LICOT: Litter-Information-Centric Ocean of Things

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***Abstract*—Marine pollution such as litter and debris, both beached and floating objects/liquids, are one of the most serious and fast growing environmental threats to the oceans and seafloors. The negative impacts of this pollution on the environment and on human and marine life are unquestionable. We propose a novel information-centric underwater Internet of Things (UW-IoT), called LICOT, to sense and collect data from different types of marine pollution in oceans or other vast water bodies, to transform it to information, and to share it with other nodes in the network using appropriate communication technologies in order to make timely decisions. Given the sparsity of the nodes, the communication limitations, and the complexity of building an underwater network, an infrastructure-free architecture is formed upon request from a bottom-up perspective, based on the situation and litter type. Considering the repetition, similarity, or correlation between the portions of detected pollution, the map of pollution is reconstructed after information fusion is performed to restructure the top-down network so as to increase the efficiency and agility of the IoT network. Experiments were conducted in the Raritan River–New Jersey in Summer'19 to evaluate the feasibility of this solution by building a small testbed in the hope to offer an efficient tool to protect the ecosystem when it scales up in the future.**

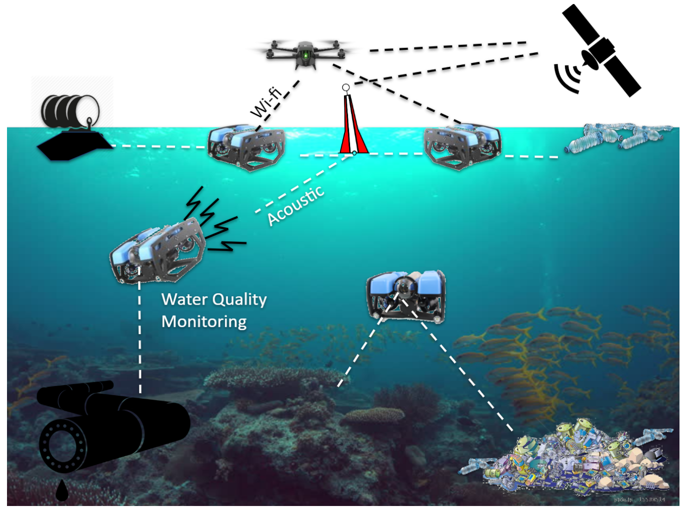

Fig. 1: System model showing different types of pollution, including litter, liquid, etc. The information extracted from the pollution is critical to form an efficient IoT network of heterogeneous nodes, since continuous and reliable communications is not available in our application as in conventional IoTs.

I. General Description

Overview: While about three quarters of the Earth surface consists of water, the rapid expansion of pollution in water bodies has become a global crisis over the last few years. Marine litter develops from various sources and causes a wide range of environmental safety and health issues. The slow degradation rate of marine litter items, combined with the growing quantity of debris collection, is leading to ocean pollution. When the debris, such as plastic, degrades over time, it turns into micro- and then nano-plastics, which is then consumed by fish and eventually by humans. According to recent studies [1], around 640,000 tonnes of gear is lost in the ocean annually. Lost nets create a huge threat to marine life as they trap and kill at least 136,000 seals, sea lions, and whales. According to the survey conducted by the United Nations Educational, Scientific and Cultural Organization (UNESCO) [2] over 80% of marine pollution comes from land-based activities. From plastic bags to pesticides, most of the waste produced on land eventually reaches the oceans. Rivers carry the litter with their currents to the seas and are one of the main sources of litter entering the seas. There is litter spread widely throughout the seafloor, but its distribution is usually patchy with densities from 1 up to around 200 items per each 10 m, as reported for the Messina Strait's channel—one of the geologically active areas of the Central Mediterranean Sea [3].

Challenges: Underwater Internet of Things (UW IoT) [4] is a novel class of IoTs in aqueous environments enabling various practical applications such as oceanographic data collection, pollution and environmental monitoring, tsunami detection/disaster prevention, and tactical surveillance [5]. Heterogeneous nodes—including sensors, buoys, vehicles, and underwater objects and creatures—that constitute UW IoT perform their regular dedicated tasks, while communicating reliably with other nodes to coordinate data aggregation and sharing [6]. While different aspects of the terrestrial IoT have been discussed in the literature [6], [7], *there is no solid and commonly accepted definition of UW IoT*, where the nodes differ with respect to (i) the type of sensed data; (ii) the area sensed; (iii) the source of energy for operation; and (iv) the mode of data transmission in terms of energy or communication cost, or both [8].

