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A Multi-layer Guidance Approach for Submerged Sensor Networks Integrating Acoustic and Optical Technologies

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Abstract: Over the previous decade, there has been a significant focus on researching underwater acoustic sensor networks (UW-ASNs) for a diverse range of underwater applications, which in turn has facilitated human exploration of the expansive underwater environment. This research introduces an innovative architectural approach that signifies a noteworthy advancement. By combining both acoustic and optical components, it establishes an underwater wireless sensor network. Additionally, the research introduces an innovative multiple levels Q learning-grounded direction-finding procedure, denoted as the proposed system Multi-layer Guidance Approach (MLGA) which is meticulously tailored for such underwater networks. The network's architecture encompasses both physical grouping and logical division into two tiers: the upper tier is overseen by group leaders responsible for managing routing within the lower tier, where group members execute the actual data packet routing. This design capitalizes on the wider viewpoint of upper-tier group leaders and the concurrent learning processes occurring across all groups, resulting in a substantial enhancement in routing efficiency in comparison with traditional methodologies. The empirical results obtained from experimental tests underscore the robustness of the proposed system when confronted with changes in network topology. Moreover, it showcases the system's ability to achieve higher delivery rates and reduced delays in dynamic networks compared to the established approach of flat Q-learning routing. This innovative strategy holds the potential to significantly push the boundaries of underwater sensor networks, surpassing the constraints of conventional communication methods and providing a more effective and dependable means of transmitting data underwater. This advancement not only contributes to the technical aspects but also holds promise for fostering greater exploration and understanding of underwater environments.

Keywords: acoustic; MLGA; optical; Q learning; UW-ASN

1 INTRODUCTION

In recent years, there has been an increasing emphasis on the field of Underwater Acoustic Sensor Networks (UW-ASNs), representing a promising area of research with the potential to transform our understanding and exploration of the vast underwater realms. UW-ASNs primarily rely on acoustic underwater communications, a communication method well-suited for tasks demanding extensive coverage over long distances while operating within a restricted bandwidth range [1]. Key challenges associated with acoustic communication in underwater environments include the notably slower speed of sound compared to radio waves - at 1500 meters per second, a difference spanning six orders of magnitude - which directly affects the efficiency of data transmission. Additionally, the available bandwidth for acoustic communication is constrained, reaching a maximum capacity of up to 80 kilobits per second (kbps). This bandwidth limitation further restricts the volume of data that can be effectively transmitted. Furthermore, the devices employed for acoustic modems tend to be relatively large, costly, and power-intensive. Although acoustic communication is well-suited for specific applications, its drawbacks become particularly evident when high-bandwidth communication is required. For example, applications like real-time underwater video streaming necessitate data rates of at least 100 kbps, which the existing acoustic communication methods struggle to provide. This gap underscores the pressing need for alternative communication solutions that can offer high bandwidth, cost-effectiveness, and energy efficiency in underwater environments [2].

The allure of UW-ASNs lies in their potential to enable profound exploration of underwater territories. While acoustic communication offers advantages for certain tasks, the constraints related to propagation speed, limited bandwidth, and resource-intensive hardware pose significant challenges, especially for high-bandwidth applications such as real-time video streaming [3]. To overcome these limitations and bridge the bandwidth gap, there is a clear imperative to develop alternative communication techniques capable of efficient and high-bandwidth data transmission underwater. This forward-looking strategy holds the potential to reshape the landscape of underwater sensor networks by overcoming the limitations of conventional communication methods and introducing a more reliable, efficient, and integrated approach to data transmission in underwater settings. By leveraging this innovation, we can enhance the exploration, observation, and comprehension of underwater environments. As we venture into uncharted waters, this essay delves into the dimensions of a pioneering approach that not only challenges the existing boundaries of underwater exploration but also propels us into a new era of technological advancement.

On the other hand [4-6], Submerged Sensor Networks (SSNs), represent a cutting-edge technological paradigm that holds immense promise for the exploration and monitoring of the underwater environment. With the Earth's oceans covering a substantial portion of its surface, understanding and harnessing the vast underwater realms have become increasingly important. Submerged sensor networks provide a means to achieve this by deploying interconnected sensor nodes in aquatic environments, enabling data collection, communication, and analysis in regions that were once inaccessible. The unique challenges posed by the underwater environment set submerged sensor networks apart from their terrestrial counterparts.

