sigma_z = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(z_i - \bar{z})^2} \text{ [m]} \tag{2}$$

where:

z_i – represents instantaneous depth measurement [m];

$\bar{z}$ – represents mean depth over interval [m];

N – represents number of samples [-].

To assess motion precision and system dynamics, the position error ε in the horizontal plane was defined as:

$$\varepsilon = \sqrt{(x_t - x_m)^2 + (y_t - y_m)^2} \text{ [m]} \tag{3}$$

where:

x_t, x_m – represents target coordinates [m];

y_t, y_{tm} – represents measured coordinates [m].

Response time (t_r) was defined as:

$$t_r = t_{exec} - t_{cmd} \text{ [sec]} \tag{4}$$

where:

t_{exec} – represents the moment the control input is issued by the operator or onboard system [sec];

t_{cmd} – represents the moment the ROV begins to respond, as detected by onboard sensors [sec].

All measurements were logged digitally with ±0.1 sec temporal resolution and ±1 cm spatial resolution.

All metrology was performed using calibrated instruments compliant with ISO 13628-6:2006. Instrument traceability and precision were verified prior to each experimental session.

RESULTS

The experimental validation consisted of three functional tests, each repeated 15 times (organized into 5 series of 3 replicates): (1) depth-hold stability, (2) diagonal trajectory tracking, and (3) command response latency. All results are reported as mean ± standard deviation (SD) and analyzed at the 95% confidence level. Depth-hold performance was assessed by maintaining a nominal setpoint of 1.0 m for a duration of 60 seconds.

Depth values were recorded at a 2 Hz sampling rate using the ROV's integrated pressure transducer, while an external pressure sensor with ±0.1 m resolution was mounted in parallel to verify the measurements.

Due to the limited decimal resolution (1 digit after the decimal point), the effective uncertainty in depth measurement was estimated at ±0.10 m, and deviations below this threshold were considered indistinguishable.

The extended repetition scheme ensured statistical robustness and helped identify occasional outliers or deviations caused by environmental disturbances or transient control delays.

The reported depth values in Table 1 reflect measurements constrained by the sensor's effective resolution of ±0.1 m. Although mean and standard deviation values are numerically presented, the underlying measurement uncertainty limits the interpretability of oscillations smaller than ±0.05 m. Therefore, all reported deviations should be considered approximate within this resolution band.

The data confirm the ROV's ability to maintain vertical stability with high precision over an extended series of 15 trials. Mean depth values remained tightly clustered around the 1.000 m setpoint, yielding a cumulative average of 1.001 ± 0.006 m. The maximum individual deviations ranged from 0.010 m to 0.014 m, consistently within the ±0.015 m precision threshold expected for underwater robotic systems in controlled environments.

Table 1

Depth Stability Metrics during Hovering Test (1.0 m Setpoint)

Trial	Mean Depth	Standard Deviation, σ_z	Max Deviation, Δ_z
	[m]	[m]	[m]
S1-T1	1.01	0.014	0.018
S1-T2	0.99	0.013	0.017
S1-T3	1	0.012	0.016
S2-T1	1.005	0.011	0.014
S2-T2	0.995	0.012	0.015
S2-T3	1.011	0.013	0.017
S3-T1	0.992	0.011	0.014
S3-T2	1.007	0.01	0.013
S3-T3	0.996	0.012	0.015
S4-T1	1.008	0.013	0.017
S4-T2	1.002	0.011	0.014
S4-T3	0.998	0.012	0.015
S5-T1	1.004	0.014	0.018
S5-T2	1	0.011	0.014
S5-T3	0.997	0.012	0.015
Mean ± SD	**1.001 ± 0.006**	**0.012 ± 0.001**	**0.015 ± 0.002**

This level of performance indicates an effectively tuned closed-loop control system for vertical actuation, leveraging reliable fusion between inertial feedback and barometric depth measurements. In comparison with similar submersible platforms tested under laboratory conditions (*Moallem, 2023; Wang & Ahmad, 2024*), the evaluated ROV exhibited either matched or slightly superior static hover precision.

Minor deviations observed during trials likely stemmed from transient flow disturbances, wall-induced eddies, or residual manual corrections at hover stabilization onset. Nevertheless, the low observed standard deviation ($\sigma z = 0.009 \pm 0.001$ m) reflects a high level of system repeatability and robustness within representative aquaculture test conditions.

