Study in Maximizing the Value of Sensed Information in Underwater Wireless Sensor Networks via an Autonomous Underwater Vehicle

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***Abstract*—The advancement and activities with the importance of underwater sensor networks (UWSNs) and effective data collection have attracted many studies around the world. This paper discusses the importance of effective data collection within the underwater sensor network and compares the various approaches for effective data collection. It illustrates the background, history, and methods of underwater data collection, challenges, and recent approaches adopted for the data collection. The sensors(nodes) underwater produce volumes of information whereas the UAV(underwater autonomous vehicle) is deployed to capture the maximum volume of information produced by the sensors to find the effective path for UAVs within the given timeframe. The paper describes the approaches for effective data collection the ILP(integrated linear programming) model, the volume-based GAAP(Greedy and Adaptive heuristic approach) GAAP with different starting surfaces for UAV, the non-volume-based simple heuristic approach, and the comparison, between [1]. The comparison between this approach was replicated as in paper [1] shows that the volume-based approach (GAAP) was much more effective and showed around 80 percent more than that of the simple TSP(traveling salesman)-heuristic approach,non-volume based approach. The result was successfully replicated and simulated.**

I. Introduction

The development of underwater wireless sensor networks (UWSN) is being facilitated by the widespread use of wireless sensor networks (WSN) in a variety of application areas and the rapid advancement of sensor technology[2]. A UWSN is made up of underwater sensor nodes, which work together to monitor underwater locations and events of interest and have the capacity to sense, analyze, store, and communicate wirelessly underwater[3]. These devices can wirelessly connect with one another to carry out real-time underwater monitoring and actuation thanks to the usage of the underwater acoustic modem[3]. The application of this includes the study and monitoring of the underwater environmental conditions, Marine life biology and conditions of soil and texture parameters, Oil and gases industries, defense and navy operations, and search and rescue operations. The potentiality of the application is very huge with the advancement of the ongoing interest and research in the field of underwater technologies and these applications. The successful implementation of these use cases requires underwater sensors to communicate and share data ground units, which are majorly audio and video data, effectively in a realistic time to ensure the effectiveness and accuracy of the deployed use case. The implementation of these models requires high-end effectiveness and the cost of the implementation and real-time testing seems to be a challenge for such kinds of work. Many of the unique issues that UWSNs encounter are limited bandwidth capacity, high and variable propagation latency, transient path loss, high noise, multipath fading, shadow zones, Doppler spreading, and high communication energy costs[3]. In this paper, we discuss several methods, the technology that was used previously, newer modules, and algorithms followed and will effectively implement the solution and algorithm presented in the paper [1], effectiveness of the applied model, real-time replication of given approaches and the use cases and difficulty of the models. The conditions considered are the sensors that are deployed underwater which produce a high volume of data that requires optical communication where the transfer rate of the data is very high(up to 10mbps). The nodes produce the events based on the value of the information. The AUV visits the nodes in the given time to collect the data periodically and dump the data to the surface. We discuss and implement the integrated learning programming model(ILP), GAAP(Greedy and Adaptive AUV Pathfinding), and heuristic TSP for AUV routing, pathfinding, and data dump.

1. The ILP model provides provable limits on the optimal network performance, including the highest possible Value of Information (VoI), for benchmarking distributed protocols. It operates independently of sensor deployment strategies and features adjustable parameters for data generation and transmission rates, as well as AUV speeds. This approach allows to calculate of an upper bound on the maximum VoI obtainable from networks, with typical sizes of 4 to 9 nodes and ideal sizes of 12 to 35 nodes in UWSNs [4].

2. GAAP(Greedy and Adaptive AUV Path-planning) is the deployable heuristic model that adapts to events that occur at unpredictable locations and times. The AUV selects the next node to visit based on the value of information(Vol) at the time. The decision to visit the next nodes is determined by the value known as event packets that are transmitted by acoustic

channel. The AUV will plan to visit a node that has sent an event packet only if doing so increases the VoI of the data it will deliver to the sink. Since it makes real-time decisions based on current conditions and continuously adapts its path planning to new information[1].

3. The Non-volume aware or the simple heuristic path-finding model is also a deployable heuristic model. Based on the distance between nodes, the heuristic is characterized as a traveling salesman problem (TSP). This heuristic states that the AUV begins from the same surface, transmission rates, and closest node of the data value, gathers all of the data provided by that node thus far, resurfaces, and sends the data to the sink. And AUV continues along the predetermined path to the next node until the time limits [1]. The path in this approach is predefined and AUV visits each node without taking care of the value of information.

