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UOWC Integration with ROVs: A Fiber-Optic Approach for Enhanced Underwater Exploration

Abstract: - Underwater Optical Wireless Communication (UOWC) revolutionizes underwater exploration, leveraging seawater's unique property—reduced absorption of blue-green light. This offers superior advantages over traditional communication methods, providing higher bandwidth and lower latency. This paper explores the integration of UOWC with Remotely Operated Vehicles (ROVs), enhancing data exchange and command capabilities in challenging underwater environments. Seawater's unique properties empower UOWC to outperform acoustic and RF methods, crucial for real-time applications. The study utilizes advanced techniques like Fiber-Optic Communication, High Order Sliding Mode Control, and Hybrid Blockage Detection for ROV integration and control. While the abstract focuses on theory and design, it sets the stage for empirical validations, emphasizing the need for future research to quantify improvements in real-world underwater scenarios

Keywords: ROV Control, High Order Sliding Mode Control, HBD, Blockage Detection, Auto notification, Fiber-Optic Communication.

I. INTRODUCTION

In contemporary times, the integration of wireless communication has become ubiquitous across terrestrial devices. However, its application in the underwater domain has particularly captured the attention of the military, industry, and scientific communities [1,2]. Notably, acoustic systems have emerged as a successful means of underwater communication, capable of transmitting data over considerable distances, sparking continuous research for further improvements.

Underwater vehicles, specifically Remotely Operated Vehicles (ROVs), are typically under the guidance of an operator stationed at the surface, controlling the vehicle through a Surface Control Unit (SCU). Enhancing autonomy for particular activities, such as accurate position monitoring, dynamic positioning (station-keeping), automated direction and depth control, blockage identification, and the facilitation of automated notifications, is a popular trend in ROV development. Consequently, the development and control of ROVs are confronted by a range of distinctive challenges:

1. **Parametric Uncertainty:** The challenge of managing parametric uncertainty becomes more pronounced as contemporary ROVs adopt modular capabilities. This set of modules includes many different types of tools and skids, such as rotary disk cutters, wire and cable cutters, pipeline camera skids, manipulator skids, water-jetting tooling skids, and rotatory brush skids. The significance of using automated alerting systems is highlighted by this diversity [3].

2. **Dynamic Underwater Environment:** Significant disruptions are introduced to ROVs by the dynamic underwater environment, especially when there are underwater currents and interactions with waves. In applications involving shallow water, this effect is particularly noticeable [4].

Addressing these challenges is pivotal in advancing the capabilities of underwater ROVs, catering to a wide array of applications and requirements.

Overview of ROV Command

This section offers an examination of the present state of the art. The primary objective of this study is to conduct a comprehensive review of control strategies for Remotely Operated Vehicles (ROVs), with a specific focus on addressing critical challenges in position trajectory and station-keeping control. A substantial amount of research

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on various control approaches, including fuzzy control, standard sliding mode control, PID-like control, and other approaches, is available in the international literature [5].The subsequent section offers a detailed examination of the most pertinent and influential works in this domain.

1.1 Visual Serving Control

A number of approaches make use of visual-based control strategies [1-4], which locate the ROV precisely and guide it along a predetermined visual path by using photographs of the seafloor or landmarks. Nevertheless, vision-based position monitoring and station-keeping management are not practicable due to the challenges presented by the dark underwater environment.

1.2 Intelligent Control

Underwater vehicle management has been proposed to benefit from intelligent control techniques such as Fuzzy Logic, Neural Networks, or their combination in Neuro-Fuzzy control, especially for tasks involving observation and blockage detection. Relevant examples can be found in [6-7]. While intelligent controllers have significant potential, they are mostly used in experimental vehicles and often need extensive parameter tweaking. There remains a potential application space for these control techniques in industrial vehicles [8].

