Optimizing Resurfacing Schedules to Maximize Value of Information in UWSNs

Fahad Ahmad Khan, Saad Ahmad Khan, Damla Turgut and Ladislau Bölöni
Department of Computer Science
University of Central Florida, Orlando, FL 32816-2450
{fahad.khan}@ucf.edu, {skhan, turgut, lboloni}@cs.ucf.edu

***Abstract*—In Underwater Sensor Networks (UWSNs) with high volume of data recording activity, a mobile sink such as a Autonomous Underwater Vehicle (AUV) can be used to offload data from the sensor nodes. When the AUV approaches the underwater node, it can use high data rate optical communication. However, the data is not considered delivered when it was transferred from the sensor node to the AUV, but when the AUV had *resurfaced* and transferred the data to the sink. If the data is not time sensitive, it is sufficient for the AUV to resurface only once at the end of its data collection path. However, for time-sensitive data, it is more advantageous for the AUV to resurface multiple times during its path, and upload the data collected since the previous resurfacing. Thus, a resurfacing schedule needs to complement the path planning process. In this paper we are using the metric of *Value of Information* (VoI) as the optimization criteria to capture the time-sensitive nature of collected information. We propose a genetic algorithm based approach to determine the resurfacing schedule for an AUV which is already provided with the sequence of nodes to be visited.**

***Index Terms*—Value Of Information, Under Water Sensor Network, AUV Path Planning, Value Of Information, Quality of Service, Genetic Algorithm.**

I. Introduction

Radio communication between nodes in an *underwater sensor network (UWSN)* is made effectively impossible by strong signal attenuation [1]. Thus, acoustic communication is preferred and used by nodes for long distance underwater transmissions. The problem with acoustic communication is low data rate and to resolve this problem, the use of optical communication has been suggested [2]. While optical communication provides high bandwidth, the communication is limited to a few meters. Both of these technologies have their pros and cons and can be used in conjunction to achieve certain goals for data delivery in UWSNs [3].

Researchers have proposed the use of a mobile sink(s) such as autonomous underwater vehicles (AUV) to gather and offload data in a UWSN [4]. The order in which the different sensor nodes are visited is an important factor in the overall performance of the system. It determines, for instance, the overall energy cost or the time taken to visit all nodes. In systems where there are "hot spots", areas where more interesting events happen, the system can achieve a better value of information if the AUV visits with more priority or more often areas where nodes are collecting more valuable data. A further complexity appears if we consider UWSN where some of the information collected is time sensitive, such as surveillance systems. In such systems, the value of information decreases in time - the later the data is delivered to the beneficiary, the less value it provides. The time when the value is realized is *not* the moment when the sensor node offloads the information to the AUV, but when it reaches the sink. The physical constraints of the underwater communication applies to the AUV as well - in order to deliver the data to the sink, the AUV needs to either return to the docking station or to resurface and transmit the data over wireless radio channels. Thus the *resurfacing schedule* is an important complement to the path planning algorithm for UWSNs which collect time sensitive information. The objective of this paper is to develop algorithms that can calculate the resurfacing schedule that complement path planning algorithms such as [5], [6].

II. Value Of Information

We define Value of Information (VoI) in the same spirit as in [7], [8], [9] - VoI is the price an optimal player would pay for a piece of information in a game theoretic setting. Let us consider a classic control theory scenario where an agent has observability and countability over a process i.e the agent can take specific actions in response to various observations so that some measure of gain can be achieved or loss be avoided. These gains and losses can be described numerically. Let these observations be termed as information. The more the information is reliable and correct the more confidence the agent can have in taking his actions. Therefore, information is a data segment that can aid in constructing a more accurate model of a real-world process such that the addition of this information to the agent's world view can lead to a measure of gain or loss. Such an information segment can be mapped to gain or loss values and these values are what are termed as Value-of-Information (VoI).

