Organizing Data from Industrial Internet of Things for Maritime Operations

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***Abstract*—The enormous amount of data collected from different sources in an *Industrial Internet of Things* (IIoT) will have to be processed, analyzed, and visualized in a timely manner. In this paper, we present a strategy for organizing IIoT data to facilitate data processing, storage, analysis, and visualization based on a typical *oil combat operation* scenario. A web-based system has been implemented and deployed and real-time data streams from the oil detectors are presented interactively, satisfying different users' needs.**

I. Introduction

It is commonly agreed that we are in the era of *big data* (BD), and it is highlighted in a statement from the United Nations that "the world is experiencing a data revolution" [1]. The Internet of Things (IoT) [2] is a new paradigm that covers technologies including ubiquitous computing, pervasive computing, wired/wireless sensors, networks, and embedded systems, forming a communicating-actuating network of a large amount of *things* including Radio-Frequency IDentification (RFID) tags, mobile phones, sensors, actuators and etc. In this way, physical environment and resources could have presence in the digital world. IoT is included by the US National Intelligence Council in the list of six "*Disruptive Civil Technologies*" with potential impacts on US national power [3]. Very recently, *Industrial IoT* (IIoT) emerges quickly as a sub-paradigm which focuses more in *safety-critical* applications in industries like aerospace, energy, and healthcare. Defects and failures in such applications would often result in dangerous situations even loss of lives, so principles of safety-critical systems must be included and stricter criteria must be enforced. The result of rapid development of IoT/IIoT is that the enormous amount of collected data from different sources will have to be processed, analyzed, and visualized in a timely manner, and that is where big data analytics (BDA) will fit in. In fact, BDA and IoT complement each other and develop as a double "helix" [4].

Norway is one of the largest nations in maritime operations. Due to the oil price crisis and increasingly fierce competition, the marine operation sector faces major challenges of increased complexity in technology, operations in Arctic deep sea, and integrated operations involving multiple vessels and autonomous units.

Technologies are being adopted for acquiring data about the oceans, the vehicles, and different components on board. This essentially is forming the IIoT for maritime operations, serving various purposes. The data come from many sources within such an IIoT, in large volume, high velocity, and different formats/frequencies. There are two major challenges, as we mentioned in [5], 1) the poor quality of the raw sensor data, therefore advanced data processing and cleaning is mandatory; 2) the presentation and user-interaction for data users in different roles, i.e., different users are interested in different aspects of the same set of data.

In the Big Data Lab in NTNU Aalesund (BDL), we are working closely with local maritime industry to build a *visual analytics* framework for the data acquired from IIoT for maritime operations. In previous editions of the OCEANS and Techno-Ocean conferences, we have presented some results of our framework [5], [6], [7], [8], which received positive feedback from academic and industrial experts in maritime operations.

In this paper, we present a strategy for organizing IIoT data to facilitate data processing, storage, analysis, and visualization based on a typical *oil combat operation* scenario, motivated by our collaborator, Ocean Visuals®.

The remainder of the paper is structured as follows: Section II reviews the background, challenges and criteria on data organization for a typical oil combat operation. In Section III, we present and discuss our strategy for data organization considering the requirements and constraints. Section IV briefly presents the implemented web-based system that interactively presents the real-time data stream directly from the IIoT. Section V concludes the paper.

II. An Oil Combat Operation Scenario

Oil spill presents a major threat to the marine ecosystems and there is an urgent need for new technologies for effective

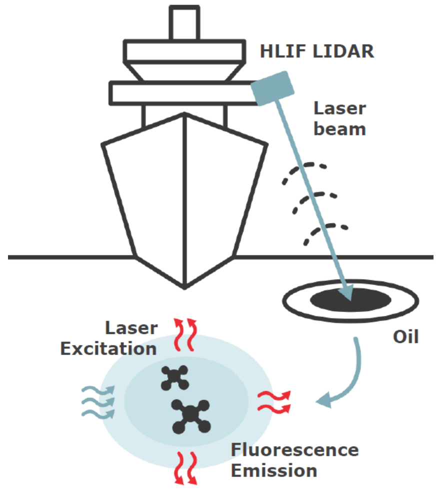

Fig. 1. Vessel with HLIF LiDAR.

and efficient oil combat operations, especially for ice-covered waters [9].