II. Background

Oceanographic sensors are typically used to monitor the ocean floor. They are placed in a fixed spot, where data is recorded, and the instruments are recovered once the operation is over.[5]. Compared to air communications, underwater communication is severely restricted because, aside from the visible band, water is essentially impenetrable to electromagnetic radiation. In the clearest waters, light barely reaches a few hundred meters even in the visible range; in waters turbid due to suspended silt or high marine life concentrations, light penetrates much less[6]. The primary drawbacks of the traditional technique are the absence of interactive contact between the many ends, the inability to access recorded data during a mission, and the destruction of recorded data in the event of a failure[5]. With the advancement of technology and research, several oppraches are practiced for effective data and smooth data collection within the underwater sensor network which we will be discussing here.

Traditionally the data collection was performed with the Radio Freduency but the special characteristics of the underwater, the RF functions poorly in UWSNs[7]. The acoustic channel creates more challenges such as the reliability of the data collection where the error rate is very high, the packets get collied, and the voids in routing. To overcome these challenges with the slow and less data transfer rate, several AUV-based approaches are been introduced where the transfer of data is more effective and transmission in optical communication takes place. Numerous programs have implemented Autonomous Underwater Vehicles (AUVs), which move between sensors to aid in data collecting, Utilizing AUV mobility allows for a large reduction in signal propagation distance, enabling the use of RF, optical, and other technologies in underwater environments [7] The realistic communication speed of optical and acoustic communication has been described below which illustrates that optical communication requires a distance of less than 100 m where the data transmission is very high but Acoustic communication range can communicate over a very long distance .

Telemetry Method	**Range**	**Data Rate**
Acoustic	Several km	1 kbps [6]
Optical	100 meters	1 Mbps[6]

TABLE I
Performance comparison of acoustic and optical telemetry

III. Literature Review

Given the importance and demand of UWSN technologies, a lot of progress has been made with the approach and architecture used to collect data and process them more effectively. The 2nd edition of the paper [1] where the researchers continued to expand their model defines the more appropriate and effective method where several other constraints like power consumption, which is very required with the underwater sensors were discussed. The paper .[4] where the experiment was conducted for the multi-model underwater sensor, sets the experiments with the indicating the comparable parameters like Delivered volume, Energy efficiency(ratio of total energy consumption to delivered volume), throughput value, end-to-end latency between the nodes. All these parameters were considered in the process and the experiment was set with GAAP, TSP-Heurstic, ILP model. The result from the experiments shows that the volume-based approach for all the parameters where much more effective for the pathfinding and value of retrieved information. The experiment's findings demonstrate that VoI decays exponentially, In networks with four nodes, GAAP delivers VoI that is at least 77% higher than TSP's, and we found that GAAP is consistently the reliable method when compared to other options.[4]. The VoI provided by all options grows when events occur closer together as the network density rises. In terms of energy efficiency, GAAP is at least 30% more effective than TSP for the nodes, and their data chunk's VoI is higher[4]. The VoI-aware behavior of GAAP enables the AUV to collect and transmit higher-value data chunks, GAAP provides 57% in networks with 35 nodes[4].

The recent development of small computing devices, IOT(internet of Things) has a broader base and impact in several areas. With the approach of the data collection through AUV aided method which several dropbacks like latency, the paper [8] proposed a mobile edge computing method where the AUV runs as the computing device and process of the data happens within the AUV. The direction and velocity of AUV mobility are fully taken into account in this model, and they are nearly identical to the mobility characteristics of AUVs in a stable three-dimensional environment. A target selection method is developed to determine the mobility path of an AUV's data gathering, taking into account the processing, storage, and mobility capabilities of the vehicle. The targeted algorithm is based on the clustering model, in which the cluster head—the node that was determined to be the most stable—was chosen by the researchers using the k-means algorithm to cluster the nodes, and an AUV then determines the path based on the cluster head. The outcome demonstrates that a realistic mobility model could increase package delivery ratio, decrease energy usage, and lengthen network lifetime.[5]

The paper [2] compares the existing methods for the data collection and hybrid model Internet of Underwater Things (IoUT) which are entwined with intelligent boats and ships, automated maritime transportation, location and navigation, underwater discoveries, catastrophe predicting and avoidance, as well as intelligent monitoring and security. The goal of the paper [2] self-deployment technique, which is based on the virtual forces of AUV in a three-dimensional environment, is to increase the random network's size while maintaining high node connectivity. The suggested approaches guarantee high connectivity and display the maximum coverage area, but they leave out the necessary dynamic modification [2], such as GAAP.