Our Contribution: We propose a novel underwater IoT, called LICOT, specifically designed for marine pollution monitoring. We investigate the feasibility of implementing an IoT testbed that connects heterogeneous nodes in an information-centric on-demand structure, given the fact that infrastructure is not provided in the oceans. Pollution information is extracted and the IoT network is structured following both a bottom-up and a top-down approach. Experiments were conducted in the Raritan River–New Jersey to evaluate the proposed method in Summer'19.

II. Technical Solution and Project Details

A novel information-centric IoT is proposed based on the required sensing, processing, and decision tasks of different classes of marine pollution. Fig. 1 shows the system model in which multiple heterogeneous static and mobile nodes form a network to detect different types of pollution. The network is flexible regarding the type of pollution and the technology that is appropriate for that scenario, as reflected in Table. I. We propose four layers for LICOT including sensing, processing, transmission/network, and perception/execution layers.

TABLE I: Types of pollution and the preferred communications technology.

Type of pollution	On surface	On seabed	Dissolved in water	Static or dynamic	Preferred communication
Oil (Numbers/ Video/ Frames)	Yes	Yes	No	Dynamic	Wi-Fi
Plastic (Video/ Frames)	Yes	Yes	Yes	Both	Wi-Fi
Acid/Base Concentration (Numbers)	Yes	No	Yes	Dynamic	Wi-Fi or Acoustic
Coral Reefs (Video/ Frames)	No	Yes	No	Static	Wi-Fi or Acoustic
Dead Zones or Dissolved Oxygen (Numbers)	No	Yes	Yes	Both	Wi-Fi or Acoustic
Conductivity (Video/ Frames)	No	No	Yes	Dynamic	Wi-Fi or Acoustic

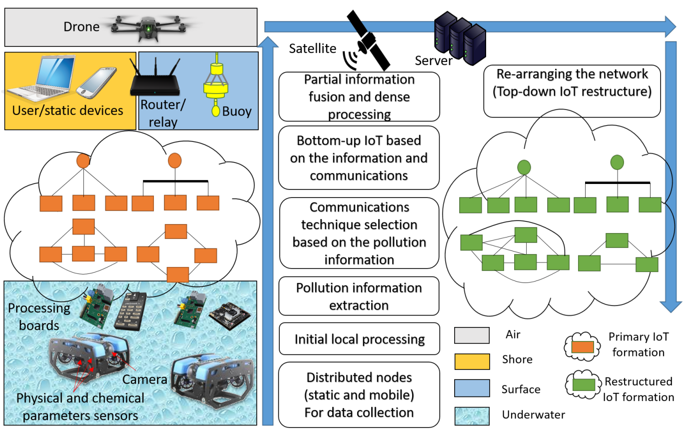

Fig. 2: The proposed strategy for data collection and pollution monitoring in an infrastructure-free underwater/surface/air media. The information is extracted from the pollution data (collected by the sensors), and the IoT is formed from bottom to top on-demand. Network restructuring might be required to unify the information in order to efficiently monitor the area of study.

An Information-centric Approach: As shown in Fig. 2, the network is initiated on-demand, when a node detects the pollution in the sensing layer. Since (i) the continuous connectivity (as usually needed in conventional IoTs) is not available in our application due to the limited communications and energy resources underwater and (ii) a-priori information on the required resources is not known due to different types of pollution that might be detected, deployment of an UW IoT requires a dynamic network in which the nodes only exchange selected information instead of the raw data. Two types of structure formations are suggested as following.

Bottom-up Approach: Since nodes in the sensing layer are sparse compared to the large water bodies we monitor, it is not feasible to have a pre-defined infrastructure, unlike the conventional IoTs. Instead, upon request, we form a dynamic structure starting from the bottom, in the sensing layer, where the node collects the data in the field. After local processing, if a sign of pollution is detected, the IoT network formation is initiated in a self-organized manner. We call this process the *bottom-up approach* since this framework merges the partial information/observations collected/locally-processed by each node to have a comprehensive understanding in the server. Since the resources and communication bandwidth are limited, the connectivity is not continuous and only the valuable information (processed data) will be transmitted in the network.

Top-down Approach: Given the framework we have already formed based on the fusion of local bottom-up networks, and considering the locations/types of pollution, we need to restructure the framework from top to down, in which we integrate the locally observed information in a unified framework, considering the potential repetition, similarity, and correlation among the collected information. Furthermore, if a network is unable to provide the required communication resources to share the information, this top-down approach handles the problem in the most efficient manner by allocating more nodes to the area of interest. Such top-down approach allows for a highly scalable solution. If an increase in the level of information in the perception layer is required, the topology changes accordingly using the nodes/sensors in the sensor layer without any change in the main framework. The processing layer depends on micro-controllers/embedded processors that a sensor is connected, which makes this system highly scalable as well.