A. The sensor

The *Oil on Water Locator* (OWL) is an oil on- and in-water detector. It uses *Hyper-spectral Laser Induced Fluorescence Light Detection And Ranging* (HLIF LiDAR) [10]. In short, the laser pulse will make oil, Polycyclic Aromatic Hydrocarbons (PAH), fluorescence. The re-emitted light is captured by a built-in telescope, diffracted and detected by a 500 channel hyperspectral detector that detects both UV and visual light. The laser operates in the UV spectrum and have a wavelength on 308 nm. The sensor is able to make 10 HLIF spectra per second. A typical installation on a vessel is showed in Figure 1.

B. COP - Common Operational Picture

In an oil combat operation, as in most maritime operations, there will be a high demand from the users to be able to aggregate all relevant information into a *Common Operational Picture* (COP). A complex oil combat operation is visualized in Figure 2. Although all these types of vessels may not be active in most operations there might easily be several vessels of different types operating together.

The acquired data from the IIoT in such a maritime operational setting must be processed and presented. The primary challenges are to store retrieve all the data, check against alarm limits and alert user, retrieve external data, provide historic data and provide all the relevant data on a map in order to give the user a COP. External data could be other sensors from different vendors, weather data from weather services, and information on the position, speed and heading of vessels such as AIS data.

Hence, in order to have a true COP the following criteria must be met:

- All relevant data from all sources (multiple vessels) must be gathered in one application program with geodesic coordinates that allow them to be plotted on a map.
- The application program must be available and updated in real time to all actors in the operation (typically across several vessels and the shore).
- The different actors must be able to personalize their presentation according to their needs/their role.

III. Organizing Data for Maritime IIoT

This section describes the relations, constrains and proposed data structure. As mention previously, the design was made with especially the OWL sensor in mind, but the purpose is to provide the data required for a COP. Hence, the data structure must be able to handle a wide range of sensors, data sources and formats.

Our strategy for organizing the data from IIoT has considered the following relationships and constraints:

- A vessel may carry several instruments. Since a vessel can be many things and in order to generalize further the carrier of the instrument is called an observer.
- An observer may be a vessel, a plane, a USV, a lighthouse, a satellite, a ground station, a service provider etc. Hence, it is useful to identify the observer type.
- Instruments are of different types. Hence it is useful to register the maker, the models, units and so on.
- Some instruments may be compound i.e. consist of several instruments inside one mechanical package. In order to identify these the compound instruments a compound field is added where a reference to the "main" instrument should be added.
- A instrument will make series of measurements, called observations at given positions and consisting of both an engineering value and optionally raw value(s).
- Since observations will be made over long time-spans the format may change during the lifetime of the instrument it is reasonable to connect a data type description to the observation.

A. Entity-Relation Diagram of Data Organization

In Figure 3 depicts the ER diagram in our IIoT data organization strategy.

The main top-level entity is the Observers. Through the entity ObserversType each Observer is grouped in types through a one to many relation to ObserverTypes. ObserverTypes are typically a vessel, a plane, a USV, a lighthouse, a satellite, a ground station, a service provider etc., and Observers are instances of these types. Hence, the number of ObserverTypes will be rather small, but there will be a large number of Observers. Each Observer will typically have a location and some information on its current status (commissioned, active, de-commissioned). Since location information will be recorded and stored together with the readings, since the observer may move, we depreciated storing current position as part of the Observer entity, however this could make sense if Observers tend to move significantly between readings and it is useful to know the observers position even if no readings are made.

