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A Framework for Underwater Rescue Operation using Wireless Sensor Networks

Research Paper

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Abstract:

Underwater rescue management using Wireless Sensor Networks (WSN) with a multi-chain protocol can greatly enhance the effectiveness and efficiency of rescue operations in underwater environments. WSNs are networks of interconnected sensor nodes that can monitor and collect data from the environment. By deploying these networks in underwater scenarios, it is possible to gather real-time information about the conditions and location of individuals in distress. While underwater person identification remains a complex problem, ongoing research and technological advancements aim to overcome these challenges. By improving detection methods, refining data processing techniques, and integrating multiple sensor modalities, the capabilities of underwater rescue operations can be enhanced, leading to more efficient and successful outcomes in water rescue scenarios. In this work, we look into the issues of long chains for effective energy consumption and data delivery delays while taking sink mobility into consideration. By introducing the idea of many head chains, we also lessen the burden on the single chain leader. In this work given area is divided into 4 equal parts and at the center of each parts a sink node is provided. Smaller chains are produced and the stress on the leader nodes is reduced because of 4 sinks in the multi-chain model. By combining WSN with a multi-chain protocol, underwater rescue management can benefit from improved data accuracy, reliability, and security. This integrated approach enhances situational awareness, optimizes resource allocation, and facilitates timely decision-making, ultimately increasing the chances of successful rescue operations in underwater environments.

Keywords: WSN, Underwater rescue, DCT

1. Introduction:

The exploration and utilization of the world's oceans have been a critical aspect of human civilization, offering invaluable resources and serving as a medium for global commerce. However, with the increased human activities in marine environments, the frequency of underwater accidents and disasters has risen significantly [1]. These incidents pose significant challenges to effective and timely rescue operations due to the harsh and unpredictable underwater conditions, limited visibility, and remote locations involved. To address this growing concern, the development of innovative and efficient underwater rescue systems is imperative.

The use of Wireless Sensor Networks (WSNs) has revolutionized various domains of science and technology, providing a flexible and cost-effective solution for data collection, monitoring, and communication in challenging environments. In the context of underwater rescue operations, WSNs offer a promising avenue for enhancing the efficiency, safety, and effectiveness of search and rescue missions [2]. This research paper introduces a comprehensive framework that harnesses the power of WSNs to optimize and streamline underwater rescue operations, potentially saving lives and minimizing the environmental impact of such incidents.

The primary objective of this research is to present a detailed framework for underwater rescue operations, which integrates state-of-the-art wireless sensor technology with advanced data analytics and communication protocols. This framework is designed to address the unique challenges posed by underwater environments, such as the need for real-time data acquisition, reliable communication, precise location tracking, and efficient resource management. Key components of the proposed framework include:

Wireless Sensor Nodes: The deployment of specialized sensor nodes equipped with various sensors, including sonar, temperature, pressure, and image sensors, to collect essential data about the underwater environment, the location of potential survivors, and the condition of the affected area.
Communication Infrastructure: A robust and reliable communication infrastructure that facilitates seamless data transmission and reception among underwater sensor nodes, surface base stations, and remote command centers. This infrastructure ensures that critical information can be relayed in real-time, enabling rapid response to emergency situations.
Data Analytics and Processing: Advanced data analytics algorithms and techniques to process the vast amount of data collected by the sensor nodes. These algorithms are designed to identify potential survivors, assess their health status, and make informed decisions regarding rescue strategies.
Localization and Mapping: Precise underwater localization techniques, such as acoustic positioning and triangulation, to accurately determine the location of survivors and guide rescue teams to the right spot.
Resource Management: Efficient resource allocation and management strategies to optimize the deployment of rescue assets, such as remotely operated vehicles (ROVs) and divers, based on real-time data and incident-specific parameters.
User Interface and Command Center: An intuitive user interface at the command center, enabling rescue operators to visualize data, monitor progress, and make critical decisions efficiently.
This research paper delves into the technical details of each component, presenting innovative solutions and case studies that demonstrate the feasibility and efficacy of the proposed framework. Furthermore, it discusses the potential impact of this framework on enhancing the capabilities of underwater rescue operations, reducing response times, and ultimately saving lives in critical situations.

2. Notable Research

In the ever-evolving landscape of underwater search and rescue operations, the integration of cutting-edge technologies has become pivotal in addressing the unique challenges posed by the world's aquatic environments. This literature survey delves into the realm of underwater rescue missions, focusing on the application of Wireless Sensor Networks (WSNs) to optimize these critical operations. The dynamic interplay between the exigencies of underwater disaster response and the capabilities of WSNs has spurred significant interest and research in recent years. This survey provides a comprehensive overview of relevant literature, encompassing studies that explore the multifaceted dimensions of underwater SAR missions, the advancements in WSN technologies tailored for underwater applications, and the intersection of data analytics, communication, and resource

2.1 Underwater Rescue Operations

Underwater accidents and disasters pose unique challenges for rescue operations due to the complexities of the marine environment, including limited visibility, extreme pressure, and the need for specialized equipment and trained personnel [3].
Research in this domain has focused on improving the safety and efficiency of underwater search and rescue (SAR) missions, often involving the use of remotely operated vehicles (ROVs) and autonomous underwater vehicles [4].

2.2 Wireless Sensor Networks (WSNs) in Underwater Environments

WSNs have gained prominence in underwater applications, offering solutions for environmental monitoring, oceanographic research, and disaster response [5].
Key challenges in deploying WSNs underwater include communication reliability, energy efficiency, and sensor node localization [6].

2.2 WSNs for Underwater Search and Rescue

Several studies have explored the use of WSNs in underwater search and rescue scenarios. For instance, research by Haque et al. [7] presented a WSN-based system for real-time monitoring and coordination in underwater SAR missions.
Yazici et al. [8] introduced an underwater acoustic WSN for precise localization of underwater objects and potential survivors, showcasing the potential of acoustic communication in underwater environments.

2.4 Data Analytics and Processing in Underwater SAR

Effective data analytics and processing are critical for real-time decision-making in underwater SAR operations. Research by Gomes et al. [9] demonstrated the use of machine learning algorithms for object recognition and classification in underwater imagery.

Loebis et al. [10] proposed data fusion techniques to enhance the accuracy of underwater object detection and localization using sensor data from multiple sources.

2.5 Localization and Mapping

Localization plays a pivotal role in underwater SAR missions. Acoustic positioning and navigation systems have been extensively explored [11], while recent research by Cheng et al. [12] introduced vision-based techniques for 3D mapping and localization underwater.

2.6 Resource Management and Optimization

Efficient resource allocation is crucial in underwater rescue operations. Research by Zhang et al. [13] presented optimization models for resource allocation in multi-agent underwater SAR scenarios, considering various constraints and objectives.