A. Challenges

The motivation behind the extensive study of the UWSNs with the promising use cases has never been easy. The deployment of such architectures requires extensive resources which we will discuss in the proposed area. The implementation of such a high network underwater has been an underlying challenge. Beyond tens of meters, acoustic waves are preferred for underwater communication since water attenuates and scatters practically all electromagnetic frequencies[9].The sharing of the information between the nodes where the data are relatively high like audio and video seems challenging. Other major challenges for the nodes are their initializations, some of the applications require precise locations which are challenging in underwater environments. Acoustic signals do not travel in a straight line in underwater acoustic channels, which are highly dispersive and dense multipath that hinder arrival estimate time delays caused by stratification and because sensor networks are being deployed widely, centralized solutions are not possible[9].

IV. Methodology

Here we discuss the three major approaches that were proposed and discussed in paper [1] for effective data collection. We will understand the approach in depth and we will implement the GAAP and TSP-heuristic we realistic parameters within the virtual environment and test the outcomes.

A. Integrated Linear Programming

The objective function maximizes the value of information collected from all nodes and delivered by time T which has been described in the paper [1]

Objective Function: Maximize the total value of delivered data chunks:

$$\text{maximize} \quad \sum_{(d_{i,p},t)\in F} v_{i,p} \cdot x_{ti,p} \tag{1}$$

[1][3][4]

B. GAAP(Greedy and adaptive path finding heuristic approach)

The approach to solving the ILP gives us the optimal approach and effective value but would require a large number of information on the events and consumes a large computation time. Here we will discuss in brief the GAAP approach, that we implemented which takes in the events, and sensed information where the event value is taken into account for finding the next node. **Purpose:** To calculate the Value of Information (VoI) from a node S_i, considering the data chunks available, the time to collect and deliver data, and the total operational time T.

Inputs:

- S_i: Node S_i (the node from which the data is collected)
- $\#$: Number of data chunks at S_i
- VoI info: Value of Information details for data chunks
- T: Total time for network operations
- t_c: Time required for data collection and delivery
- T_i: Maximum time available for operations

Outputs:

- VoI_{S_i}: Value of Information from node S_i
- t_f: Delivery time of data chunks from node S_i
- S: Strategy for collection and delivery

Algorithm 1 VoIFromNode(S_i, $\#$, VoI info, T, t_c, T_i) [1][4]

Initialize:
$\text{VoI}_{S_i} \leftarrow 0$
$t_f \leftarrow 0$
$S \leftarrow$ "Not determined"
Create a queue L_d based on the VoI of data chunks available at S_i:
$L_d \leftarrow$ VoI-based queue of data chunks in descending order of VoI
for each data chunk j in L_d **do**
  Calculate the VoI of the data chunk:
  $\text{VoI}' \leftarrow$ VoI of data chunk j
  Calculate the time required to collect and deliver data chunk j:
  $t' \leftarrow$ Time to collect and deliver data chunk j
  if $t_c + t' > T_i$ **then**
    Break the loop (Cannot process due to time)
  end if
  if $\text{VoI}' \geq \text{VoI}_{S_i}$ **then**
    $S \leftarrow$ "Deliver data chunks at a time"
    $t_f \leftarrow t_c + t'$
    $\text{VoI}_{S_i} \leftarrow \text{VoI}'$
  end if
end for
Return: VoI_{S_i}, t_f, S

C. TSP-Heurstic (Non-volume based approach)

The TSP-Heurstic approach used the predefined path based on the equilateral distance between the nodes. The path for the AUV is initially set at the beginning based on the distance between the nodes and the value of information is collected based on the same nodes.