On board or co-located at the same site, as a part of the Observer we have several Instrument entities. The Instruments

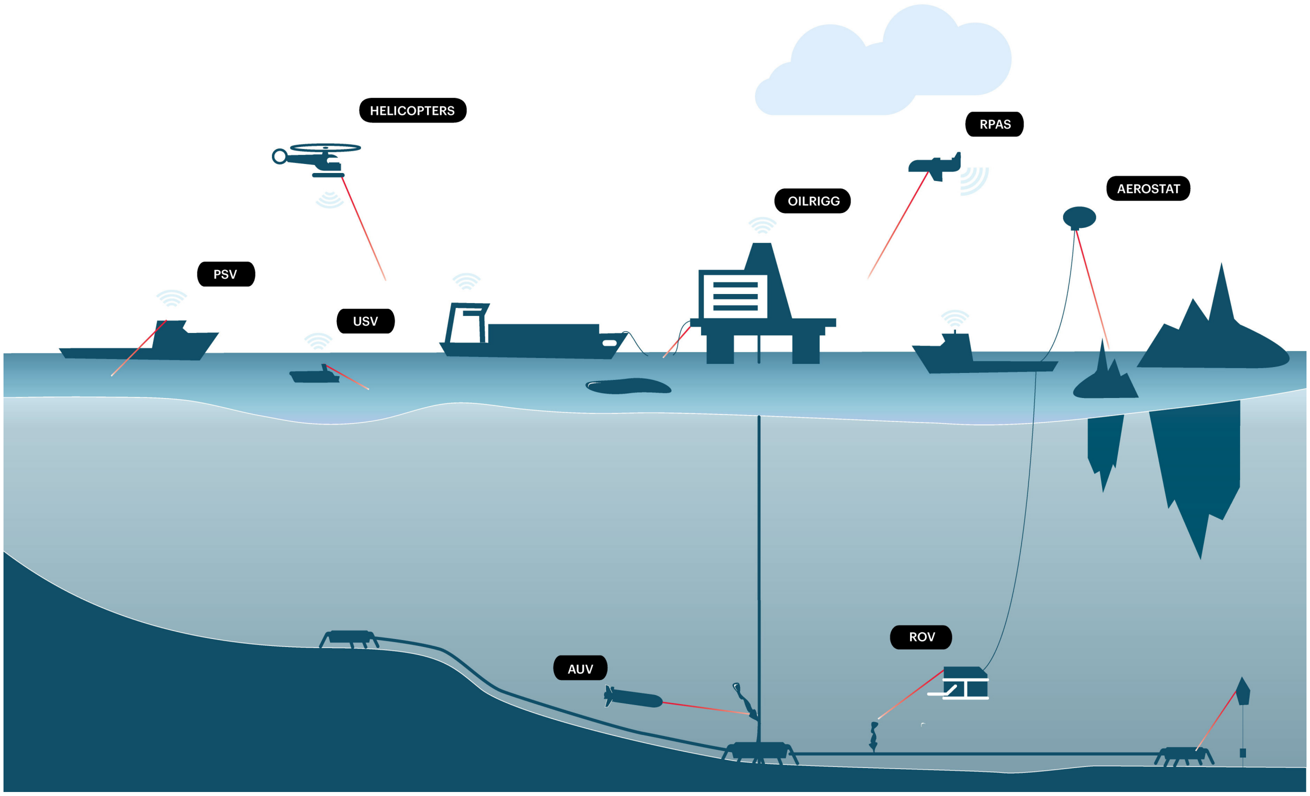

Fig. 2. Complex Oil Combat Operation Scenario

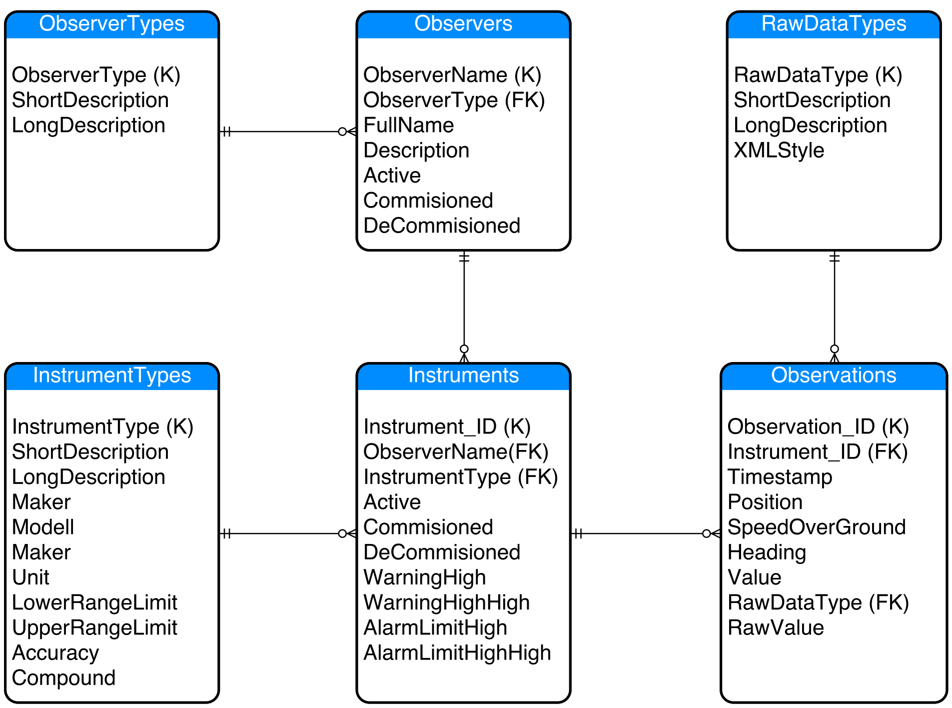

Fig. 3. ER Diagram

have a one-to-many relationship with the Observer. Each instrument have, analogous to the Observer, an InstrumentType and a current status. In addition, the Instrument have warning and alarm limits. The InstrumentTypes entity has a one-

