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# Intelligent Oil Spill Detection in Ocean using Internet of Underwater Things

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***Abstract*—About two-third of the earth is covered with water. Oceanographic research is one of the prominent area of research. A major area of oceanic research is detection of oil spills. Ocean is a home for several aquatic creatures. Every year many aquatic creatures loose life because of pollution that occurs through the leakage of oil. Oil leakage occurs due to several reasons like breakage of oil pipes, leakage of oil from ships and through industrial wastes. Oil spill detection is a very important challenge faced by researchers in oceanographic domain. In this paper we present a new scheme of detection of oil spill using Internet of things. We propose a method of applying Wireless Sensor Networks (WSNs) to detect oceanic oil spills. In addition we propose inclusion of intelligence at multiple aggregation levels to improve efficiency of deployed network. As additional intelligence is granted to sensor nodes, instead of being passive detectors, they work as intelligent observers, thereby making the detection process, an inter-network of intelligent nodes.**

***Index Terms*— Oil-spill, IOT, Sensor, WSN, intelligent surveillance.**

## I. INTRODUCTION

About 70% of the earth is water. This percentage in volume is 332,519,000 cubic miles of water. Of this vast volume of water, NOAA's National Geophysical Data Center estimates that, 321,003,271 cubic miles is in the ocean [1]. Of the tiny percentage that's not saline water of the oceans, about two percent is frozen as glaciers and ice caps. Less than one percent of all the water on Earth is potable or fresh. A tiny fraction of water exists as water vapor in earth’s atmosphere. Climatic activity is determined by the interaction of oceans, winds and land masses [2]. Oceans are most necessary for running of gaseous cycles, bio-chemical cycles, for formation of clouds and the most vital water cycle. Human activities in and around the world’s oceans is hampering the delicate balance maintained by the presence of such a huge water body [3]. Most evident and well researched effect of human activity on oceans is in the depletion of coral reefs [4]. Oceans act as a sink of many gases and help create a life supporting environment on earth [5]. Any pollution caused in the ocean had direct as well as indirect after effects. Direct effect includes harm caused to underwater flora and fauna. Indirect effects may span from simple yet manageable effect like disruption caused to human activity like fishing and navigation to subtle but environmentally tragic consequences like alterations caused to climatic, bio-geo-chemical cycles. One of the much pollution that affects Earth’s oceans is oil spills. Oil spills kill fish, planktons by cutting off sunlight and oxygen. Oil spills also harm beaches and thereby destroys breeding grounds of amphibians, migratory birds.

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Keeping these disastrous consequences in mind, a recommendation has been adopted by the United Nations Conference on human environment (Stockholm, 1972). Organizations like CDI (Center for Documentation and Information) and the WMO (World Metrological Organization) have launched a monitoring program of marine pollution by hydrocarbons. This initiative is part of the Integrated Global Ocean Station System (IGOSS). Wireless sensor networks (WSN) are utilized here to monitor vast areas of oceanic surface as well as sub surface waters. F. Regan et.al have demonstrated in [6] that a WSN framework can be effectively applied to the problem of monitoring water for extended periods of time. The challenges however are many; detection of spill is event-triggered observation. Oil by nature does not dissolve in water and forms a film on the surface instead. The film thus formed is neither stationary, nor is it limited in its expanse. Gaining an insight in to these specific matters is the aim of our work. We intend to add intelligence to the application of WSN and Internet of Things (IOT) to oceanic oil spill monitoring.

## II. Related Work

A lot of work has been carried out in detection of oil spills. Pangilinan et.al, have focused on determining the thickness of oil spill. Their hypothesis is that thicker the spill graver the effects of the pollution. They have determined the pixel intensity concerned with many competing parameters [7].

Reem Alattas, has also worked on image analysis in oil spill detection. A threshold method is suggested to detect oil spill. SAR image processing is applied based on minimum cross-entropy with gamma distribution. A major drawback of the work is its intrinsic time lapse involved in data analysis. Oil spill like pollution must be combated as quickly as possible. Real time detection, if possible is most suitable for such problems. Additionally, the method proposed in [8] works with bi-modal images that have two classes of pixels only.

A.Gasul et.al [9], have proposed and tested a new method for SAR image analysis to detect oil spills. Their method works well with low resolution and distorted images as well. In spite of multi stages analysis algorithm implemented, ensuring error free end result is still difficult.

Kruti Vyas et.al in [10] have applied feature extraction of SAR images in oil spill detection. They have recognized three independent features for this purpose. They have performed a battery of experiments while considering types of images.