1.3 PID Control

In the realm of underwater robotics, practicality often leads to the widespread use of Proportional Derivative (PD) or Proportional Integral Derivative (PID) controllers in industrial underwater robots [8, 10]. Their straightforward structures and efficacy under specific conditions make them the go-to choice. PID-like controllers generally exhibit good functioning. Nonetheless, they fail to account for system nonlinearities, which can potentially degrade performance or introduce instability [9-10].

In [11], the authors propose a sequential linear controller employing P and PI techniques to regulate position (x) and vehicle velocity (u). Experimental results involving the THETIS (UROV) are presented.

In [12], researchers suggest a control strategy that integrates linearizing control with PID techniques for depth and heading station-keeping. Linearizing control necessitates knowledge of the vehicle's model and parameters. Simulations and swimming pool tests illustrate the strategy's effectiveness in maintaining depth and heading control.

[13, 14] introduces an adaptive control law for underwater vehicles, which incorporates PD action with adaptive compensation to address hydrodynamic effects. This approach is tested in real-time and simulation using the ODIN vehicle and its mathematical model, demonstrating asymptotic tracking without requiring current measurements or exact system dynamics knowledge.

The notion of self-tuning autopilots is introduced in [15], featuring two schemes: an implicit linear quadratic online self-tuning controller and a robust control law based on a first-order approximation of open-loop dynamics, coupled with online recursive identification. The performance of these controllers is assessed through simulations.

The rest of the paper is organized as, In Section II, an in-depth discussion of optical aspects provides essential background information. Section III offers a comprehensive depiction of the proposed model and details the design and construction of the Remotely Operated Vehicle (ROV). Section IV extensively discusses the results obtained from the research, critically analyzing the data and outcomes. Lastly, in Section V, the developed blockage identification and classification model, emphasizing its utilization of optical fiber, is succinctly summarized, encapsulating the key findings and contributions of the research.

II. OPTICAL FIBRE

Fibers with attenuations exceeding 1 dB/km have limited utility in communication networks. Poorly matched fibers may experience attenuations surpassing 1 dB/km per connector or splice, particularly if mishandled during installation. Achieving optimal coupling effectiveness requires precise fiber positioning to center the cores. To minimize connector losses, a straightforward method is to permanently splice the fiber ends, either through adhesive bonding or high-temperature fusion. Losses in gaps, akin to Fresnel losses, occur due to the presence of an air gap introducing 2 media interfaces, each associated with Fresnel reflection losses. Two primary losses are considered: One originates from the inner surface of the transmitting fiber, while the other arises from reflections off the second fiber's surface. To mitigate these losses, introducing a coupler designed to match the optical impedances of both materials is effective [11-13].

2.1 Advantages of Fiber Optic Transmission

Fiber optic transmission has largely supplanted copper wire communication in developed world core networks, primarily due to its advantages over electrical transmission. The key advantages of fiber optic transmission include:

Extremely High Bandwidth: Fiber optics outperform other cable-based data transmission mediums in bandwidth. They transmit a significantly larger volume of data per unit of time compared to copper cables.

Longer Distance: Fiber optic transmission permits data to travel over longer distances, thanks to minimal power loss, which surpasses the capabilities of copper cables.

Resistance to Electromagnetic Interference: Fiber is highly resistant to electromagnetic interference, making it a preferred choice for deployment in environments with substantial interference sources.

Low Security Risk: Fiber optic transmission enhances data security, as information is transmitted via light, rendering it difficult to intercept or eavesdrop on the data being transmitted.

Small Size and Lightweight: Fiber optic cables have a compact diameter and are lightweight, saving space and facilitating installation [17].

2.2 Model-Based Control (Linearizing Control)

Addressing underwater control challenges, model-based strategies become essential, taking into account system nonlinearities. While they require a mathematical model of the system and precise knowledge of robot parameters, creating a complete nonlinear six Degrees of Freedom (6 DOF) dynamic model can be complex and time-consuming. A variety of model-based trajectory-tracking controllers intended for a fully actuated underwater vehicle are evaluated experimentally in a preliminary manner in [16]. The analysis comes to the conclusion that while various controllers exhibit similar effort, model-based approaches perform better. The OTTER vehicle is used in real-time tests at the Monterey Bay Aquarium Research Institute (MBARI) [18], which demonstrate how well a model-based linearizing control method can improve station-keeping skills. This approach takes observation and detection of blockages into consideration, as well as interaction forces resulting from arm movements. Furthermore, [19] uses a different accurate linearizing model-based control approach.

