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REMOTE OIL SPILL DETECTION AND MONITORING BENEATH SEA ICE

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ABSTRACT

The spillage of oil in Polar Regions is particularly serious due to the threat to the environment and the difficulties in detecting and tracking the full extent of the oil seepage beneath the sea ice. Development of fast and reliable sensing techniques is highly desirable. In this paper hyperspectral imaging combined with signal processing and classification techniques are proposed as a potential tool to detect the presence of oil beneath the sea ice. A small sample, lab based experiment, serving as a proof of concept, resulted in the successful identification of oil presence beneath the thin ice layer as opposed to the other sample with ice only. The paper demonstrates the results of this experiment that granted a financial support to execute full feasibility study of this technology for oil spill detection beneath the sea ice.

1. INTRODUCTION

To date, oil which has been spilt in the ice affected water, tends to disappear beneath the ice and it is not possible to detect and monitor where it has travelled or at which point it will emerge from the edge of the ice into open sea. This poses very significant challenges to any extenuating activities until well after the emerging oil has been located.

There is vast range of techniques available for the open water oil spills monitoring, including various satellite and airborne remote sensing methods [1, 2, 3]. However the detection of oil spills in ice affected waters differs significantly and proved to be much more difficult. Current approaches for oil under ice detection can be divided into two groups: on or above the surface sensing and the detection from underneath the ice. Extensive survey of available techniques for surface remote sensing is presented at [4] while [5] presents focused survey on the oil detection from underneath the ice surface. Various detection techniques, including for example Synthetic Aperture Radar (SAR), Microwave Radiometers (MWR) and Tunable Diode Laser Spectroscopy (TDLS), were presented in these reviews, but most of them are described as not applicable for the oil under ice detection. Hyperspectral imaging (HSI) was also included in these studies and similar to the other techniques it was identified as not applicable for this task. Authors of this work decided to challenge this statement and conduct additional verification of the HSI application for the oil under ice detection.

Hyperspectral imaging is an emerging technology which uses a new type of camera to capture the spectral signature of a scene. Detail description of this technique can be found at [6]. Spectroscopic techniques can then be brought to bear on a particular spatial region in order to look for the spectral signatures which reveal the molecular nature of the material under observation. The signal processing techniques which are implemented upon the data set resulting from hyperspectral imaging brings true potential to this technique and is able to extract specific information from the measurement data.

This paper demonstrate a proof of concept experimental results, preceding an extensive feasibility study of HSI application for the detection of the oil beneath the sea ice.

2. MATERIALS AND METHODS

A small scale experiment was conducted to verify applicability of available HSI equipment for oil detection from underneath the ice. Two separate tests were performed with two different imaging hardware - a passive hyperspectral camera operating in the near-infrared (Near-IR) wavelength range (900 - 1700 nm) (Red Eye 1.7, inno-spec GmbH) and an active, laser based, mid-infrared (Mid-IR) (2500 - 3750 nm) hyperspectral imager (Firefly IR Imager©, M Squared Lasers) featuring also short range of Near-IR band (1490-1850 nm).

2.1. Passive system

A test with passive system was performed on the premises of University of Strathclyde. Small container (WxLxH: 5x15x3 cm) was half filled with the sea water (about 15 mm depth) obtained from Scottish shore and

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was frozen in the laboratory freezer at a temperature of -30°C (see Fig. 1 a).

The passive system used for imaging is based on pushbroom technique [6, 7] and therefore requires relative movement of the sample versus detector. As the dimensions of the ice container were small, a linear translation stage (Zolix KSA 11-200S4N) was used to image the ice. Of-the-shelf halogen lamps were used to provide illumination for the sample. The container with ice was taken from the freezer and imaged in the room temperature. After the imaging of pure ice, the ice block was removed from the container and layer of about 15 mm of-the-shelf engine lubrication oil was poured into the container and the ice block was placed on top of the oil (see Fig. 1 b). There was no liquid sea water beneath the oil layer during this test. The imaging of this new condition was performed in the same way as for the pure ice block. Whole imaging procedure was finished before melting of the ice could be observed.

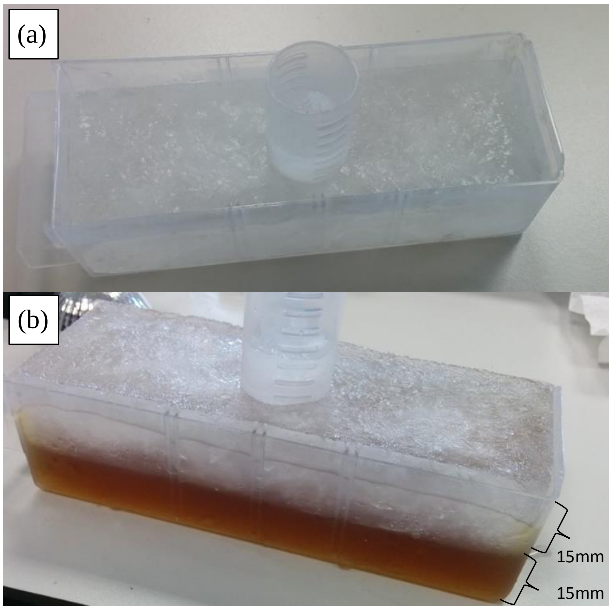

Figure 1. Small container with ice (a) and oil introduced beneath the ice layer (b)

