Smart Detection of Marine Spills
Project report

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1 Introduction

On a daily basis, the airplanes of the Dutch coastguard perform surveillance flights of the North Sea. One of the goals is to detect illegal discharges of oil or harmful dangerous substances on behalf of Rijkswaterstaat (Ministry of Infrastructure and Water Management).
These observations are part of the Bonn Agreement, in which the countries surrounding the North sea cooperate on oil spill response as well as on surveillance of the area to detect spills. Each of the participating states performs routine surveillance on its own EEZ (Exclusive Economic Zone). In addition, larger area wide surveillance tours are performed and exercises are organized.
Spill observations made during these surveillance flights are based on the interpretation of the observer based on the different qualitative sensor(/camera) outputs available on the aircraft.

The Bonn Agreement is the mechanism by which the North Sea States, and the European Union (the Contracting Parties), work together to help each other in combating pollution in the North Sea Area from maritime disasters and chronic pollution from ships and offshore installations; and to carry out surveillance as an aid to detecting and combating pollution at sea.
In other areas similar collaborations are in place, for instance the HELCOM or Helsinki Convention focusing on the Baltic sea, and the Regional Marine Pollution Emergency Response Centre for the Mediterranean Sea (REMPEC).

The Centre of Expertise in Computer Vision and Data Science at the NHL Stenden University of applied sciences, specializes in image-recognition on large and complex datasets based on deep-learning and computer vision technology. The group has a state of the art laboratory with a number of the most advanced (hyperspectral) cameras and specialized supercomputers for performing complex and computing-intensive machine learning techniques.

1.1 Goal

The project Smart Detection of Marine Spills aims to understand how these techniques can be employed in the aerial observation on the North sea. The central research question therefore is:

“How can available new techniques in terms of camera and sensor systems as well as image recognition optimally benefit in aerial observations of Marine Spills on the North Sea.”

Potential benefits can either lei in enhance capabilities of the hydrocarbon detection or in detection of other features:

- Increased reliability of volume calculations.
- Indication of oil type or properties (‘chemical composition’)
- Detection and/or identification of substances other than oil
- Detection of other natural or anthropogenic marine features: algal blooms, plastic soup or floating objects.

1.2 Project outline

Within the project, brief feasibility studies are performed on two of the extremes in development routes:
The least complex development in full scale would be image recognition on the images of the existing camera systems. Feasibility study of this development will be an image recognition test on a set of images.
Furthermore the possibility of using more complex camera systems will be studied with a literature review and a small pilot-test using a hyperspectral camera. Implementation of such development to full scale of course is a more complex route.
The results of these two studies give insight in where a development will be most beneficial. Therefore in the second phase of the project, possible development routes for the surveillance system will be defined, and benefit and complexity of these developments are compared.

1.3 Acknowledgements

This research project is financially supported by a 'KIEM - Smart Industry' grant, provided by the Taskforce for Applied Research (SIA) of the Dutch Organization for Scientific Research (NWO).
Project partners include: NHL Stenden University of Applied Sciences, Rijkswaterstaat (Ministry of Infrastructure and Water Management), Skeye BV and ASCC group.

2 State-of-art: Remote sensing of marine (oil) spills

2.1 Aim of aerial observations of oil spills

The surveillance flights serve different goals: Firstly they aim at early detection of oil spills, while they are still in a state that allows for clean-up operations. (An oil slick on the water surface will either weather (evaporation and emulsification) into a high viscosity emulsion that is very difficult to clean-up or develop a thin slick rapidly disappearing into the water column and the air by dissolution and evaporation. In both cases, response is no longer possible.) Moreover, the opportunity to catch a polluter in the act and collect the evidence to enforce the regulations, is aimed to deter potential polluters from spilling[1].
Although the annual data appear to show an overall downward trend in number of observations per flight hour over the years (Fig. 1), the data is considered too sparse to allow reliable analysis about oil input in the entire Bonn Agreement area[2].

During a (major) pollution incident, additional ad-hoc aerial observations are performed. Apart from gathering evidence, these observations aim to aid the spill response[1,3]. In addition to determining the exact spill location, the observers can also indicate type and amount of oil and assess whether spill response is feasible within the mobilisation time. After mobilisation of the response equipment, aerial assistance can help guide them to the thickest parts of the oil slick, optimizing response efficiency[1,3]. Furthermore, the weathering and attenuation of the oil slick can be observed and provided as an input for modelling[1,3].

2.1.1 Observation outputs

In order to fulfil the aims outlined in the previous paragraph, the observations should provide the following information[4]:

- The extent of the spill, obtained from the dimensions of the slick or patches including the degree of coverage and thickness.
- The spill position at the time of observation.
- The type of pollutant and it's degree of weathering as derived from appearance of the oil slick (shape colour and formation).

For the purpose of easy information transfer between countries, there are oil pollution reporting formats, available from different cooperation organisations as IPIECA[5], IMO[6] and the Bonn Agreement[6].

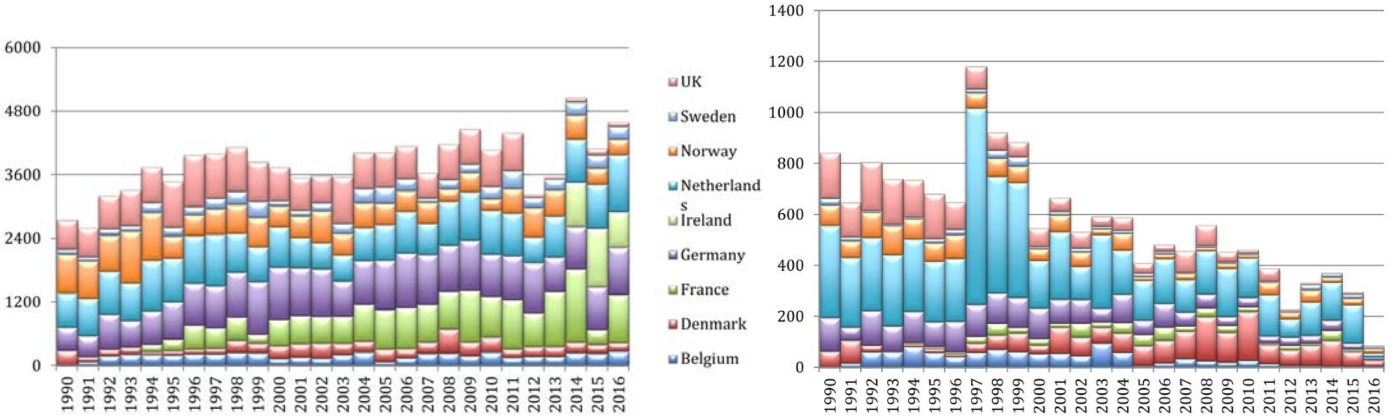


Fig. 1 Number of flight hours (left) and number of observed spills (right) per (Bonn Agreement) country per year. The graphs exclude 'detections of other substances' (61 in 2016) and 'detections of unknown substances'(188 in 2016). Figure and data source: Bonn Agreement. Annual report on aerial surveillance for 2016[2].

2.2 Marine oil spill observation techniques

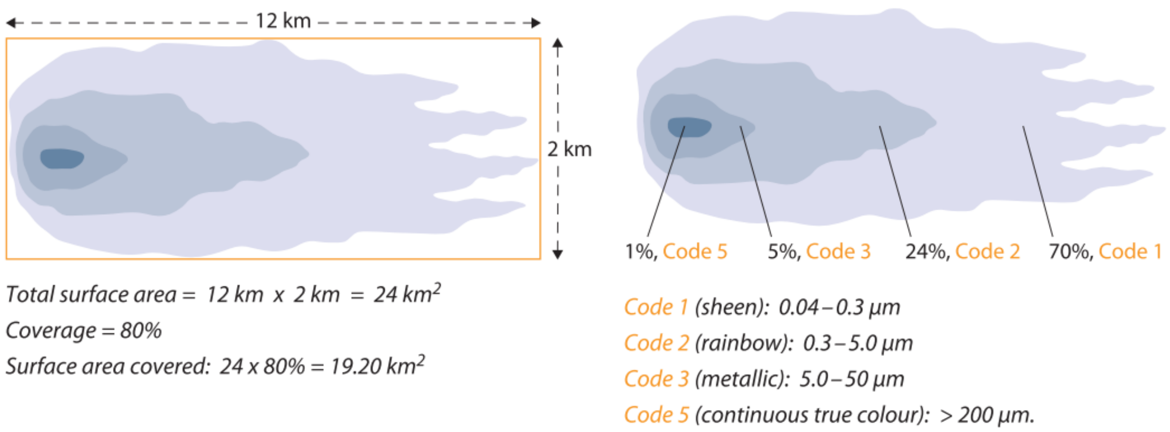
2.2.1 Techniques currently in use

Visual observation: VIDEO/FOTO

An oil slick on the water surface is visible as the colour of the oil or as a shimmer on the sea surface. A trained observer can obtain quite some information about the slick: The shape of the slick can indicate the cause of a spill (a long line for a continuous spill during transit, a triangular shape for a spill under the water surface upstream, …)[7].
Through light refraction, different oil thicknesses show up as different colours on the water surface. The Bonn Agreement Oil Appearance code (BAOAC) describes the colours as ‘sheen’, ‘rainbow’, ‘metallic’ and ‘true oil colour’ in increasing thickness[7]. However, the colour of metallic can vary with the oil’s original colour, and residual fuels can block all light and show up black even as thin layers[7]. The viewing angle in relation to the sun is also critical in visual oil slick observations[8]. In addition observations can be influenced by type of oil, presence of clouds, sunlight and sea state[7,8].

