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Analysis of Hyperspectral Imagery for Oil Spill Detection Using SAM Unmixing Algorithm Techniques

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Abstract

Oil spill is one of major marine environmental challenges. The main impacts of this phenomenon are preventing light transmission into the deep water and oxygen absorption, which can disturb the photosynthesis process of water plants. In this research, we utilize SpecTIR airborne sensor data to extract and classify oils spill for the Gulf of Mexico Deepwater Horizon (DWH) happened in 2010. For this purpose, by using FLAASH algorithm atmospheric correction is first performed. Then, total 360 spectral bands from 183 to 198 and from 255 to 279 have been excluded by applying the atmospheric correction algorithm due to low signal to noise ratio (SNR). After that, bands 1 to 119 have been eliminated for their irrelevancy to extracting oil spill spectral endmembers. In the next step, by using MATLAB hyperspectral toolbox, six spectral endmembers according to the ratio of oil to water have been extracted. Finally, by using extracted endmembers and SAM classification algorithm, the image has been classified into 6 classes. The classes are 100% oil, 80% oil and 20% water, 60% oil and 40% water, 40% oil and 60% water, 20% oil and 80% water, and 100% water.

Keywords: Oil Spill, Hyperspectral Imagery Unmixing Algorithms, Hyperspectral Toolbox, SpecTIR, SAM

1. Introduction

Several times over the past few decades, the Chesapeake Bay has experienced considerable oil spill accidents, which are a threat to coastal habitats and species. This threat to marine resources of Chesapeake Bay has started since sharing the coastal areas with key interstate commerce routes, wide development, underground pipelines, extensive development, large industrial installations facilities constructed in the coastal areas, and considerable shipping traffic to the Norfolk and Baltimore ports were began, and Chesapeake Bay's marine resources were threatened. In order to protect species in jeopardy effectively, first a quick and exact program is required for the effective protection of endangered species, particularly for the oil spill leak risk hazard. This research is trying to show the application of hyperspectral remote sensing in the Gulf of Mexico during the British Petroleum oil

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spill.

The current research is a prototype case study of the Gulf of Mexico (16 May 2010) oil spill from the DWH1 platform and the related image analysis using a hyperspectral imagery system for discovering oil leaks and finding the oil pollutant impacts on soil, quality of water, wetland, and vegetation by using hyperspectral imagery system. According to Goetz et al. (1985), hyperspectral sensors or imaging spectrometers, which are remote sensing instruments tools, combine the analytical capabilities of a spectrometer with an imaging sensor's spatial performance. These tools possibly have up to hundreds of 10 nm or narrower spectral bands. As shown in Figure 1, a complete full spectrum is generated for each pixel of the image using narrower imaging spectrometers.

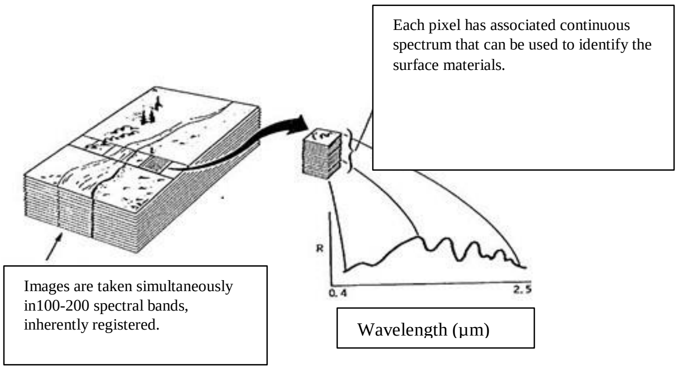

Figure 1
A schematic of hyperspectral imaging (Goetz et al., 1985).

For comparison purposes, broadband multispectral scanners like Landsat enhanced thematic mapper plus (ETM+), which is a broadband multispectral scanner with just eight spectral bands and its spectral resolution is on the order of 100 nm or more, was employed. Consequently, the utilization of broadband sensors only differentiates between materials, while identifying materials is possible with using a high spectral resolution of an imaging spectrometer.

In the case of accidents of the oil spill, this information can retrieve precise spectral information to help authorities for providing an effective plan to deal with the pollution and protection of environment and reduce damages. Spectral information is prepared by hyper spectral data to identify the specifics of objects and substances and to better approximate their influence. Materials with various spectral information, including mineral information, can be identified more effectively using this data compared with their multi-spectral images. Detection of oil spill is possible by visually interpreting aerial photographs as well as multi-spectral images, but other types of information about the properties of the oil spill cannot be realize by this data.

Researchers by the use of hyperspectral images are able to differentiate between various thicknesses of crude oil and the other properties of them from their spectral signature. Oil spill can be detected using high spectral and spatial resolution of hyperspectral images by applying the spectral signature matching for recognizing oil spectra based on chemical composition. The extraction of oil signatures for various levels of oil can be performed in order to recognize the oil levels of the polluted areas, which is needed to determine suitable cleaning processes.

In the current study, hyperspectral images (HSI) are used to minimize some of the problems of conventional techniques for identifying oil spill using the spectral signature not matching with the visual interpretation of the image. These kinds of data information should be utilized for differentiating between oil spill and other substances. The initial results of this study indicate that by using HSI spectral information data, the oil signature can be applied to detecting minute concentrations of hydrocarbon (crude oil) on the sea and to differentiating between various levels of oil dispersant floating on water.