2.2. Active system

Test with the active system was performed on the premises of Scottish Association for Marine Science (SAMS). The ice was grown in big cylindrical container (height: 1 m, diameter: 0.7 m) placed in a cold room with controllable temperature. The container was filled with the sea water obtained from Scottish shore and was maintained in the temperature of -30°C. The Firefly IR Imager was placed above the ice container to capture the hyperspectral data (see Fig. 2 a). As it is a laser based device providing active illumination during imaging, it did not require any external illumination. Additionally, this imager employs a whiskbroom scanning technique [6, 7] and the surface of the ice was scanned by two oscillating mirrors without movement of the sample or detector. Temperature control of the cold room during the imaging was disabled and the data collection was performed in the varying temperature, rising from approx. 10°C at the start, to the room temperature at the end of the imaging. It was observed that the ice surface was affected by this temperature increase.

After collection of the pure ice data, a hole was drilled at the side of ice layer and an oil layer (the same engine lubrication oil as used for test with passive system) was introduced over the hose inserted through the drilled hole beneath the ice. The thickness of the oil layer was not tested at that stage, but based on the dimensions of the container and the volume of injected oil, the approximate oil surface thickness was 10 mm. The data for the new conditions was collected in the same way as for pure ice. After the test was completed, the ice was cut and it was measured that the time of water freezing prior the experiment allowed to grow approx. 80 mm thick ice layer (see Fig. 2 b), maintaining cooled down liquid sea water underneath.

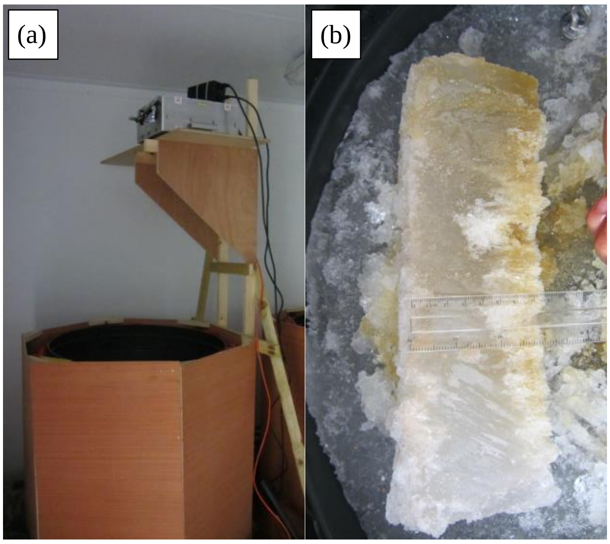

Figure 2. Scanning setup with the Firefly IR Imager above the container with ice (a); ice block of approx. 80 mm thickness cut after the imaging (b)

3. RESULTS

The data sets captured with both hyperspectral imagers were analysed using state-of-the-art techniques. Due to the fact that the main objective of this experiment was to conclude if the HSI is able to detect the oil beneath the ice, the classification technique was employed to distinguish a pure ice and oil under ice scenarios. The analysis was performed with the help of Support Vector Machine (SVM). SVM is a machine learning technique characterised by robust and consistent performance, that makes it a very popular technique for solving classification problems [8, 9].

Due to the limited amount of data available for classification, the same hyperspectral images were used for training the algorithm as well as for classification purpose. For the training of the classifier always only subset of the analysed image was used (illustrated on Fig. 4 and Fig. 5 as coloured ellipses drawn on the intensity image of one chosen band from hyperspectral data cube). To check the classification performance on different sizes of the training data, two sizes of approximately 5% and 25% of total available data were tested. All classification results are presented in the graphical form, where a colour illustrates the class assigned during the training process and the one identified by the classification algorithm. In all the figures red colour of the training region ellipse and classification result represents pure ice case, while green represents the situation with oil underneath.

3.1. Passive system

The images from the two test cases (ice with and without oil underneath) have been stitched together as a one classification problem for the algorithm, and the training data was chosen from each case as described above. Fig. 3 demonstrate the spectral response of both samples used a training set for the classifying algorithm.

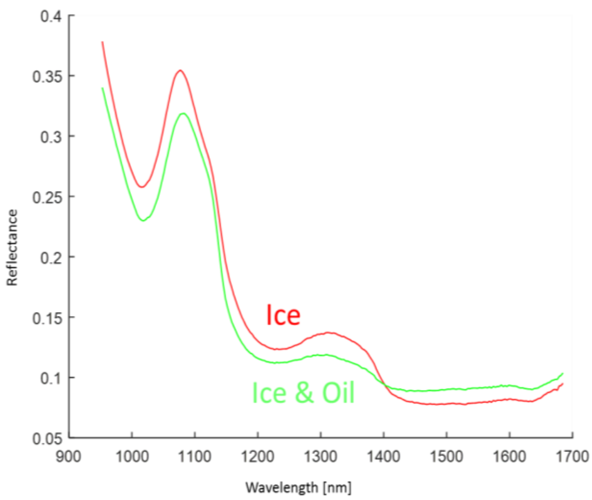

Figure 3. Spectral response of pure ice and ice with oil underneath

To provide a clear illustration of the results, additional class was assigned in this case, to demonstrate the background of the image (blue colour). Fig. 4 illustrates the classification result for both mentioned sizes of training data.