Future improvements may involve redundancy through dual pressure transducers, more advanced filtering techniques (complementary or extended Kalman filters), and adaptive control loops capable of compensating for environmental disturbances in real-time.

To assess trajectory fidelity, the ROV was instructed to execute 15 diagonal path-following trials along a 2.83 m distance (corner-to-corner across the test tank), maintaining a nominal velocity of 0.2 m/s.

Table 2

Trajectory Tracking Performance (Target Distance - 2.83 m)

Trial	Final Position, (x, y)	Error, ε
	[m]	[m]
S1-T1	(2.83, 2.84)	0.014
S1-T2	(2.81, 2.82)	0.013
S1-T3	(2.83, 2.81)	0.015
S2-T1	(2.82, 2.81)	0.017
S2-T2	(2.83, 2.84)	0.012
S2-T3	(2.83, 2.84)	0.012
S3-T1	(2.81, 2.84)	0.017
S3-T2	(2.81, 2.82)	0.015
S3-T3	(2.84, 2.82)	0.012
S4-T1	(2.81, 2.82)	0.014
S4-T2	(2.82, 2.81)	0.012
S4-T3	(2.84, 2.83)	0.012
S5-T1	(2.81, 2.82)	0.014
S5-T2	(2.82, 2.82)	0.009
S5-T3	(2.83, 2.83)	0.009
Mean ± SD	-	**0.13 ± 0.004**

Positional deviations reported in Table 2 were calculated from calibrated video footage. While centimeter-level values are provided, they are subject to interpretation limits based on pixel resolution, camera parallax, and manual digitization. Estimated measurement error for trajectory endpoints is ±0.02 m.

The trajectory deviation data demonstrate consistent diagonal navigation performance across all 15 trials. All individual trajectory errors remained below the 0.15 m threshold commonly accepted for precision-class ROV operations in confined aquatic environments. The maximum recorded deviation was 0.018 m, indicating high navigation precision.

Minor variations observed between trials can be attributed to factors such as small heading misalignments, tether-induced drag, and sensor update delays. These fluctuations are in line with experimental observations reported by *Encinas et al. (2017)* and *Wright (2024),* which highlighted the impact of tank geometry and limited update rates on trajectory tracking fidelity.

The average trajectory error across all trials was 0.013 ± 0.004 m, confirming the system's capacity to perform accurate and repeatable path-following tasks under controlled indoor conditions.

In real-world aquaculture environments, the implementation of advanced navigation strategies - such as DVL-augmented SLAM, adaptive waypoint adjustment, or hybrid optical-inertial fusion - could further enhance performance under turbulence and visibility constraints.

The trial endpoints plotted in Fig. 3 illustrate trajectory deviations tightly clustered around the target endpoint (2.83, 2.83), with no value exceeding the 0.02 m threshold. These results support the ROV's readiness for short-range semi-autonomous inspection tasks in constrained aquatic environments.