2.7 Human-Computer Interaction (HCI)

The design of user interfaces and command centers is essential for effective coordination and decision-making in SAR missions. Research by Zhang et al. [14] discussed HCI considerations in the context of underwater rescue, emphasizing the need for intuitive interfaces.

2.8 Case Studies and Practical Implementations

Several practical implementations and case studies have demonstrated the feasibility and effectiveness of WSNs in underwater SAR. Notable examples include the successful utilization of WSNs in shipwreck exploration (Eldred et al., [15]) and cave diving rescues (Waart et al., [16]).

In summary, the literature survey highlights the growing importance of integrating WSNs into underwater rescue operations. While individual studies have made significant contributions to specific aspects of this field, the proposed framework for underwater rescue operations using WSNs in this research paper aims to provide a comprehensive and integrated solution that addresses the diverse challenges associated with underwater SAR missions.

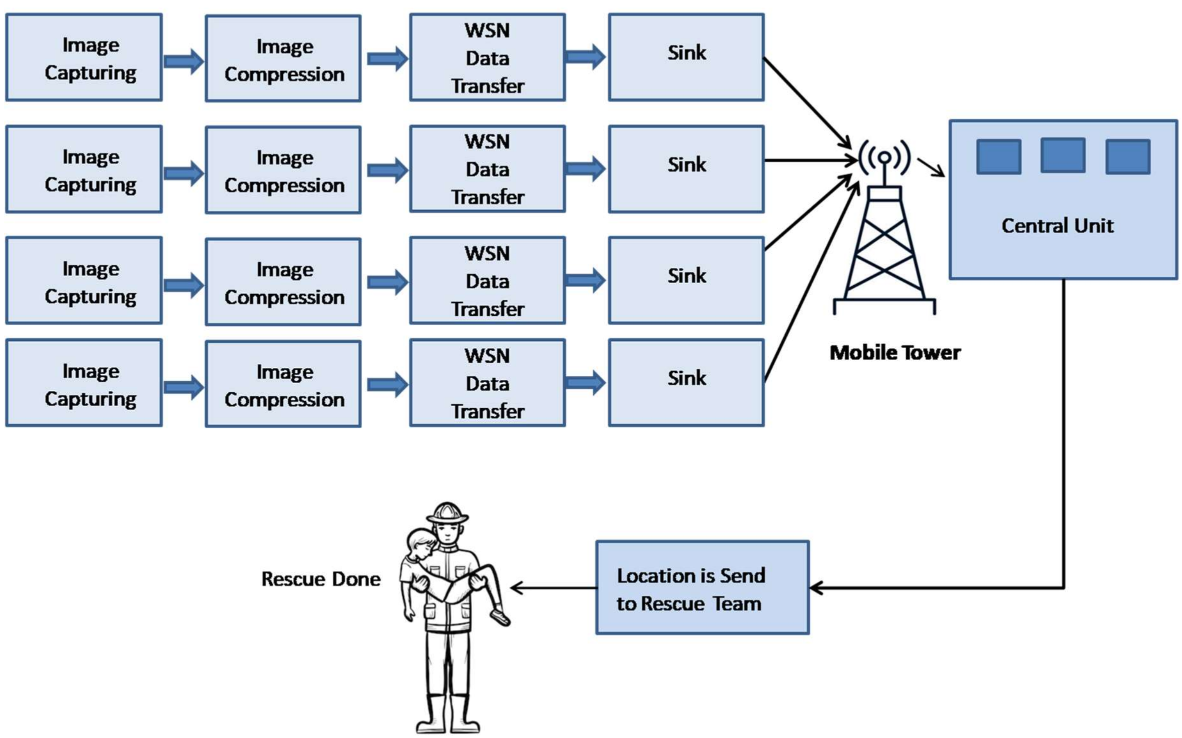


Figure 1: Block diagram of the proposed method

3. Proposed Framework

The proposed method for underwater person identification utilizes an image capturing-based scheme, as depicted in Figure 1 of the research work. This block diagram represents the overall framework and flow of the method. Here is an expanded description of the components and assumptions mentioned:

A. Image Capture

The first step of the proposed method involves capturing underwater images using appropriate imaging devices. It is assumed that the captured images are of good quality, meaning they have sufficient resolution, clarity, and contrast. High-quality images are crucial for accurate identification and analysis of submerged individuals. The choice of imaging devices may vary based on the specific requirements of the research or application.

B. Preprocessing

After capturing the images, preprocessing techniques are employed to enhance the image quality and optimize it for further processing. Common preprocessing steps may include noise removal, contrast enhancement, image denoising, and image stabilization to compensate for any motion or distortion caused by water currents or camera movement. These preprocessing steps aim to improve the visual clarity of the underwater images.

C. Image Compression

In the second stage of the proposed method, image compression is performed using 2D-DCT (Two-Dimensional Discrete Cosine Transform). This stage is crucial for achieving data reduction, which is a significant advantage of the compression process. Here is an expanded explanation of this stage and its benefits: Image compression is the process of reducing the size or amount of data required to represent an image while preserving its essential visual information. It aims to remove redundancies and irrelevant details from the image, resulting in a more compact representation. Compression is particularly valuable in scenarios where storage or transmission bandwidth is limited, allowing efficient utilization of resources.

D. 2D-DCT

The 2D-DCT is a widely used transform technique employed in image and video compression algorithms. It converts a spatial-domain image into a frequency-domain representation by decomposing the image into a series of frequency components. The 2D-DCT operates on blocks of pixels in the image, typically using square blocks of 8x8 or 16x16 pixels. Each block is transformed independently, resulting in a set of coefficients that represent the image's frequency content.

E. Data Reduction

The primary advantage of the image compression stage using 2D-DCT is data reduction. The transformation process allows for the concentration of image energy in a smaller number of coefficients, while the remaining coefficients contain less significant information or noise. By discarding or quantizing these less significant coefficients, the overall data size of the image can be significantly reduced without perceptible loss in visual quality.

F. Efficient Storage and Transmission

The reduced data size obtained through compression offers several benefits. Firstly, it enables more efficient storage of images, allowing for the storage of a larger number of images within a given storage capacity. This is particularly advantageous in applications where a vast number of images need to be stored, such as in surveillance systems or large-scale image databases.

Secondly, compressed images require less bandwidth for transmission over networks or communication channels. This is essential for scenarios where limited bandwidth is available, such as in remote monitoring applications or when transmitting images over wireless networks. By reducing the data size, image compression enables faster transmission, reduced latency, and more efficient use of available network resources.