There are several systems of remote sensing, including side-looking airborne radar, microwave radiometer, laser fluorescence, infrared ultraviolet line scanner, SAR, ERS 1, 2, and Landsat satellite systems, and they have their own limitations. Remote sensing data has the potential to be used as a useful tool in environmental monitoring due to their time sequence images and universal extent as well as lower cost compared to the field works (Fingas, 1991). The limitation of some remote sensing systems is their poor spectral resolution observed during detecting oil spill features because of their poor spectral resolution. Recognizing and quantifying oil spill are other problems of these systems. As the spill progresses, many of these systems have problems with detecting oil spill. Ice, internal waves, kelp beds, natural organic compounds, pollen, plankton blooms, cloud shadows, jellies, algae, changes in the color of the water surface caused by phytoplankton, and guano washing off rocks are detected as oil spill (Pavia and Payton, 1983; McFarland et al., 1993).

Another limitation in estimating the coverage area with the use of some sensors, including sensors recording data in visible wavelength, is weather conditions; for example, high waves and wind speed typically cause difficulties in estimating the area of coverage (Payne et al., 1984). Oil will be mixed with water during oil spill because of increased disturbance on the water surface caused by waves. Observers should note that the ability of the oil detection reduces by increasing the speed of the wind (Ministry of Transport 1992). Submerged oil visual observation is really hard except when the water is so clear and shallow. Spill characteristics are different under two conditions of low light and strong winds (Fingas, 1991). The interpretation of observations in the direction of sun is usually problematic. A week contrast between the water and oil sheen as a result of glare and very low angles of sun and direct sunlight overhead causes difficulty in observations. Shortly after occurring oil spill, oil floats on the surface of water and its physical features are changed through different physical, biological, and chemical processes (Schriel, 1987). The false incorrect reports adumbrate information about the true place location and description of the lake. In addition other parameters make several common conventional remote sensing methods unreliable. Space shuttle photography is one of these conventional approaches to track the movements of oil spill. In this method, images were sequentially taken by using space shuttle photography at the same time of oil spill.

The national oceanographic and atmospheric administration (NOAA) has typically been pioneer for developing oil spill-related sensing, monitoring systems, tracking systems, and protocols. The assessing methods for assessing oil spill were first standardized by NOAA started in 1976 as the tanker Argo Merchant ran aground on Nantucket Shoals, and NOAA began to standardize methods for assessing oil spill and provided a series of trajectory and fate modeling programs to afford the USCG with predicting the movement of oil spill. The responsibility to assess, track, and monitor oil spill incidents changed over time and became more collaborating between governmental agencies and industry. Over the decades, new detecting and tracing technologies gently advanced. Trajectory modeling became more reliable while computing speed and capability grew. In contrast to the remarkable progress of the remote sensing, tracking and trajectory modeling and technology slightly advanced, particularly in terms of subsea plume modeling. Using synthetic aperture radar and Doppler shift radar in detecting and tracking oil spill were examples of the exceptional improvements in this area, but these progresses were mostly motivated by a specific occasion or program. The sensing technology tools remains private and accessible for government and its contractors as a response option, while it is inapproachable for oil spill response workers. Consequently, the deduction of the currents, weather, time, tides, and visual data information is utilized in trajectory modeling to guess tracking. A lot of the information in the ecological resources is not real-time information data and is scattered predicting. On the other hand, there is outdated information or no information on the spill place, and a best-fit solution will be utilized based on the needs.

1.1. Technologies that is used for oil spill detection

Radar technology like SAR has a good ability to distinguish differences in the capillary action at the surface which is dampened by oil. The advantage of these systems is their viability at night, and cloud covers have no impact on them. Appropriately, dampened capillary action is not essentially revealed of oil on the water, so on-site or other more discriminating remote approvals are needed for determining whether oil is truly there. In spite of the high sensitivity of ultraviolet and infrared sensing to cloud cover, rain, and waves on the surface of water, this is a very better mechanism for detecting oil on the surface of water. Furthermore, it has not been demonstrated that their commercial viability or enough flexibility have not been indicated for providing the anytime- anywhere coverage which would be preferred in a huge and quick accident.

High frequency radio wave surface current monitoring (CODAR) provides a high resolution view of the currents in locations where these systems have been placed; however, CODAR monitors are still very limited by area of their coverage. They are also only viable in determining what has happened and what is happening now. In a predictive mode, wind impacts must be removed from the signal and no winds would be in the currents of the background in order to determine what the water movement related to tides and background currents would be without winds.

The original aim of designing underwater acoustics and sonar technology was not tracking oil spill. However, this technology can be likely used to progress a system or platform designed definitely to track subsea oil if the DWH response indicates any sign. Currently, ad hoc systems are being deployed with some success. However, even if it can be proven highly effective, using sonar in the oceans is known to disrupt and injure marine mammals, making it a less attractive choice. The base of laser fluorosensors is similar to the fluorescence phenomena applied in fluorimeter except for its light source, which is a UV laser commonly airborne with the detector. This technology may be the only reliable method for differentiating vegetation in terms of oiled and unoiled types and for identifying oil on various types of beaches as well as snow and ice. This type of laser fluorosensors can also be utilized for predicting the approximate depth of slick and can also be used to be combined with other sensors, including ultraviolet (UV), infrared (IR), SAR, and microwave to increase the efficiency.