The Bonn agreement colour code is used to estimate volume of oil on the water surface (Fig. 2). Comparing the volume calculation of different operators on the same slick in a large international exercise[9,10], showed that the difference between observers mainly stemmed from differences in the estimation of the slick area and oil appearance coverage percentage[11]. The area estimations thus are a source of error in the volume estimation[7]. Technical means are available to aid operators in this estimation: through GPS annotation of images[12] the true size of a slick can be obtained.

A *NADIR camera* is a visible light camera pointed directly downwards from an aircraft. This configuration allows for easy geo-referencing based on the aircraft location and orientation. Combining such a camera with other sensors with the same orientation, allows for cross-comparison between the different sensor outputs and the visual image.



a) Minimum estimation

Code 1	19 x 70% x 0.04 =	0.532 m³	(532 litres)
Code 2	19 x 24% x 0.3 =	1.368 m³	(1,368 litres)
Code 3	19 x 5% x 5.0 =	4.75 m³	(4,750 litres)
Code 5	19 x 1% x 200 =	38 m³	(38,000 litres)
	Total:	**44.65 m³**	**(44,650 litres)**

b) Maximum estimation

Code 1	19 x 70% x 0.3 =	3.99 m³	(3,990 litres)
Code 2	19 x 24% x 5.0 =	22.8 m³	(22,800 litres)
Code 3	19 x 5% x 50 =	47.5 m³	(47,500 litres)
Code 5	19 x 1% x 200 =	38 m³	(38,000 litres)
	Total:	**112.29 m³**	**(112,290 litres)**

Fig. 2 Example oil volume estimation based on the Bonn Agreement colour code. Figure taken from “Aerial observation of oil spills at sea” by IPIECA/OGP, 2015. [4]

A *Low Light Level TV Camera* can provide possibility of imaging ships names or identifying features in near darkness[3].

Optical satellite observations can be used to assess the extent of the spill. Observations are limited to timing and location of the satellite overpass and the absence of clouds. Developments in recognition of oil against the background improve: In case of the Exxon Valdez spill (1968), where spill coordinates were exactly known, experts spent 2 months isolating the oil from background in order to provide an image for the slick[13]. Over time the number of satellites has increased, making time & space constraints of this observation technique less prominent. Developments in recognition algorithms, for instance by isolating and removing the effects of sun glint[14], allow for better delineation of the oil slick. As a result, very clear images are available of the Deep Water Horizon oil spill (Fig. 3).

Radar

Generally, on a clean sea surface the radar signal is reflected back, visible as radar backscatter. An oil slick on the water surface suppresses the capillary waves mainly responsible for this backscatter; it shows up as a darker spot on the radar image[3]. As other phenomena (for example algae, sand banks or upwelling of colder water) are also capable of suppressing backscatter, there is a possibility of mis-identification or false positives[3,15,16]. Furthermore, the radar detection doesn't work in dead-calm conditions without waves (< 1 BFT).

A *Side Looking Airborne Radar (SLAR)* is fitted as two beams on the side of an airplane. Under suitable conditions, the field of observation extends up to 40 km on either side of the aircraft[3], with a blind spot directly beneath the aircraft. Due to the large range of detection, the SLAR is a very useful tool for the initial recognition of an anomaly, however additional confirmation is necessary.

Synthetic Aperture Radar(SAR) is very similar to SLAR. SLAR generally employs a real aperture radar, meaning the antenna length is related to the physical size of the antenna. SAR systems employ the movement of the antenna, to simulate a larger antenna (synthetic aperture)[3,17]. As a result, a higher resolution image can be obtained.

As SAR resolution can be tuned independent of observation height, it can be employed from **satellites**. The SAR installed on EnviSat and Radarsat has been proven to detect water surface phenomena as small as 200 cubic meters[3]. Although these observations are limited to the time and place of the satellite orbit[3], they do provide a regular recurring monitoring tool: In the first 10 years of operation the European CleanSeaNet system has monitored 4300 million square kilometres of sea surface[18]. As

Fig. 3 A visble satellite image of the DeepWaterHorizon oil spill captured on April 29 from the NASA TERRA satellite. Credit: NASA/Earth Observatory/Jesse Allen, using data provided courtesy of the University of Wisconsin's Space Science and Engineering Center MODIS Direct Broadcast system.

with the other radars, there are limitations in wind speed (between 2-3 m/s and 15 m/s)[18], and confirmation is needed after the first detection.
The use of SAR from smaller unmanned aircraft (**Unmanned Aerial Vehicle, UAV**) is a more recent development[15]. As the radar frequency employed is equal to that in commercial air traffic control, a 24 hour notice has to be given before any flight. As a result it is not an urgent response platform but only used in research. Initial results seem promising as they claim to differentiate between thick and this oil and possibly recognizing emulsions. Similar limitations in wind speeds apply.
Ship based oil radar systems can help guide the ship to the oil slick, as visual detection of the floating oil is very difficult from this limited height. Available systems have a range up to 3,5 km from the ship[19]. The same limitations (wind is needed, potential false positives) for radar systems apply.

UV

Oil is a very good reflector of the UV component of sunlight, therefore a UV (passive) sensor can distinguish oil on the water surface[3]. A UV sensor can see very thin layers of oil, but can't distinguish between thicknesses[20]. UV systems are used from aircraft, and are limited to daylight conditions (presence of sunlight) and clear skies.

IR

The different thermal properties between oil and water, enable a passive IR sensor on an aircraft to detect certain aspects of an oil slick[3]. Thin oil layers (from 10-70 µm up to 50-150 µm)[13] cool down by evaporation and initially can show up grey on the IR image. Thick layers (upwards of 50-150 µm)[13] absorb sunlight and heat up, thereby showing up white in the IR image[3]. The limits for the different detections are not fixed, and attempts to calibrate with thickness were unsuccesfull[8]. An IR sensor can work in darkness, but it does need a clear sky (no clouds or fog)[3].

A *combined IR/UV sensor* can help identify the location of the thick parts (IR sensor) within the total extent of the slick (through the sensitive UV sensor)[3], and thereby help guide response efforts to those thick parts.

UV and IR systems can be employed in different aircraft mounting versions: A **UV/IR line scanner** looks directly below the airplane and needs to pass over a slick for observation[3]. This configuration is very useful for combination with other sensors. A **Forward Looking IR (FLIR)** system is mounted on a gimble. The aircraft can stay at a distance from the slick and look at it from an angle. Most systems can lock onto a 'target' for observation[3]. Downside of this configuration is that older systems do not readily provide geospatial information as true size, location and orientation of the slick[3].

MWR

The microwave radiometer (MWR) works with a principle similar to IR and UV, this passive sensor detects radiation at a certain wavelength[3]. Within the detection range (>100 µm to 3 mm) this sensor can provide thickness information, provided a careful pre-processing is performed[3]. One intensity can represent several thicknesses as the relation between intensity and thickness is not linear but cyclic[8]. Furthermore, intensity is also influenced by weather and sea conditions and type of oil[8]. Uncertainty about thickness can be reduced by using multiple channels[8].

Laser Fluorosensor

The laser fluorosensor is an active sensor that emits a laser beam straight down from the aircraft. The sensor detects and analysis the resulting fluorescence of the pollutant[3]. The flight altitude must be very low (150-180m) for this detection technique[20]. Originally the LF sensor only measured a thin line directly below the aircraft, a more recently developed scanning technique makes it possible to observe a swath of 200m width[20]. Operational testing indicates a possibility to also obtain information on type of pollution[21]. However, operational application is limited, due to the high cost & one-of-a kind nature of the sensor[20].

Sensor combinations

As a result of their working principles, the different sensor types mentioned above have different observable thicknesses (Fig. 4). Observing a slick with multiple sensors, will therefore provide more information on the thickness profile or mass distribution within the oil slick.

2.2.2 Developments in observation techniques

Developments and research into observation techniques continue. Most developments aim at better identification of thickness (and mass), and include:

- Development of a 2 step identification system on aerial multispectral sensor (450,551,600,710 nm) output[20]. Step 1: A neural network classification to identify areas that contain oil vs no oil. Step 2: obtaining thickness distribution by comparing oil pixels with clean-water pixels.
- Analysis of high resolution (< 10 m) satellite images to classify oil into four major (thickness) features[22].
- Employ existing *satellite based Near infrared (NIR)* (wavelengths of 0.75–1.4 µm) observations to map oil and oil layer thickness[13].
- Satellite and aircraft based *Compact Airborne Spectrographic Imagers (CASI)* obtaining multispectral images for detection of oil on water[23,24].
- A laser acoustic method, *Laser Ultrasonic Remote Sensing of Oil Thickness (LURSOT)*, for oil layer thickness determination. This method is based on the speed of sound and measures the time it takes to travel from the top (slick) surface to the water-oil interface[8].

2.2.3 Observations platforms

Currently, the operational surveillance mostly occurs by (manned) aircraft, supplemented by satellite recognition. Satellites are mainly useful for regular surveillance and/or observation of very long-lasting spills due to their fixed orbit. However they do complement the continuous observation of the sea area.