2D-DCT

Assume that the data array has finite rectangular support on $[0, \mathrm{N}_1, -1] \times [0, \mathrm{N}_2 - 1]$, then the 2-D DCT is given as [17]

$$X_C(k_1,k_2) = \begin{cases} \sum_{n_1=0}^{N_1-1} \sum_{n_2=0}^{N_2-1} 4x(n_1,n_2) \cos\frac{\pi k_1}{2N_1}(2n_1+1) \cos\frac{\pi k_2}{2N_2}(2n_2+1), & \text{for } (k_1,k_2) \in [0, N_1-1] x [0, N_2-1] \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Note that unlike the DFT, where the highest frequencies occur near $(N_1/2, N_2/2)$, the highest frequencies of the DCT occur at the highest indices $(k_1, k_2) = (0,0)$. It turns out that eigenvectors of the unitary DCT are the same as those of the symmetric tridiagonal matrix,

$$Q = \begin{bmatrix} 1-\alpha & -\alpha & 0 & \cdots & \cdots & 0 \\ -\alpha & 1 & -\alpha & 0 & \cdots & 0 \\ 0 & -\alpha & 1 & -\alpha & \ddots & \vdots \\ \vdots & 0 & -\alpha & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & 1 & -\alpha \\ 0 & \cdots & \cdots & 0 & -\alpha & 1-\alpha \end{bmatrix} \quad (2)$$

and this holds true for arbitrary values of the parameter α.

3.1 WSN Data Transfer

The data collected via different sensors need to be transferred in the effective way, as in each round of transmission some of the energy of the sensor nodes get lost. The energy lost during each transmission is proportional to (d^2 or d^4) depending on free space or multipath propagation.

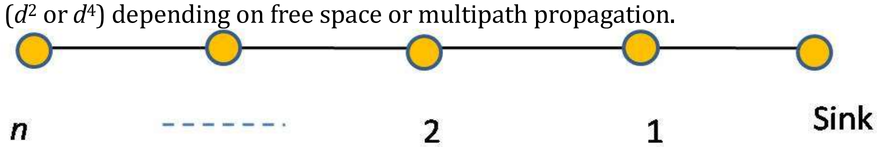


Figure 2: Schematic diagram of node to sink transfer

For simplicity assuming free space model, the energy lost in case of direct sink transfer by each node will be proportional to

$$E_{Lost} = d^2 + (2d)^2 + \ldots + (nd)^2 \quad (3)$$

$$E_{Lost} = d^2\left[1^2 + (2)^2 + \ldots + (n)^2\right] \text{ or} \quad (4)$$

$$E^d_{Lost} = d^2\left[1^2 + (2)^2 + \ldots + (n)^2\right] = d^2\left[\frac{n(n+1)(2n+1)}{6}\right] \quad (5)$$

In chain based structure, each node transmits its data to neighbour node which is towards the sink (Figure 2). In such a case the energy lost will be proportional to

$$E^C_{Lost} = d^2 + (d)^2 + \ldots + (d)^2 = nd^2 \quad (6)$$

Therefore, chain based structure is much better in comparison to direct transfer.

3.2 Sink to Tower Transmission

In the proposed system, the sink node serves as a central point for data aggregation and transmission in the WSN. The sink node is responsible for collecting the data from various sensor nodes within the network and forwarding it to the appropriate destinations. The system architecture, as shown in Figure 3, includes the transmission of data from the sink node to both a mobile transmission tower and an onshore station. Here is a detailed description of these transmission processes:

3.3 Mobile Transmission Tower

The sink node in the WSN has the capability to transmit data to a mobile transmission tower using radio waves. The mobile transmission tower refers to a cellular tower or base station that is part of a mobile communication network. The sink node, equipped with wireless communication capabilities, establishes a connection with the mobile transmission tower to transfer the collected data. When the sink node receives data from the sensor nodes in its vicinity, it aggregates and processes the information. Subsequently, it establishes a wireless communication link with the mobile transmission tower using radio waves. The sink node encodes the collected data into a suitable format for transmission, modulates it onto the radio waves, and transmits it to the mobile tower. The mobile transmission tower acts as a gateway between the wireless sensor network and the wider communication infrastructure. It receives the data from the sink node and forwards it to the appropriate destination, such as a data center or a cloud-based server, via the cellular network. This enables the dissemination of the collected data for further analysis, storage, or decision-making.

3.4 Onshore Station

In addition to the mobile transmission tower, the sink node also has the capability to transmit data to an onshore station. An onshore station refers to a fixed location or facility located near the water body or disaster-affected area where the wireless sensor network is deployed.

The sink node, after aggregating and processing the collected data, can establish a direct communication link with the onshore station. This communication link can be achieved using various wireless technologies, such as Wi-Fi, WiMAX, or other suitable protocols.

By transmitting data to the onshore station, the sink node provides a local access point for data retrieval and analysis. The onshore station can be equipped with more powerful computing resources and storage capacity, allowing for more in-depth data processing and real-time monitoring. It serves as a central hub for data analysis, decision support, and coordination of rescue or disaster management operations.

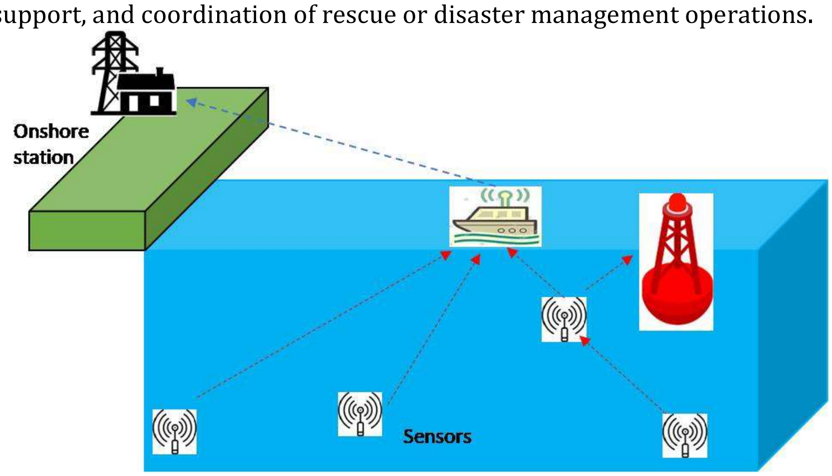


Figure 3: Schematic diagram of sink node to onshore transmission

3.5 Tower to Central Unit Transmission

Finally, data is transferred to central unit for processing. Here, main processing of the data is done (Figure 4). Here, the received image is first passed through the application software. Here, in the initial step image pre-processing is done and image enhancement is done (if required). Next using DNN human detection is performed.