1.2. AISA hyperspectral sensor

The airborne imaging spectro-radiometer for applications (AISA), which is a push broom sensor determining 360 spectral bands in the range of visible to thermal infrared. The data information used in this study is extracted from the SpecTIR remote sensing (SRS) division as the accident of oil spill deep water horizon (DWH) occurred (Figure 2). Virtual dimensionality (VD) algorithm could acceptably identify three endmembers in the image since high spectral resolution images are provided through SpecTIR sensor. SpecTIR hyperspectral imagery has a great potential in oil spill detection. Virtual dimensionality, endmember extraction, and unmixing algorithms effectively recognize the oil spill using the automated version of the suggested approach. Airborne hyperspectral data can efficiently detect oil spill; unfortunately, such data are not yet broadly available (Dimitris Sykas at al., 2011). More data are provided for spatial and spectral details through a high spatial and spectral resolution. Airborne imaging spectro-radiometer for applications (AISA Dual) with a high spatial and spectral resolution prepare more information about spatial and spectral details, and this results in more exact outcomes than multi-spectral systems or traditional monitoring methods. Time series images of the oil are useful for real-time monitoring as they provide relative levels and correct locations, which are useful for real-time monitoring (Galt, 1994). Environmentally vulnerable areas such as wetlands and oceans can be quickly and accurately mapped, measured, and characterized with the use of these data. In the regions contaminated by oil, AISA Dual can be employed for generating a spectral library for oil leak on water and land. The spectral signature can be utilized to detect shoreline properties and determine the level of oil pollution (heavy or moderate) particularly in regions which are ecologically sensitive. This can be beneficial for cleanup procedures.

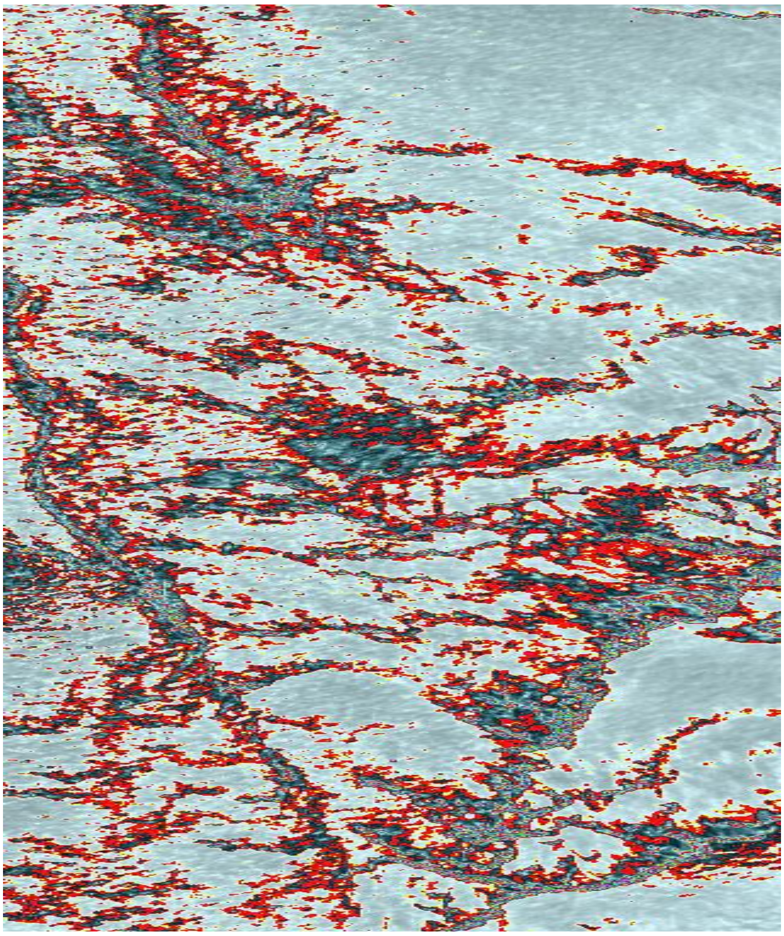

Figure 2
An AISA hyperspectral image of an oil spill due to deep water horizon platform in Gulf of Mexico (10 may 2010).

In the rapid changing conditions of water, field checks are needed for the real time analysis of the images because of wind, tides, and current. Specific spectral signatures are extracted using HSI for producing a spectral library of various types of oil on water and wetland. Moreover, it has the ability to be applied to the determination of the concentration of oil pollution onshore (Figure 3).