Similarly, we define a VoI function as a relationship that encodes the temporal decay of VoI of an information segment. This is intuitive as later arrival of an information segment may lead to higher losses [5], [10]. The functions that we consider are monotonically decreasing in time. All of these functions have parameters of the form $A_x \& B_y$. These parameters control the magnitude and decay rate of VoI. The functions that we deploy in our experimental setting are decaying exponential and are completely described by parameters $A_x \& B_y$

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III. UWSN Setting

This section describes the UWSN arrangement that we will employ for defining the AUV resurfacing scheduling problem for VoI maximization. The UWSN has n sensor nodes $S = \{s_1 \dots s_n\}$. The recorded data is saved in the form of information chunks. Until time t the i_{th} sensor node has k information chunks $D_i = \{d_{i1} \dots d_{ik}\}$. The sensor nodes classify the recorded data q different categories based on their urgency and significance $C = \{c_1 \dots c_q\}$. Data chunks are mapped to the information classes in a surjective manner i.e. the classification mechanism α may assign multiple information chunks to the same information class $\alpha : D \to C$.

These different classification categories are uniquely mapped to VoI functions. The VoI functions that we use are of the form

$$\upsilon(t) = Ae^{-B(t-\tau_o)} \tag{1}$$

These classification details are stored in a tag that is appended to each information chunk. This tag comprises of the minimum necessary details required to reconstruct the VoI definition at retrieval by the end-processing agent. The end-processing agent is considered to be a computing node that can process information received by it in such a way that it can direct a meaningful actuation as a response to the information. The aforementioned VoI functions are completely defined by constants A, B and time stamp τ_o where τ_o is the instant at which the information chunk was recorded and, therefore, these parameters are what constitute the tag. The tag for the j_{th} information chunk at the i_{th} sensor node is

$$\lambda_{ij} = (A_{ij}, B_{ij}, \tau_{o_{ij}})$$

When the data is retrieved and processed by the end-processing agent, another a time stamp $\tau_{f_{ij}}$ is appended to the information chunk. This aids in calculating the current VoI from the original VoI function. The final VoI is

$$\upsilon_{ij} = A_{ij}e^{-B_{ij}(\tau_{f_{ij}}-\tau_{o_{ij}})} \tag{2}$$

There are two ways to determine the time stamp τ_f depending on what we consider to be the end-processing agent. If the AUV is equipped with the ability to process the information retrieved such that it can start an actuation response then τ_f is the time it retrieves the information from the respective sensor node. But if the end-processing agent is above the sea surface then τ_f is determined when the AUV resurfaces and transmits the information to the end-processing agent. The time stamp τ_f definition can crucially impact the design of AUV path planning algorithms for VoI maximization.

IV. Problem Definition

A. VoI Maximization Definition

The VoI retrieved from the i_{th} sensor node is given as,

$$\Upsilon_{s_i} = \sum_{j=1}^{k} \upsilon_{ij} = \sum_{j=1}^{k} A_{ij}e^{-B_{ij}(\tau_{f_{ij}}-\tau_{o_{ij}})} \tag{3}$$

Therefore, the cumulative VoI retrieved from the sensor network is given as

$$\Upsilon_S = \sum_{i=1}^{n} \Upsilon_{s_i} = \sum_{i=1}^{n}\sum_{j=1}^{k} A_{ij}e^{-B_{ij}(\tau_{f_{ij}}-\tau_{o_{ij}})} \tag{4}$$

The problem definition, given in Equation 5 is to maximize the cumulative VoI

$$\Upsilon_S^{\max} = \max \sum_{i=1}^{n}\sum_{j=1}^{k} A_{ij}e^{-B_{ij}(\tau_{f_{ij}}-\tau_{o_{ij}})} \tag{5}$$

B. Scheduling AUV Resurfacing

In this paper we consider the end-processing agent to be above the sea surface. Therefore, the AUV will have to resurface to transmit data to a base station which serves as a part of the end-processing agent system. Three of the many possible tours (paths) involving resurfacing schedules are shown in Figure 1. The instant at which the AUV resurfaces and transmits data to the base station will serve as our final time stamp so as to determine the VoI gained. This resurfacing affects the VoI gathered. A balance is required in terms of the number of times an AUV resurfaces because resurfacing at each node visit or resurfacing after visiting all nodes may not be the most optimal option. We discuss this by presenting two contrasting scenarios and then draw an intuitive inference from this. We will work with two sensor nodes to illustrate the concept in similar setting as described in Figure 1. Both sensor nodes have a solitary information chunks that were generated at the same time and have the same VoI profile e^{-Bt}. The AUV can take two routes, the visitation sequences of which are:

- $P_1 : s_1 \to r_1 \to s_2 \to r_2$
- $P_2 : s_1 \to s_2 \to r_2$

where s_1 and s_2 are sensor nodes while r_1 and r_2 are the resurfacing points above them.