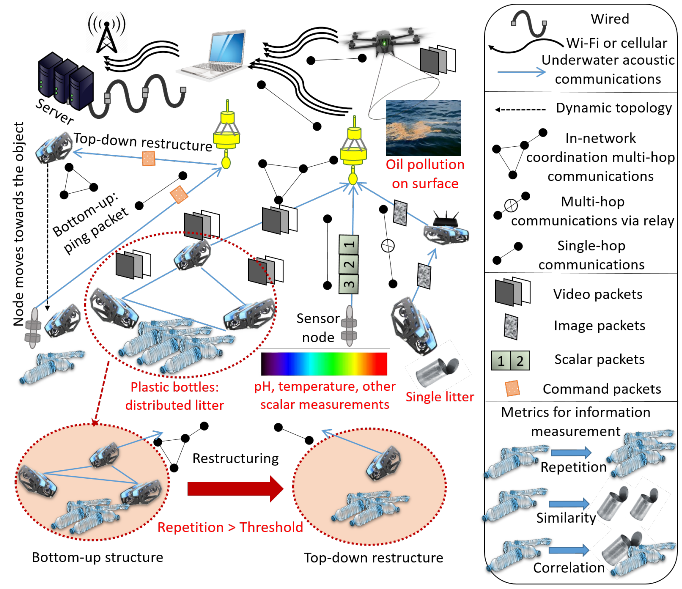

Fig. 3: Impact of pollution type on the network topology and the communications method. In-network coordination, single hop and multi-hop topologies are shown in the figure given the information extracted from the pollution. The extracted information from the pollution based on the metrics including independence, repetition, similarity, or correlation, will impact the communications/topology in LICOT as shown in the figure.

Impact of Pollution Type on Communication: Different communication techniques should be utilized according to the type/size of pollution, distribution of pollution, rate of temporal and spatial changes of pollution in the area of study. For instance, to measure a chemical parameter, such as pH or Dissolved Oxygen (DO), a small data packet is sufficient; whereas to describe the physical shape of an object, an image or multiple images from different angles should be transmitted, which leads to different communications solutions. If a patch of objects are detected, multiple nodes should cooperate from different angles to be able to extract the map of pollution, which leads to a different IoT topology compared to the case when a single object is detected. A schematic is shown in Fig. 3 in which different types of pollution are assumed in the region of interest.

III. Social Impact on Humanity/Local Community

The Raritan River is a major river of central New Jersey and is a unique laboratory available to Rutgers, i.e., a perfect case study. It is also the New Jersey's largest contiguous wildlife corridor offering refuge to numerous threatened and endangered species [9]. This river has experienced pollution from industrial facilities toxic dumping for over 100 years. The watershed is also impacted by contaminated sites and sewage treatment systems. Pollution from contaminated sites leaks into the river and harms the environment and public health. According to the Environmental Protection Agency (EPA) reports [10], over 16 noxious chemicals and solids were found infecting the section of the Raritan River that borders New Brunswick, NJ. Three of those chemicals—arsenic, benzopyrene, and the pesticide heptachlor epoxide—have the potential to adversely affect the drinking water supply. Fig. 4 shows the map of contaminated areas in the Raritan River watershed [9], and identifies contaminated sites in the basin and along the river. The watersheds should be monitored regularly to provide usable data about water quality and the overall health of the Raritan watersheds. The Raritan Headwaters Association [11] holds a specific stream monitoring program; based on visual assessment and on manual collection of water samples at each site, they can classify coarsely the sites as "excellent", "good", "fair", or "poor". *Our project will enable streamlined and improved monitoring of such an important area.*

IV. Implementation Status/ Experimental Results

Testbed Setup: The system mainly consists of underwater/surface vehicles, static buoys/nodes, drones, and any onshore computers or smart devices. For these experiments, the BlueROV2 underwater vehicles developed by BlueRobotics [12] have been used to collect and process data from the Raritan River. These devices will predominantly be connected through wireless comms standards such as Wi-Fi, acoustic communications (using hydrophones), or cellular network. The underwater vehicles are also capable of wired connection if and when it is required. To detect different types of pollution, the underwater vehicles are equipped with a 1080p camera and a number of sensors in the sensing layer (connected to a Raspberry Pi processor through a serial connection) including a temperature, dissolved oxygen, pH, conductivity, and pressure sensor. The vehicle also has a Global Positioning System (GPS) module attached to its Pixhawk controller board, which can only be used when the vehicle is on surface or close to surface. Surface vehicles can communicate to each other when connected to the router, nearby node or hydrophone. Using these vehicles, we can practically go to any specific location and conduct thorough testing in that area such as to label any type of pollution in that area depending on its seriousness. Fig. 5(a) shows the developed underwater vehicle equipped with the acoustic modems. Fig. 5(b) presents the setup for the experimental analysis in the Raritan River including the underwater vehicle and a drone in the air.

