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An Oil Slick Detection Method Based on Advanced Spectral DNA Encoding Strategy by Chinese Zhuhai-1 Satellite Imagery

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Abstract

In recent years, the wars have gradually increased the risk of marine oil spill accidents. Marine oil spill monitoring becomes more and more important for preventing marine oil pollutions. Chinese Zhuhai-1 satellite can capture abundant spectral reflectance signals. It is a significant way of detecting marine oil spills. Most of the traditional oil spill detection methods only used a small amount of spectral information. It made it difficult identify oil spills accurately from the inhomogeneous marine environment. In order to mine the key differential spectral information of oil slicks, inspired by the encoding method of spectral DNA, an advanced spectral DNA encoding (ASDE) strategy was proposed to describe the spectral details in Zhuhai-1 images. On this basis, two kinds of key spectral information extraction methods were proposed to mine the spectral genes of oil slicks. Finally, the extracted spectral genes were used to detect the marine oil spills. Three Zhuhai-1 satellite images were used to validate the performance of the proposed method based on ASDE strategy. The experimental results indicated that the proposed method could precisely describe the spectral differences of oil slicks and sea-water in Zhuhai-1 images. In addition, the extracted spectral genes could detect marine oil spills correctly.

Keywords: Chinese Zhuhai-1 satellite; marine oil spill; hyperspectral remote sensing; spectral encoding; DNA encoding

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1. Introduction

With the continuous development of global society and economy, the demand for crude oil is expanding. More and more marine oil transportation and exploitation activities lead to increased risk of oil spills [1,2]. At present, many wars around the world make oil spill accidents inevitable. Thus, it becomes very necessary to monitor the oil spills at sea [3,4].

Hyperspectral satellites acquire many spectral reflection signals of surface targets over a wide range. It can produce hyperspectral images (HSI) for identifying and monitoring marine oil spills [5,6]. Researches on marine oil spill detection methods based on HSI help to prevent and control the pollutions. Most of the current satellite oil spill de-taction methods are based on images captured by Sentinel-1/2, Hyperion, MODIS, Proba, and etc. [7–10]. Chinese Zhuhai-1 (02) hyperspectral satellite can get images of 32 bands and Zhuhai-1 (03) hyperspectral satellite can get images of 256 bands [11,12]. Zhuhai-1 satellite imagery gains the advantages of wide coverage and short revisit period. It is a favorable way of monitoring marine oil spills [13,14]. In this research, the oil spill detection method is based on Zhuhai-1 satellite (02) imagery.

The main way to identify marine oil slicks caused by spill accidents is mining the distinctive spectral signals in HSI. Many innovative researches were proposed in this field. In 2003, Carl Brown and Mervin Fingas proposed that the spectral reflection signals of the surface oil slicks in the infrared

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bands were higher than that of the background seawater. The infrared spectral reflection signals could be used to identify marine oil spills [15]. In 2011, Yingcheng Lu et al. proposed a decision tree method of spectral characteristic bands to identify marine oil spills based on HJ-1 satellite imagery. This method performed well in the Gulf of Mexico oil spill remote sensing data [16]. In 2012, Eduardo Loos et al. demonstrated that the ability of fluorescence index (FI) and rotation absorption index (RAI) to distinguish oil slicks and "false targets" through MODIS satellite data [17]. Li Ying et al. proposed a sea surface oil slick identification method combining texture features, principal component analysis (PCA), and directional gradient edge detection method based on the Penglai 19-3 oil spill HJ-CCD data. This method improved the accuracy of oil spill identification. In 2013, Sun Peng et al. analyzed the correlation between oil slick thickness and various spectral indices [18]. Sankaran Rajendran et al. discussed the ability of Snow Water Index (SWI), Normalized Difference Vegetation Index (NDVI) and Normalized Water Index (NDWI) to identify oil spills [19]. Traditional methods mostly used the original spectral reflection signals or spectral indices of HSI to distinguish the surface oil slicks from the background seawater. However, these methods only took advantages of a part of the spectral characteristic signals. They ignored a large number of spectral detail signals.