Table 1. Comparative Analysis of Classifiers

Classifiers	Merits	Demerits
K-nearest neighbor	a) Provides an intuitive and easily understandable approach.	a) Vulnerable to noise or irrelevant data. b) Testing entails significant time due to distance calculation to all known instances.
Support Vector Machine	a) Apt for datasets with numerous dimensions and intricate structures.	a) Kernel function and parameter selection for higher-dimensional data mapping poses challenges. b) Training processes can be time-intensive. c) Only handles two classes adeptly.
Decision Tree	a) Easy to interpret for small-sized trees.	a) Tendency to overfit in datasets with noisy classification/regression tasks.

Artificial Neural Network	a) Effectively learns non-linear data relationships.	a) Faces scalability issues. b) Requires ample training samples. c) Demands increased processing time.

Table 1 above provides a comparative analysis of available classifiers, here we list out the merits and demerits of classifiers. The chief contributions of the research works are outlined as follows:

Development of a New Predictive Algorithm (HBD) for Blockage Detection:

The research introduces a novel predictive algorithm, termed HBD, designed specifically for the detection of overflow and blockage within pipes. This algorithm employs Fiber-Optic Communication, integrating Ethernet/WiFi for communication, and is tailored for use at significant depths (ranging from 100 to 120 meters). The processing approach is parallel, and the system's physical dimensions are specified at 18.4 × 29.5 × 33.5. The primary goal of this algorithm is to significantly reduce the time required to detect blockages within pipes.

Integration of Enhanced Machine Learning for Feature Extraction and Classification:

An advanced machine learning architecture is incorporated to extract and classify features based on images and video data captured during the research. This architecture is optimized through suggested techniques to enhance the identification of blockages while providing real-time location tracing of Remotely Operated Vehicles (ROVs) in the images and video data.

Introduction of an Energy-Efficient Routing Algorithm:

A novel energy-efficient routing algorithm is introduced, aimed at minimizing energy consumption and enhancing throughput and Packet Delivery Ratio (PDR). This algorithm's performance is optimized to improve the detection of overflow and blockages within pipes using the proposed model.

Evaluation of Overflow and Blockage Detection Model:

The research conducts a comprehensive evaluation of the proposed overflow and blockage detection model within pipes, comparing its performance with existing algorithms and classifiers. Various performance measures, including the utilization of machine learning classifiers with a deep learning approach for prediction, are employed to assess the model's effectiveness.

These contributions collectively advance the field of blockage detection and contribute to more efficient, real-time solutions for addressing overflow and blockage issues within pipe systems

III. PROPOSED MODEL

Figure 1 depicts system block diagram on which the proposed controller is tested. In contrast to the research conducted in reference [25], the experiments in this study were performed on a one Degree of Freedom (DOF) underwater system. This choice was made because such a system effectively retains the primary characteristics of an underwater system, as established in reference [20].