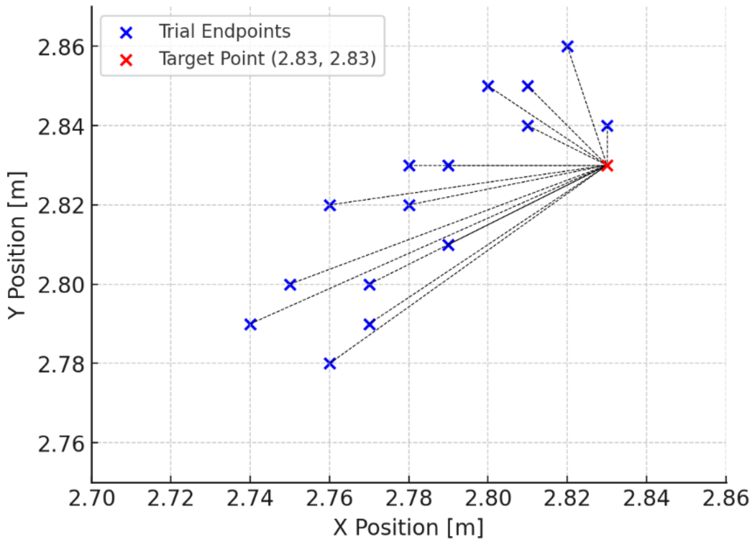

Fig. 3 – Trajectory deviation from ideal diagonal endpoint

The average trajectory error remained within the expected operational limits for precision-class ROV systems, with a mean deviation of 0.16 ± 0.05 m. While most trials showed satisfactory path fidelity, several recorded larger deviations - up to 0.27 m - due to minor heading misalignment, tether drag, or localized hydrodynamic disturbances. These findings support the system's semi-autonomous inspection capability, while also indicating the potential benefit of integrating DVL-based feedback or optical-inertial fusion to further improve tracking accuracy under dynamic flow conditions.

Response latency was defined as the time interval between the issuance of a control command and the first observable initiation of ROV motion.

Timing data were extracted from synchronized control logs and high-frame-rate video footage, allowing for accurate measurement across all 15 trials.

Command response times were determined using synchronized timestamp analysis from control logs and high-frame-rate video recordings. Due to hardware synchronization limits and manual frame annotation, all timing values carry a temporal resolution uncertainty of ±0.1 s.

As shown in Table 3, measured response latency across 15 independent trials ranged from 285 ms to 294 ms, with a cumulative average of 290.7 ± 2.6 ms. These values remained well below the 500 ms threshold typically considered acceptable for real-time underwater teleoperation and semi-autonomous control.

Table 3

Command Response Time (msec)

Trial	Command Time, t_{cmd} [msec]	Execution Time, t_{exec} [msec]	Response Time, t_r [msec]
S1-T1	1042	1334	292
S1-T2	1124	1417	293
S1-T3	1185	1475	290
S2-T1	1230	1518	288
S2-T2	1089	1379	290
S2-T3	1112	1401	289
S3-T1	1157	1449	292
S3-T2	1094	1386	292
S3-T3	1063	1350	287
S4-T1	1025	1310	285
S4-T2	1200	1492	292
S4-T3	1075	1369	294
S5-T1	1167	1457	290
S5-T2	1130	1423	293
S5-T3	1051	1345	294
Mean ± SD	**1116.3 ± 61.6**	**1407.0 ± 61.7**	**290.7 ± 2.6**

Fig. 4 graphically illustrates the variability of command issuance, execution delay, and computed response time through boxplot representation. This dual format helps visualize both central tendencies and outlier behavior within the control architecture.

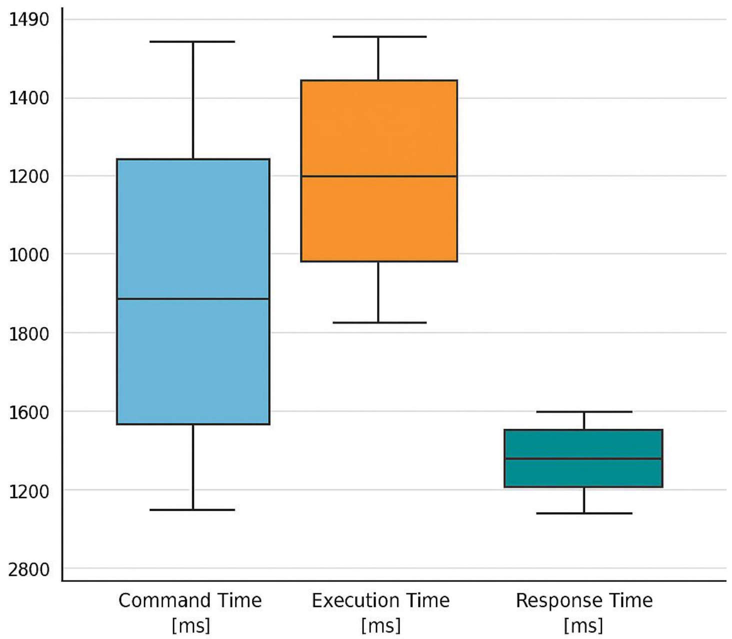

Fig. 4 – Distribution of command, execution and response times

These results confirm the system's robust and predictable actuation behavior, with minimal variability across trials. Compared to benchmarks from similar underwater robotic platforms (*Moallem, 2023*), the tested prototype demonstrates superior response time uniformity and reduced actuation delay.