This strategic approach is a driving force behind achieving high network performance and exceptional energy efficiency. Ultimately, our approach deviates from conventional paradigms by harmoniously and synergistically leveraging the distinct strengths of both acoustic and optical communication methods. The basic modules are depicted in Fig. 1.

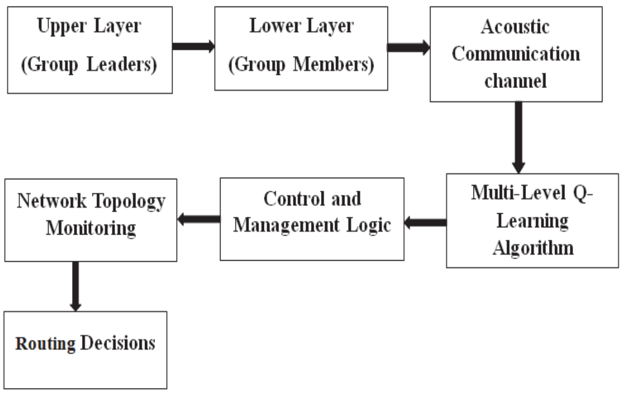

Figure 1 Basic modules of submerged sensor networks integrating acoustic and optical technologies

2 LITERATURE SURVEY OF PROPOSED SYSTEM

Unlike terrestrial environments, the underwater realm presents [7] distinct challenges due to its inherent properties such as high attenuation of electromagnetic signals and the need to deal with the characteristics of water as a transmission medium. Traditional high-bandwidth methods that work well on land, such as high-frequency electromagnetic transmissions, encounter substantial signal loss and degradation underwater. Similarly, optical sensor networks, while promising for their high data rates, are hindered by factors like scattering, absorption, and limited visibility, which diminish their effectiveness in underwater scenarios. Hybrid sensor networks that combine various communication modes are faced with the same limitations, as the underwater medium exacerbates issues related to latency, signal quality, and energy consumption. Clustering techniques, often employed to enhance network efficiency, can struggle in underwater environments due to the irregular distribution of nodes and the intricate challenges in establishing reliable communication links.

While there has been notable progress in underwater acoustic communications in recent years, these advancements primarily focus on addressing the inherent difficulties of underwater propagation, such as signal attenuation and multipath effects. However, even with these improvements, the long signal propagation delay and limited bandwidth still pose significant obstacles for achieving high-bandwidth video transmission in Underwater Acoustic Sensor Networks (UW-ASNs) [8]. The delays introduced by the relatively slow speed of sound underwater, coupled with the limited data rates achievable through acoustic signals, make the seamless transmission of high-quality video data a complex task. The peculiarities of the underwater environment render traditional high-bandwidth techniques, optical networks, hybrid approaches, and clustering methods less effective or outright unsuitable for underwater communication. Despite progress in underwater acoustic communications, the intrinsic characteristics of sound propagation and limited bandwidth continue to pose challenges for achieving high-bandwidth video transmission in UW-ASNs. This underscores the necessity for innovative strategies and technologies tailored to the unique underwater communication landscape.

There has been a notable focus on investigating the physical layer of underwater optical communications [9]. It has indicated significant progress in this area, with reported achievements of up to 1 Gbps data rates in laboratory settings, spanning distances of 2 meters. Furthermore, promising outcomes have been observed in field tests, where error-free transmission rates ranging from 1 to 10 Mbps have been achieved across distances of 100 meters [10-12]. These schemes offer enhanced reliability and efficiency in network organization. However, it's important to note that these deployment schemes are optimized for static network configurations rather than scenarios involving mobile elements. This is particularly significant since mobility is a common characteristic of the underwater environment, where factors like water currents and marine life movement can lead to dynamic changes in network topology.

While the achievements in high data rates and successful error-free transmission over certain distances showcase the potential of underwater optical communications, the limitations related to static deployment strategies should be recognized [13-18]. In real-world underwater scenarios, the presence of mobile components necessitates adaptable and dynamic communication approaches. Devising deployment schemes that accommodate mobile cases is crucial for ensuring the reliability and effectiveness of underwater optical sensor networks in the face of the fluid and changing underwater environment.