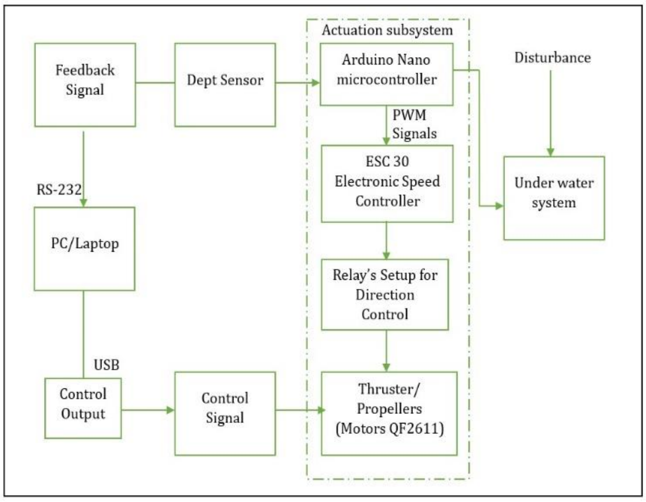

Figure 1. System block diagram

3.1 Mechanical system

The one Degree of Freedom (DOF) underwater system is equipped with speed variation capabilities using a control voltage range of +/-5. The thruster is attached to a base, and the system is made up of two vertical metal bars that are designed to restrict the thruster's movement to the depth direction alone. The complete mechanical structure is submerged in a predetermined-sized water container that is 20 meters long, 10 meters high, and 33 meters in diameter. The thruster is capable of moving within a range of 5 meters in the depth direction, allowing for controlled and precise depth adjustments within the underwater environment.

Algorithm for Sewage Detection System

The process for detecting blockage in a pipe using sensor measurements can be summarized in the following steps:

STEP 1: Begin by measuring the length of the pipe using a sensor and establish this measurement as the Standard Reference.

STEP 2: Utilizing the Standard Reference distance (D), calculate the time it takes for the sensor signal to travel to the end of the pipe and return. Record this time as the Standard Reference Time (T).

STEP 3: The sensor generates periodic reports at predefined intervals, such as hourly or every 30 minutes, to monitor the conditions inside the pipe.

STEP 4: Calculate the velocity or speed of the wave within the pipe using the formula: Velocity = Distance Traveled / Time. In this case, since the signal travels to the end of the pipe and back, you can simplify this to Velocity = 2 * Pipe Length / Time, which equals 2L / T, where L is the length of the pipe, and T is the time taken.

STEP 5: Calculate the value 1, which is the product of the calculated velocity (Speed of the wave) and the time (T) divided by 2, giving you 1 = (Velocity * T) / 2.

STEP 6: If 1< DSR there is possibility of blockage, so issue warning.

This process allows for the continuous monitoring of the pipe's condition based on the speed of the wave and can help detect blockages or restrictions in the flow of material through the pipe.

Algorithm above provides insight into the process of monitoring a pipeline for blockages. In the initial step, when the first Ultrasonic pulse is released, it serves to measure the total length of the pipe, establishing this measurement as the Standard Reference with respect to Distance. Subsequent Ultrasonic pulses are released at regular intervals to continuously monitor the pipe for potential blockages. If a blockage occurs, the Ultrasonic pulse sent into the pipe will return in a shorter time duration, as referenced in [21]. This return time is compared with the Standard Reference time. If the return time is less than the Standard Reference time, it indicates the presence of a blockage in the specific pipeline, confirming the need for further action or intervention.

3.1 Proposed ROV Design

The block diagram of the suggested hardware system, which displays the electronic design, is shown in Figure 2. The remotely controlled vehicle (ROV) and the remote control interface are its two essential parts. Detailed specification is listed in table 2 below. These two subsystems are interconnected via a WiFi network, enabling users to control the ROV using a personal computer, laptop, or mobile device, all accessible through Virtual Network Computing (VNC) connectivity [22]. The ROV's hardware configuration incorporates a System on a Chip (SoC) Raspberry Pi, creditworthy executing parallel tasks, including: The system has multiple functions: (i) using a digital camera to record video; (ii) collecting and recording information from multiple sensors within the system; (iii) controlling motors in conjunction with an Arduino Nano microcontroller; (iv) keeping an eye on battery voltage to assess internal temperature and energy consumption; and (v) managing communication with the remote control. The used digital camera has an IP68 waterproof housing, which makes it easier to deploy it underwater for obstruction surveillance. In addition, the system has two power sources: one incorporates an electronic speed controller and relays for motor control, while the other is a 5V, 10,000mAh power bank that powers the Raspberry Pi, Arduino Nano microcontroller, and digital sensors [23]. Regarding wireless control, users can effortlessly operate the ROV using this arrangement, which consists of a WiFi network router connected to a computer or mobile device.