A multi-class object detector can be created to carry out the task of underwater human body component detection. First, a multi-class object detector is created using a DNN-based model with pre-trained weights and a dataset of submerged human body parts. The trained detector is then fed an underwater human image as input to identify human body parts, producing detection results for the arm (A), head (H), torso (T), and leg (L). The detection results are then mapped back to the original image as various rectangular bounding boxes [18]. The DNN body component detector serves as the foundation of the suggested architecture, which is seen in Figure 5.

To differentiate between alive and dead body, in place of imaging a small video may be considered, and using the video frames movement of body parts can be detected.

3.6 Location Transmission to Rescue Team

Once human body is detected, the location of the sensor node is send to the rescue team and rescue is performed. It is clear that the human body rescue operation is multi step process. In this work, we only interested in the WSN protocol designing with lesser energy dissipation.

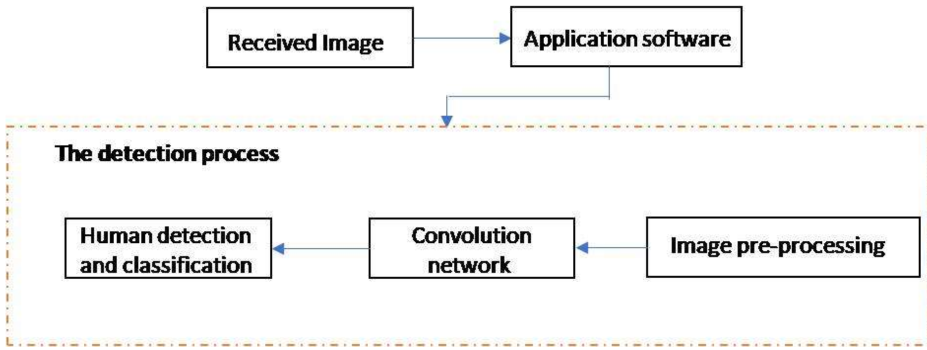


Figure 4: Block diagram for the underwater object detection

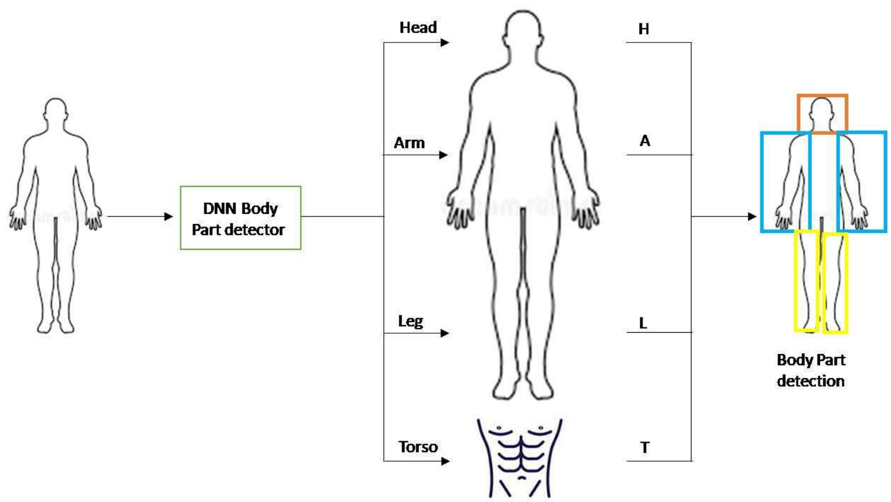


Figure 5: Block diagram for human body part detection

3.7 PEGASIS: Power-Efficient Gathering in Sensor Information Systems

In chain based methods sensors broadcast their acquired data to their nearby nodes, forming a lengthy chain. Except for the sensor nodes at the end of the chain, all sensor nodes in the chain turn into aggregation nodes. This protocol is known as Power Efficient Data Gathering Protocol for Sensor Information Systems (PEGASIS) [19]. In this protocol, every sensor node is considered to be aware of the network's overall knowledge. The chain's formation is started by the node that is located the furthest from the sink. Every time a chain is formed, the neighbouring node that is closest to the sink is chosen to replace the sensor node. After the chain has been formed, each sensor node receives sensed data from its neighbour. The information is combined with its own sensed information and sent on to its successor farther down the chain. Until all of the network's aggregated data reaches the sink, the cycle is repeated.

The most expeditious and straightforward method for transmitting data from network nodes located at a distance to the base station (BS) is direct broadcasting. Nevertheless, this approach has the potential drawback of accelerating the depletion of the nodes' batteries due to the extra energy required to reach the farthest BS. An alternative strategy, which is more energy-efficient, involves the utilization of the network's sensor nodes to establish cluster heads and cluster members. The fundamental idea of PEGASIS [19] revolves around having all nodes communicate or receive data from their closest neighbors. This is achieved through a process called chain forming, illustrated in Figure 6. Each node collects information, integrates it with the data received from its neighboring node, and forwards it to the nearest neighbor in a sequential manner. In this way, all nodes obtain and transmit their data in a chain-like fashion until they are interconnected with the BS. To relay the aggregated data collected along the chain to the BS, each node within the network takes turns serving as the leader of the chain.

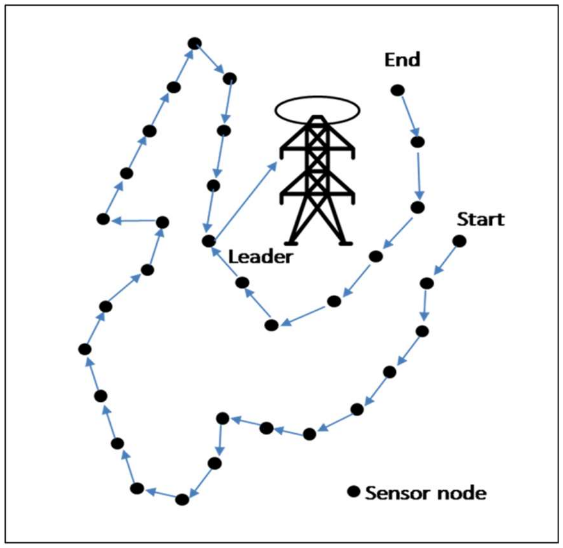


Figure 6: PEGASIS Protocol chain structure

Within this approach, the energy consumption of each node, on average, is reduced. To ensure the engagement of every node during the chain formation, we employ efficient greedy algorithms. It is not mandatory for each node to possess knowledge of its neighbouring nodes. Nodes can identify their neighbours either by transmitting signals, or the base station can orchestrate the chain's formation or path establishment for all nodes. In response to signal strength, nodes adjust their signals, ensuring they only communicate with their closest network neighbours.