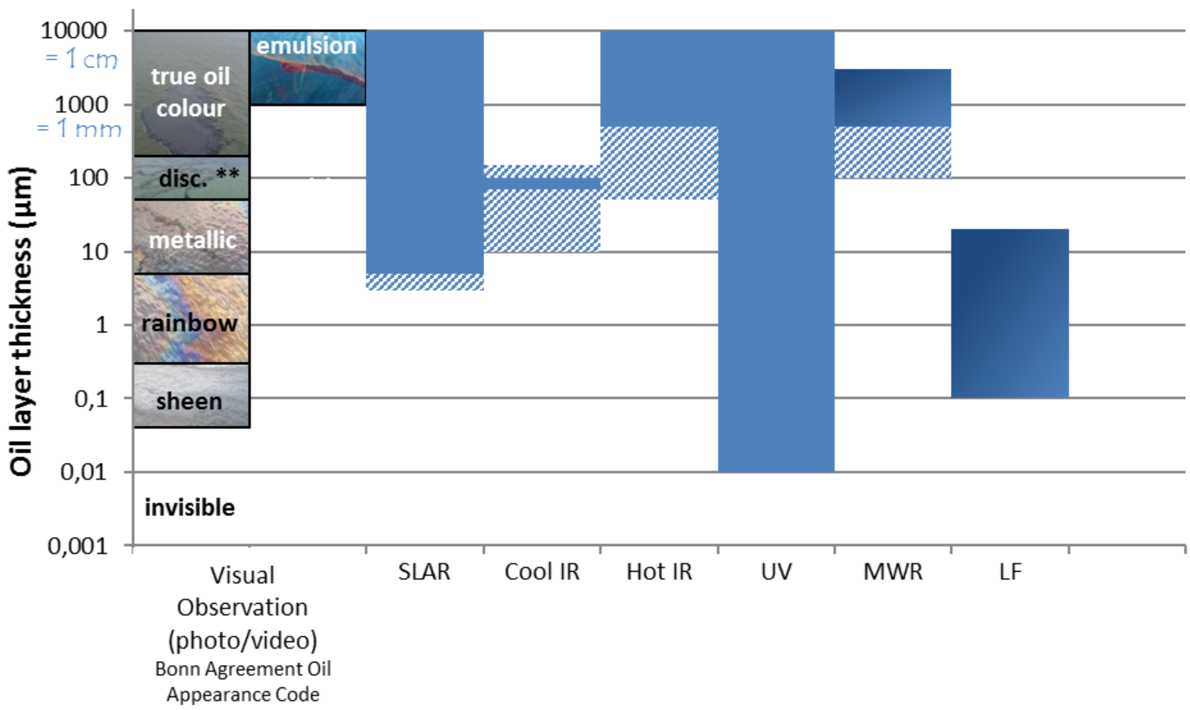


Fig. 4 Oil layer thickness detection limits per remote sensing technique. Solid areas indicate the sensor can certainly observe this thickness, hashed areas indicate uncertain or condition-dependent observation. A colour gradient indicates this sensor can identify different thicknesses. (Data: Appendix 1: Observation methods summary.)

Unmanned Aerial Vehicles (UAVs) or Remotely Piloted Aircraft Systems (RPAS) are ‘considered of significant benefit as they would complement existing tools’ in pollution monitoring and response[25–27]. However, despite promising experiments[15], they are not yet very commonly used in this field.
Radar oil slick detection can be performed from a ship. Additionally, during an active spill response, a balloon containing camera equipment can be deployed from the ship[3] to observe the pollutant in the direct vicinity.

3 Project activities

This section describes two experiments performed. The goal of the first work package is to investigate if the Bonn Agreement Oil Appearance Code (BAOAC) can be learned by a machine using Artificial Intelligence (AI). The goal of the second work package is to investigate if oil thickness can be determined using Short-Wave-Infrared (SWIR) Hyperspectral imaging.

3.1 WP1: Machine learning Bonn Agreement Oil Appearance Code

Oil slick thickness is typically determined by using a visual observation. In this work package an AI system is trained to learn oil appearances from human operator.

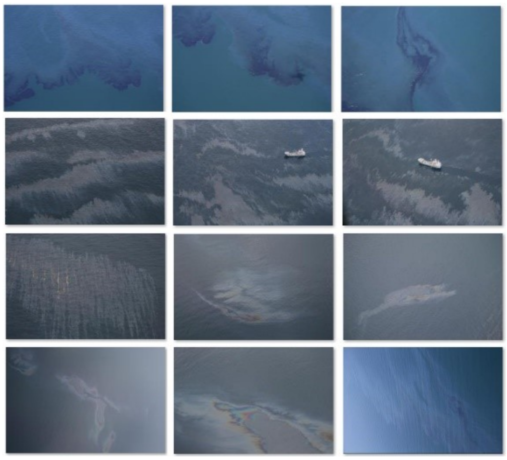


Fig. 5 Images of oil spills.

3.1.1 Dataset

A dataset consisting of 12 colour images has been used for this experiment. Each image contains an oil spill (Fig. 5). These images show a variety of oil appearances (e.g. rainbow, sheen, etc.) By manually annotating each image the operator can teach the system where the occurrences of each oil appearance can be found. This can be visualized as a colour map (Fig. 6). This is the information an AI needs to learn, and is called a ground-truth.

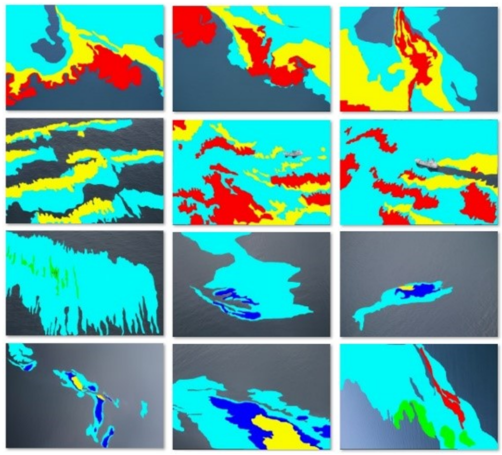


Fig. 6 Manual annotation of all oil appearances.

3.1.2 Experiment

When training an AI system from data, a training set is used, which is a subset of the original data. The performance is always measured on a held-out set, to measure generalization behaviour.

Generally, when learning from a limited amount of data the variation between images should not be too large. For this reason the dataset is divided in two parts: part 1, containing three images (using two for training and one for validation.) Dataset 2 consists of four images (three for training and one for validation.)

3.1.3 Results and conclusion

The detecting results for the oil appearances: discontinuous true color and rainbow look promising. Sheen and metallic are difficult to distinguish because of visual similarity. Fig. 7 shows some results of detecting the presence of Sheen.

From this experiment it is clear that (many) more images are needed to develop a robust detection system, especially for the visually similar oil appearances.

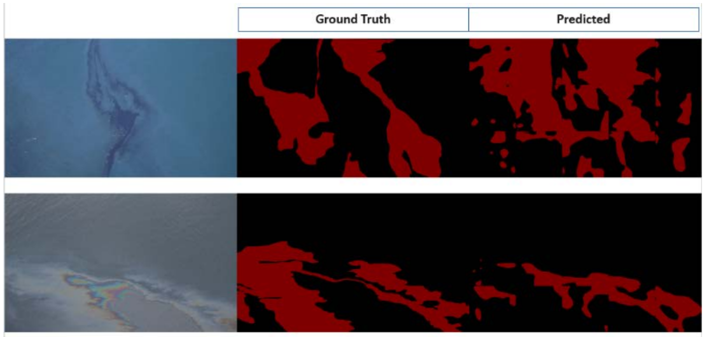


Fig. 7 Left shows the original RGB images, middle shows the manual annotation of Sheen and right shows the output of the AI system. The AI system is fairly able to separate Sheen from other appearances.

3.2 WP2: SWIR hyperspectral imaging on oil films

New and increasingly cheaper imaging technologies make innovations possible. Recently, hyperspectral imaging technology in short wave infrared (SWIR) has become cheaper and more compact. With hyperspectral imaging the reflectance between narrow wavelengths of light can be measured. In this case, up to 224 spectral bands measuring from 900 to 1700 nm.

In a laboratory setting, NHL Stenden has shown that this type of camera can be used to distinguish several types of plastic polymers (PET, PE, PVC, etc.) With the use of AI technology, further improvements have been possible by letting algorithms learn directly from hyperspectral image data.

Because plastic and oil are closely related, hyperspectral SWIR imaging might be an interesting option to measure oil slick thickness.

3.2.1 Dataset

A dataset consisting of several types, compositions and thicknesses of oil on water is created. Thicknesses vary from a thin film to pure oil. Pure water is added as a base line. In Fig. 8 several water-filled cups are shown, having a thin layer of oil.

Fig. 8 Several cups with different oil films.

3.2.3 Experiment

The idea is to investigate if there are specific spectral bands which respond differently to certain oil films and compositions. By measuring the spectral response of a specific rectangular region of each oil slick/cup, and by plotting the average response, the goal is to find a difference which correlates to the thickness.

3.2.4 Results and conclusion

Fig. 9 shows the spectral responses of the oil film in the cups. The result shows that pure water produces a peak at a specific spectral band. Also it seems that this peak is attenuated depending on the thickness and composition of the oil.

The results look promising, but no definite conclusions should be drawn from these results because the data is very limited. Future research might focus on investigating if this peak can be used to quantitatively measure the oil thickness.