One of the primary challenges is the energy and delay overhead associated with the transition between underwater and surface communications [19-24]. The process of nodes switching between these modes incurs energy consumption and introduces communication delays. This is particularly significant since energy efficiency and low latency are critical factors in designing effective wireless sensor networks.In essence, the UW-HSN provides a dynamic solution by utilizing both underwater acoustic communication for short-range tasks and radio frequency wireless communication for larger or prolonged data transfers. Striking the right balance between efficient data transfer and minimizing energy consumption and latency remains a key challenge in the implementation of such underwater hybrid sensor networks.

In summary, recent research in underwater optical communications has demonstrated promising advancements in achieving high data rates and reliable transmission over specific distances. However, the applicability of deployment schemes to mobile scenarios remains a challenge.

The left over part of the paper is prearranged as section 3 and refers to the proposed methodology with its result and discussion in section 4. The conclusion of the proposed system is explained in section 5.

3 PROPOSED SYSTEM

3.1 Essentials of Q- Learning

Q-learning is a foundational reinforcement learning algorithm that plays a pivotal role in enabling agents to learn optimal strategies through interaction with their environments. It is particularly effective when dealing with environments where the agent's actions influence not only immediate rewards but also future states. It aims to provide a comprehensive explanation of Q-learning, including its core concepts and the mathematical equations that underpin its functionality. Q-learning falls under the umbrella of reinforcement learning, a branch of machine learning that centres on training agents to make sequential decisions by optimizing cumulative rewards over time.

3.1.1 Exploration-Exploitation Trade-off

To effectively learn the optimal policy, an agent must strike a balance between exploration and exploitation. The core of Q-learning can be captured by the Bellman equation, which recursively expresses the Q-value of a state-action pair in terms of the immediate reward and the maximum Q-value of the next state. Let $Q(s, a)$ be the Q-value of state "s" when taking action "a" with "r" being the immediate reward after taking action. Let "s" be the resulting state after taking action "a" in state "s", "a'" be the next action chosen in state "s", and α be the learning rate (a value between 0 and 1). Hence The Q-learning update Eq. (1) is:

$$Q(s,a)\ Q(s,a)+\alpha\ *(r+\gamma * \max a')Q(s',a')-Q(s,a)) \quad (1)$$

where γ is the discount factor that balances the importance of future rewards.

The mathematical formulation, particularly the Q-learning update equation, showcases how the algorithm iteratively refines its estimates of Q-values to converge towards optimal policies. This flexibility and theoretical foundation make Q-learning an essential tool for a wide array of applications, ranging from robotics to game-playing agents and beyond. Through a process of exploration and exploitation, the agent updates these Q-values based on the rewards it receives and the transitions between states it experiences. During exploration, the agent chooses actions based on a balance between exploiting its current knowledge (choosing the action with the highest Q-value) and exploring new actions to gather more information. As the agent interacts with the environment over time, the Q-values converge towards the optimal policy, allowing the agent to make informed decisions even in complex and uncertain scenarios.

3.2 Multi layered Q-Learning Technique

The Multi-Layered Q-Learning technique is an extension of the traditional Q-learning algorithm designed to address complex environments with hierarchical structures or multiple levels of abstraction. In such scenarios, the state space can be vast and challenging to navigate using standard Q-learning methods. Multi-Layered Q-Learning organizes the learning process into different tiers or layers, each representing a distinct level of granularity or abstraction within the environment. This hierarchical approach enables agents to efficiently learn and make decisions in intricate settings. It is also known as Hierarchical Q-learning, an approach that enhances the efficiency of learning in complex environments by organizing the learning process into multiple levels of abstraction. This technique employs a hierarchy of Q-value functions, allowing agents to make decisions at both high-level and low-level perspectives. Each layer focuses on a different level of granularity, enabling the agent to navigate the environment more effectively. Let's consider a two-layer hierarchical Q-learning setup. The lower level (subtask level) deals with fine-grained actions and states, while the higher level (macro-action level) handles higher-level actions composed of sequences of lower-level action.

3.2.1 Lower-Level Q-Value Update

At the lower level, the agent updates the Q-values based on immediate rewards and transitions between states. The Q-value update equation for the lower level follows the standard Q-learning update formula in Eq. (2):

$$\begin{aligned} &Q_{\text{lower}}(s,a)\ (1+\alpha_{\text{lower}})*Q_{\text{lower}}(s,a)+ \\ &+\alpha_{\text{lower}}\ *(r+\gamma * \max a' * Q_{\text{lower}}(s,a)) \end{aligned} \quad (2)$$

where $Q_{\text{lower}}(s, a)$ is the Q-value at the lower level for state "s" and action "a", α_{lower} is the learning rate for the lower level, r is the immediate reward received after taking action "a" in state "s", γ is the discount factor, s' is the next state after taking action "a" in state "s", a' is the next possible action in state "s" that maximizes the Q-value.