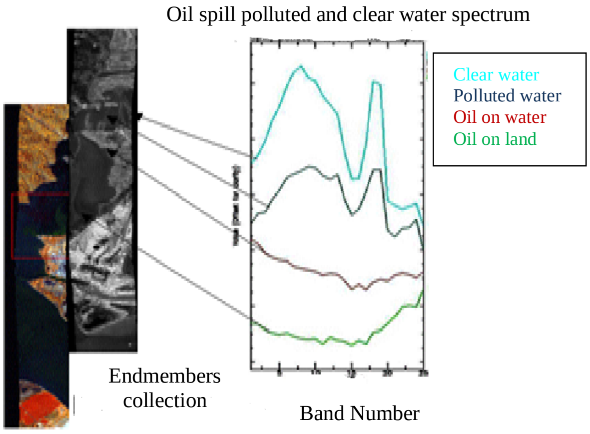

Figure 3
The spectra of oil on water, land, polluted water, and clear water is shown in red, green, gray, and cyan respectively. The spectral library is created using the oil and water spectra derived from the image; the spectra are utilized as an endmember collection group for training the spectral angle mapper classifier (Salem et al., 2002).

1.3. Hyperspectral data

The creation of an effective and continuous reflectance spectrum is possible for each pixel in the scene using hyperspectral sensors like the airborne imaging spectro-radiometer for applications (AISA Dual). These systems can also be employed for differentiating earth surface properties from each other. Hyperspectral data provide spectral information data to identify substances and materials in details and to better approximate their influence. This data can increase the accuracy of classification and makes possible identifying oil spill properties, which conventional sensors such as multi-spectral are not able to differentiate accurately (McFarland et al., 1993). Up to hundreds of selected wavelengths reflecting from earth properties can be recorded by hyperspectral sensing. Scientists can use this spectral information to extract the oil spectral signature for detecting the trace amount of hydrocarbon on the surface of sea, and to differentiate between different levels of crude oil. The hyperspectral sensing applications comprise identifying mineral resources and contamination of soil, shallow water, wetlands, sand beaches, and shoreline with high spectral accuracy; exact spectral information data can be provided by HSI for analyzing properties with a higher spectral variety.

1.4. Spectral mixing

Spectral mixing occurs when the materials with different spectral signatures are available in a single image pixel. The mixing scales and linearity have been studied by several researchers in a study conducted by Singer and McCord (1979); the mixing behavior was linear at a macroscopic level, while it was generally nonlinear at a microscopic level (Nash and Conel, 1974; Singer, 1981).

In the linear model, it is assumed that materials have no interaction. The mixing spatial scale and physical distribution of materials are applied to determining the non-linearity level. Mixing the surface materials is performed in a nonlinear behavior, although linear unmixing is a good estimator of it in many situations (Boardman and Kruse, 1994). The linear techniques never have been as accurate as the nonlinear approaches, while they can sufficiently represent the surface conditions. The linear model is the simplest model for describing mixed pixels, which are assumed to contain the linear hybrid of the pure spectra (Figure 4).

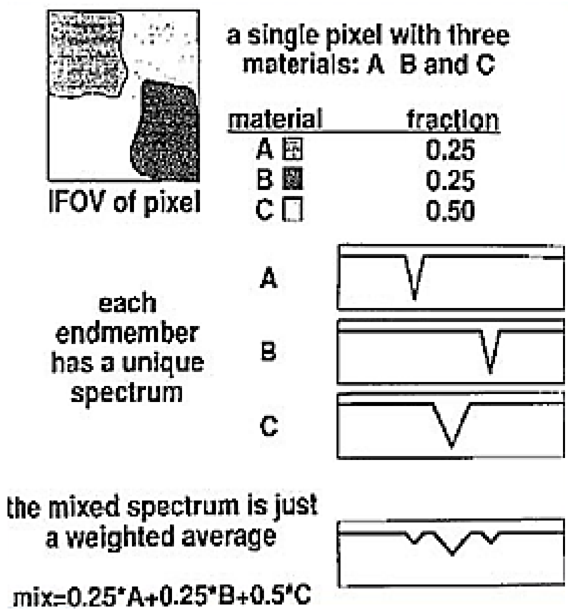

Figure 4
Linear mixing for a single pixel (Nash and Conel, 1974).

In general, three models of physical, mathematical, and geometrical can be used to formalize simple linear mixing. The key parts of physical models are ground instantaneous field of view (GIFOV) of the mixed pixel, the incoming irradiance, the interactions of photon material interactions, and the resulting combined spectra. In order to simplify the issue and permit inversion, or unmixing, the needed model is a more abstract mathematical model. Primary data matrix is produced by a spectral library for the analysis. The perfect spectral library comprises of pure spectra, which are linearly combined to generate that when the linearly mixed spectra can produce all the other spectra. To make the problem simpler and allow inversion, a more explicit mathematical model is necessary. For analysis, the spectral library produces the primary data matrix when the linearly mixed spectra can produce all the other spectra; this means that the perfect spectral library consists of pure spectra. In a mathematical model, the observed spectra (a vector) are assumed to be resulted by the multiplication of the mixing library of the pure end member spectrum (a matrix) with the abundance of endmembers (a vector). The multiplication of the orthogonal matrices with the reciprocal values of the diagonal matrix will led to an inverse of the original spectral library matrix (Boardman, 1993). In the case of the unidentified spectrum, a simple vector-matrix multiplication of the inverse library matrix and an observed mixed spectrum are used to estimate the library endmembers abundance. Geometric mixing model provides an alternate, intuitive means for understanding spectral mixing. In an n-D scatter plot (spectral) space (where n is the bands number), mixed hybrid pixels are visualized as points. The hybrid pixels fall in a line when only two endmembers are combined in a 2D space. The pure endmembers are located at both ends of the mixing combining line. The mixed pixels fall in a triangle form when three endmembers are combined. The combination of endmembers falls in the distance between the endmembers. All hybrid spectra are interior to the pure endmembers, which are inside the simplex shaped via the vertices of the end member, since all the abundances are positive and sum up to unity. This convex collection of mixed hybrid pixels can be utilized for measuring the number of available endmembers and for predicting their spectra. The geometric model can be extended to higher dimensions where mixing endmembers number is one or more units higher than the inherent dimensionality of the combined information.