Algorithm 2 auvTsp(sensors, eventRate, auvSpeed, videoSizeBits, opticalDataRate, timeUnit)

[4][10]

Initialize:
currentTime ← 0
auvPosition ← $(0, 0, 0)$ (Initial position at the surface)
totalVoI ← 0
path ← [auvPosition] (Store the path of the AUV)
Generate initial events for sensors:
for sensor in sensors **do**
  if random.random() ¡ eventRate * timeUnit **then**
    sensor.generateEvent(currentTime)
  end if
end for
Compute the TSP path using the nearest neighbor heuristic:
tspPath ← nearestNeighborTsp(sensors)
for sensor in tspPath **do**
  distance ← calculateDistance(auvPosition[0], auvPosition[1], auvPosition[2], sensor.x, sensor.y, sensor.z)
  travelTime ← distance / auvSpeed
  currentTime ← currentTime + travelTime
  auvPosition ← (sensor.x, sensor.y, sensor.z)
  path.append(auvPosition)
  Collect data and calculate VoI:
  for event in sensor.events **do**
    eventTime, value, duration ← event
    if currentTime - eventTime ¡ duration **then**
      voi ← value * math.exp(-(currentTime - eventTime) / duration)
      totalVoI ← totalVoI + voi
    end if
  end for
  Surface and transmit data:
  surfaceTime ← sensor.z / auvSpeed
  currentTime ← currentTime + surfaceTime
  auvPosition ← (auvPosition[0], auvPosition[1], 0) (Move to surface)
  path.append(auvPosition)
  transmissionTime ← videoSizeBits / opticalDataRate
  currentTime ← currentTime + transmissionTime
  Add a unit time for the next step:
  currentTime ← currentTime + timeUnit
end for
Return: `path, totalVoI`

V. Simulation and Results

The simulation of GAAP and TSP-heuristic was conducted using the simulation in Python and Google colab, a cloud-based Python integrated development environment[10]. The simulation was run with T4 GPU in Google Collab. We simulated the GAAP and TSP with realistic parameters. The sensors were considered as nodes and were randomly distributed within the surface of $2000 \times 3000m$ in the rectangular format. The number of sensors was $s = |4, 5, 9, 12, 18, 35|$. The depth of the surface was considered between 500 to $1000m$ randomly. The speed of the vehicle was considered $1.8m/s$.The optical communication between AUV and nodes was set to be 10mbps and it must be within the range of $100m$. The data rate produced by the nodes was taken $9mb$ where each node produces the data every 5 min. The data rate was converted in the bits so the data produced by each node were $9mb \times 8 \times 10$. The event produced by the node was set using the poisson where the arrival rate was set to 60×60 sec. The value for the event was set between 0.4 to 20. The time unit for the simulation was set for an hour and the process was repeated almost 100 times and the results were recorded.

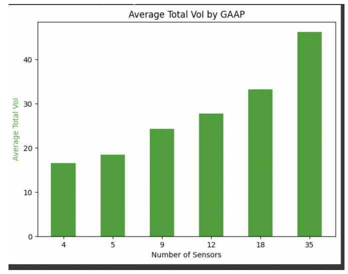

Fig. 1. GAAP-Result

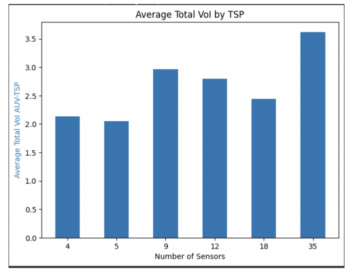

Fig. 2. TSP-heuristic Result

A. Results-GAAP

The result of the simulation conducted for the GAAP we obtained that the value of information decomposed at the surface was very as follows: Number of sensors: 4, Average GAAP VoI: 16.499344254036814 Number of sensors: 5, Average GAAP VoI: 18.441833965158718 Number of sensors: 9, Average GAAP VoI: 24.31217007808305 Number of sensors: 12, Average GAAP VoI: 27.767764831959244 Number of sensors: 18, Average GAAP VoI: 33.20959800209222 Number of sensors: 35, Average GAAP VoI: 46.145729362617715. This is as seen in Figure 1

B. Result-TSP-heuristic

The simulation was created with similar parameters as above for the GAAP but the path planning for the AUV was based on the equilateral distance between the nodes. The value of the information obtained from the simulation was as follows. Number of sensors: 4, Average Tsp VoI: 2.131848745891194 Number of sensors: 5, Average Tsp VoI: 2.050586130851999 Number of sensors: 9, Average Tsp VoI: 2.9653667059350566 Number of sensors: 12, Average Tsp VoI: 2.7964797194328037 Number of sensors: 18, Average Tsp VoI: 2.440258655045498 Number of sensors: 35, Average Tsp VoI: 3.6142395812423094 This is as seen in Figure 2

Comparision and discussion After multiple simulations of the model, we considered different scenarios. The result with GAAP, TSP-heuristic, and to see the influence of the starting point of AUV TSP-heuristicAUV we also considered changing the starting location of the AUV. We considered three different scenarios, first where we considered the central starting point on the surface, second we calculated the worst starting point based on the localization of the nodes and third we calculated the ordinary starting point. We performed this simulation under GAAP. We can see that the volume-based approach where the path for the AUV was defined showed a clear result and the volume of the information obtained was recklessly high about 80 percent higher as compared to that of the TSP-heuristic. The ILP shows effective results as per the paper [1] but the optimization of ILP requires high computation power and requires a huge amount of time.