In order to comprehensively describe the spectral detailed characteristics of oil slicks in HSI and detect oil spills by extracting the key differential information, an advanced spectral DNA encoding (ASDE) method was proposed to carry out the task. The ASDE method was used to detect oil spills in Zhuhai-1 satellite images. First, the original spectral reflection signals of Zhuhai-1 satellite imagery were translated into spectral DNA codeword sequences. Then, the key differential spectral codewords, called spectral genes, of the oil slicks were obtained through two kinds of gene extraction strategies. Finally, calculate the matching rate between encoded pixels and the extracted spectral genes. The calculation results would be used to produce oil spill detection result. In this research, 3 Zhuhai-1 satellite images were used to validate the performance of the ASDE method. The experimental results showed that the ASDE method could accurately describe the spectral details of the sea surface oil slicks in the Zhuhai-1 satellite data. In addition, it can accurately detect the oil spills in the Zhuhai-1 satellite data.

2. Materials and Methods

2.1. Marine Oil Spill Detection Theory in Hyperspectral Data

Marine oil spills are mainly divided into three types: natural leakage from submarine oil reservoirs, crude oil exploitation leakage, and ship leakage (Figure 1). Marine oil spills will form oil slicks on the sea surface. From the thinnest to thickest, oil slicks can be categorized into silvery oil slicks, rainbow oil slicks, metallic oil slicks, discontinuous true-colour oil slicks, continuous true-colour oil slicks, and emulsified oil slicks. Oil slicks of different origins, thicknesses, and degrees of weathering exhibit very different visual, morphological and spectral characteristic information (Table 1). Hyperspectral satellites can acquire rich spectral reflection signals on the earth's surface over a wide range. Using the spectral differences to distinguish sea-surface oil slicks and background seawater is an important way of detect marine oil spills.

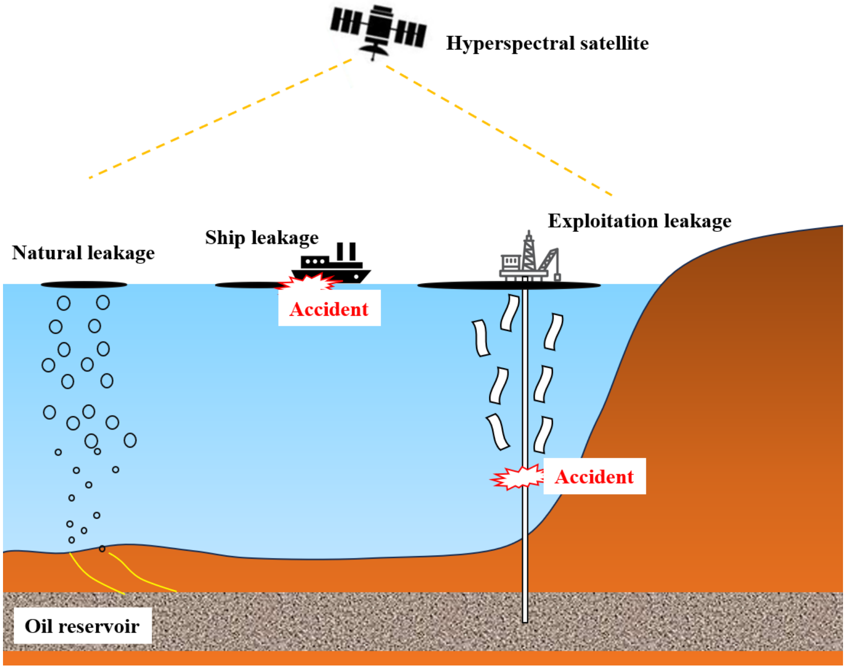

Figure 1. Oil slicks on the sea surface formed by the oil spills.

Table 1. Oil slicks with different thicknesses and their characteristics.

Oil slicks	Thickness/μm	Bonn code	Characteristics
Silvery oil slicks	0.04 ~ 0.3	Code 1	Silvery oil slicks are silver, rainbow oil slicks are iridescent, metallic oil slicks exhibit metallic shine. They are collectively called sheens. Sheens slightly change the colour of the background seawater and is distributed around the thick oil film. Sheens have little spectral difference from the seawater.
Rainbow oil slicks	0.3 ~ 5.0	Code 2	
Metallic oil slicks	5.0 ~ 50	Code 3	
Discontinuous true-colour oil slicks	50 ~ 200	Code 4	Discontinuous true-colour oil slicks are thicker than sheens. They are orange-yellow and distributed in sheets on the sea surface. Their infrared reflection signal is slightly higher than that of seawater.
Continuous true-colour oil slicks	200 ~ 500	Code 5	The thickness of continuous true-colour oil slicks is larger than the discontinuous true-colour oil slicks. They distribute in short strips and cannot exist on the sea surface in a large area. They look dark gray or black. Their infrared reflection signal is significantly higher than that of seawater.
Emulsified oil slicks	500 ~	-	They are weathered oil slicks with huge thickness differences. They look orange-red color. They are band-like distribution up to several kilometers in length. They have strong infrared reflection signals.