1.4.1. Practical unmixing methods

The known endmembers and derived endmembers are two common types of unmixing methods, which are significantly different. Known endmembers are applied to deriving the obvious fractional abundance of each material of endmember material in every pixel, given a group of known or supposed spectral endmembers. These known endmembers can be drawn from the information (means of areas chosen according to earlier knowledge), drawn from a library of pure materials via interactively looking over the imaging spectrometer data information for determining available pure materials in the image, or determined by professional systems as abovementioned or other ways of identifying materials. The matrix of mixing endmembers includes spectra of the image or a reference library. The issue can be cast as an over-determined, linear, least-squares problem. In order to achieve least square approximations of the unknown endmember abundance fractions, the mixing hybrid matrix is reversed and multiplied by the observed spectra in order to provide positive fractions, which sum up to unity, and constraints, which can be located on the solutions. Shadow and shade as endmembers are involved either implicitly (fractions sum equals to 1 or less) or explicitly as an endmember (fractions sum equals to 1).

In the second unmixing method, the imaging spectrometer data information is used for deriving the mixing endmembers (Boardman and Kruse, 1994). The determination of inherent dimensionality of the information was performed through a special orthogonalization process associated with principal components:

- Derive a linear sub-space (flat) that spans the entire signal of the information
- Project the data information onto this subspace, drop the dimensionality of the unmixing, and eliminate most of the noise
- Find the convex hull of this projected information
- Shrink-wrap the information via a simplex of *n*-dimensions simplex, providing the pure endmembers
- Apply the hyperspectral images to detecting oil spill leak and determining its characteristic features, and predestine the success of spread or mitigation.

2. Methodology

The hyperspectral images are used to detect oil spill leak and determine its characteristic features, and then the success of spread or mitigation is predestined. The steps for reaching this goal are as follows:

a. Predict oil spill spread direction and flow rate characteristics

Hyperspectral image analysis for oil spill must be conducted on time for operational environmental monitoring. By analyzing airborne HSI temporal image, we can predicts how oil spill spread on water bodies based on current environmental conditions and which sensitive sites can be affected.

b. Reorganization of oil spill shoreline properties and intensity

HSI with a high spectral and spatial resolution can be used for detecting shoreline properties and regions ruined because of leaked oil. Affected environmentally sensitive areas, including wetlands with shallow water, seagrass, salt marshes, tidal flats, channels, or sandy coastlines with remarkable biodiversity must be investigated since these areas are environmentally sensitive.

c. Determination of the contaminant type

The oil characteristic features (e.g., oil types and concentration level) are important and can be employed for selecting the best technique of cleanup process, for estimating environmental consequences of burning oil, and for modeling the oil leak phenomena (such as predicting the flow path, the speeds of dispersion rates, and time before the slick reaches the beach) (Jordan and Payne, 1980). For example, evaporation rate of light oil is faster compared to crude oil, while it could be more poisonous for different marine species (Massin, 1998).

2.1. Spectral angle mapper method (SAM)

The spectral angle mapper (SAM) is an automated technique utilized to compare image spectra with individual spectra or with a spectral library (CSES, 1992; Kruse et al., 1993). This algorithm supposed that the information was decreased to apparent obvious reflectance (correct reflectance multiplied by some unknown gain factors, controlled through shadows and topography). The likeness of two spectra is determined using the algorithm through computing the spectral angle between them and treating them in place of vectors in an *n*-D space, where *n* refers to the band number (Figure 5).

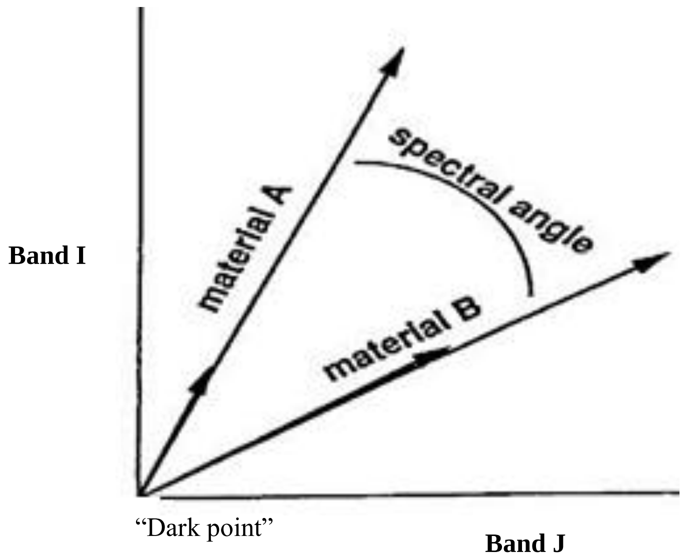

Figure 5
Principle of SAM algorithm (CSES, 1992; Kruse et al., 1993).