Consider the case when the sensor nodes are very near to the sea surface such that the distance of the sensor nodes to the sea surface is almost zero and the inter-node distance is much greater than this i.e. $d_s \cong 0$ and $d_{ij} \gg d_s$. Let us calculate the VoI accumulated by the two paths assuming $d_{ij} \neq 0$ and $d_s = 0$:

$$\begin{aligned}
\Upsilon_{S-P_1} &= e^{-Bt_1} + e^{-Bt_2} \\
&= e^{-B(t_{d_{ij}}+t_{d_s})} + e^{-B(t_1+t_{d_s}+t_{d_{ij}}+t_{d_s})} \\
&= e^{-Bt_{d_{ij}}} + e^{-B(t_1+t_{d_{ij}})} \\
&= e^{-Bt_{d_{ij}}} + e^{-2Bt_{d_{ij}}} \\
\Upsilon_{S-P_2} &= e^{-Bt_2} + e^{-Bt_2} \\
&= 2e^{-B(t_{d_{ij}}+t_{d_{ij}}+t_{d_s})} \\
&= 2e^{-2Bt_{d_{ij}}}
\end{aligned}$$

Clearly $\Upsilon_{S-P_1} > \Upsilon_{S-P_2}$ which implies that it is better to resurface and transmit data at each node in the given distance (d_{ij}, d_s) settings.

In contrast, consider the case when the sensor nodes are deep in the sea such that inter-node distance is much smaller than the distance to the surface of the sea i.e. $d_s \gg d_{ij}$. Let us calculate the VoI accumulated by the two paths assuming $d_s \neq 0$ and $d_{ij} = 0$:

$$\begin{aligned}
\Upsilon_{S-P_1} &= e^{-Bt_1} + e^{-Bt_2} \\
&= e^{-B(t_{d_{ij}}+t_{d_s})} + e^{-B(t_1+t_{d_s}+t_{d_{ij}}+t_{d_s})} \\
&= e^{-Bt_{d_s}} + e^{-B(t_1+2t_{d_s})} \\
&= e^{-Bt_{d_s}} + e^{-3Bt_{d_s}} \\
\Upsilon_{S-P_2} &= e^{-Bt_2} + e^{-Bt_2} \\
&= 2e^{-B(t_{d_{ij}}+t_{d_{ij}}+t_{d_s})} \\
&= 2e^{-Bt_{d_s}}
\end{aligned}$$

Clearly $\Upsilon_{S-P_2} > \Upsilon_{S-P_1}$ which implies that it is better to resurface and transmit data after both nodes have been visited.

From this we can infer that there should be a ratio of d_s to d_{ij} at which $\Upsilon_{S-P_2} = \Upsilon_{S-P_1}$ and an increase or decrease in this ratio will lead to one path performing better than the other in terms of accumulating VoI.

C. Path Planning Problem

The problem definition for including an AUV resurfacing schedule in its planned path is to maximize VoI of the information chunks D retrieved from the set of sensor nodes i.e. for an already given path P_S over sensor nodes S, what is the set resurfacing points R that will give a path $P_{R,S}$ such that it will result in $\Upsilon_S^{\max}$.

$$\big[P_{R,S}, \Upsilon_S^{max}\big] \leftarrow Optimize\big[P_S, R, D, \Upsilon_S\big] \tag{6}$$

- $P_{R,S}$ is a path comprising of sensor nodes and resurfacing points generated by algorithm $Optimize$
- $\Upsilon_S^{\max}$ is the maximum VoI obtained due to traversal of $P_{R,S}$
- P_S is a path comprising of sensor nodes only
- R is the set of resurfacing points
- D is the set of all information chunks
- Υ_S is the cumulative VoI function of information chunks retrieved from the sensor nodes in the path
- $Optimize$ is an algorithm that generates path $P_{R,S}$ such that $\Upsilon_S^{\max}$ is obtained

V. Genetic Algorithms for Resurfacing Schedules

We propose two alternative genetic algorithms - G_{PR} and G_{Opt} the former having quick convergence while latter offers a more optimal solution.