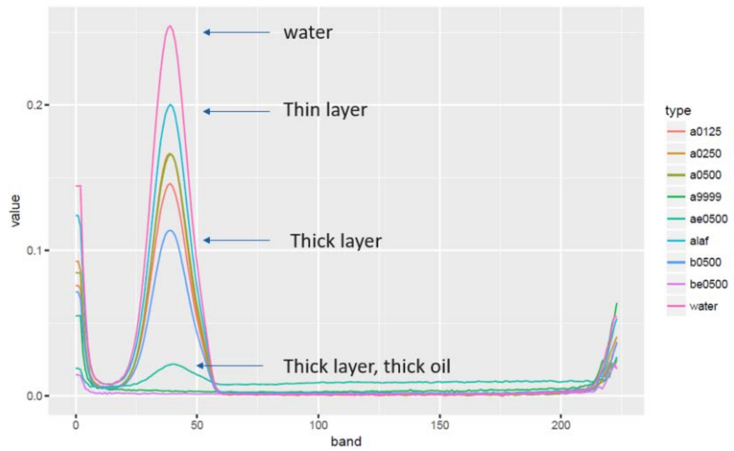


Fig. 9 Spectral peak of water and the attenuation caused by the oil film.

3.3 WP3: Scenario's

The outcomes of the practical experiments were presented to the committee of project partners (Table 1).

Subsequently, the participants discussed how new developments could aid the surveillance of the North Sea. *Side note: Because the brainstorm occurred in Dutch, the outcomes are also noted in Dutch (Appendix 4: Brainstorm output).*

Table 1 Brainstorm participants

Simone Luijendijk	ASCC group
Pieter Franken	Skeye BV
Wopke Kuipers	Rijkswaterstaat
Abel Spanninga	Rijkswaterstaat
Sandra Heins	NHL Stenden
Marieke Zeinstra	NHL Stenden
Klaas Dijkstra	NHL Stenden

For this discussion the (translated) central question was:

"How can available new techniques in terms of camera- and sensor systems as well as image recognition optimally benefit in aerial observations of Marine Spills on the North Sea."

To avoid reducing new developments to monetary terms, instead of cost-benefit, the following aspects of each development were discussed:

- Added benefit (*meerwaarde*): What is enabled by this development?
- Preconditions (*randvoorwaarden*): What is needed beforehand to be able to do this development?
- Complexity (*complexiteit*): How complex is this development?
- Optional additions (*optionele aanvullingen*): What are easy added options?

The outcomes of the brainstorm can be found in Appendix 4: Brainstorm output.

For oil spill response, the most important information is the size of the oil slick, the thickness and the resulting oil volume. Automatic identification of the features (colour & areas) needed to obtain this information appears to be a desired development. As explained in paragraph 3.1, this can be feasible with some preconditions that are not yet available (a very diverse dataset to train an algorithm, and georeferenced images).

To aid in creating such a large dataset, a potential development route would be to create a tool that observers can use to annotate images. If we can provide a tool that is beneficial for the operational and reporting tasks of the observers, we can store the uploaded information for use in the algorithm development.

When automatic detection of spill size and location is feasible, the information could potentially be uploaded directly into the operational transport & weathering models of the onshore spill response team.

Adding more cameras/sensors to the observation system has also been mentioned. In addition to improved size & volume observation, this could provide indication of oil properties and/or visibility in darkness or otherwise unsuitable conditions. The suggested routes included a separate research project to investigate which sensor combinations would give the most useful information for spill responders.

Further comments indicated that, when choosing to start a development to enhance the surveillance capabilities, we should also consider:

- Does the development only benefit the Dutch observations, or should it be applicable to a broader user-base?
- It is usable in harbors or on open waters?[1]
- Is it aimed at large or small spills?

[1] A few recent spill events in harbors show that visibility of the spill from shore is limited, both because of the viewing angle as well as the limited field of view. When a new development should also be of use in harbors, we have to bear in mind whether the working principle of the technique also applies to harbor conditions.

4 Future Perspectives

There are many different techniques for observing oil spills, each with their own pro's and cons'. In addition, development of new sensor and observation techniques in the field of marine spill surveillance is ongoing. Operationally, most organizations use the traditional methods (RGB, SLAR, IR, UV) and rely on operator judgement, possibly due to difficulty in accurately calibrating novel sensor techniques for the wide array of potential (environmental) conditions.

A potential development route is the development of new sensor systems to detect other features or provide more information about an oil slick. As with image recognition on existing sensors, the validation and calibration in the field requires sufficient data. Especially when a novel technique is only applied to one observation aircraft, obtaining sufficient field data can be a lengthy task.

The most concrete development wish appears to be the automated recognition of the Bonn Agreement Oil Appearance Codes in the camera (RGB) images. As our feasibility study indicated, a comprehensive training set is needed to make a robust system for automatic detection of the color code. A big advantage in this case is the fact that RGB images (photo or video) are already collected by all the observation aircrafts.

A potential development route would be: Develop an annotation tool that operators upload their images into that allows them to annotate the different colors. This tool should be useful to the responders, either by automatically filling in the Standard Pollution form or even by direct coupling to the oil weathering and transport model. The annotation tool can have active learning capabilities, meaning it gives suggestions to the user based on earlier input. Development of such tool is not limited to the field of oil spill response, and can be part of a much larger scope within the field of computer vision and data science. If the finished annotation tool is used by the observers, the dataset will start to grow. Once enough images have been collected, work can commence on training an automated recognition system.

This development does require cooperation with a large group of (international) collaborators/contributors. As oil spill occurrences and observations are scarce, we need as many observing organizations on board, contributing data.

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Appendices

Appendix 1: Observation methods summary

Sensor	Platform	Principle	Observable substances	spill size	Thickness	Field of View	Resolution	Required conditions
Visual observation Photo/video					Bonn agreement oil appearance code			Good visibility clear sky
Radar		Surface roughness. [3] Attenuation of capillary waves						
SLAR Side Looking Airborne Radar	Airplane		Floating liquid layer		> 3-5 μm [4]	40 km either side [3] 20 NM either side [4]	20 m [3]	U_w: 1 – 7 BFT [3,4] Can penetrate clouds
SAR Synthetic aperture radar	Satellite			> 200 m^2 [3]				2-3 m/s < U_w < 15 m/s [18]
SAR Synthetic aperture radar	UAV							1.5-2 m/s < U_w < 1 m/s [15]
Oil Detection Radar	Ship		Floating liquid layer	> 3 l [28] > 5 l [29]		0.1-3.5 km from centre [19]	< 3.75 m	U_W > 2 m/s [29]
Infrared (IR)								
IR line scanner	Airplane				> 10 μm [4]	1000m swath width [4]		Daylight & darkness. Clear sky [3]
FLIR Forward Looking Infra Red	Airplane				> Rainbow/Metallic [4]			Clear sky
Ultra Violet (UV) Ultra Violet								
UV line scanner	Airplane	Detects UV (sun)light [4] reflected by oily liquid			> 0.1 μm [3,4]	1000m swath width [4]		Clear sky Daylight [3]
IR UV line scanner	Airplane							
MWR Microwave Radiometer	Airplane		thickness		> 100 μm. With [3,4] calibration: gradient 0,50 mm to 3mm [30]	1000m swath width [4]		Clear sky
LF Laser Fluorosensor	Airplane		(oil type)		0.1 – 20 μm. With calibration. [4]	200 m swath width [20]		
CASI Compact Airborne Spectrographic Imagers	Airplane							Clear sky [31]

Appendix 2: 'Detection of marine spills using deep learning' presentation

Detection of marine spills using deep learning.

Klaas Dijkstra
NHL Stenden University of Applied Sciences
Center of Expertise in Computer Vision & Data Science

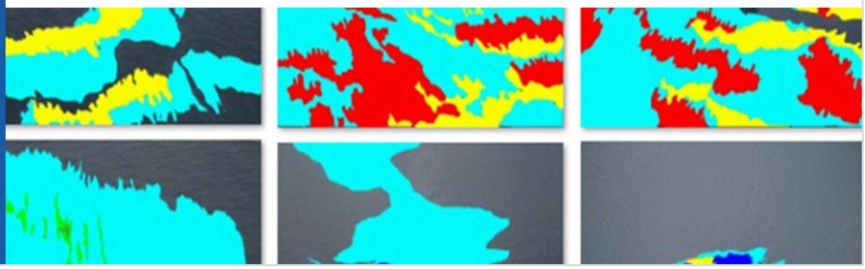

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Table of contents

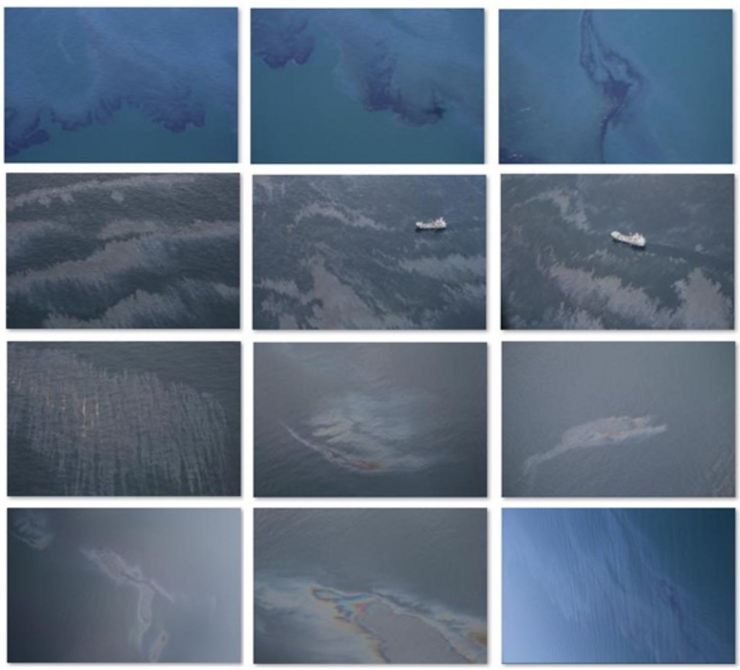
- Dataset
- Deep learning
- Results
- Conclusion

"Can a per-pixel classification of oil thickness be achieved using deep learning, based on the color of the RGB image?"