Zhuhai-1 satellites can acquire hyperspectral imagery of 32 bands on the earth's surface, with a spectral resolution of 2.5 nm and a spatial resolution of 10 m. The revisit period of the satellite

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constellation is as short as 1 day. Zhuhai-1 satellites can quickly respond to oil spill accidents and provide services for industrial applications such as oil tanker leakage, oil production platform damages etc. It is an important data platform for marine oil spill identification and monitoring.

2.2. Detecting Marine Oil Spills by ASDE Method

The spectral DNA encoding method is an excellent method for describing spectral information. It uses 4 codewords {T, C, A, G} to describe the amplitude of spectral signals. It shows excellent performance for describing spectral characteristics. The spectral feature mining method based on spectral DNA encoding results gains strong target discrimination ability [20,21]. However, the traditional spectral DNA encoding method only describes the spectral amplitude information in four intervals. It is inevitable to miss the detailed differences in spectral amplitudes. In addition, the traditional spectral DNA encoding method describes 9 waveform modes of the spectral shape characteristics through 4 codewords {T, C, A, G}, which causes the codeword ambiguity problem in pattern recognition. To address these problems, an ASDE method is proposed in this research to describe the amplitude and waveform details of Zhuhai-1 satellite imagery. The proposed method contains 3 core procedure:

(1) Divide the amplitude and waveform information of hyperspectral satellite data into 9 modes (Formula 1-6). Use a pair of DNA codewords to describe the modes of spectral signals (Figure 2).

(2) Use fuzzy clustering algorithm to extract the spectral genetic fragments of the sea-surface oil slicks (Formula 7-8).

(3) Calculate the similarity between spectral genes and encoded pixels. Extract oil slick objects in the Zhuhai-1 satellite imagery based on the calculation results.

$$T^{middle} = \frac{\alpha}{N}\sum R_i, \quad i \in [1, N] \tag{1}$$

$$T_j^{upper} = \frac{j \times \sum R^{upper}}{4 \times N^{upper}}, \quad j \in [1,2,3] \tag{2}$$

$$T_k^{lower} = \frac{k \times \sum R^{lower}}{4 \times N^{lower}}, \quad k \in [1,2,3] \tag{3}$$

$$Code^{Amplitude}(i) = Amp\left(T^{middle}, T^{upper}, T^{lower}, R_i\right) \tag{4}$$

Equation 1-4 describes the amplitude encoding process of the spectral reflection signal of hyperspectral satellite data. The ASDE method uses 7 amplitude thresholds (T^{middle}, T^{upper}, T^{lower}) to divide the reflected signal into 8 intervals. Different DNA codeword pairs are used to describe spectral reflection signals whose amplitudes lie within the interval. T^{middle} represents the average threshold of the spectral reflection signal. In the formula, Ri represents the spectral reflection signal of the i-th band, and N represents the number of bands. R^{upper} represents the spectral reflection signal with an amplitude higher than T^{middle}, N^{upper} represents the total number of spectral bands with an amplitude higher than T^{middle}, R^{lower} represents the spectral reflection signal with an amplitude lower than T^{middle}, and N^{lower} represents the total number of spectral bands with an amplitude lower than T^{middle}. α is an adaptive parameter of amplitude encoding, which is used to adjust the distribution range of amplitude symbols. The larger the value of α, the more detailed the description of high reflectivity signals. Conversely, the more detailed the description of low reflection signals. When the original spectral signal is distributed among the code element blocks delineated by the amplitude threshold, the amplitude signal of the band is described by the DNA codeword pair corresponding to the code element interval.

$$\Delta = \beta \times \frac{\sum\left(R_{j+1} - R_j\right)}{N-2}, \quad j \in [1, N-1] \tag{5}$$

$$Code^{Shape}(k) = Ptn\left(\Delta, R_k, R_{k+1}, R_{k+2}\right), \quad k \in [1, N-2] \tag{6}$$