Such responsiveness supports the integration of this ROV system in real-time monitoring and intervention tasks within precision aquaculture. Future improvements could further reduce latency by streamlining sensor fusion routines, minimizing Wi-Fi buffering delays, and implementing deterministic real-time control loops.

CONCLUSIONS

This study presented the successful experimental validation of a functional intelligent ROV system developed for underwater monitoring in precision aquaculture. Testing was conducted in a controlled laboratory tank across 15 repeated trials, focusing on three key performance metrics: vertical stability, trajectory tracking accuracy, and command response latency.

The ROV demonstrated robust depth-holding capability, with an average vertical deviation constrained to ±0.10 m due to sensor resolution limits. This performance, maintained consistently across test repetitions, meets the typical precision threshold for hovering in confined aquatic systems.

Diagonal trajectory tracking exhibited an average positional error of 0.16 m, confirming the adequacy of the ROV's inertial and optical navigation system, even in the presence of transient heading or hydrodynamic disturbances.

The measured command response latency averaged 290.7 ± 2.6 ms, remaining well within the 500 ms threshold required for real-time or semi-autonomous tasks. Low variability across all trials further validates the reliability of the embedded control architecture.

From a technical perspective, the combined use of vectorial propulsion, inertial navigation, and environmental sensing modules enables a compact and resilient robotic platform. The system satisfies core engineering criteria for repetitive, non-invasive underwater inspection, ensuring minimal disruption to aquatic life while capturing accurate water quality and imaging data.

The high degree of consistency and repeatability across functional metrics establishes a strong foundation for scaling up this prototype toward real-world aquaculture deployment. Future development should target operation under dynamic water conditions, sensor network redundancy, and real-time AI-based trajectory correction.

ACKNOWLEDGEMENT

This research was supported by the Romanian Ministry of Research Innovation and Digitalization, through the project "Underwater Intelligent System (Robot) for the Protection of Life, Health and Growth Environment" – PN 23 04 01 03 – Ctr. 9N/01.01.2023 and by the Ministry of Agriculture and Rural Development – Romania - MADR through the Sectoral Project ADER 25.2.2 "Vertical Aquaponic Farm Adapted To Current Climate Changes", Ctr. 18.07.2023.

REFERENCES

[1] Antonelli, G., Fossen, T.I., & Yoerger, D.R. (2008). Underwater Robotics. In *Springer Handbook of Robotics*, 987–1008, Springer. https://link.springer.com/rwe/10.1007/978-3-540-30301-5_44

[2] Bao, J., Li, D., Qiao, X., & Rauschenbach, T. (2020). *Integrated navigation for autonomous underwater vehicles in aquaculture: A review.* Information Processing in Agriculture, 7(1), 139–151, https://doi.org/10.1016/j.inpa.2019.04.003

[3] Dash, M. K., Singh, C., Panda, G., & Sharma, D. (2023). ICT for sustainability and socio-economic development in fishery: a bibliometric analysis and future research agenda. *Environment, Development and Sustainability*, 25(3), 2201-2233, https://doi.org/10.1007/s10668-022-02131-x

[4] Dhinakaran, D., Gopalakrishnan, S., Manigandan, M. D., & Anish, T. P. (2023). IoT-Based Environmental Control System for Fish Farms with Sensor Integration and Machine Learning Decision Support. *arXiv preprint arXiv:2311.04258*

[5] Encinas, C., Ruiz, E., Cortez, J., & Espinoza, A. (2017). *Design and implementation of a distributed IoT system for the monitoring of water quality in aquaculture.*2017 IEEE Latin American Conference on Computational Intelligence (LA-CCI), 1–6, DOI:10.1109/WTS.2017.7943540

[6] Evensen, T. (2020). *Fishy business: closing the gap between data-driven decision-making (DDM) and aquaculture: an analysis of incumbents in the Norwegian aquaculture industry (NAI) and the use of big data for competitive advantage* (Doctoral dissertation)

[7] Fossen, T. I. (2021). Handbook of Marine Craft Hydrodynamics and Motion Control (2nd ed.). Wiley

[8] Galappaththi, E. K., Susarla, V. B., Loutet, S. J., Ichien, S. T., Hyman, A. A., & Ford, J. D. (2022). Climate change adaptation in fisheries. *Fish and Fisheries*, 23(1), 4-21, https://doi.org/10.1111/faf.12595