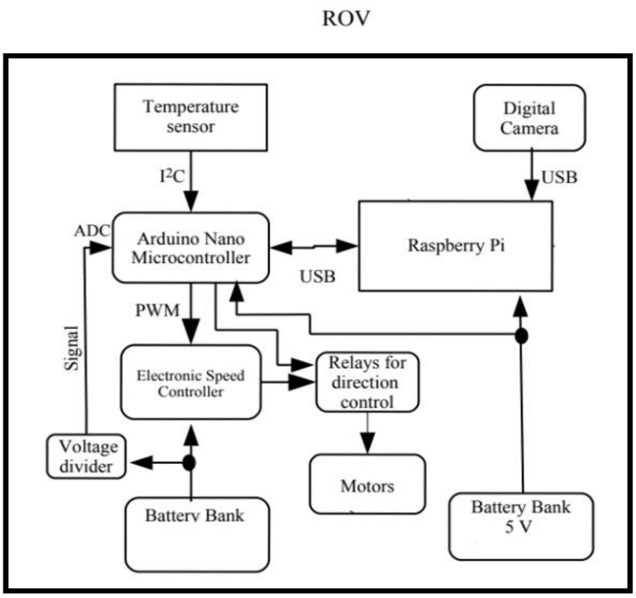

Figure 2: Architecture of ROV

The electronic speed controller (ESC) controls the operation of the brushless motors, which are linked in a star arrangement. An Arduino Nano microcontroller produces a pulse width modulation (PWM) signal that powers the three-phase output signal produced by the ESC.

In my previous research, I conducted an analysis of frequency domains. When a partial blockage occurs inside a pipe, the pressure signal exhibits a distinctive pattern that differs from the typical signal in an unobstructed pipeline. This dissimilarity arises from the way pressure waves interact with the partial obstruction, resulting in unique frequency characteristics.

Table 2: System Specification

Software	Hardware
Simulation Proteus 8 Professional	Arduino Uno
Arduino	Humidity & Temp Sensor (DHT 11)
	Water level Sensor
	Gas Sensor(MQ2)

	LCD
	DC Motor
	Adaptor
	12V Relay Module
	GSM Module (SIM 808)

Due to the inherent high frequency and measurement noise in pressure signals, distinguishing pressure variations between unobstructed and partially obstructed pipes in the time domain can be challenging. Consequently, time domain information is transformed into the frequency domain to facilitate the identification of these variations [24]. In this study, the parameter F is employed, calculated as the average of the average distances between the left and right neighbors of 50mm intervals (1). This parameter helps quantify and analyze the frequency characteristics of pressure signals, allowing for more effective differentiation between normal and partially obstructed pipe conditions.

$$F = \frac{\frac{(x_i - x_{i-1} + x_i - x_{i-2} + \cdots + x_i - x_{i-k})}{k} + \frac{(x_i - x_{i-1} + x_i - x_{i-2} + \cdots + x_i - x_{i-k})}{k}}{2}$$

In this analytical approach, X represents a vector of frequency domain amplitudes derived from a time-domain pressure signal through the Quick Fourier Transform. Each element xi in X signifies the amplitude at a particular frequency component. The analysis introduces the parameter k, which determines the window size for evaluating local features in the frequency domain. Each xi has two values: the right difference mean and the left-differences average, which measure the mean of the differences between xi and its k right surrounding points and the variances between xi and its k left nearby points, respectively. These statistical measures serve to determine whether xi represents a meaningful peak or a significant feature within the frequency domain signal, facilitating the identification of relevant characteristics (1).

IV. EXPERIMENTAL RESULTS

The experimental results are shown, including a breakdown of the hardware resources allotted to each algorithm and running processes, using the Raspberry Pi as the onboard computer for underwater blockage detection in the ROV. The photographs from both real sea conditions and controlled aquatic habitats are included in the results; these images form the basis for the analysis of the data that follows. Additionally, the research introduces the outcomes of implementing a smart controller and provides a comparative analysis of key features against commercial ROVs.