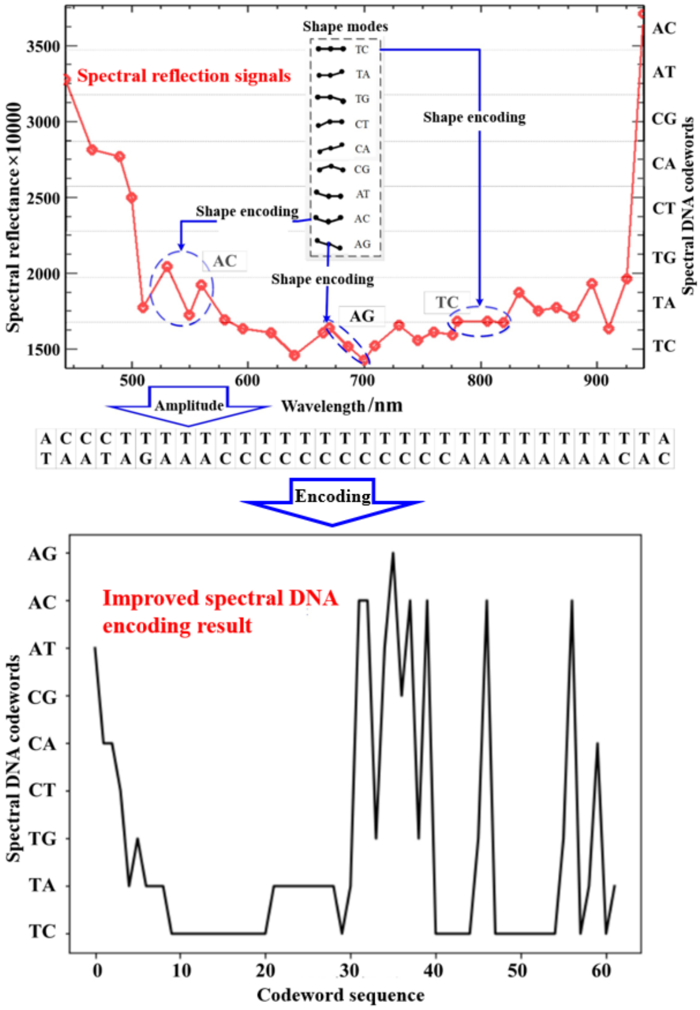

Figure 2. The schematic diagram of the principle of ASDE method.

Equation 5-6 describes the waveform encoding process of the original spectral signal. First, calculate the waveform change gradient Δ of the original spectral signal. Then the waveform mode (Figure 2) is determined based on the gradient relationship of the reflected signals in three adjacent bands. Finally, the waveform information of the spectral reflection signal is converted into DNA codeword pairs according to the waveform mode. β is the adaptation parameter of the waveform gradient, which is used to adjust the sensitivity of the waveform encoding. The larger the β value, the stronger the tolerance of the spectral codeword to noise. The smaller the β value, the stronger the sensitivity of the spectral codeword to noise.

$$Gene(s) = \begin{cases} Code(S), & F(Code(s)) \geq \delta \\ 0, & F(Code(s)) < \delta \end{cases} \tag{7}$$

$$Gene(s) = \begin{cases} 0, & G(Code(s)) \geq \delta \\ Code(S), & G(Code(s)) < \delta \end{cases} \tag{8}$$

After the spectral encoding process, the spectral genes in the DNA code chains of seawater and oil slick samples are extracted through fuzzy clustering method. In this research, two spectral gene extraction strategies are used: the largest intraclass similarity (LIS) strategy (Equation 7) and the largest interclass difference (LID) strategy (Equation 8). The LIS strategy extracts DNA codewords with high frequency (> δ) in similar samples as spectral genes for this type of objects. The LID strategy extracts specific DNA codewords (frequency < δ in other categories of samples) as spectral genes for this type of objects.

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Finally, the extracted spectral genes are used to match the encoded satellite imagery pixels. The marine oil spills and background seawater are distinguished based on the degree of matching. Figure 3 shows the process of detecting oil spills in Zhuhai-1 satellite imagery using the ASDE method.