Dataset

Original images

- Originally 12 images
- Resolution of ~5100x3450

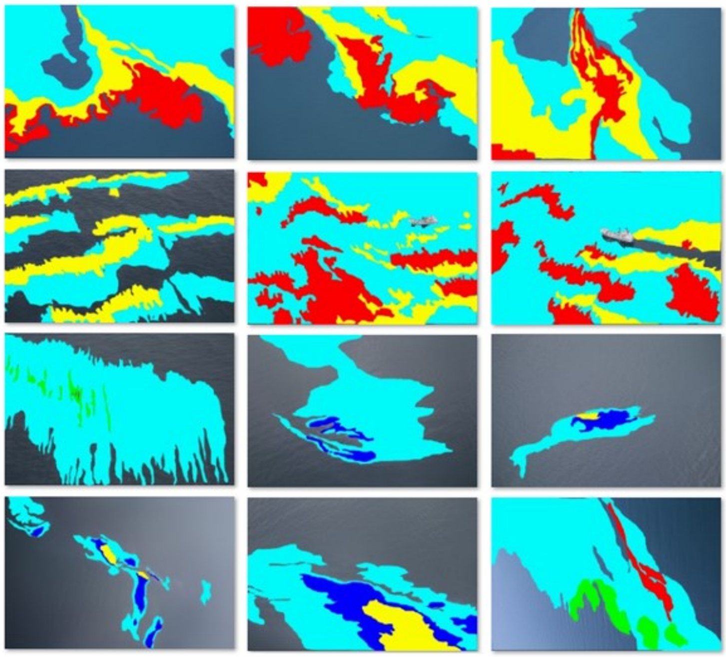


Annotations

- Dataset annotated into 5 types of oil spills:

  1. Sheen (light blue)
  2. Rainbow (blue)
  3. Metallic (yellow)
  4. Discontinuous (red)
  5. Continuous (green)

- Highly unbalanced dataset



Selected data

- Decision was taken to divide this dataset into further 2 datasets due to:
  - Too much variation in image quality with camera angle w.r.t sea
  - Different camera make and different camera settings

- Each new dataset has the same camera make and settings

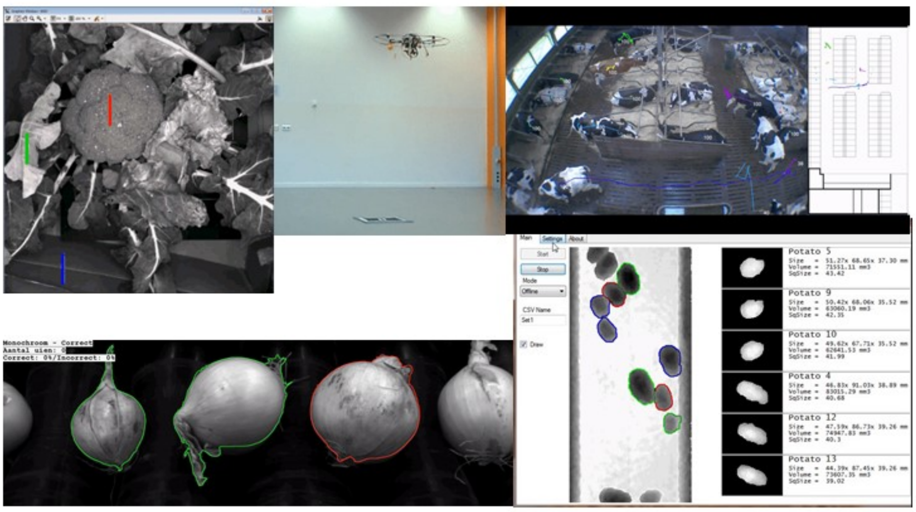
- This would be a more reliable analysis to check if the marine spill classification is possible

Dataset 1

Dataset 2

Deep Learning

Traditional Computer Vision



Deep Learning – A revolution

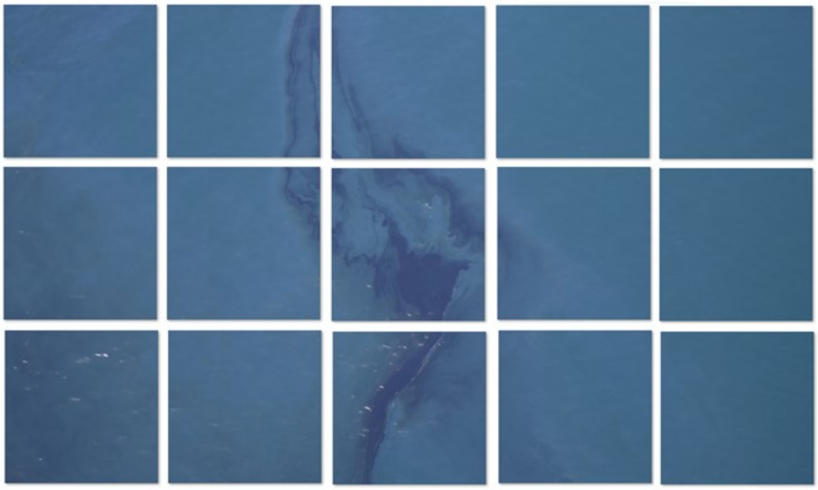
- Up to now:
  - Software Engineers would write 100% of the software
  - But systems were becoming too complex to manage.
  - Error rates were often too high. Data was too big to process.
- Today:
  - Software Engineers program self-learning algorithms.
  - Data Scientists train these algorithms to perform complex tasks.
- Tomorrow:
  - Off-the-shelf artificial brains that learn from humans to perform tasks.

Increasingly harder problems can be solved by systems that often exceed human performance.

Results

Tiling

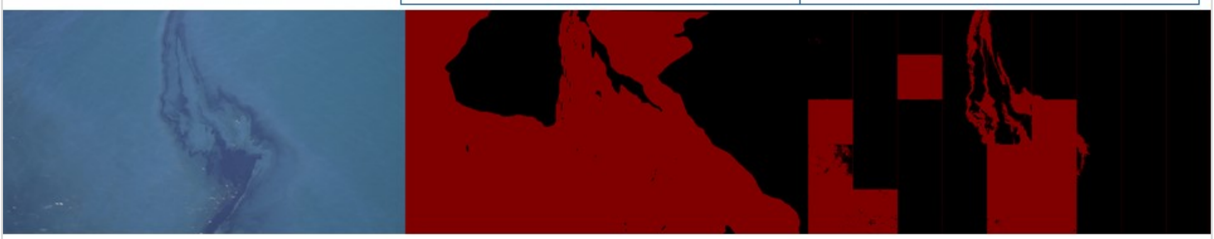
- Each image split into 15 tiles
- Dataset 1:
  - ➢ Training – 2 images, 30 tiles
  - ➢ Validation – 1 image, 15 tiles
- Dataset 2:
  - ➢ Training – 3 images, 45 tiles
  - ➢ Validation – 1 image, 15 tiles



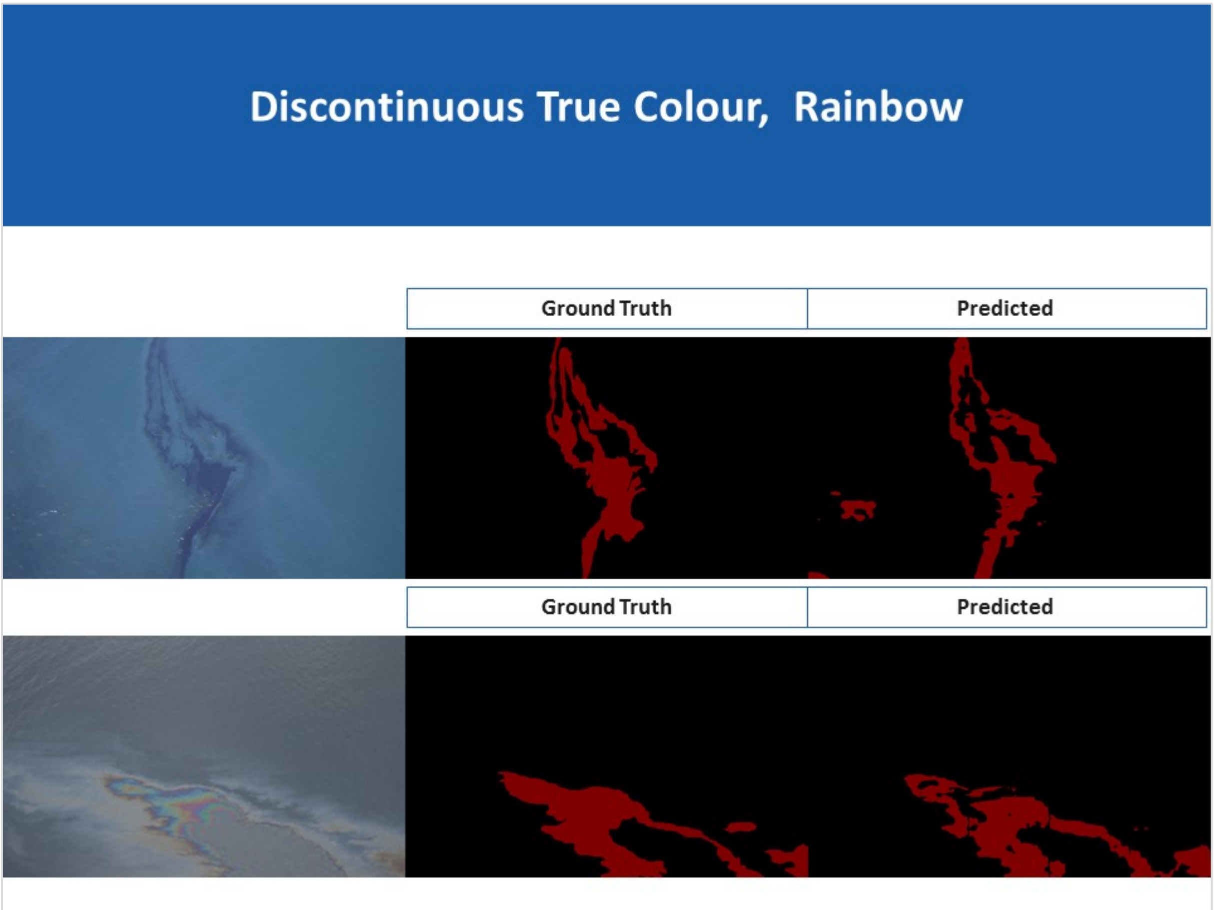
Binary (Oil-No Oil)

