Recap

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SAR images specifities

SAR is an active sensor that measures the sea-surface roughness. It is not affected by cloud cover and can image the ocean surface at a meter to tens of meters of spatial resolution under all weather conditions, day and night. The nature of SAR coverage is low. Therefore, scientists have also tried to extract IW (Internal Waves) information from geostationary satellite images that have lower spatial (250–500 m) but higher temporal (10 minutes) resolution under suitable solar-illumination conditions. Cloud cover and solar flares make the IW signatures much weaker and more challenging to extract from geostationary satellite images than that from the SAR images.

SAR is a suitable sensor for oil-spill detection because the oil dampens the sea-surface capillary waves so that they appear dark in SAR intensity images. Besides, oil slicks also modulate the surface-scattering matrix received by advanced polarization SAR. As a result, oil slicks also have significant signatures in the full-polarization SAR images.

The UAVSAR is a full-polarization SAR with fine resolution (7 m), stable calibration and low noise floor. *Note : the level of noise conditions the efficiency of DL and/or traditional algorithm. Segnet and FCN8S 2 DL algorithms have been shown to be more stable and robust.*

From : Deep-learning-based information mining from ocean remote-sensing imagery. *Xiaofeng Li, Bin Liu, Gang Zheng, Yibin Ren, Shuangshang Zhang, Yingjie Liu, Le Gao, Yuhai Liu, Bin Zhang, Fan Wang* ; **link**.

Oil slicks and lookalikes

The texture of the oil slicks is continuous, smooth and delicate, while the texture of the lookalikes is scattered, rough, and discontinuous. The oil film suppresses the capillary ripple and short gravity waves on the surface of the ocean. Dark spot detection is the first step in distinguishing oil slicks from lookalikes. In the SAR images, oil slicks and lookalikes appear much darker than surrounding areas. Any region that is darker than its surrounding area should be studied in further detail.

Method/Data

Five quad-polarimetric SAR oil slick scenes were acquired by C-band Radarsat-2 polarimetric mode. The first three sets of data are used for the establishment and validation of CNN model, which contain training and test data. The last two data are mainly used for the prediction of the established model CNN, which contain test data only.

Quad-polarimetric SAR images are susceptible to noise. Pauli decomposition has the advantages of anti-interference and general high adaptability [41]. The Pauli decomposition graph is clearer than original quad-polarimetric SAR graph, and it benefits the detection of dark spots and image post-processing. Image preprocessing stages are as follows :

— The original quad-polarimetric SAR data are decomposed by Pauli.

— The obtained Pauli decomposition graph is filtered by Boxcar filtering.

In the area covered by oil slicks, the difference between the minimum and the maximum eigenvalue is not high, and the PH is large (PH is the ratio of the minimum and the maximum eigenvalue of the complex coherency matrix, the eigenvalue is related to the optimal backscattering polarization).

We performed experiments to show the effect of different input sizes on the classification results considering input samples of 20×20, 24×24, and 28×28. The consistency of the classification increases with the increase of the input samples. We can see that the accuracy increases slowly after the sample size of 24×24, which means the classification accuracy tends to remain stable. Larger samples will increase the burden on the network and require longer testing and training periods. For this reason, we set the size of the input patch to 28×28.

Results

The result shows that if the difference of sea condition (such as climatic, geographical, sea temperature and environmental conditions) between test and training data is too large, classification accuracy would be a big decline.

Limits

The five images used do not contain typical lookalikes caused by low wind or biogenic materials, which are also regarded as major challenges in oil slicks detection. It is very difficult to obtain the priori probabilities of all oil slicks and lookalikes accurately.

From : Discrimination of Oil Slicks and Lookalikes in Polarimetric SAR Images Using CNN. *Hao Guo, Danni Wu and Jubai An* ; **link**.

Deep Networks to Oil Spill Detection

Polarimetric synthetic aperture radar (SAR) remote sensing provides an outstanding tool in oil spill detection and classification, for its advantages in distinguishing mineral oil and biogenic lookalikes.

Synthetic aperture radar (SAR) is one of most promising remote sensing systems for oil spill monitoring, for it can provide valuable information about the position and size of the oil spill. Moreover, the wide coverage and all-day, all-weather capabilities make SAR very suitable for large scale oil spill monitoring and early warning.

The ideal sea surface wind speed for oil spills detection is 3–14 m/s. Some other manmade or natural phenomena can result in very similar low scattering areas on the sea surface, e.g., biogenic slicks, waves, currents and low-wind areas, etc. Conventional oil spill detection procedures use intensity, morphological texture, and auxiliary information to distinguish mineral oil and its lookalikes, with its processing chain divided into three main steps : (1) dark spot detection ; (2) features extraction ; and (3) classification between mineral and its lookalikes.