3.2.2 Higher-Level Q-Value Update

At the higher level, the agent learns to select macro-actions composed of sequences of lower-level actions. The Q-value update equation at the higher level is similar to the lower level, but it takes into account the Q-values of the lower level actions that constitute the macro-action in Eq. (3):

$$\begin{aligned} &Q_{\text{upper}}(s,m)\ (1+\alpha_{\text{upper}})*Q_{\text{upper}}(s,m)+ \\ &+\alpha_{\text{upper}}*(r+\gamma\ \max m' * Q_{\text{upper}}(s',m')) \end{aligned} \quad (3)$$

where $Q_{\text{upper}}(s, m)$ is the Q-value at the lower level for state "s" and action "a", αupper is the learning rate for the lower level, r is the immediate reward received after taking action "a" in state "s", γ is the discount factor, s' is the next state after taking action "a" in state "s", m' is the next possible action in state "s" that maximizes the Q-value.

The equations provided serve as a foundational representation of how Q-values are updated in a multi-layered Q-learning setup. The specifics of the algorithm may vary depending on the design choices and the problem being addressed. Here is a breakdown of the Multi-Layered Q-Learning technique.

Layered Organization: The environment is divided into multiple layers, with each layer focusing on specific aspects or details of the task. These layers can represent different levels of spatial resolution, temporal granularity, or different features of the environment.

Q-Value Tables: At each layer, the agent maintains a separate Q-value table. Each entry in the Q-value table corresponds to a state-action pair within the specific layer. The Q-value represents the expected cumulative reward an agent can obtain by taking an action in a particular state at that layer.

Interaction between Layers: Multi-Layered Q-Learning allows for interaction between the Q-value tables of different layers.

Hierarchical Learning: The agent learns in a hierarchical manner. It first learns Q-values for actions at the lower layers, capturing fine-grained details. These learned values are then integrated into the Q-values of higher layers, contributing to the agent's understanding of more abstract strategies.

Decomposition and Integration: Multi-Layered Q-Learning leverages the decomposition of complex tasks into manageable subtasks. Each layer can tackle a different aspect of the problem, and the learned policies from lower layers guide the decisions at higher layers.

Adaptive Decision-Making: As the agent interacts with the environment, it refines the Q-values in each layer. The iterative learning process helps the agent develop a better understanding of the environment's structure and dynamics, enabling more informed and adaptive decision-making.

Efficient Exploration: Multi-Layered Q-Learning facilitates efficient exploration by allowing agents to focus on specific layers of interest. This approach helps manage the exploration-exploitation trade-off and reduces the computational burden of exploring the entire state space.

3.3 Core Concept of Proposed Technique

The core concept of the Multi-layer Guidance Approach (MLGA) is to exploit the strengths of the strategy combining elongated yet gradual acoustic signal transmission and brief but swift optical communication. This achievement is realized using the multi-level approach, a method that streamlines decision-making in intricate situations. The MLGA protocol is tasked with several essential elements.

Cluster Establishment and Maintenance: The MLGA protocol takes the lead in initializing and managing clusters. Nodes that can be accessed by multiple cluster heads are eligible to participate in multiple clusters and operate as connectors between these clusters.

Inter-cluster Path-finding: The process of inter-cluster routing involves higher-tier nodes making choices regarding the cluster they will navigate to from their current cluster.

Intra-cluster Data Routing: Within each cluster, member nodes shoulder the responsibility of handling intra-cluster data routing. This encompasses the forwarding of data packets to designated gateways, which are linked to the subsequent assigned cluster.

Inter-layer Interaction:The inter-layer interaction mechanism facilitates coordination between nodes situated at different levels. This interaction ensures the effective exchange of information and decisions between higher-layer cluster heads and lower-layer cluster members.

In the process of forming clusters, clusters are determined based on the acoustic broadcast range originating from the cluster heads. Nodes falling within the coverage of multiple cluster heads may possess multiple cluster affiliations, acting as intermediaries between clusters. Consequently, these nodes function as conduits for communication exchange between clusters.