VI. Related Work

In recent days, UWSN has developed huge attention following the growing use cases and activities in an ongoing underwater environment. The advancement in sensor technology aided the study and research. One of the difficulties is that there are significant disadvantages to both the optical and auditory underwater communication options. And the need for quick data transfers for surveillance applications—particularly those involving large data productions (such as video and sonar-generated files—many research projects combine various data transfer techniques, including acoustic networking, short-distance optical transport, and physical data transport using an AUV [1]. With the acoustic communication latency and the communication between them being very low, the AUV-aided strategy has been applied for the data collection underwater. A mobicast protocol that circumvents the network's low efficiency was developed by author[11]. This involves the formation of a 3-D ZOR, or nearby 3-D geographic region, by sensors for every AUV underwater. The results in [11] showed that the increase in the network increases the delay time. In AUV-assisted underwater protocol (AURP), multiple AUVs are utilized as the relay nodes for collecting data packets from gateway nodes to get data reached sink node [3].

The author in the [3] assumes the optimal communication where the communication rate is around 10mbps between the AUV and nodes within the 100 meters with the implementation of GAAP shows the maximum volume of the information being conveyed at the surface as compared to that of other methods. Similarly in the paper [6],[3] shows that the integrated optical and audio capabilities system, an application in which data is sent from a seafloor borehole observatory to an AUV. The AUV can use audio communication to interact with multiple adjacent sensor nodes In acoustic networks, however, the likelihood of packet loss rises with distance [1],[3]. This results in the formulation of a problem wherein the AUV's path needs to be chosen in a way that optimizes the trade-off between path cost and the total quality of information of the data collected, as evaluated by a probabilistic algorithm[1]. The architecture works with the influence of the value of information(VOl) which takes into account this value. Initially, the path planning algorithms didn't take into account the concept of the value of information(vol). The sensors underwater produce a huge amount of information Some of the values of the data might not be relevant and it's almost impossible to capture all the data, so the AUV must make the decision which value of information must be selected or plan the path based on the value of information generated from the each node of the source. The concept of the value of information was originally published in paper[12]

The author [13] and the author [14] provide descriptions of two of the first instances of this type of UWSN. Sensor nodes and mobile AUVs running TinyOS have integrated acoustic and optical communication protocols. It is expected that nodes generate data at a constant pace of equal, non-decaying value and that nodes never lose data due to overflow[1][2]. In this instance, AUV pathfinding can be boiled down to an AUV pre-loaded route that directs the nodes to be visited one after the other in a sequential manner[2]. Considering the scenario, with the movement of the AUV there have been some recent studies with mobile edge computing devices, where the AUV acts as a small computing unit and follows the predefined path based on the routing algorithm. The author in [8] describes a model where the AUV acts as a small edge computing device and by far follows the path based on the defined algorithm. The model properly accounts for both velocity and direction of motion, which closely resembles the mobility characteristics of autonomous underwater vehicles in stable three-dimensional environments[8]. A target selection method is created to determine the mobility path of data collection for AUVs by utilizing the computational, storage, and mobility capabilities of AUVs. The proposed method follows the K-means clustering-based approach for finding the next path where clustering-based) the most stable clusters act as the next path. This shows that effective data collection leverages energy consumption and maintains data privacy.

VII. Conclusion

We successfully conducted a detailed study on underwater sensor network technologies. We briefed the background of the underwater sensors data collection technologies, the history, preliminary used technologies, and the challenges with the deployment, testing, and effective data collection underwater. We also successfully discussed the new proposed emerging architectures. We discussed in detail the three major algorithms ILP, GAAP, and TSP-heuristic, and tested their simulations. We successfully replicated the model and showed that the GAAP where the value of the information is, and the volume-based approach where the sensors emit the value of information greatly exceed other non-volume-based approaches and were able to capture maximum data.

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