SAM describes the likeness of an unknown spectrum "*t*" to a reference spectrum by applying the below equation (CSES, 1992):

$$\propto = \mathbf{cos^{-1}}\left(\frac{\vec{\boldsymbol{t}}.\vec{\boldsymbol{r}}}{\|\vec{\boldsymbol{t}}\|.\|\vec{\boldsymbol{r}}\|}\right) \tag{1}$$

which can also be stated as:

$$\cos^{-1}\left(\frac{\sum_{i=1}^{nb} t_i r_i}{\left(\sum_{i=1}^{nb} t_i^2\right)^{\frac{1}{2}}\left(\sum_{i=1}^{nb} r_i^2\right)^{1/2}}\right) \tag{2}$$

where *nb* equals the number of bands in the image.

The algorithm was coded in MATLAB.

2.2. Remote sensing satellite data and the resolution problem

Improvements in recent satellite sensors in applying satellite information and resolution provide high resolution data information for the researchers in terms of radiometric, spectral, spatial, and temporal.

The first problem, which does not simply permit to enhance spectral resolution, arises from spectral resolution and signal to noise ratio (SNR) tradeoff. This problem does not simply allow increasing spectral resolution and is due to the enhancement of spectral bands and output sensor SNR reduction. Consequently, the balance between high spectral resolution and low SNR should be made by applying some approaches. For this purpose, the data dimensionality reductions like minimum noise fraction (MNF) and principle component analysis (PCA) transformation are used.

The next problem is tradeoff between data size and finer spatial resolution. Increasing spatial resolution makes a fast increase in data size. A balance must be kept between the size of data information collected by satellite sensor and transmission rate capacity and the data information processing abilities. Therefore, several approaches toward solving this dilemma include enhancing spatial resolution while declining other parameters like swath width, spectral bands, and radiometric at the same time. The third dilemma is associated with tradeoff between the resolutions of spatial and spectral. In order to detect an object by the satellite sensor, the energy reflected from it must be large enough. The signal level of the reflected energy can be improved by collecting information over a large instantaneous field of view (IFOV) or over a border spectral bandwidth. Collecting reflected energy from terrestrial features over a larger IFOV reduces spatial accuracy, while accumulating energy over a board range of spectrum decreases the spectral resolution. Most of the optical satellite sensors carry two sensor sorts to solve this problem: the panchromatic (PAN) sensor and multispectral (MS) sensor. The MS sensors collect reflected energy over a board IFOV, while the PAN sensor captures signals over a slenderer IFOV and larger bandwidth. Thus, the MS sensors have a better spectral resolution, but lower ground resolution compared to PAN bands and vice versa. Image fusion methods are used to overcome this problem and take advantage of spatial and spectral resolution at the same time. Image fusion belongs to the extensive area of data information fusion. The image fusion origin goes back into the 1950's and 1960's when the scientists were attempting to create new approaches toward combining images of various sensors. Image fusion method is the integration of images with various spatial and spectral resolutions to obtain spatial with high spatial quality while the same spectral resolution is preserved for the high spectral resolution information. Image fusion or more exactly pan sharpening is applied since several researches simultaneously require both spectral and spatial with a high resolution. This technique often fuses panchromatic band with multispectral bands. Panchromatic band is higher spatial with a low spectral resolution, but multispectral bands are low spatial with a high spectral resolution. For this means, most of the latest remote sensing methods like Ikonos, Quick Bird, IRS, and Landsat 7 and 8 simultaneously have the sensors of panchromatic and multispectral. Numerous methods were used for fusing multiresolution data. The image fusion methods can generally be divided into two categories, namely color-based techniques, and statistics-based techniques or numerical approaches. The first category group like hue, intensity, saturation (HIS) color transformation generates red, green, blue (RGB) color composite bands via separating a standard RGB image into spatial (I) and spectral (H, S) information. The statistical methods apply statistics approaches such as correlation (like principal components analysis (PCA)), regression, and filters (high pass), while numerical methods utilize the operation of arithmetic and mathematical methods such as wavelet transformation. Although this methods are so valuable for study areas such as urban studies where the spatial resolution accuracy is the important parameter compared to spectral accuracy, the accuracy of spectral resolution is crucial for the applications such as mining. The fused image color distortion is the common problem related to the existing approaches. Another common problem related to the existing approaches is that the quality of the fused images depends on operator and information, and different operators or information set groups might lead to various qualities.

The last problem corresponding to resolution dilemma is a tradeoff between signal to noise ratio and radiometric resolution. No point is available in having a step size less than the noise level in the information. An instrument tool with a low-quality and high noise level would be required, so a lower radiometric resolution compared to a high quality, high signal-to-noise ratio tool is required. Moreover, a higher resolution of radiometric may conflict with information storage and speeds of transmission rates.

Spectral resolution and signal to noise ratio (SNR) tradeoff problem appears as hyperspectral images are used to reach the purpose. In order to overcome this problem, MNF transformation was used to decrease information dimensionality of data and to preserve almost entire data information variance at the same time (more than 95%). This technique also removes data redundancy and minimizes the data noise.