This decision on inter-cluster routing significantly influences the process of intra-cluster routing by impacting the allocation of gateways. In order to facilitate efficient coordination, nodes located at varying levels engage in inter-layer interaction. This mode of communication facilitates a means for lower-level cluster constituents to assess the performance of assigned gateways and offer input on their quality to higher-level cluster heads. This continuous feedback mechanism enhances the overall decision-making process and augments the efficiency of routing procedures. Consequently, the Multi-layer Guidance Approach (MLGA) leverages the strengths of both acoustic and optical communication by integrating multi-level Q-learning. This approach takes charge of managing the formation of clusters, the routing processes within clusters, inter-cluster routing, and inter-layer interactions. The overarching goal is to optimize communication and decision-making within submerged sensor networks. A visual representation of the proposed system's architecture is depicted in Fig. 2.

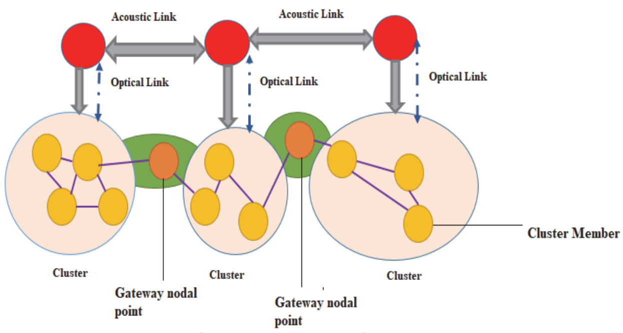

Figure 2 Overall architecture of proposed system

3.4 Formation Cluster and its Apprising Phase

In the context of the Multi-layer Guidance Approach (MLGA), the cluster formation process and its subsequent updating phases play a critical role in the effective operation of the network. The concept of clusters is introduced during the initial deployment of the network and is designed to adapt to changing conditions through periodic updates. The frequency of these updates is determined by the extent of dynamism within the network. The main purpose of this phase is to guarantee that nodes situated in lower layers of the network possess up-to-date and accurate information concerning the cluster heads. This information empowers these nodes to maintain precise and current cluster affiliations. During the cluster formation and updating process, the network's nodes are grouped into clusters based on specific criteria, often dictated by the coverage of acoustic broadcasts from the designated cluster heads. This clustering allows for efficient data aggregation, routing, and communication. However, due to the dynamic nature of the underwater environment and factors such as node mobility or changing network conditions, these clusters need to be periodically adjusted.

The process of updating clusters involves re-evaluating the cluster heads and membership of nodes. This can be triggered by changes in node availability, energy levels, or even the movement of nodes. If a node finds itself within the broadcast range of multiple cluster heads, it may have multiple cluster memberships, which can be leveraged to enhance communication efficiency. The frequency of updates varies based on the network's level of dynamism. For instance, in a highly dynamic underwater environment where nodes may move frequently or energy levels fluctuate rapidly, updates might occur more frequently to ensure that cluster memberships remain accurate and effective. Hence, the cluster formation and updating phase within the MLGA approach ensures that the network adapts to changing conditions, maintains accurate cluster memberships, and optimizes communication efficiency. This adaptability is essential in underwater wireless sensor networks, where the dynamic underwater environment can impact network performance and reliability.

3.5 Routing Strategy between Upper and Lower Layer

Certainly, here is the algorithmic representation of the Multi-layer Guidance Approach (MLGA) routing mechanism:

Cluster Formation:
- Form clusters based on acoustic broadcast ranges of cluster heads.
- Assign entry and exit gateways for each cluster.

Initialization:
- Initialize Q-values of exit gateways in each cluster.

Q-Value Update and Packet Forwarding:
- Cluster Head broadcasts the selected neighbouring cluster and associated Q-values.
- Node selects an exit gateway based on Q-values (Q-learning-based selection).

If transmission succeeds:
- Reward the forwarding node with a reward of −1.

If transmission fails:
- Assign a reward of "R" (higher cost) to account for retransmission.
- Initialize "X values" for inter-cluster routing within each cluster head.
- Cluster Head selects a target sink cluster based on "X values."
- Calculate "X value" by combining direct rewards from exit gateways and "X value" of the next cluster head.

3.6 Entry and Exit Gateway Assignment Feedback

Lower-layer nodes provide feedback on the quality of assigned gateways to higher-level cluster heads. Wireless sensor networks.