G_{PR} is modeled with an intuitive heuristic H_{PR} - a periodic resurfacing template. The algorithm has a low computational (running) cost as compared to G_{Opt} as it explores only a subset of the range of all the possible solutions. Due to the reduced search space, the algorithm might not yield the most optimal solution.

G_{Opt} has higher time complexity as it searches in the full domain of the possible solution set. Hence, it leads to a more optimal solution in comparison to G_{PR}. To improve the convergence time of G_{Opt}, and hence, the algorithmic run time, we provide the algorithm with good seeds (based on H_{PR}) as a part of the initial generation of the population.

A. Periodic Resurfacing Heuristic - H_{PR}

From the derivations in Section IV-B, we infer that intermediate resurfacing points may improve (or degrade) the accumulated VoI. Moreover, shifting a resurfacing point in the schedule changes the potential VoI accumulated up to that point. VoI functions are time dependent and a reconfiguration in resurfacing points affects the distance travelled by AUV, thereby affecting the final time stamp of a batch of information chunks.

Let S be a UWSN with n sensor nodes as defined in Section III. Let the AUV resurface after every p sensor nodes, implying, that after visiting p nodes the AUV will resurface and transmit the batch of the information to the base station. The AUV will then visit the next p nodes before resurfacing and transmitting and will keep on doing this until all n nodes have been visited. Period P can take on values

$$P = \{1, 2, \ldots, p, \ldots, n\}$$

As the number of the periods is n, a basic linear search based on H_{PR} will be of the order of $O(n) * O(V)$, where $O(V)$ is the complexity of the VoI evaluation procedure. In contrast, a basic linear search to find the most optimum schedule (maybe periodic or not) will have a complexity of the order of $O(2^n) * O(V)$, hence, advocating our use of H_{PR} for reducing complexity, albeit sacrificing optimality.

The number of resurfacing iterations for an AUV would be

$$\alpha = \lceil n/p \rceil$$

One anomaly to this periodic visitation is that in the last iteration, the AUV might not be able to visit p nodes as n may not be exactly divisible by p. Besides this anomaly the rest of the schedule will have a periodic resurfacing pattern. In this last iteration the number of nodes the AUV will visit will be

$$n - \lfloor n/p \rfloor \times p$$

B. Genetic Algorithms

Both of the proposed genetic algorithms, G_{PR} & G_{Opt}, use the same fitness function for evaluating the chromosomes. Based on Equation 4, the fitness function is,

$$F_C = \sum_{i=1}^{n} \Upsilon_{s_i} = \sum_{i=1}^{n}\sum_{j=1}^{k} A_{ij} e^{-B_{ij}(\tau_{f_{ij}} - \tau_{o_{ij}})} \tag{7}$$

1) GA for Optimal Periodic Resurfacing Schedule - G_{PR}: This GA is based on the heuristic H_{PR} to find the optimal period for a resurfacing schedule that maximizes the VoI accumulated. The optimal period is an integer that varies between 0 and n (number of sensor nodes), therefore, the chromosome is simply a binary string where each gene can take on a binary value (0 or 1). G_{PR} employs the *Uniform*

