Real time Oil and Gas source Identification using Unmanned Aerial Systems

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Motivation

Gas exploration and environmental compliance and assessment are critical activities for the energy industry.

- ∗ The reliability of natural gas pipelines is critical in terms of public, environmental and system safety; however, their deterioration rate is high.
- ∗ Annually 1,300,000 t oil enter the oceans
	- ∗ Tanker vessel spills 100,000 t
	- ∗ Run-off 140,000 t
	- ∗ Pipeline leaks 12,000 t
	- ∗ Natural seepage 600,000 t
- ∗ Deep Water Horizon oil spill (April 20 July 15, 2010) 7.0 x 105 m3 volume of oil spilled
- ∗ Satellite sensors used for preliminary oil spill assessment suffer from low spatial and temporal resolution.
- ∗ Time is particularly critical for an oil spill occurring in the open ocean as wind and current can rapidly spread the oil over a large area in a short time.

Oil Slick Science

∗ UAV equipped with active and passive sensors can provide detailed oil spill analysis and offer better spatial and temporal resolution than their satellite counterparts.

Spill Detection Sensors

- ∗ Optical Sensors
- ∗ Infrared
- ∗ Ultraviolet
- ∗ Laser fluorescense
- ∗ Microwave sensors
	- ∗ Radar

Typical wavelength range 400-1100 nanometers (nm)

PASSIVE SENSORS

Visible EM sensor

∗ Wavelength 400 – 700 nm

Wavelength (nm)

- ∗ Oil has higher surface reflectance than water
- x Sun glitter
- x Poor contrast
- x Poor discrimination between oil and background
- x Not operable at night/cloudy condition
- \checkmark Better suited for documentation purpose
- \checkmark Inexpensive and easily available

Infrared Sensors

- ∗ Thick oil appears hot and thinner cool
- ∗ At night, oil appears cooler than water
- x Thin sheens not detectable
- x Sea weed and shorelines provide false positive result
- \checkmark Provide relative thickness of oil slicks \checkmark Operable at night but contrast not as good as on daylight

Ultraviolet sensors

- ∗ Oil has stronger reflectivity than water
- \checkmark Can detect very thin sheens (<0.1 micron) \checkmark Inform about relative thickness of oil slicks
- x Cannot detect thick slicks (>10 micron) x False positive due to sun glint, wind, sea weeds x Cannot operate at night

Synthetic Aperture Radar

- ∗ Used extensively for remote sensing of oil spills
- ∗ Active sensor
- ∗ side-looking distance measuring systems
- ∗ measures the time delay between transmission and reception of a pulse

synthetic aperture (antenna)

The data from multiple view of the target are processed in such a way that a longer antenna is synthesized.

SAR Images Showing Black Patches Caused by (a) Oil Pollution and (b) Natural Phenomena

Single polarimetric SAR

- ∗ Gray level features
- ∗ Geometric and statistical features
- ∗ Dual and Quad polarimetric SAR
	- ∗ Polarimetricdecomposition parameters such as entropy (H), anisotropy (A), Mean scattering angle (α) provide oil-spill information

UAVSAR

The UAVSAR L-band radar

Feature Extraction by Polarimetric **Decomposition**

Polarimetric features of SAR

- ∗ Cloude-Pottierradar target decomposition:
- ∗ Cloude-Pottier decomposition is the eigenvector-eigenvalue based target decomposition. It is based on the eigen decomposition of coherency matrix .

$$
\left\langle \begin{bmatrix} T_3 \end{bmatrix} \right\rangle = \begin{bmatrix} U_3 \end{bmatrix} \begin{bmatrix} \sum_3 \end{bmatrix} \begin{bmatrix} U_3 \end{bmatrix}^{-1}
$$

$$
\begin{bmatrix} \sum_3 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix}
$$

Feature Extraction by Polarimetric Decomposition (contd.)

$$
H = -\sum_{i=1}^{3} p_i \log_3(p_i) \qquad p_i = \frac{\lambda_i}{\sum_{k=1}^{3} \lambda_k}
$$

- ∗ Measure of randomness
- ∗ High for oil spill and low for water
- ∗ Anisotropy (A)

$$
A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3}
$$

∗ Higher in oil spill region than in oil-free water

Feature Extraction by Polarimetric Decomposition (contd.)

∗ Mean Scattering angle

∗ Lower mean alpha for oil spill region

∗ Co-polar correlation coefficient

 $\rho = \frac{\langle S_{HH} S_{VV}^* \rangle}{\sqrt{\langle S_{\text{max}} S_{\text{max}}^* S_{\text{max}}^* \rangle}}$

∗ Low values for oil-covered region

Feature Extraction by Polarimetric Decomposition (contd.) Degree of polarization (DoP)

- ∗ Lower DoP for oil covered region
- ∗ For oil slick, DoP ≈ 0
- ∗ For oil-free surface, DoP ≈ 1

PauliRGB color-coded image IS_{HH -} S_{VV}IIS_{HV}IIS_{HH +} S_{VV}I a) PauiRGB of image 101 b) PauliRGB of image 102, c) PauliRGB of image 103

anisotropy, d) co-polar correlation coefficient, e) degree of polarization

The red region has the highest probability of oil on water surface and the blue region has the lowest probability of oil on water surface

AVRIS Hyperspectral Cube

Airborne Visible/Infrared Imaging Spectrometer

224 spectral channels

400 – 2500 nm spectral resolution

Data reduction

- ∗ Curse of dimensionality
- ∗ Linear Algorithms
	- ∗ Principal Component Analysis (PCA)
	- ∗ Inaccurate Representation of High Dimensional Data
- ∗ Nonlinearities are often exhibited in the data due to the effects of multipath scattering, variations in sun-canopy-sensor geometry, nonhomogeneous composition of pixels, and attenuating properties of media

∗ Non-Linear Algorithms

- ∗ Manifold Learning
- ∗ Increase in Algorithm Complexity

(a) Small Oil Spill Scene

Summary of Challenges

- ∗ Large size images (~100 GB each)
- ∗ Complex analysis (SAR, hyperspectral)
- ∗ Multiple Sensors- Data fusion
- ∗ Machine Learning
- ∗ Time is critical (both for data fusion and also validation)

Thank you for your attention