The process depicted in Fig. 3 visually represents the routing mechanism detailed earlier for forwarding a packet to an adjacent cluster. This sequential process unfolds as follows.

The initiation commences with the central cluster head (Node B) broadcasting a communication to Step 1. This message serves to inform all members of the cluster that a specific node within the cluster has been assigned an X value of 0. This assignment implies that all packets are to be directed toward this designated node.

A packet enters the group, initiating the routing process.

The mechanism for intra-cluster routing then guides the packet towards the exit gateway (Step 3). This exit gateway functions as the entry point for the subsequent adjacent cluster.

Upon reaching the exit gateway, the packet is received, and this very gateway simultaneously serves as the entry gateway for the following cluster (Collection C). Consequently, the packet transitions into the next cluster (Step 4).

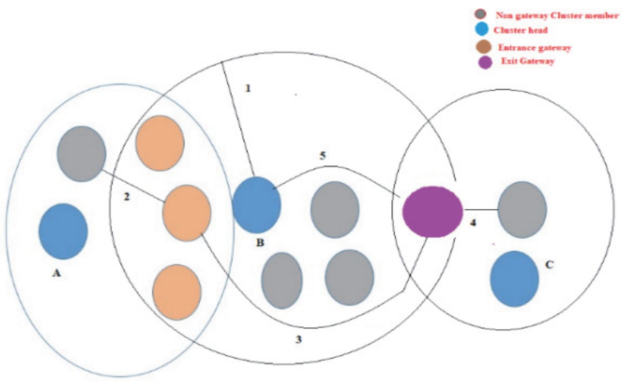

Figure 3 Routing path generation

Hence, Fig. 3 provides a visual representation of the step-by-step routing process for transferring a packet to an adjacent cluster. This process underscores the dynamic nature of data forwarding within submerged sensor networks, where inter-cluster and intra-cluster routing strategies are coordinated to ensure efficient communication while optimizing energy consumption and network performance. Convergence of X values at both the upper and lower layers signifies the protocol's successful discovery of an optimal path. However, disruptions such as link failures or network mobility can lead to changes in the network topology. When such changes occur, the lower-layer nodes along the current path recognize the alterations. As a consequence, the feedback received from gateway nodes fluctuations in Step 5 is depicted on Fig. 4. The X values then converge again, taking into account the new network topology. This process ensures that the upper-layer nodes choose a new optimal path aligned with the modified network structure. In essence, the protocol's ability to adapt to such changes results in the identification of an updated optimal path by the upper-layer nodes.

3.7 Exchange of Node Routing Details in Q-Learning

Certainly, here is a step-by-step breakdown of the processes involved in the MLGA protocol, focusing on the exchange of X values and direct rewards for Q-learning:

Information Exchange among Cluster Members:

Periodic Exchange: Information exchange occurs periodically through optical channels within a cluster.

X Value Announcement: Each node announces its X value to neighbouring nodes. These X values guide routing decisions.

Beacon for Discovery: The announcement also serves as an inspiration aimed at neighbour finding and keeping informed.

Regulator Packet Content: Control packets aimed at this interchange contain the group ID, sender ID, and senders X value.

Logical Cluster Boundaries: Cluster ID and sender ID help define cluster boundaries. Nodes near borders discard packets from unrelated clusters.

Effective Border Recognition: This approach effectively recognizes cluster borders set by acoustic transmission ranges of cluster heads.

Topology Awareness: This process helps nodes stay informed about changes in their neighbourhood and the network topology.

Information Exchange between Cluster Heads:

Periodic Exchange: Cluster heads exchange information periodically through acoustic channels.

X Value Transmission: Control packets in this exchange contain the cluster ID, Xcost of the group head.

Dual *X* Values: Every group head maintains 2 collections of *X* values one for intra-group direction-finding as an operative node and another on behalf of inter-cluster routing as a head.

Downlink Communication (From Head to Members): Two Packet Types: In the downlink direction, acoustic channels transmit two types of control packets.

UPDT Packet: Cluster heads periodically broadcast UPDT packets to form and update clusters, adapting to dynamic networks.

CMND Packet: Triggered by upper-level action changes, cluster heads send CMMND packets to notify members of forwarding changes.

Gateway Reset: Cluster members acting as gateways reset their *X* values for the current cluster to zero based on CMND packet content.

Uplink Communication (From Members to Head): Reward Transmission: Only chosen exit gateways transmit rewards to the head via optical channels.