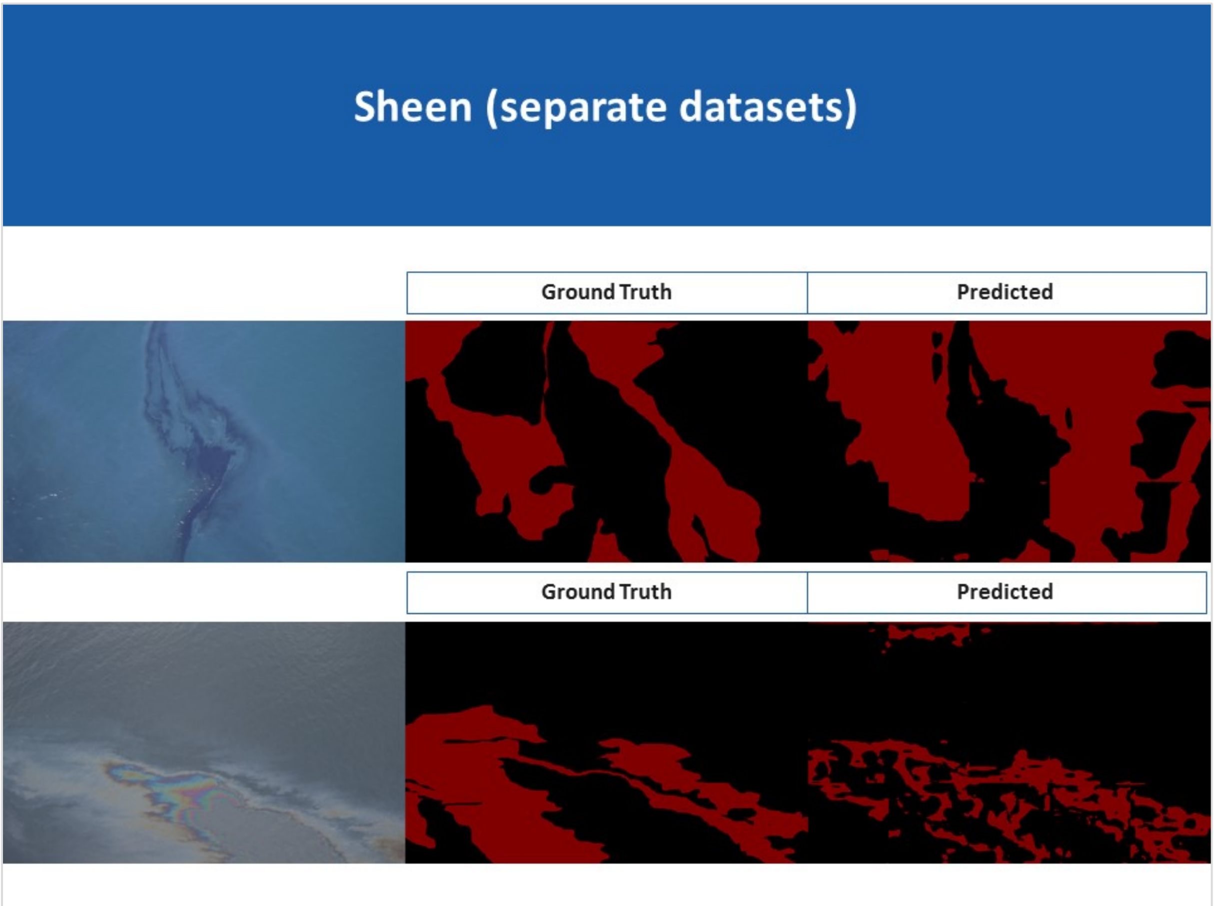
- Initially, tests were performed for binary classification to segment an image into oil and no-oil classes
- The inter-class variance between the different oil types was too high
- In some instances, some oil classes (sheen, metallic) appear similar to the background