The experiments reveal that a 1 µs time interval is optimal for ensuring the ROV's stability underwater, particularly for video capture and blockage observation. The circuit design incorporates a pair of relays per motor, allowing for the alteration of motor rotation direction in response to operational requirements [25]. Given the absence of a line of sight between the wireless access point and the ROV several meters underwater, precise position and orientation measurements become essential. To address this, a 3D angular position determination system employing accelerometers and gyroscopes is employed. The measurements indicate minor variations (noise vibrations) present in both static and dynamic conditions, which are attributed to the forces acting on the ROV and subsequently impact its stability. To mitigate these variations, a complementary filter is utilized to reduce undesired effects. The Raspberry Pi is tasked with processing these filter outputs. The filter design considers the accelerometer measurements for the low-pass filter's cutoff frequency and the gyroscope-based signal for the high-pass filter. The schematic of the complementary filter is depicted in a provided figure 3.

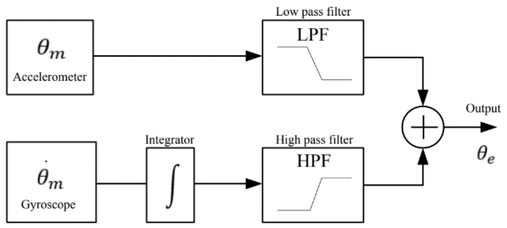

Figure 3: Diagram of the ROV's complementary filter implementation.

The next transfer function for the complementary filter is derived by fusing data from both the accelerometer and gyroscope sensors. Implementation of this complementary filter results in enhanced stability for the ROV, as visually demonstrated in the provided figure. The application of the complementary filter is instrumental in reducing noise significantly, leading to improved ROV stability. Consequently, this enhancement contributes to an overall improvement in the quality of the captured images, which is a crucial factor in underwater operations and blockage detection.

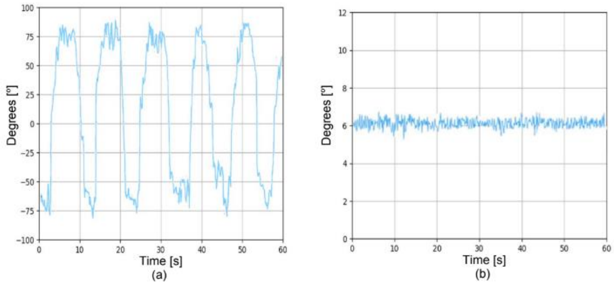

Figure 4: Output signal of the MPU6050 sensor without conditioning: (a) ROV in motion with direction in y; and (b) ROV without movements (parked).

Figure 4 shows the output signal results generated with and without conditioning and Figure 5 shows motion sensor signals generated using complementary filter.

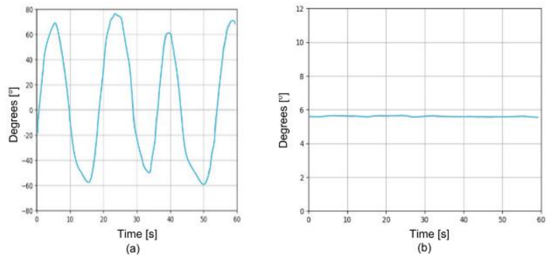

Figure 5: Motion sensor signal by using complementary filter: (a) ROV in motion with direction in y; and (b) ROV parked.

4.1 Stability Performance

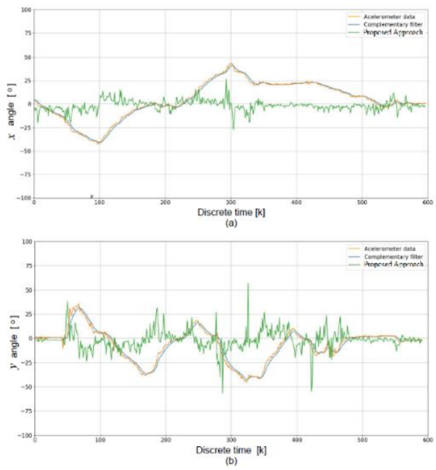

Figure 6: stability testing of the ROV using the suggested method on the filter's output. both x- and y-axis movements (a and b, respectively).