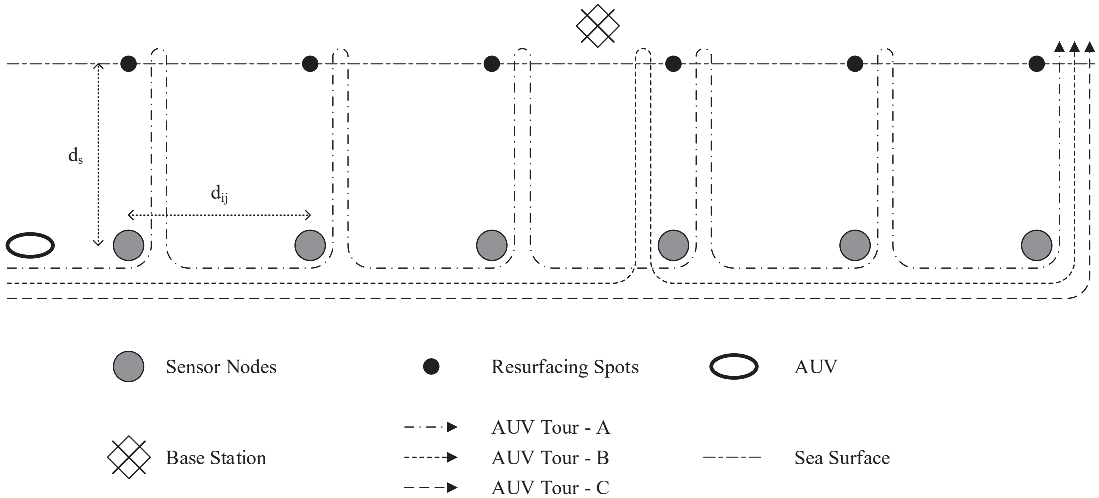

Fig. 1: Side view of the underwater sensor network showing inter-node distance vs node depth from sea surface

Crossover Operator and *Tournament Selection* for evolving the population. It also uses *Elitism* to retain the best solution after each generation during evolution.

2) GA for Optimal Resurfacing Schedule - G_{Opt}: The chromosome for this optimal resurfacing schedule is a strand of genes where each gene represents a unique resurfacing location. The number of genes in each chromosome is equal to the number of resurfacing locations. Each gene can take on two values encoded to represent whether the corresponding resurfacing location should be visited or not. G_{Opt} construction is similar to G_{PR}. The crossover operator is *Uniform* and the selection methodology is *Tournament Selection*. *Elitism* is employed to retain the best combinatorial solution while evolving through the various population generations.

The initial population is supplemented with good seeds i.e. chromosomes with high fitness score that will yield good solutions. These seeds are obtained from the top best solutions generated by G_{PR}. This small variation could lead to a fast convergence time towards the optimal solution.

Parameter	Values	
UWSN Deployment Parameters		
Deployment Area	10 x 10 km^2	
Node deployment	Uniform Grid	
Inter-node Distance - S_I	1 km	
Network Deployment Depth - S_D	Ratio * S_I	
Ratio - R_{DI} - S_D/S_I	0 - 1000	
Number of sensor nodes	100	
Transmission range	120 - 140 m	
Sensing range	70m	
Mobile sink speed	2 m/s	
Experimental Parameters		
Genetic Algorithms	G_{PR}, G_{Opt}, R_{End}, R_{All}, R_{Rand}	
A_{ij}	1	
B_{ij}	Solve $E(\lambda_{ij}) = 0.05 * \lambda_{ij_{max}}$	
Runs per Experiment	50	
Genetic Algorithm Parameters		
Genetic,Algorithm	G_{PR}	G_{Opt}
Generations (Iterations)	20	100
Population Size	25	50
Selection Mechanism	*Tournament Selection*	
Tournament Size	5	5
Elitism	*Yes*	
Crossover Operator	*Uniform Crossover*	
Crossover Rate	0.5	0.5
Mutation Rate	0.1	0.15

TABLE I: Simulation Parameters

VI. Simulations, Results & Conclusions

The scenario for our simulations is described by Table I. It is a 100 node UWSN deployed in a uniform grid over a 10 km x 10 km area. An AUV moving with a speed of 2 m/s is used to collect the data. The AUV can offload data from sensor nodes using 10 Mbps optical links.

A. Studying the effect of Deployment Depth on AUV Resurfacing

This study is to validate inferences made in Sec IV-B by shedding light on the relationship between the number of times an AUV resurfaces and the ratio R_{DI}.

$$R_{DI} = S_D/S_I$$

where S_D is the network deployment depth and S_I is the inter-node distance. The tour size for these experiments is 25 sensor nodes. The results in Figure 2 are averaged over 50 simulation runs per experiment.