For example biogenic slicks and mineral oil are difficult to distinguish by single polarimetric SAR images. Yet, their polarimetric scattering mechanisms are largely different : for oil-covered areas, Bragg scattering is largely suppressed, and high polarimetric entropy can be documented. In the case of a biogenic slick, Bragg scattering is still dominant, but with a low intensity. Hence, polarimetric features can largely help the image classification between mineral and biogenic lookalikes

Results

The results show that oil spill classification achieved by deep networks outperformed both support vector machine (SVM) and traditional artificial neural networks (ANN) with similar parameter settings, especially when the number of training data samples is limited.

Feature dimension reduction can be seen as an early fusion step. Fusion at different stages of classification procedures is a booming research field that has shown capabilities for improvement of classification results.

A few pixels in the area covered by the biogenic slick are classified as mineral oil the possible reason of these "misclassifications" is the affection of signal noise on space-borne SAR data or the uniform distribution of the mineral oil and biogenic slicks. This misinterpretation can be further eliminated by a simple postprocessing step. Corrosion and swelling algorithms can be applied on the binary classification result to fix the small holes (missing alarm) in large oil-covered areas and isolated positive targets (false alarm) in the sea surface area.

Limits

A key discovery of this paper is that given insufficient number of data samples, deep learning algorithms such as SAE (Stacking of AutoEncoders) and DBN (Deep Belief Network) can achieve better performance than traditional algorithms by initializing their parameters from a position closer to the optimum solution.

From : Application of Deep Networks to Oil Spill Detection Using Polarimetric Synthetic Aperture Radar Images. *Guandong Chen, Yu Li, Guangmin Sun and Yuanzhi Zhang* ; **link**.

Dark Spot Detection - Segnet

Taravat et al. used a Weibull multiplication filter to suppress speckle noise, enhance the contrast between target and background, and used a multi-layer perceptron (MLP, a class of feedforward artificial neural network (ANN)) neural network to segment the filtered SAR images.

Data/Method

Five SAR oil slick scenes acquired by Radarsat-2 (fine quad-polarized mode), and some information on those data (e.g., wind direction, water temperature, etc.) is described in detail in Guo's studies. In order to ensure that each sampling window includes oil slicks and seawater, the window size cannot be too small or too large, and the window sizes were selected to be 500×500, 1000×1000, 1500×1500, and 2000×2000 for each scene of the quad-polar SAR image, respectively.

Samples, including oil slicks and seawater, were selected from those sub-images, 420 samples were selected from each scene data, totaling 2100 samples. The boundary complexity and weak boundary were the main factors affecting the segmentation accuracy.

To ensure the balance of the sample distribution, 105 samples (21 samples in each scene) in 2100 samples were added with multiplicative noise and additive noise, respectively, among which multiplicative noise had 10 levels (peak signal-to-noise ratio (PSNR) was between 50 and 30) and additive noise had 10 levels (PSNR was between 50 and 30). A total of 20 different levels of noise were applied to each sample. In this way, the number of samples per scene was extended from 420 to 840, and the total number of samples was up to 4200.

Results

Due to the influence of the sea surface environment (such as waves, ocean currents, and low wind belts) and the characteristics of SAR sensors, high noise and weak boundaries are commonly found in SAR images of oil spill. Segnet shows high robustness in terms of additive noise, FCN8S is not as stable as Segnet when the additive noise is relatively high. Segnet and FCN8s show high stability and tolerance to multiplicative noise, although the overall performance of FCN8s is not as good as that of Segnet.

Overall, by comparing the four parameters (PA : pixel-classification accuracy, MA : mean accuracy, MIoU : mean intersection over union, and FWIoU : frequency weighted intersection over union) of the additive and multiplicative noise, the **traditional machine algorithm performed poorly in detecting dark spots compared with semantic segmentation algorithms**.

Due to the complex structure of the deep learning model, its running time was much longer than that of the classical machine learning model. To reduce the computational and storage pressure of GPU, we chose a Segnet's batch size of 1 (i.e., inputting one sample at a time), and found that in this case, the Segnet achieved a better segmentation effect without using the batch normalization layer.

Limits

However, Segnet's training process was supervised, and its training relies on a large number of label images. The production of labels was not only time-consuming and laborious in the data preparation stage, but also the training effect could be easily affected by human factors. In the future, we hope to shift to a weak or unsupervised training process to improve the convenience of application.

From : Dark Spot Detection in SAR Images of Oil Spill Using Segnet . *Hao Guo, Guo Wei and Jubai An* ; **link**.

External Links

- Synthetic Aperture Radar (SAR) Satellites
- code (2013) Oil Slick Detection Evaluation : link
- code (2018) Convolutional Neural Network for Classifying oil spills in Niger Delta : link
- code (2020-21) DL/ML and SAR & Denoising section : link