The image fusion is not needed to achieve our goal, as the used information has a spatial resolution of 1 meter. Nearly all image fusion approaches distorts spectral resolution somehow and does not optimize hyperspectral images; hence, novel approaches must be discovered for preserving spectral resolution entirely.

2.3. Extracting hyperspectral information

The basic method is about seeking a more essential understanding of signal spaces with a high dimension in the context of multispectral remote sensing, and then about applying this knowledge for extending the conventional multispectral analysis methods to the domain of hyperspectral in an optimum or almost optimum fashion. Much more spectral information in detail is produced than before by introducing hyperspectral sensors that provide more abilities for extracting beneficial information from the data stream they generate. Discriminating between any specified group of classes of data is theoretically possible with enhancing the data dimensionality far enough. In fact, the present hyperspectral data information makes this essentially possible by providing several hundred spectral bands (Landgrebe, 1998). However, a more sophisticated data analysis process is needed for this more detailed data information with large bands number to apply their full potentials. Many things learned about the essential processes are not extremely intuitive, but they are counter-intuitive in many cases. In the current study, not only several of these counter-intuitive aspects are illuminated, but also a guide for the practical technique of making optimum analysis processes is presented. In order to train the spectral angle mapper classifier, the spectra are employed as an endmember collection to train.

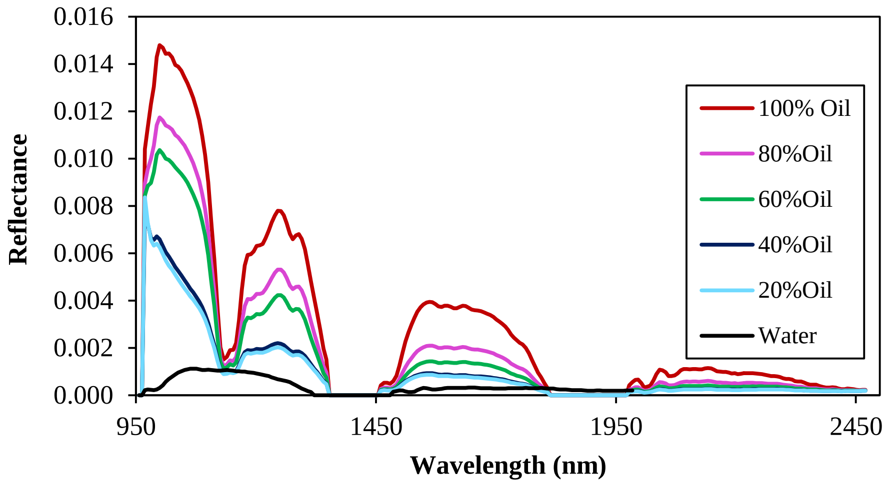

Figure 6
Oil dispersant spectra appeared in red; total of 360 bands from 183 to 198 and from 255 to 279 were used; low signal to noise ratio (SNR) were removed by FLAASH program; from band 1 to 119 due to their irrelevancy to extracting oil spill spectral endmembers were eliminated.

2.3. Ground truth

Arial photographs of the research area are used for sampling and getting information from the image scene, and these samples are utilized as the training sites for enhancing the accuracy of classification. Endmember signatures are extracted according to these samples and according to image statistics for detecting oil spill and the oil to water ratio. Furthermore, ground truth information data corresponding to the day of data acquisition permits the development of quantitative relations between materials on the ground and the one measured through the remote sensing tool. These relationships help with the real approximations of the amounts and densities of materials.

3. Oil spectra features analysis

In the oil spectral, a number of available interesting properties can be employed to extract the endmembers from the image (Salisbury, 1993). A specific peak is observed at 580-600 mµ corresponding to the dispersant oil absorption; an enhancement in oil concentration leads to a linear dip in the peak at 675-685 mµ (Figure 5). By increasing the oil concentration on water, the levels dip out in such a way that it will be utilized as a good indication for high and low level of oil. A strong reflectance corresponding to the spread oil is observed at 580 mµ and 700 mµ in the visible and near IR regions. A reflectance related to water is in the blue band at 800 mµ, and the absorption of water is at 670 mµ, which offers data for the total level of oil and water turbidity next to the shore line.

4. Results and discussion

We used extracted endmembers as training spectra for spectral angle mapper to classify the image. Since the data were collected at the radiance, work began with atmospheric correction (Figure 7); the correction was performed using FLAASH algorithm in ENVI environment. Then, in the MATLAB environment, we use extracted endmembers as training spectra for spectral angle mapper to classify the image in six classes, namely 100% oil, 80% oil and 20% water, 60% oil and 40% water, 40% oil and 60% water, 20% oil and 80% water, and finally 100% water (Figure 8).