Experimental Results: The *processing layer* consists of processing the data we receive and finding trends or interesting results from this data, which we call *information*. This layer employs the camera and various sensors discussed in the testbed section. For example, from a camera we can use computer-vision algorithms to process the frames of a video feed and detect trash floating on the surface of the water of interest to us. Another example involves finding areas of low habitation in the water using an oxygen sensor. We would have to process the data to notice that there exists some areas with low oxygen levels that we can explore further to figure out what the cause is. Another way to detect pollution can be through the conductivity sensor. Since it changes with more salt and/or dissolved impurities, a spike or sudden drop in conductivity can signal more dissolved pollutants in the area. Conductivity data can then be combined with temperature—as shown in Fig. 6(a)—and dissolved oxygen data to warn the user about possible dead zones or low habitation areas. In the United States, the conductivity in freshwater normally ranges from 150 to 1500 $\mu\mathrm{S/cm}$ for a healthy aquatic life, but it can go down after heavy rain falls. As seen in Fig. 6(b), the conductivity of the Raritan River stays relatively constant in the range of 125–130 $\mu\mathrm{S/cm}$, which is slightly lower than 150 $\mu\mathrm{S/cm}$ mentioned before. This is because of the heavy rain the day before the experiments combined with other dissolved pollutants. The cameras equipped inside the underwater vehicle and the drone are used for the object feature detection in order to identify the marine waste. When trying to detect the objects either floating on surface or underwater, the keypoints are extracted and they are used to identify the object. Fig. 7 shows how a plastic bottle underwater and a floating ball on surface are being detected. The vehicle also monitors any

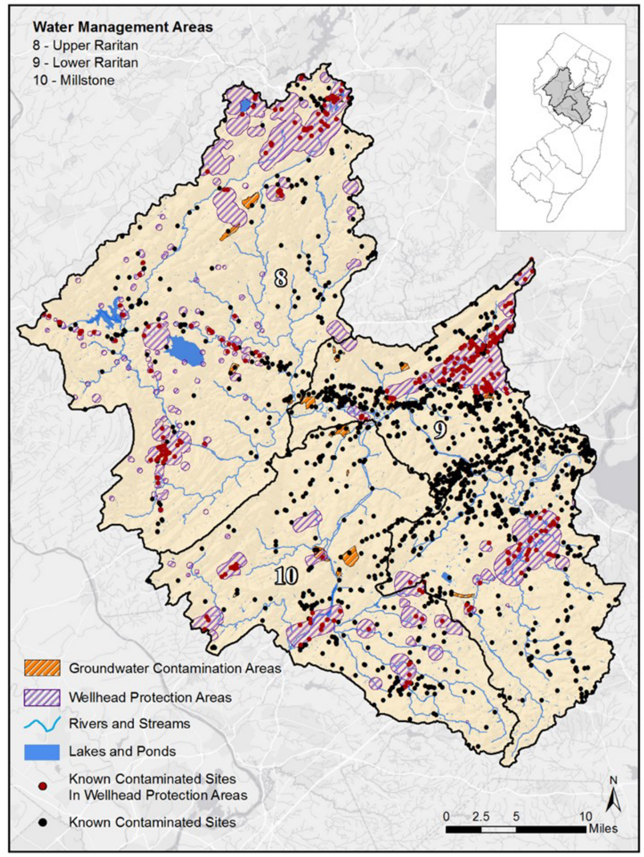

Fig. 4: Contamination in the Raritan River (2016) [9].

(a) (b)

Fig. 5: (a) BlueROV2 vehicle equipped with an acoustic transducer; (b) Network of connected devices in an experiment conducted in the Raritan River, New Jersey. The surface vehicle is moved in certain direction with the help of drone to detect the floating objects/waste.