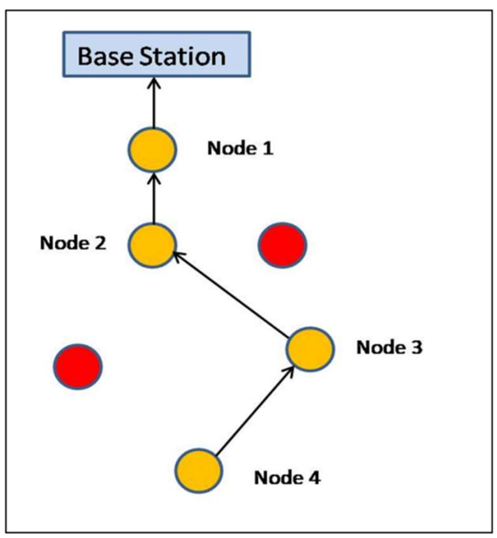


Figure 7: PEGASIS Protocol chain structure (Data Flow)

Figure 6 illustrates the operational concept of PEGASIS, where an efficient greedy algorithm links the most suitable nodes in a chain, ensuring that they are just one hop away from the base station. The initiation of data transmission begins with the selection of the farthest node, as depicted in Figure 7. In this scenario, if Node 4 takes the lead in the chain formation process and instructs network nodes to identify their nearest neighbour, it identifies Node 3 as the closest and subsequently forwards the data to Node 3. Node 3 then commences the search for its nearest neighbour by transmitting signals, merging its data with that received from Node 4, and transmitting the combined data to Node 2 upon determining that Node 2 is the nearest. Following Node 2's assessment of Node 1 as the closest, Node 2 transmits the sensed data along with the fused data. Eventually, Node 1 assumes the role of the leader and transmits all data since it is now the nearest node to the BS. This approach efficiently utilizes every network node for chain formation and fundamental data forwarding tasks, ensuring an equitable distribution of the energy load among the network's sensor nodes. When a node within the chain becomes inactive, a new chain is formed, effectively eliminating the non-operational nodes. However, it is worth noting that the quality of service is not particularly high due to data transfer delays and limited processing capabilities on either end. In the transmission of information packets to other nodes within the chain, each node supplements specific data with the packet. Network instability, such as connection errors, node malfunctions, or power outages, can potentially result in information loss.

The main limitations of PEGASIS are as under:

1. Due to the distance between the sink and the chain leader, there is a significant load on the single chain leader during chain construction, which requires a lot of energy.
2. Long single chains cause a significant delay in data delivery, making it unsuitable for time-sensitive applications. Long mutual distances during an unstable phase have a negative impact on the network's sparse nodes.

3.8 Proposed Multi-chain Protocol

In this work, we look into the issues of long chains for effective energy consumption and data delivery delays while taking sink mobility into consideration. By introducing the idea of many head chains, we also lessen the burden on the single chain leader. In this work given area is divided into 4 equal parts and at the center of each parts a sink node is provided. Smaller chains are produced and the stress on the leader nodes is reduced because of 4 sinks in the multi-chain model. Chain leaders are chosen in this section based on the forwarding function assigned to each node, which are calculated by dividing the node's residual energy (E_r) by its distance ($d_{i,sink}$) from the base station. The network compares the weights of each node in the chain and determines which node has the highest weight and is selected as the chain's primary chain leader.

$$CF(i) = \frac{E_r(i)}{d_{i,\sin k}} \tag{7}$$

The area is divided into 4 equal areas by the sinks, and nodes are distributed uniformly at random inside each region. Using compressive sampling, each sensor reduces the received bits by a data aggregation (DA) factor of 0.6.

In order to maximise network longevity, we assume that the sinks have infinite energy and they are static and are placed at (25m, 25m), (25m, 75m), (75m, 25m), and (75m, 75m).

Token is sent to the end nodes by the chain leader. The token is passed to the following node as the end node provides its data. As a result, each node i sends a token to node *i*-1 in the chain after transferring its data using the same procedure. As a result, the chain heads deliver data to the sink after receiving data from all of the chain's nodes. The same procedure is repeated in each of the four areas when the sink advances into the region of the first chain, receiving data from the first chain's chain leaders.

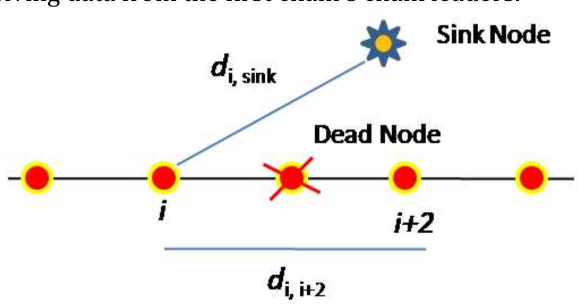


Figure 8: PEGASIS Protocol chain structure (Data Flow)

However, if an intermediate node of the chain dies, the preceding node will bypass this node and transfer data to the next successor node. In this case, the node will also evaluate its distance with the sink, and whichever distance is smaller, the node will transmit either to the sink node or the next node in the chain (Figure 8).

Referring Figure 8, let the node (i+1) dies in the chain, then node 'i' will evaluate its distance with next alive node in this case (i+2) as

$$d_{i.i+2} = \sqrt{(y_{i+2} - y_i)^2 + (x_{i+2} - x_i)^2} \; . \tag{8}$$

The node 'i' also evaluate its distance with sink node as

$$d_{i.\sin k} = \sqrt{(y_{\sin k} - y_i)^2 + (x_{\sin k} - x_i)^2} \; . \tag{9}$$

If $\left(d_{i.\sin k}, d_{i.i+2}\right) \le d_0$ then, data will be forwarded to node with min ($\left(d_{i.\sin k}, d_{i.i+2}\right)$).

However, if $\left(d_{i.\sin k}, d_{i.i+2}\right) > d_0$

The nodes will try to re-organize the chain, and if chain can't be formed the remaining alive node directly transmit to sink. Again each node evaluates its distance from neighbouring nodes and if neighbouring node distance is lesser as compared to its distance from sink then it will become part of new chain, and node with least cost function will become chain leader.

Advantages

1. Smaller chains will be formed thus lesser dissipation of energy as compared to single chain in PEGASIS.
2. Less frequent chain re-formation due to the dead node bypasses mechanism.
3. Provision of direct transfer in case of dead node further saves energy.
4. Delay gets reduced due to the smaller chains.