The MPU6050 sensor plays a pivotal role in tracking the ROV's orientation and facilitating its stability. The complementary filter amalgamates data from both the accelerometer and gyroscope, resulting in a smoothed signal. For short-term operations, gyroscope data were preferred for their precision and resilience to external forces, while accelerometer data were relied upon for long-term stability due to their lack of drift. In this experiment, the accelerometer was set to a sensitivity of 16,384 LSB/g, and the gyroscope to 131°/s. Figure a and Figure b, presented for reference, illustrate stability tests on the complementary filter's output, showcasing minimal noise and drift in both accelerometer and gyroscope data. The utilization of the complementary filter significantly enhances the ROV's stability, ultimately improving the quality of captured images. Notably, the implementation of the complementary filter is lightweight and straightforward for embedded systems like the Raspberry Pi.

1.2 Comparative Analysis

Table 2 provides a comparative analysis of features between the proposed ROVs and commercial counterparts. While some features are similar, the proposed ROV distinguishes itself with its parallel computing capability, enabling concurrent execution of multiple tasks and image capture. The ROV's remote control operates via a Python-coded graphical user interface compatible with various operating systems, including GNU/Linux, Windows, Android, and OS X. The payload capacity of the ROV, which includes additional sensors, measurement instruments, and ocean-collected samples, benefits from the design's mechanical and hardware characteristics, allowing for convenient maintenance and component replacement. This technological independence fosters flexibility in ROV operations, setting it apart from traditional ROV manufacturers.

Table 3. Comparison of characteristics of the proposed ROV vs. commercial ROV

Features	Open ROV	Proposed ROV
Architecture	Open	Open
Internet connectivity	Yes	Yes
Maximum depth [m]	100 to 120 M	100 to 120 M
Processing type	Serial	Parallel
Frames per second	30	42 to 45
Controller algorithm	PID	Smart PID
RC	Joystick for	Graphic user
Payload [kg]	1.000	3.128
Dimensions (length×width×height) [cm]	8 × 20 × 40	18.4 × 29.5 × 33.5 15.64

V. CONCLUSION

The integration of Underwater Optical Wireless Communication (UOWC) with remotely operated vehicles (ROVs) represents a groundbreaking leap in technology for efficient high-speed data transmission and control in underwater environments. This advancement holds immense promise, particularly for applications demanding substantial data throughput, such as real-time video streaming and ROV operations. The ROV system proposed in this study showcases outstanding capabilities, executing precise translational and rotational movements across three axes to capture blockage images in video graphic array format.

Engineered to operate seamlessly at depths ranging from 50 to 100 meters, this ROV surpasses the limitations of human divers, whose typical depth reach is limited to 30 meters. Utilizing the four cores of a System-on-Chip (SoC) Raspberry Pi, the system shows proficiency in simultaneous motion control, 3D location, temperature sensing, video capture, and underwater blockage identification. An operating system-neutral graphical user interface written in Python facilitates seamless communication between the ROV and the wireless access control.

The ROV's six brushless motors are intelligently governed by a PID controller, augmented by a complementary filter that enhances sensor data, thereby contributing to elevated stability and video quality during processing on the Raspberry Pi. Boasting an impressive autonomy of 2 to 3 hours, the system's open-source algorithms provide adaptability for integrating additional sensors and functionalities, catering to diverse underwater operations ranging from surveillance and fishing to marine research and environmental monitoring.

The versatility of the mechanical design and the use of cost-effective hardware underscore the system's technological independence, positioning it as a robust solution with the potential for a myriad of underwater applications without compromising data acquisition quality.

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