Section IV-B hypothesizes that if nodes are nearer to the water surface then more frequent resurfacing is required as compared to when the the nodes are deeper in the sea. From the results in Figure 2 we can validate this. As R_{DI} increases i.e. the nodes are placed deeper into the sea, the number of times the AUV resurfaces reduces. Note that there is a range of R_{DI} for which there is a significant change in the number of times an AUV resurfaces. Below that range the AUV almost always resurfaces after every single node visit and above that range the AUV rarely resurfaces before the end of the tour. In this experiment (at least) up to $R_{DI} = 0.5$ the AUV resurfaces 25 times in it's 25-node tour and after $R_{DI} = 25$ it starts to

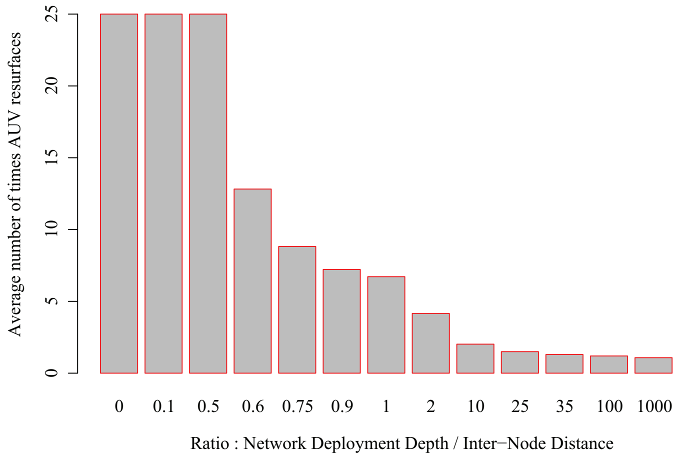

Fig. 2: The average number of times the AUV resurfaces function of the ratio $R_{DI} = S_D/SI$. The results are averaged over 50 simulation runs.

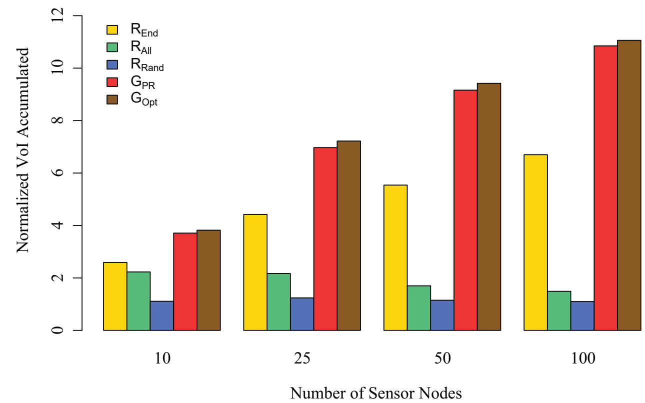

Fig. 3: The VoI accumulated (Υ_S) by different schedulers function of the number of sensor nodes. The results are averaged over 50 simulation runs and have been normalized w.r.t. R_{End}.

taper to 1 (a single resurfacing event at the end of the tour). This implies that the scheduling algorithms for our setting of VoI functions (setting parameters A_{ij} and B_{ij}) are only effective within this range. Outside this range a deterministic approach such as R_{Every} and R_{End} would suffice.

B. Studying the performance of G_{PR} & G_{Opt}

We use R_{Every}, R_{End} & R_{Rand} as scheduling procedures that will serve as a baseline for comparison with the GA schedulers G_{PR} & G_{Opt}. These schedulers are described below:

- R_{Every} - AUV resurfaces after every node that it visits.
- R_{End} - AUV resurfaces at the end of the tour i.e. after visiting all of the sensor nodes in the tour.
- R_{Rand} - AUV randomly chooses as to how may times it will resurface during a tour and also as to after which node visit should it resurface.

The performance of a scheduler will be determined by the amount of VoI it accumulates i.e. Υ_S. The results are shown in Figure 3. We use tour lengths of 10, 25, 50 and 100 sensor nodes for our experiments. In light of the results in Section VI-A, the ratio of S_D to S_I is set 1.0 for this experiment. Υ_S is an absolute measure and does not have units in our definition. Any amount of difference is a good result as it implies that more information has been gained in time for actuation purposes. The amount of difference can be magnified or diminished by controlling A_{ij} & B_{ij} settings but the results will still signify the same information content. We have normalized all results w.r.t. R_{End} for interpretation purposes. All results are averaged over 50 simulation runs for each experiment.

From the results in Figure 3 we can infer that G_{PR} & G_{Opt} perform better than the baseline schedulers. The effectiveness of Heuristic H_{PR} is validated by the better results of G_{PR} over the baseline schedulers. Moreover, G_{Opt} generates more optimal schedules than G_{PR}, albeit its higher running cost. Choosing between G_{PR} & G_{Opt} is run time versus optimality trade-off.

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