Ground Truth	Predicted

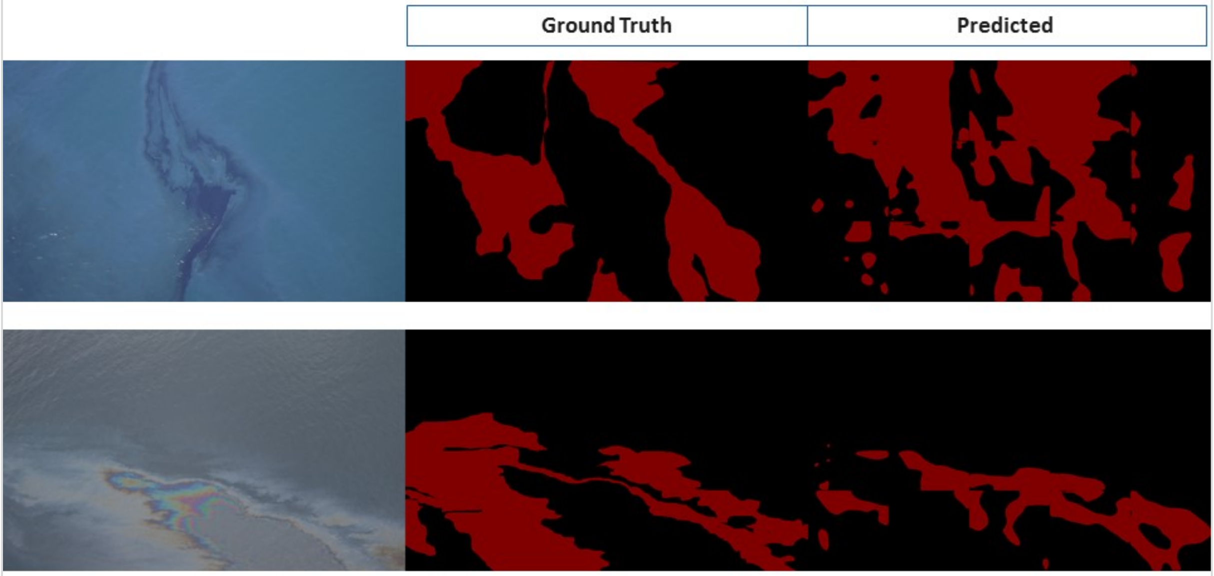


Ground Truth	Predicted


Discontinuous True Colour, Rainbow
Ground Truth
Predicted
Ground Truth
Predicted


Sheen (separate datasets)
Ground Truth
Predicted
Ground Truth
Predicted

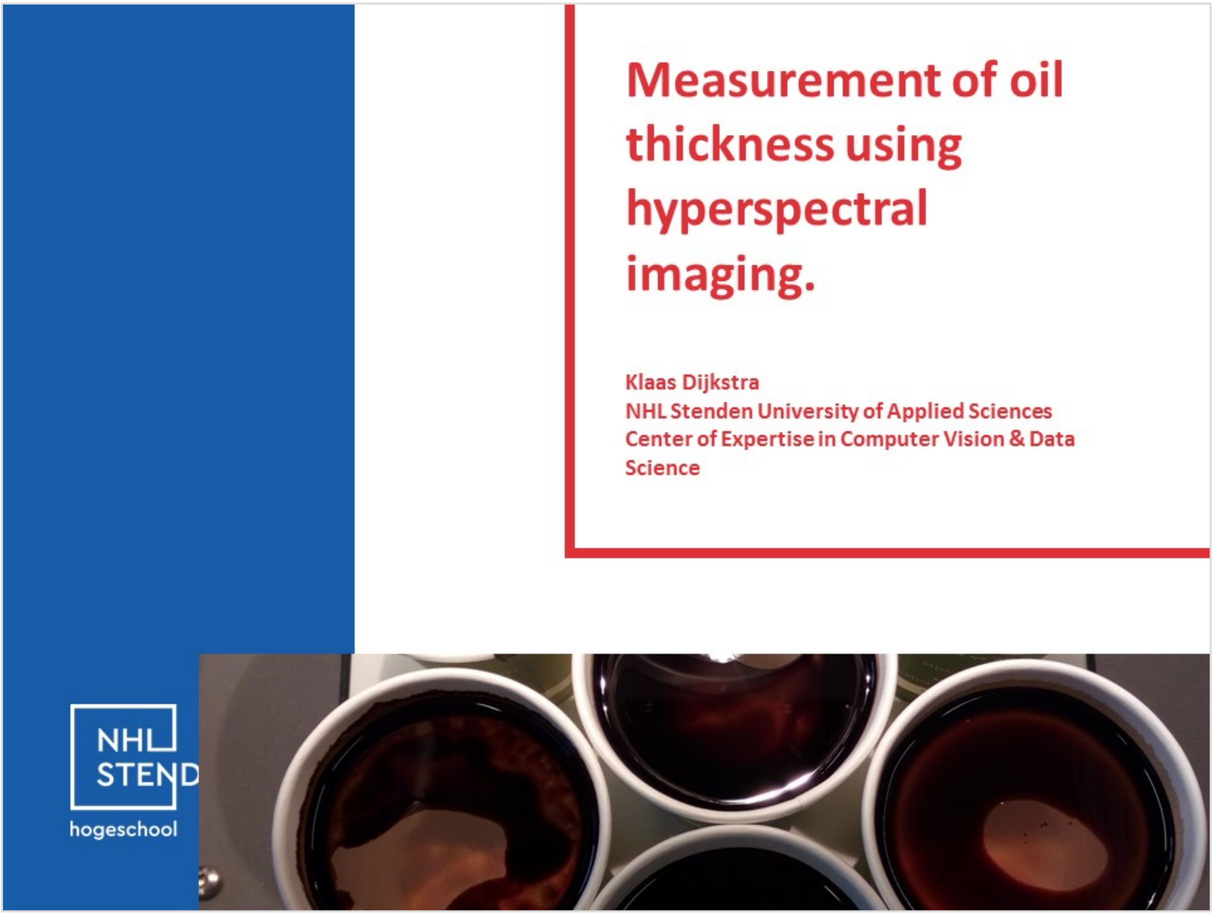
Sheen (integrated datasets)

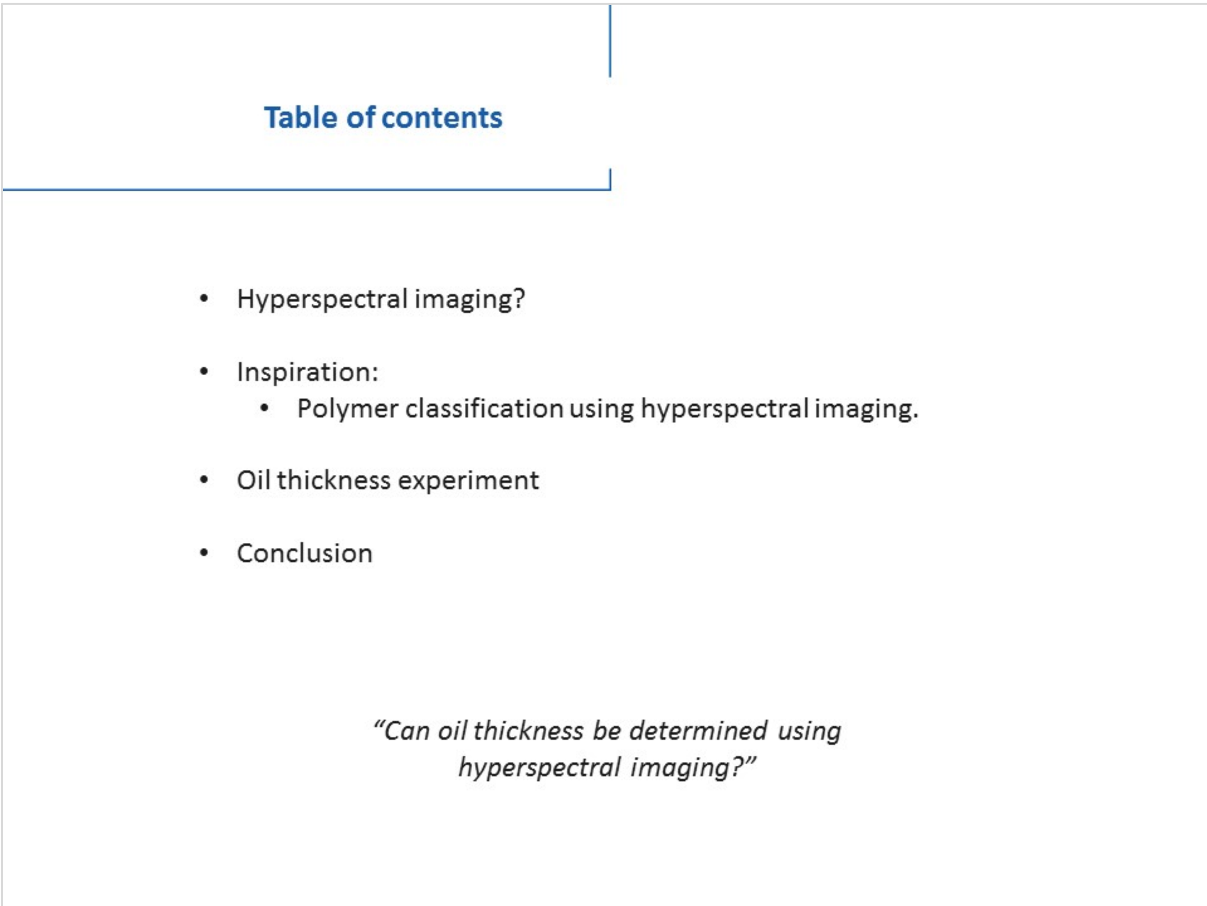


Conclusion

- Segmentation results look promising.
- Sheen vs. Metallic is challenging because of visual similarity.
- More annotated data required to achieve robust segmentation of multiple classes.

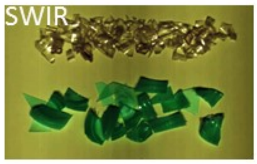
Appendix 3: ‘Measurement of oil thickness using hyperspectral imaging’ presentation

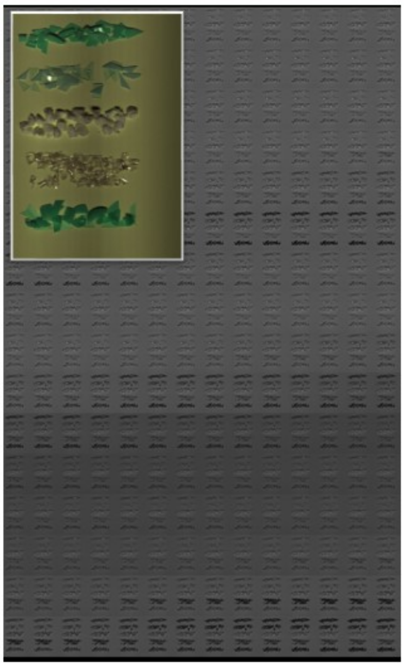




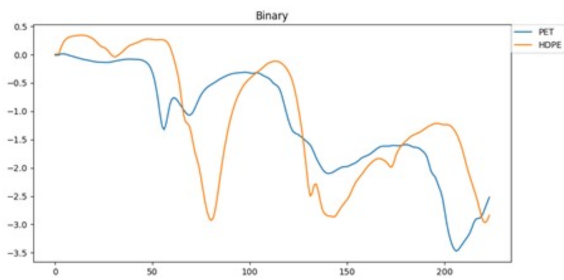
Hyperspectral imaging?

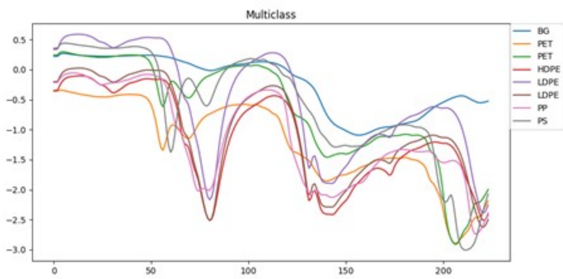
Hyperspectral imaging





The SWIR absorbance depends on the type of polymer

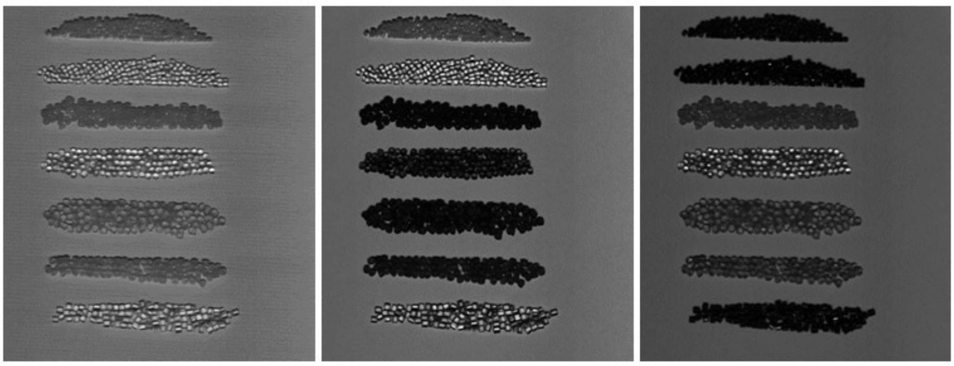




Polymer classification using hyperspectral imaging

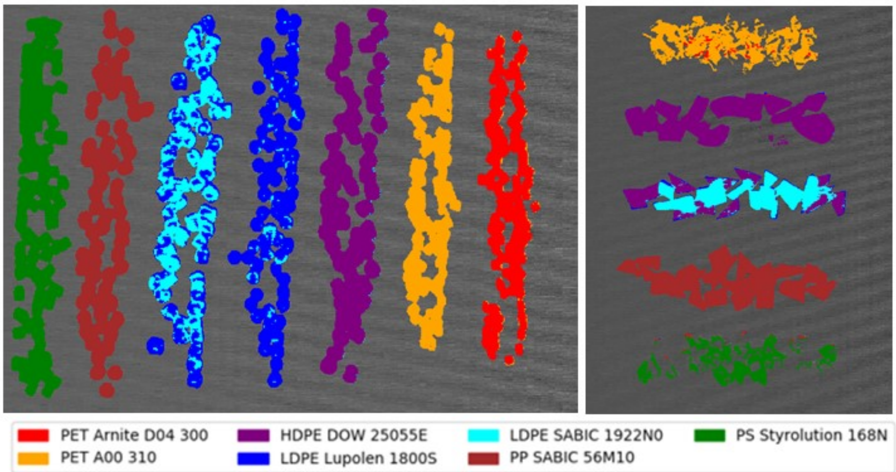
Different polymers

- Image taken with the Specim FX17 (900-1700nm, 224 bands)