Mario Monteiro et.al, have made an extensive study of various aspects and challenges of detection of oil spills. Their work is particularly in connection with the seagull project. Their contribution is specifically in application of camera fitted unmanned aerial vehicles in combating water pollution. [11] documents various challenges involved in detection of spills, with emphasis on time lapse between actual spill and its detection.

Unmanned surface vehicle is developed and analysed for performance in [12] by Deqing Liu et.al. Their work concentrates on frequent oil spills that happens at harbors, oil rigs and drilling platforms. They have designed a fluorosensor laser detector to achieve this aim. A feasibility analysis is also carried out by the authors.

Md. Shafi.K.T, et.al have developed a simple resonance based application to detect oil spill using planar microwave[13]. Proposed sensor is developed, deployed and tested in their work. The sensor designed is capable of detecting pollution beyond 5%.

Sicong Liu et.al have presented a solution to oil spill detection problem in a multi-temporal domain in [14]. Their basic architecture is based on a coarse to fine framework. Their framework requires minimum human intervention and is almost automatic. It is applicable on large scale detection of spills.

## III. Proposed Work

Following are the assumptions made in deployment of nodes in the WSN test bench.

1. Grid based deployment of nodes: to specifically determine location of each individual node. This assumption is safe and valid as, there is a commercially available underwater robot capable of deploying nodes at specific coordinates of latitude and longitude.
2. Number of nodes per grid is fixed: this assumption helps us compute statistically significant results after data collection is done and analysis is to be performed
3. Node density is uniform: non-uniform node deployment does not allow implementation of intelligence.
4. Each node in a grid represents a single unit area: data collected is representative of a fixed area under surveillance.
5. 4 unit squares form a cell: helps in aggregation of data across levels of nodal deployment.

6. Every cell has a cell-sink node: this is an architectural requirement of WSN
7. Four cells combine to form a level 2-cell: helps implement the second layer of intelligence and additional aggregation
8. One of the unit cell's cell-sink also works as a sink for four adjacent level-2 cells: based on energy levels, s suitable cell-sink is elected as the sink of adjacent cells
9. All level-2 cells combine to form the region under observation: highest level of aggregation implemented under our scheme

*A. Restriction on each node*

Each node will communicate the observation only if the quantity observed is above a fixed threshold.
*Tier- 1Local aggregation (level 1)*
Spatial aggregation: based on the percentage of area generating similar readings. Each unit cell has a designated high power node acting as cell-sink. Communicate reading only if at least three out of four nodes report similar readings.
*Tier-2 Aggregation (level 2)*
Boundary value aggregation: region under observation has a sink node that acts as a data aggregator. Radial survey is made periodically at three lengths of radii- minimum, nominal and maximum. Minimum is close to the sink, maximum is distance from sink to boundary of region under observation, and nominal is an intermediate distance.
*Intelligence added:*

1. Percentage of area of oil spill is known without actual survey
2. False alarms are filtered at levels 1 and 2

*B. Node deployment phase and network establishment:*

1. Four different levels of nodes are deployed.
   - **Ground level sensor nodes:** They are capable of sensing the oil density at the preliminary level and intensity of light.
   - **High power node at the ground level:** They acts like grid head they can also sense the information.
   - **Anchor nodes at middle level:** They act like second level grid head. They gather the data from multiple grids and transfer it to surface buoyant node.
   - **Surface buoyant node:** They are at the surface level, they can sense the PH level of the water.

2. These nodes are deployed at the required locations using an underwater automatic vehicle (UWAV).
3. The area of interest is divided into equal sized grids. Ground level nodes and high power nodes are deployed at each grid. High power node will be the grid head of that particular grid
4. Each High power node broadcast a beacon message to the ground level sensor node to indicate its presence in the grid.
5. Each ground level nodes respond back to their grid heads by sending the response beacon. Same Procedure is followed between grid heads and anchor nodes, Anchor nodes and surface buoyant nodes.

*C. Routing Phase*

1.All the ground level sensor nodes sense the data and send the sensed data to its Grid head. Grid head aggregates the received data..
2.Grid Head sends data to Anchor node. Anchor node aggregates the data.
3.Anchor nodes sends the aggregated data to surface buoyant node. Surface buoyant node sends the data received as well as PH information to sink.