As it can be observed on the Fig. 4, the classifier properly identified most of the pixels on the image, even with very low amount of training data. With increased training set the only misclassified region corresponds to the plastic container and a plastic holder that the algorithm was not trained for.

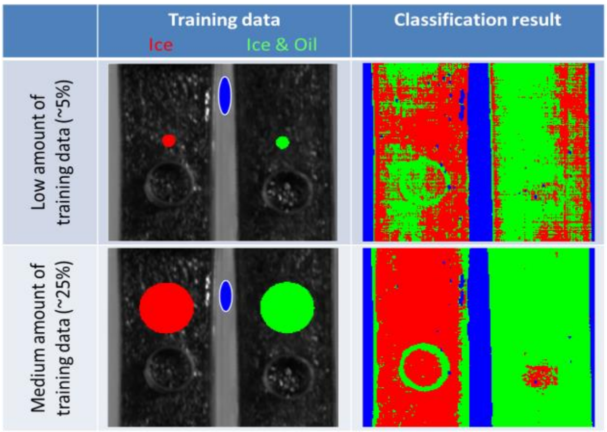

Figure 4. Illustration of two sizes of training data and colour representation of classification result for the data set from passive equipment.

3.2. Active system

During the analysis of the data collected with the active system, the same approach was taken as in case of passive system data analysis. The two data sets (of pure ice and ice with oil cases) were stitched together and analysed with the classification algorithm as one problem (the line of stitching is illustrated by dashed line on the intensity image with training data selection). The consideration of the two training data set sizes was also maintained. Since the Firefly IR Imager is able to capture the data in a two distinct spectral regions, the analysis of the data from these bands was considered separately. The results for near and mid-infrared spectral bands covered by the imager are demonstrated respectively on Fig. 5 a) and b).

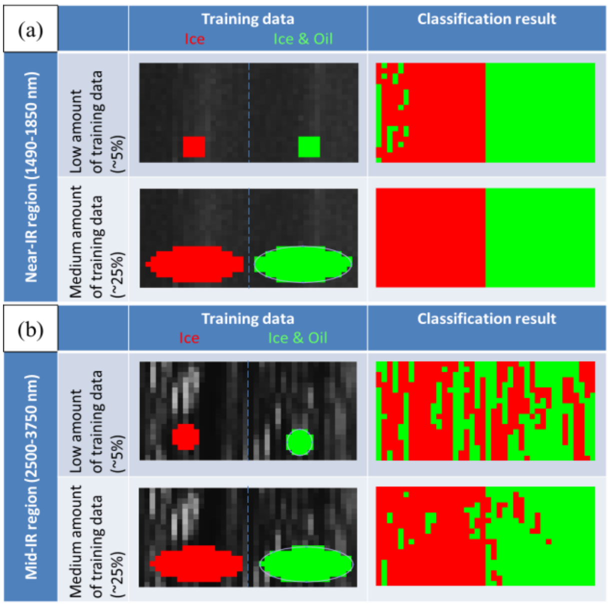

Figure 5. Illustration of two sizes of training data and colour representation of classification result for the data set from active equipment operating in the Near-IR region (a) and Mid-IR region (b).

By cause of the nature of the active imager (laser point illumination) and the ice surface (rough structure with highly specular reflectivity), significant variation in the detected reflected energy was observed across the acquired image. Due to this fact, the classification algorithm requires sufficient amount of training data to understand this variation. During the analysis it was observed that the training set of approx. 25% of total data provides good classification result despite of the location of this data, however results based on training with approx. 5% of total data were highly dependent on the spatial area of the image where the training set was taken from.

4. CONCLUSIONS AND FUTURE WORK

The presented experimental results demonstrate that hyperspectral imaging empowered by signal processing techniques is able to detect the oil underneath a thin layer of ice. The oil under ice scenario could be correctly distinguished from the pure ice case based on the data from both employed HSI cameras. Within this experiment the detection was tested only through 15 mm ice layer for passive system and 80 mm ice layer for active system, however clearly the potential of this technology for oil under ice detection was demonstrated. Results from presented experiment served as proof of concept for extensive feasibility study, exploring the capabilities of HSI for the oil spill detection underneath the sea ice. This project will quantify the limits of this detection and seek to answer the following questions:

- What is the maximum thickness of ice that Hyperspectral Imaging can detect oil underneath it?
- What is the minimum oil layer thickness that can be detected with various HSI systems?

By understanding these limits of detection we will have the knowledge to design a system ready for deployment in the field for oil spill detection beneath ice.

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