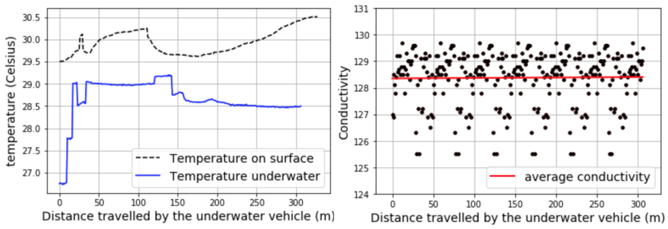

Fig. 6: (a) Temperature (°C) heatmap in an experiment conducted in the Raritan River, NJ, USA on August 23, 2019; (b) Conductivity ($\mu\mathrm{S/cm}$) recording in the Raritan River, NJ, USA on August 23, 2019.

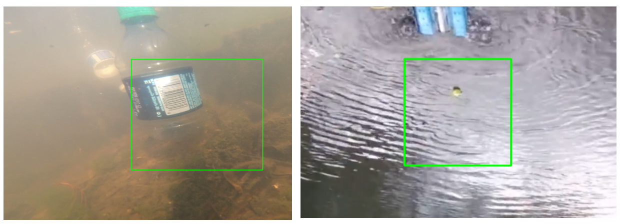

Fig. 7: (a) Underwater object detection results in the Raritan River, New Jersey; (b) Detecting objects on the surface of the Raritan using drone video.

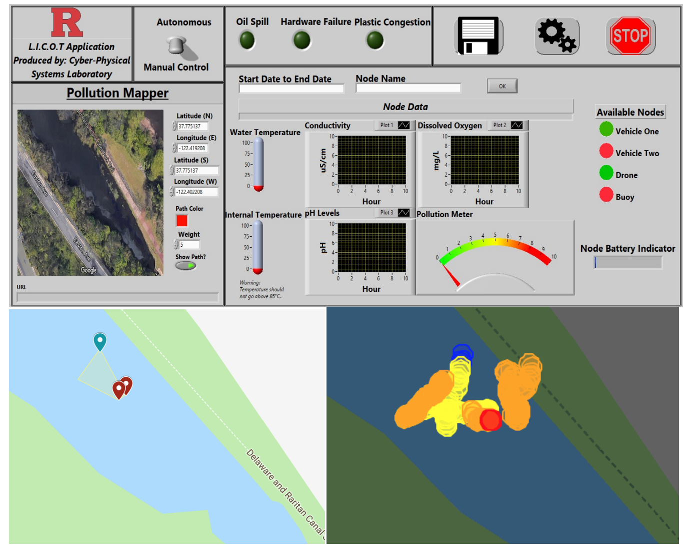

Fig. 8: The designed Graphical User Interface (GUI) for LICOT to create the map of pollution and to show irregular changes in the parameters that we control. The top figure shows the active nodes. The bottom figure shows an irregular change in the recorded temperature in the testing area in the Raritan River, NJ, on August 23, 2019.

abrupt changes in the environmental data such as temperature, pressure, and oxygen levels to build some context for decision making. For example, in Fig. 8, it is seen that the location with maximum and minimum temperatures have been marked.

The *transmission layer* enables communication between our various devices. We mainly communicate through Wi-Fi, acoustic transmission, or wired connections. By default, we will fall back to wired networking if possible since this is the most reliable and fast form of networking for our systems. Otherwise, if we are underwater, we will default to acoustic networking. We can get the depth of the vehicle from the built-in depth sensor and use that to see if we are underwater or on surface to prioritize the best communication method.

For the *perception layer*, we choose to display specific data to the user based on what data we receive and aggregate. This data can be stored in a database and the user can retrieve it through a web client. Once the data is processed and transmitted, we can aggregate it and store it into a database that can be accessible to the public through a simple API. We can also see the data being collected in real time through the use of a Graphical User Interface (GUI) application (see Fig. 8). Through the GUI, we can monitor the data being collected by different vehicles while visualizing the data on the map. We can also see the pollution that was detected by all of the active devices.

Feasibility and Scalability: Our proposed architecture is highly scalable. Since most processing is done locally on the node, we can add many more nodes to our UW IoT. As long as the devices have the capability to send data to another node, we can include those devices in our IoT network. Since we treat communication as a *costly* action, we try to limit the size of data we send but increase the information, which also increases the scalability of the proposed architecture.

V. Conclusion and Future Work

There is major pollution crisis in the water bodies, especially oceans, and majority of the pollution is carried there by rivers. Our solution is a novel information-centric underwater Internet of Things (UW-IoT), called LICOT, which monitors different types of pollution in rivers by utilizing an underwater IoT based on the information collected from the pollution. This solution will allow for better and more timely monitoring of pollution compared to conventional methods, which will lead to a better understanding of pollution. Experiments were conducted in the Raritan River–New Jersey in Summer'19 by building a small testbed in the hope to offer an efficient tool to protect the ecosystem when it scales up in the future.

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