## IV. Experiment Result

We have made use of MATLAB as the simulation tool to check the efficiency of our proposed work. Initially we considered a volume of interest with dimensions 250m (length) x 250m (breadth) x 250m (depth). Then the volume under consideration is divided into equal sized grids of size 50m each at ground level. Table 1 shows the various parameters used in simulation. Figure 1 depicts the test bed created through simulation. Here blue color nodes represent nodes deployed at ground level. Red color nodes represent anchor nodes and the magenta color nodes indicate nodes that are buoyant on oceanic surface. Figure 2 shows the grid layout in the network.

TABLE I: SIMULATION PARAMETERS

| Parameter Type | Parameter Value |
|---|---|
| Area of application region | 250 X 250 $m^2$ |
| Sea Depth | 250 m |
| Grid range | 25 m |
| Number of Ground level node in each grid | 4 |
| Number of High power nodes in each grids | 2 |
| Number of Anchor node in each group of grids | 1 |
| Number of Surface buoyant nodes in each group of grids | 1 |
| Simulation Time | 150sec |
| Payload length | 512 Bytes |
| **Parameters of Ground level node** | |
| Initial Energy | 4J |
| Transmission range | 20m |
| Data rate | 4kbps |
| **Parameters of High power node** | |
| Initial Energy | 7J |
| Transmission range | 25m |
| Data rate | 6kbps |
| **Parameters of Anchor node** | |
| Initial Energy | 10J |
| Transmission range | 30m |
| Data rate | 8kbps |
| **Parameters of Surface buoyant node** | |
| Initial Energy | 14J |
| Transmission range | 35m |
| Data rate | 12kbps |

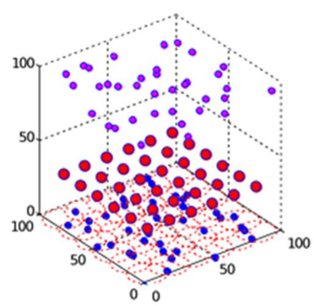


Figure 1: Test bed

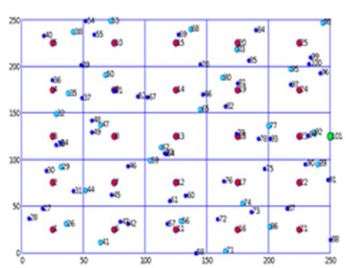

Figure 2: Grid Layout

Figure 3 shows amount of time required to detect the oil spill versus the oil spread area. Time required to detect spills of larger area is evidently greater. From this we can analyze the spreading rate of oil in the water and intensity of oil leakage. As underwater communication is slower than normal environment redundant information transmission can be reduced to ensure the timely delivery of information and to avoid collision in the network Figure 4 helps us understand that the number of redundant transmission in various techniques compared with our work are much greater. Our method requires lesser number of packet transmissions compared to without aggregation deployment, in-network architecture and cluster based approach. It is clear that proposed work reduces redundant data transmission significantly.

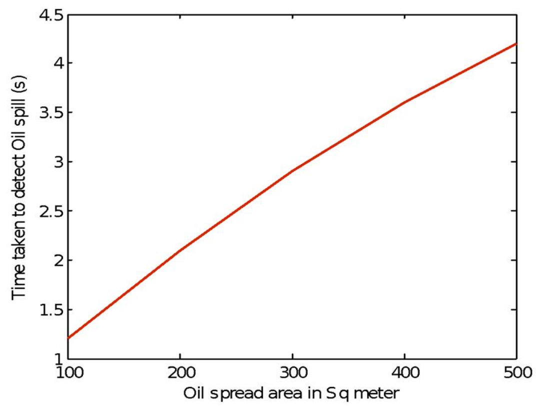


Figure 3: Time required for detecting the spreading of oil leakage

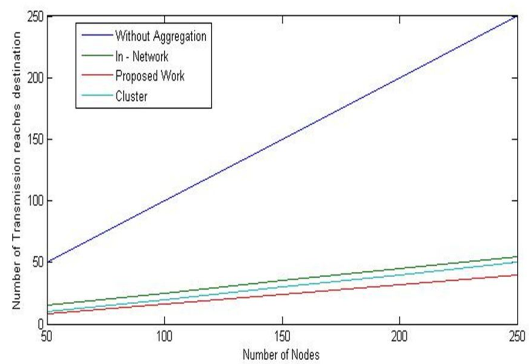


Figure.4. Number of redundant transmission in various approaches

## V. Conclusion

Adding intelligence to oil spill detection makes detection real-time and provides insight in to combating the pollution in the future. Collecting raw data triggered by an event gives minimal insight into crucial facts like thickness of oil film, expanse of oil spill and also reduces number of redundant transmissions. Adding intelligence to sensor nodes to make decision on oil spill can be considered for future enhancement.

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