4. Simulation Results

The radio model is employed to account for the characteristics of the wireless medium. Over time, several radio models have been suggested for WSNs. In a broad sense, it has been observed that the first-order radio model, as detailed in [20], is well-suited for WSNs. According to the first order radio model, the transmission channel's energy loss is proportional to d^2 where the distance between the transmitter and receiver is represented by d. The first order radio model equations are defined as in Figure 9.

$$E_{TX}(S,d) = E_{TX-elec}(S) + E_{TX-amp}(S,d) \tag{10}$$

In case of free space model the transmitted power is given by

$$E_{TX}(S,d) = E_{TX-elec} \times S + E_{TX-amp} \times S \times d^2 \tag{11}$$

In case of multipath space model the transmitted power is given by

$$E_{TX}(S,d) = E_{TX-elec} \times S + E_{TX-amp} \times S \times d^4 \tag{12}$$

The received power is given by

$$E_{RX}(S,d) = E_{RX-elec}(S) \times S \tag{13}$$

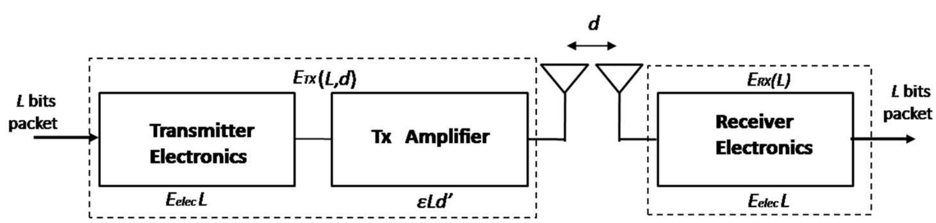


Figure 9: First order radio model

where E_{TX} and E_{RX} stand for the energy used during transmission and reception, respectively, and $E_{TX\text{-}elec}$ and $E_{RX\text{-}elec}$ are the energies required for the operation of the electronic circuit of the transmitter and receiver. The term "E_{amp}" refers to the amount of energy used by the amplifier circuit. S represents the size of each packet.

The simulation of WSN routing protocols involves the consideration of various parameters to evaluate their performance and efficiency. The list of parameters commonly used in WSN routing protocol simulation is shown in Table 1.

These simulation parameters help in analyzing the energy consumption, performance, and coverage of the WSN. By varying these parameters, researchers and practitioners can evaluate the behavior and efficiency of different routing protocols, data aggregation techniques, and network configurations in WSNs.

Table 1: Simulation Parameters [20]

Parameters	Value
Initial Energy E_0	0.5, 1.0 and 1.5 J
Energy for data aggregation E_{DA}	5 nj/bit
Transmission and Receiving energy	5 nj/bit
Amplification energy for short distance E_{fs}	10 pj/bit/m^2
Amplification energy for long distance E_{amp}	0.013 pj/bit/m^4
Number of nodes	100
Field Area	100×100 m^2

4.1 Compression results

In figure 10 and 11 compression results are shown. In Figure 10, DCT matrix mosaic is shown. In Figure 11 an underwater image is shown.

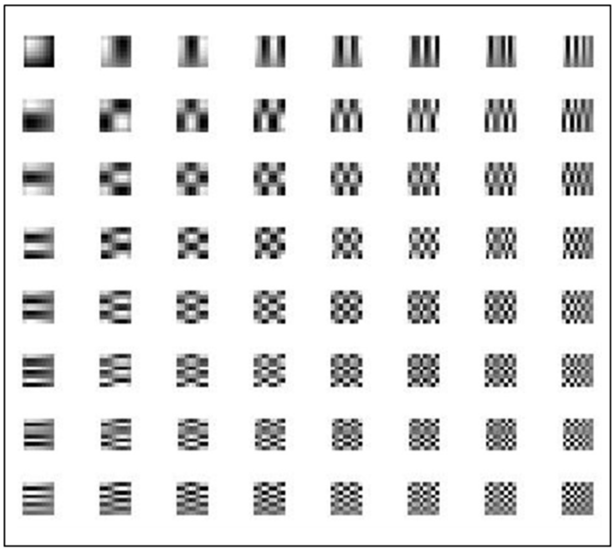


Figure 10: 8×8 Block Size

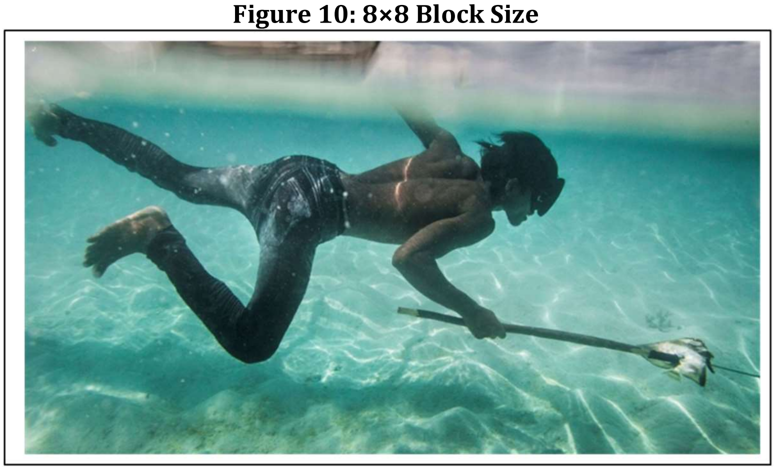
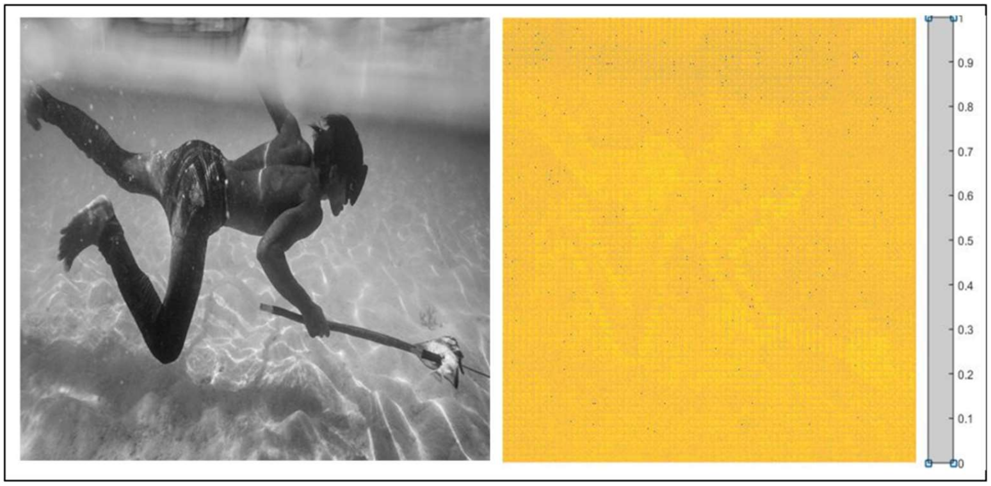