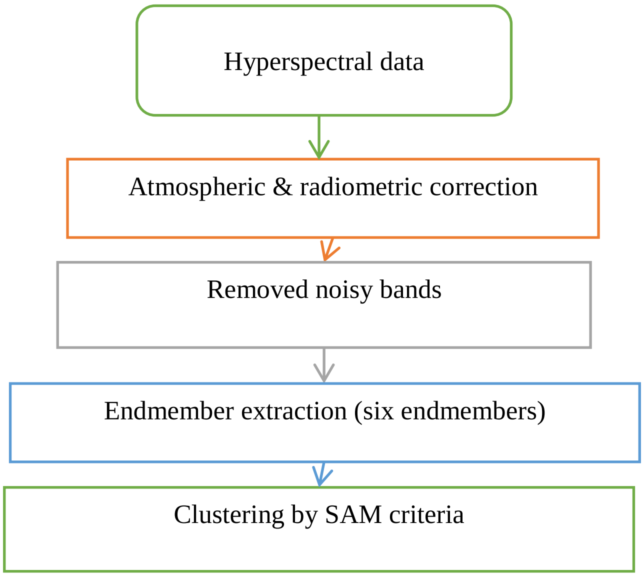

Figure 7
Oil spill detection steps.

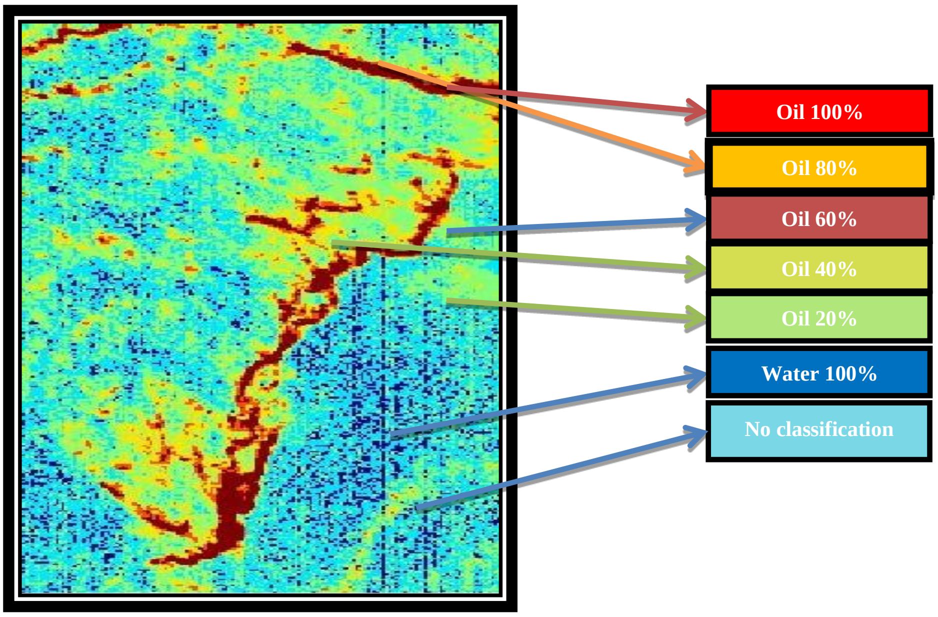

Figure 8
The oil to water ratio: 100% oil (clear oil), red; 80% oil, orange; 60% oil, dark red; 40% oil, lime; 20% oil, light green; 100% water, blue (clear water); and no classification, light blue.

Finally, ground truth information provides the basic information for post-processing accuracy assessments. The estimated numbers of pixels by SAM algorithms are shown in Table 1.

Table 1
The area of each class (in pixels).

Algorithm	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
SAM	3992	17812	17121	5246	1788	2041

5. Conclusions

1- The hyperspectral imagery is a reliable advanced remote sensing technology for minimizing the limitations of the conventional remote sensing methods to detect oil leak.

2- The visual interpretation of the space shuttle images indicates many limitations, including wrong outcomes resulted by natural phenomena such as oil appearance changing because of sun angle.

3- The results obtained from this study indicate that the signature matching technique is a more exact technique compared to the conventional methods, which are based on the oil color visual interpretation and the appearance of the images of space shuttle.

4- Various levels of the dispersion of oil in terms of their contamination are recognized using HSI 2 spectral information. The detection of trace levels of hydrocarbon (crude oil) was performed using the oil signature.

5- Among supervised classification methods, spectral angle mapper classification is a more accurate method than other methods for analyzing the image of oil spill. The classified image accuracy is reduced due to low SNR resulted by increasing the number of spectral bands when the selection of trained samples from the image is performed based on the pixels. Signature matching method can differentiate between materials by considering their chemical composition with no use of visual appearance, and, as a result, the accuracy of classification is improved.

6- For operational monitoring of the environment in detection of oil spill, hyperspectral imagery is a more accurate technique than multi-spectral systems. By using the airborne HSI temporal image, it can predict how oil spill spread on water bodies and which sensitive places can be affected in the existing ecological environments.

6. Future work

1- Several approaches will be used to assess the accuracy of the classification results and the performance of the classification.

2- In order to recognize contaminated coastal properties, the linear unmixing signature technique will be utilized to differentiate between the mixed signatures of various materials, including soil, water, and grass polluted with oil.

Nomenclature

EDM:	: Euclidian distance measure
EO-1	: Earth observing-1
FCLS	: Fully constrained least squares
FPPI	: Fast pixel purity index
ICA	: Independent component analysis
MNF	: Minimum noise fraction
NIR	: Near infrared
NMF	: Non-negative matrix factorization
SAM	: Spectral angle mapper

SAR	: Specific absorption rate
SCM	: Spectral correlation measure
SNR	: Signal to noise
VD	: Virtual dimensionality

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