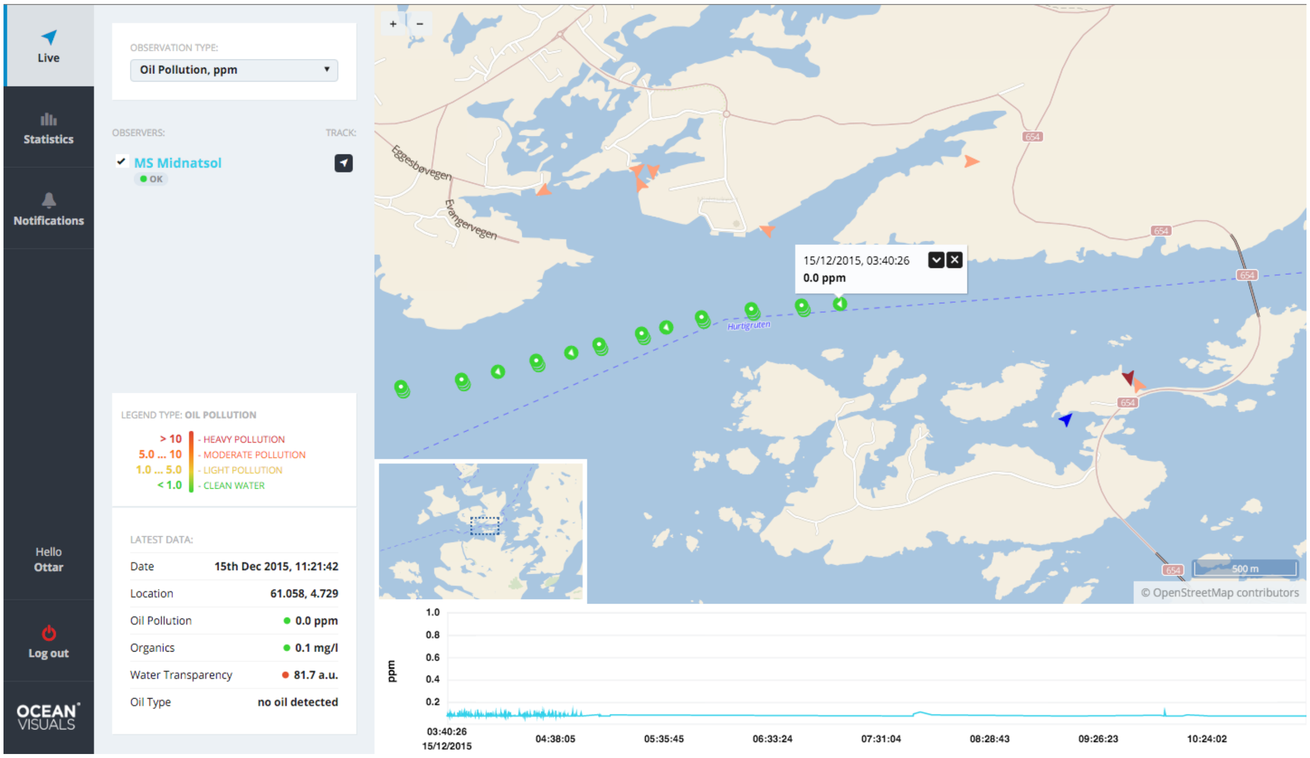

Fig. 4. Implemented System

to-many relationship to Instruments and store information of identical instruments maker information, ranges etc, i.e., information that is related to the instrument as it has been manufactured, not as how it is currently used/installed. Hence the Instruments entity could have some more attributes such as current calibration values, but for simplicity this has not been added, but should be considered as a possible future expansion.

The actual readings/measurements are stored in the Observations entity. Naturally this has a many-to-one relationship with Instruments and contains, in addition to the reading itself, also information about where the reading was made (geodesic coordinates) and the Observers current heading and speed. In order to allow for observations in the air, at sea-level and into the water columns the coordinates must be coordinates in (North, East, Down) or NED, where negative values are South, West, Up respectively. It is important to note that it is the position of the reading and not the observer that is stored, this is of great significance for remote sensing.

Some advances sensors, such as the OWL sensor, produces a reading after processing some raw data. As in the OWL case this raw data can be quite complex and voluminous. In the OWL case 500 channels spectral intensity data combined with environmental data such as temperature is processed by an algorithm that give 3 values, ppm oil in water, amount of organics in water (mg/l) and water transparency (a.u.). Since these raw values may be of great value for off-line analysis they should be stored. Likewise the algorithms that process the raw data could change over time and the format of the raw data may change over time. Hence, it makes sense to store some information on how to interpret the raw data. For this purpose the RawDataTypes entity has been added and have a one-to-many relationship to Observations. Hence, the raw data stored in Observations entity is ”black box”, but RawDataType give the key to how to process the raw data. This approach presents a common way of storing highly diverse raw data from different instruments.

In the above modeling, the 3rd Normal Form / Boyce-Cod Normal Form (3NF/BCNF) has been the modeling aim, but some practical adjustments have been made, like the ”black box” storage of raw-data.

The fact that the Observers move in space and vary in numbers is what really separates this kind of control systems from the standard *Supervisory Control and Data Acquisition* (SCADA) systems where all instruments are geographically located relative to the process plant, does not move (at best on rails) and are of constant size according to the engineering design documentation, such as *Process and Instrument Diagrams* (P&ID) for the system.

IV. System Implementation

Figure 4 shows the implemented system.

The web-based system visualizes the oil detection reading by different observers in real time with abundant interactive facilities for different user roles and purposes. The main view on the right shows the trajectories of one or several observers with each colored dot showing one reading from the oil detector. The line chart below the map shows the historic numerical values. The left panel allows the users to choose one or several observers to be shown in the mapview and the bottom part shows the latest detailed reading.

V. Conclusion

The requirements resulting in the proposed solution is based on the needs of Ocean Visuals for their OWL sensors, hence the design is not inherently general. However, the nature of the requirements is applicable to a wide range of maritime applications. Therefore, the authors argue that the proposed structure may with none or minor adjustments be applicable to a wide range of maritime applications.

Acknowledgment

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