Band 1 | Band 80 | Band 208

Segmentation with log. derivative



95% accuracy

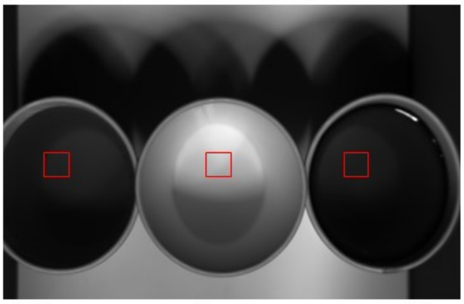
87% accuracy

Oil thickness experiment

Three cups

Visible

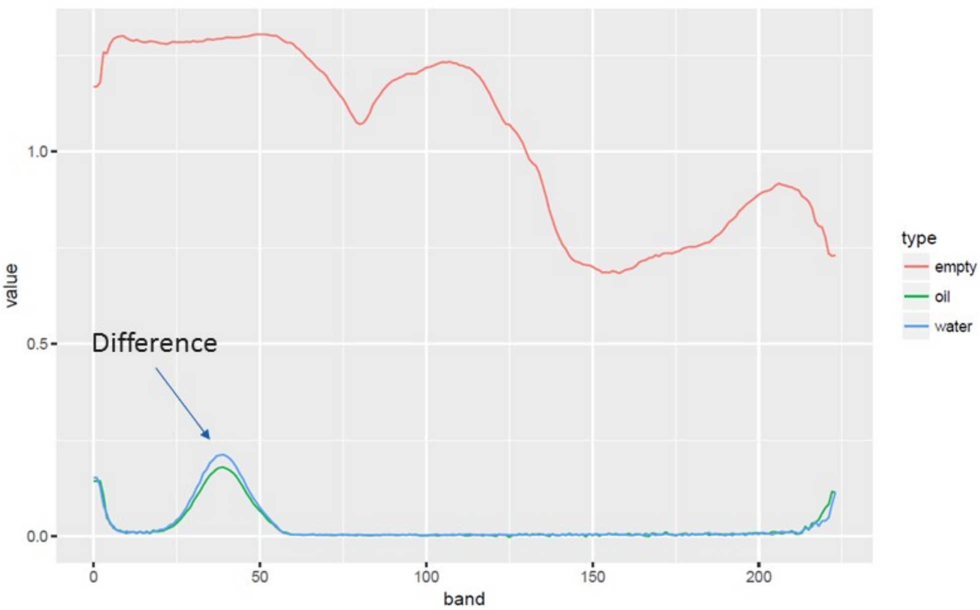
SWIR



Water Empty Oil

Sample a small image patch from each cup.

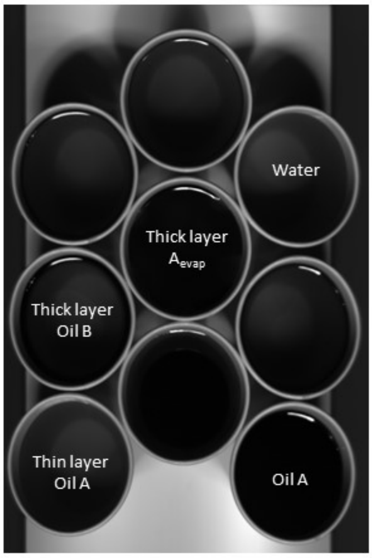
Three cups



Multiple oils

Oil types:
- A
- B
- A_{evap}
- B_{evap}

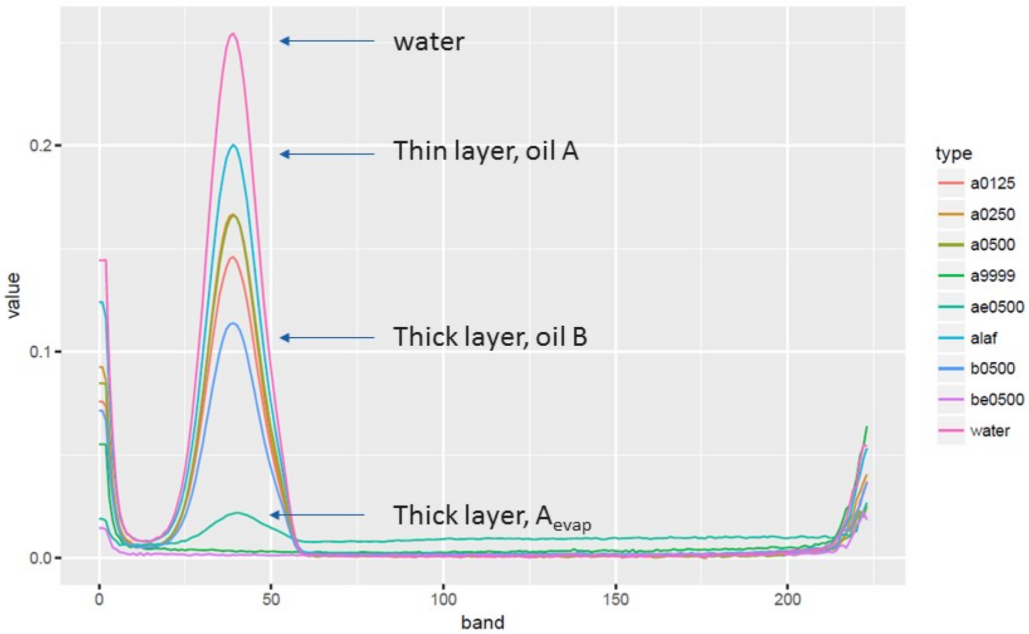
Layers:
- Thin
- 0.125 mm
  ↓
- 0.500 mm



SWIR

Visible

Multiple oils



Conclusion

Conclusions

- Results look promising
- Results should be verified with a larger experiment

Appendix 4: Brainstorm output

Ontwikkelrichting	Meerwaarde	Randvoorwaarden	Complexiteit	Optionele aanvullingen
Ontwikkeling beeldherkenning BAOAC **Automatische detectie van de Bonn agreement kleuren in foto's**	•Uitkomst niet meer afhankelijk van persoonlijke interpretatie •(objectieve meting)	•Veel input-data nodig (geannoteerde foto's) •Voor volume-inschatting: Geogerefereerde beelden	•Variatie in opnamecondities •Variatie visuele eigenschappen olie •Ontwikkelen algoritme	
Annotatietool voor dataverzameling RGB **Tool verspreiden onder operators: foto's uploaden, maskeren vertrouwelijke elementen, aanklikken kleuren & ingeven**	•Creëren van input-data ↑ •Informatie-uitwisseling tussen partijen	•Medewerking partijen internationaal	•Bouw tool	•'Meedenkende' tool die zelf aanvult
Georefereren & stitchen fotos			•Bestaat mogelijk al •Globaal goed mogelijk •Moeilijkheid: referentiepunten op open zee?	
Automatische verwerking in operationele systemen	•Geen handmatige actie nodig voor verwering/verplaatsingsberekening •Verwering op realistische data voor spreiding & dikte	•Automatische detectie van locatie, grootte & kleuren	•Invoer is passend •Bouw koppeling	
Drones uitbreiden met camera's	•Betere beelden •Snel kunnen handelen	•Kosten •Te snelle ontwikkelingen •Multi purpose	•Werkbaarheid, cursus personeel •Gewicht camera's	•(weersafhankelijk)
Vliegtuigen of helikopters verder uitbreiden met camera's	•Niet de vliegbeperkingen die gelden bij drones	•Multi purpose •Juiste software	•Cursus personeel •Beeldhoek beperkter •Welke camera kan olie goed in beeld brengen	
Keuze combinatie sensoren (RGB/UV/IR/…?) **Afweging verschillende camera's** **Geschiktheid bepalen van de verschillende technieken**	•Omvang olievlek bepalen •Hoeveelheid olie bepalen •Juiste inzetcapaciteit •Ook in donker goed observeren	•Testen moeten geschikt zijn voor een juiste analyse	•Veel verschillende systemen. •Bepalen van de juiste testanalyse die dicht bij de werkelijkheid ligt	
Combinatie RGB met hyperspectraal voor olie-eigenschappen Dikte uit RGB, resterende informatie in hyperspectraal moet olieeigenschappen zijn	•Olie-eigenschappen observeren	•Theoretisch kader of dit lukt	•Theoretisch kader ontbreekt •Werkt het op zee?	

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