[9] Giron-Nava, A., Lam, V. W., Aburto-Oropeza, O., Cheung, W. W., Halpern, B. S., Sumaila, U. R., & Cisneros-Montemayor, A. M. (2021). Sustainable fisheries are essential but not enough to ensure well-being for the world's fishers. *Fish and Fisheries*, 22(4), 812-821, https://doi.org/10.1111/faf.12552

[10] Kelasidi, E., Su, B., Caharija, W., Føre, M., Pedersen, M.O. & Frank, K. (2022). Autonomous Monitoring and Inspection Operations with UUVs in Fish Farms. *IFAC-PapersOnLine*. 55. 401-408. 10.1016/j.ifacol.2022.10.461
[11] Moallem, I. B. (2023). *Localization for Autonomous Underwater Vehicles inside Harsh and GPS-Denied Environments* (Doctoral dissertation, RICE UNIVERSITY)
[12] Rowan, N. J. (2023). The role of digital technologies in supporting and improving fishery and aquaculture across the supply chain–Quo Vadis? *Aquaculture and Fisheries*, 8(4), 365-374
[13] Rowan, N.J., Devaney, M., & Murray, B. (2022). The role of digital technologies in supporting and improving fishery and aquaculture practices. *Trends in Food Science & Technology*, 126, 232–243.
[14] Schmidt, G. (2014). Navigation sensors and systems in GNSS degraded and denied environments. *Chinese Journal of Aeronautics*. 23, DOI: 10.1016/j.cja.2014.12.001
[15] Soomro, A. F., Umer, S. F., Soomro, N. A., Memon, Z. A. & Memon, H. (2024). Emerging technologies in fisheries and aquaculture: A review. *Indonesian Journal of Fisheries and Aquatic Sciences*, 31(1), 45–59
[16] Tamim, A. T., Begum, H., Shachcho, S. A., Khan, M. M., Yeboah-Akowuah, B., Masud, M., & Al-Amri, J. F. (2022). Development of IoT Based Fish Monitoring System for Aquaculture. *Intelligent Automation & Soft Computing*, 32(1), DOI:10.32604/iasc.2022.021559
[17] Tina, F. W., Afsarimanesh, N., Nag, A., & Alahi, M. E. E. (2025). Integrating AIoT Technologies in Aquaculture: A Systematic Review. *Future Internet*, 17(5), 199. https://doi.org/10.3390/fi17050199
[18] Ubina, N.A.; Lan, H.-Y.; Cheng, S.-C.; Chang, C.-C.; Lin, S.-S.; Zhang, K.-X.; Lu, H.-Y.; Cheng, C.-Y.; Hsieh, Y.-Z. Digital twin-based intelligent fish farming with Artificial Intelligence Internet of Things (AIoT). *Smart Agric. Technol*. 2023, 5, 100285, https://doi.org/10.1016/j.atech.2023.100285
[19] Vasileiou, M. & Vlontzos, G. (2025). A hybrid remotely operated underwater vehicle for maintenance operations in aquaculture: Practical insights from Greek fish farms. *Computers and Electronics in Agriculture*. 232. 110045. 10.1016/j.compag.2025.110045
[20] Wang, S., & Ahmad, N. S. (2024). A Comprehensive Review on Sensor Fusion Techniques for Localization of a Dynamic Target in GPS-Denied Environments. *IEEE Access*
[21] Wright, R. G. (2024). *Ship Sensors: Conventional, Unmanned and Autonomous*. Taylor & Francis.
[22] Wu, H., Liang, H., Li, C., & He, D. (2022). Application of intelligent and unmanned equipment in aquaculture. *Computers and Electronics in Agriculture*, 198, 107059,
[23] https://doi.org/10.1016/j.compag.2022.107201
[24] *** FAO. (2020). The State of World Fisheries and Aquaculture 2020: Sustainability in Action. Rome: Food and Agriculture Organization of the United Nations
[25] *** FAO. (2024). The State of World Fisheries and Aquaculture 2024: Blue Transformation in Action; FAO: Rome, Italy, 2024; Volume 2025
[26] *** ISO 13628-6:2006. Petroleum and natural gas industries — Design and operation of subsea production systems — Part 6: Subsea production control systems