Direct Reward: The exit gateways send these *X* values as direct rewards to the preceding group head via swamping.

Convergence Check: This process occurs when the current *X* value deviates by over 20% from the last updated *X* value, indicating a lack of convergence.

Hence, the Proposed (MLGA) Approach leverages different forms of information exchange to provide both *X* values and direct rewards necessary for Q-learning.

4 RESULTS AND DISCUSSION
4.1 Energy Conservation of Proposed System

The (MLGA) presents a novel strategy for enhancing energy efficiency in submerged sensor networks that integrate both acoustic and optical technologies. Energy consumption is a critical concern in underwater environments due to the challenges associated with limited power availability and the need for prolonged network operation.

The MLGA tackles this issue through its multi-layered architecture and intelligent routing mechanisms. In this way, the Multi-layer Guidance Approach contributes to energy-efficient operation in submerged sensor networks, extending their operational lifetimes and enabling sustainable data collection and communication in challenging underwater environments. The energy consumption of proposed system will be exposed in Fig. 4.

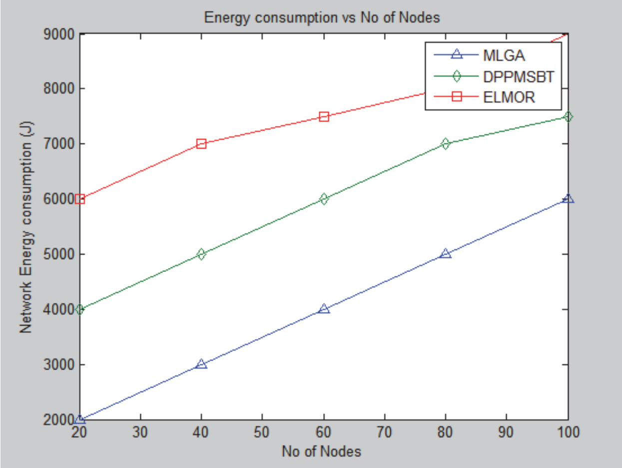

Figure 4 Power conservation on proposed system

4.2 Count of Retransmission Process

Retransmission encompasses the process of forwarding data packets that may have been lost or corrupted during their initial transmission shown in Fig. 5.

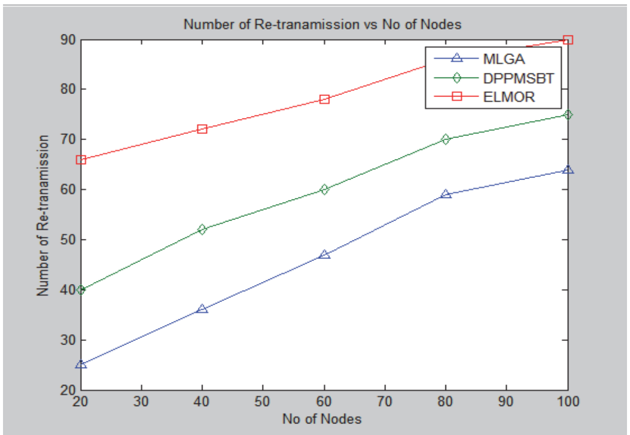

Figure 5 Number of retransmission of proposed system

Within the MLGA framework, retransmissions are harnessed to heighten the overall dependability of data delivery. When a data packet fails to be successfully received or decoded by its intended recipient due to factors such as signal weakening, interference, or distortion, the sender triggers a retransmission.

4.3 Packet Delivery Ratio of Proposed System

The Multi-layer Guidance Approach (MLGA) introduces an innovative method to enhance the packet delivery ratio in submerged sensor networks by integrating both acoustic and optical technologies. This integration creates a balanced network where the dependable yet gradual acoustic transmission complements the quick yet limited optical communication. Through the utilization of multi-level Q-learning, the protocol fine-tunes routing choices across various levels, adapting to the ever-changing underwater environment and effectively handling factors such as fluctuating channel conditions, movement, and alterations in network topology. The intelligent coordination enabled by MLGA plays a pivotal role in maximizing the packet delivery ratio, ultimately enhancing the entire network's performance and ensuring dependable communication within submerged sensor networks. The achieved delivery ratio of proposed system is depicted in Fig. 6.