Figure 11: Underwater human image

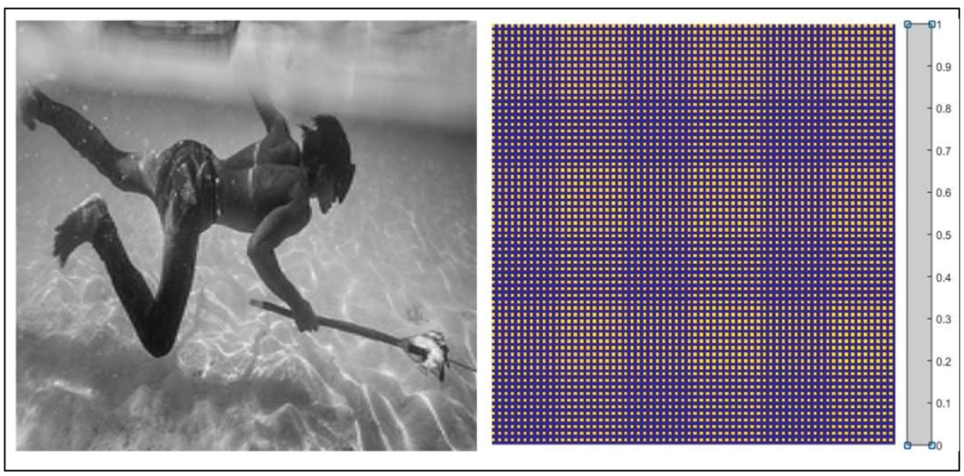
In Figure 12, the DCT of the underwater image is shown. As an initial step, the image in Figure 12 is converted into gray image, as shown in Figure 12(a) and in Figure 12 (b) its map is shown. In Figure 13 (a) reconstructed image of 20 Co-efficient is shown and corresponding map is shown in Figure 13 (b). The size of colour image is

205 KB, which reduces to 37 KB after gray conversion, and finally after compression the size of image reduces to 22 KB. Thus nearly 40% reduction in size is observed, without deteriorating the image quality.



(a) Original Image (Grey) (b) Image Map

Figure 12: Underwater human image processing



(a) Reconstructed image (20 Co-efficient) (b) Reconstructed image map

Figure 13: DCT of the underwater image and its map

The human body portion accuracy with CNN for head is 77.26%, for arm accuracy is 62.64%, for torso accuracy is 62.28%, leg accuracy is 52.44% with human identification accuracy is 88.34% and the speed for the human recognition form an image is 468ms [18].

4.2 WSN Protocol Results

In the Figure 14, the schematic of chain creation in PEGASIS protocol is shown. Here, distance between some of the chain forming nodes is very large; this will lead to the faster depletion of the energy of the nodes, leads to the break of chain. The operational nodes vs. transmission rounds without data compression for PEGASIS protocol are shown in Figure 15. Here, in case of energy E_0 = 0.5 Joule, the stability period is only 212 rounds. The stability period increases to 452 rounds in case of the energy E_0 = 1.0 Joule, the stability period further improves as the energy is increased, i.e., for the energy E_0 = 1.5 Joule, the stability period is 1045 rounds. The operational nodes vs. transmission rounds with data compression for PEGASIS protocol are shown in Figure 16. Here, in case of energy E_0 = 0.5 Joule, the stability period is only 522 rounds. The stability period increases to 786 rounds in case of the energy E_0 = 1.0 Joule, the stability period further improves as the energy is increased, i.e., for the energy E_0 = 1.5 Joule, the stability period is 3573 rounds.

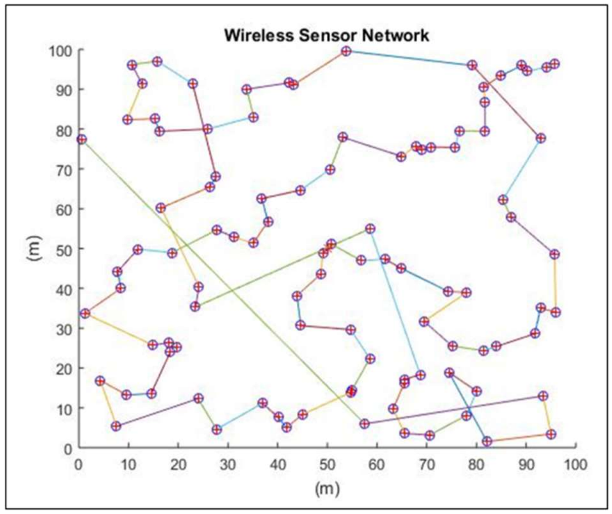


Figure 14: Schematic of chain creation in PEGASIS protocol

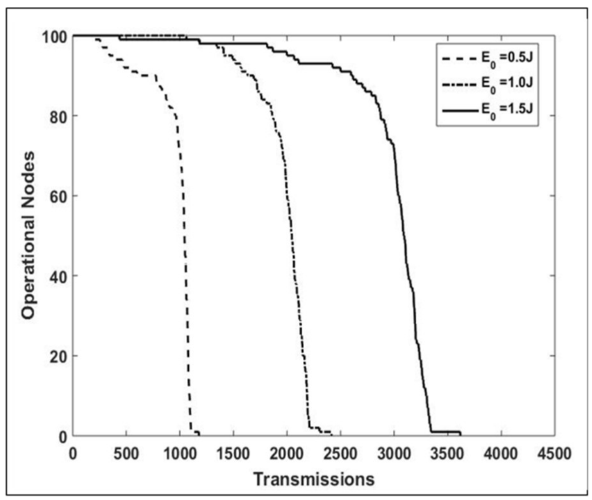


Figure 15: Schematic of operational nodes vs. round of transmission (PEGASIS protocol without data compression)

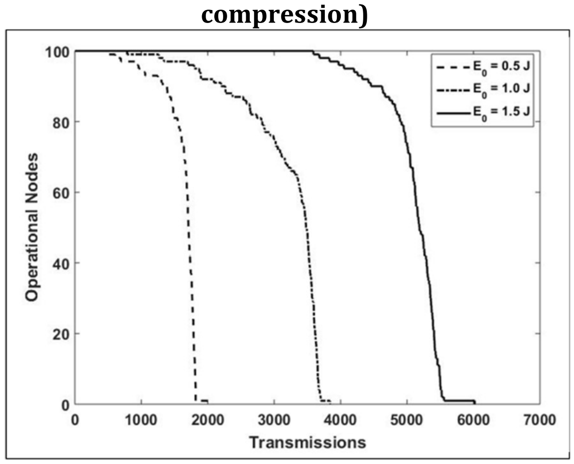


Figure 16: Schematic of operational nodes vs. round of transmission (PEGASIS protocol with data compression)

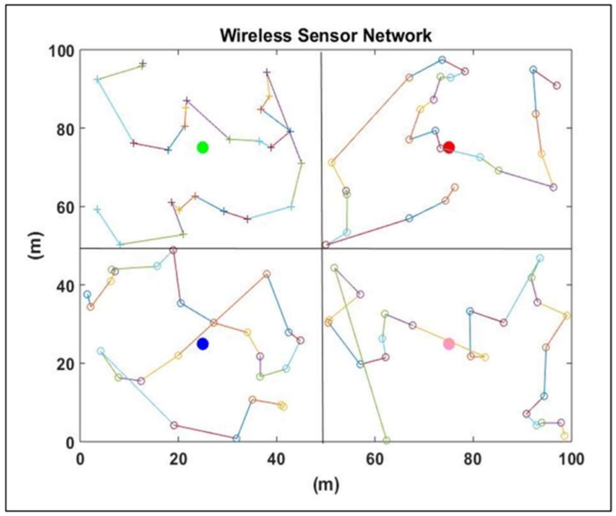


Figure 17: Schematic of chain creation in proposed protocol

In the Figure 17, the schematic of chain creation in proposed protocol is shown. Here, distance between the chain forming nodes is small; this will lead to the slower depletion of the energy of the nodes, leads to the longer survival of the chain.

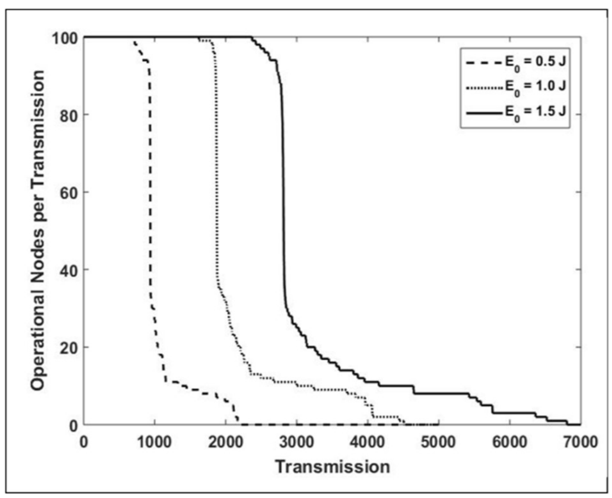


Figure 18: Schematic of operational nodes vs. round of transmission (Proposed protocol without data compression)

The operational nodes vs. transmission rounds without data compression for proposed protocol are shown in Figure 18. Here, in case of energy E_0 = 0.5 Joule, the stability period is only 702 rounds. The stability period increases to 1627 rounds in case of the energy E_0 = 1.0 Joule, the stability period further improves as the energy is increased, i.e., for the energy E_0 = 1.5 Joule, the stability period is 2372 rounds.

The operational nodes vs. transmission rounds with data compression for proposed protocol are shown in Figure 19. Here, in case of energy E_0 = 0.5 Joule, the stability period is only 1245 rounds. The stability period increases to 2645 rounds in case of the energy E_0 = 1.0 Joule, the stability period further improves as the energy is increased, i.e., for the energy E_0 = 1.5 Joule, the stability period is 3769 rounds.

The stability period is an important criterion for the evaluation of the WSN protocols. The stability period is defined as the number of rounds of transmission until all the nodes in the WSN network is alive. This is important for the survival of the chain. The stability period under various schemes are detailed in Table 2.

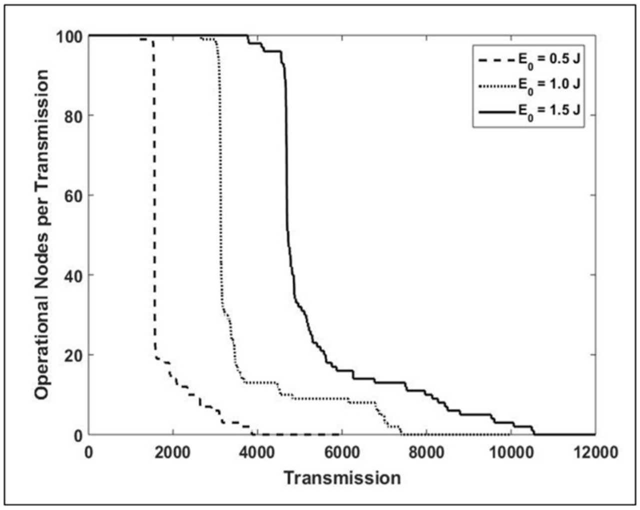


Figure 19: Schematic of operational nodes vs. round of transmission (Proposed protocol with data compression)

Table 2: Comparison of various protocols

Protocol	Energy	Stability Period (Rounds)
	0.5 J	212
PEGASIS	1.0 J	452
	1.5 J	1045
	0.5 J	522
PEGASIS (Data Compression)	1.0 J	786
	1.5 J	3573
	0.5 J	702
Proposed	1.0 J	1627
	1.5 J	2372
	0.5 J	1245
Proposed (Data Compression)	1.0 J	2645
	1.5 J	3769

4.3 Delay Analysis

Delay analysis is important in real-time rescue operations. Here, an estimate of delay is presented from the image capturing to the information send to rescue team.

Image transmission delay: The Transmitters and receivers in WSN can transmit and receive data at the data rate of 250kbps.The size of reduced image is 22KB. Therefore time needed for the transmission is (22×8)/250=0.7 second. In the longest chain it may traverse through the 24 intermediate nodes. Thus the overall delay will be 0.7×24=16.8 seconds. The propagation delay can be neglected as data will travel with speed of light. The delay at the control unit is 468 ms. Thus, the total delay will be 16.8+ 0.46=17.26 seconds. In case of videos for alive person detection while considering 5 frames for motion detection total time would be 17.26×5 seconds or nearly 1.5 minutes.

5. Conclusions

In conclusion, the framework presented herein harnesses the potential of Wireless Sensor Networks to revolutionize underwater rescue operations. Through a synergy of advanced sensor technologies, communication infrastructure, data analytics, localization methods, and resource management strategies, this framework offers a comprehensive solution to the unique challenges of underwater disasters. While facing ongoing challenges in communication reliability and power efficiency, the promise of enhanced survivor detection, reduced response times, and optimized resource allocation is undeniable. As we navigate an era marked by rapid technological advancement and increasing marine safety needs, this framework serves as a pivotal milestone, offering hope for safer and more efficient underwater rescue missions, ultimately benefiting both human lives and marine ecosystems.

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