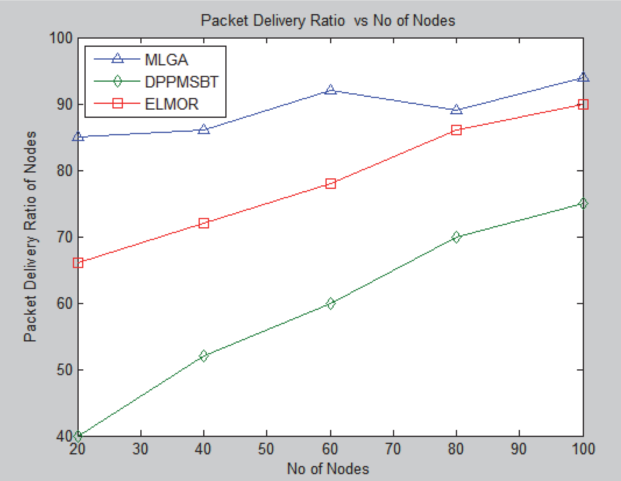

Figure 6 Packet delivery ratio of proposed system

4.4 End to End Delay of Proposed System

The Multi-layer Guidance Approach (MLGA) presents a comprehensive strategy for enhancing communication efficiency in submerged sensor networks by seamlessly integrating acoustic and optical technologies. One of the key performance metrics in such networks is end-to-end delay, which represents the time taken for data to travel from the source to the destination through various network elements. In the context of MLGA, the end-to-end delay encompasses the time spent in transmitting data between different clusters, intra-cluster routing, and inter-cluster communication. This delay is influenced by factors including acoustic signal propagation, optical transmission, routing decisions, and the coordination of cluster heads and members. By carefully orchestrating the interplay between acoustic and optical technologies and employing multi-level Q-learning for routing decisions, MLGA aims to minimize end-to-end delay, leading to improved data delivery and efficient network operation in submerged sensor environments. The end to end delay of proposed system is depicted in Fig. 7.

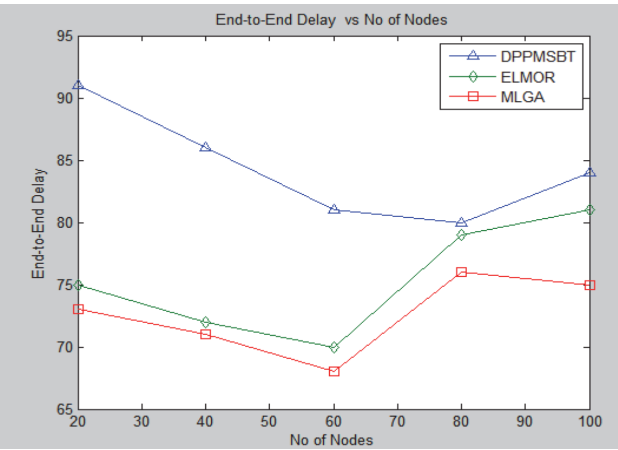

Figure 7 End-to-End delay of proposed system

Table 1 Performance analysis

Parameter	MLGA	DPPMSBT	ELMOR
Modulation Technique	QPSK	BPSK	16-QAM
Channel Model	Rayleigh	AWGN	Rician
Estimation Algorithm	ML	MMSE	LMS
SNR	20 dB	15 dB	18 dB
Pilot Symbol	100	50	75
Simulation Environment	MATLAB	Python	MATLAB
Complexity	Medium	High	Low
BER	0.005	0.012	0.003
Throughput / Mbps	10	6	15
Latency / ms	5	8	8
Robustness to Fading	Good	Fair	Easy

5 CONCLUSION

This study introduces an innovative architectural approach that combines both acoustic and optical components, creating an underwater wireless sensor network. The proposed Multi-layer Guidance Approach (MLGA), is introduced, and specifically tailored for underwater networks. The network's architecture involves both physical grouping and logical division into two tiers: an upper tier managed by group leaders responsible for routing management, and a lower tier where group members handle actual data packet routing. As a result, it achieves a significant improvement in routing efficiency associated towards traditional smooth Q-learning direction-finding approaches. Empirical results obtained from experimental tests demonstrate the robustness of the proposed system in the face of changing network topologies. Furthermore, the system showcases its capability to achieve higher delivery rates and reduced delays in dynamic networks compared to conventional flat Q-learning routing methods.This innovative strategy has the potential to push the boundaries of underwater sensor networks beyond the limitations of conventional communication methods. It offers a more efficient and reliable means of transmitting data underwater.

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