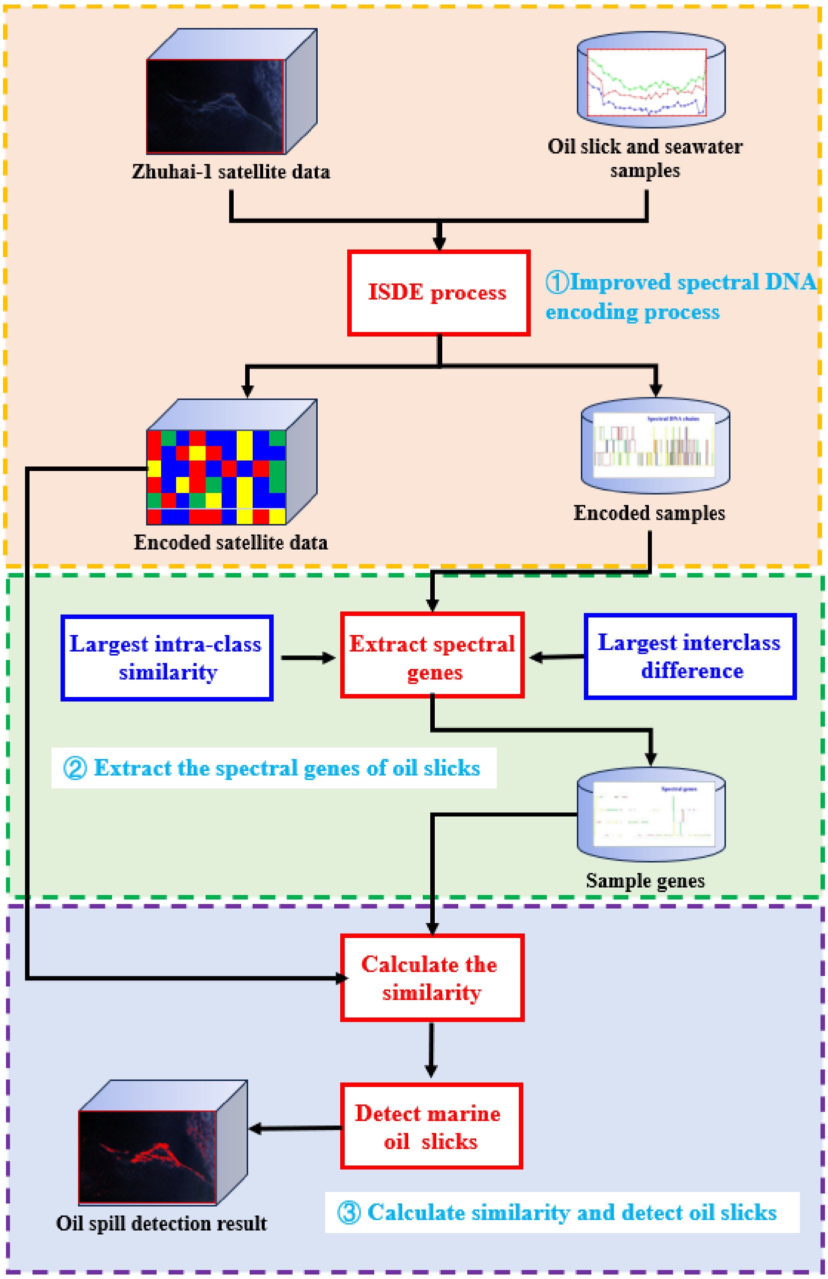

Figure 3. Flow chart of oil spill detection by the ASDE method utilizing Zhuhai-1 data.

3. Results

Three Zhuhai-1 satellite images were used to validate the marine oil spill detection ability of the ASDE method. Since the original satellite data was too large, the oil spill areas were selected for the experiments. Table 2 exhibited the experimental data information. The experimental data were collected from different sea areas. It was beneficial to verify the applicability of the proposed method. It should be stated that the marine oil slicks were dynamic and non-quantitative, ground truth could not be produced. In this research, manually selected samples were not adopted for calculating oil spill detection accuracy like overall accuracy (OA). The oil spill detection performance was evaluated directly.

Table 2. Information of the experimental data.

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Zhuhai-1 satellite Data NO.	Shooting date	Area	Oil spill type
HEM1_20210418142028_0008_L1B_CMOS2	2021-04-17	Tainan Basin	Natural oil spill
HCW2_20200722124480_0025_L1B_CMOS3	2020-07-21	Yinggehai Basin	Exploitation accident
HAM1_20210820212223_0018_L1B_CMOS1	2021-08-19	Yinggehai Basin	Exploitation accident

Figure 4 showed the true colour composite image of experimental data 1 (Figure 4.A) and its thematic map of oil spill identification result (Figure 4.B). The result was produced by the parameters of α=0.7, β=1.0, and δ=0.6. The study area (9.28 km × 4.43 km) was located in the Tainan Basin which was rich in oil and gas reserves. Oil slicks produced by natural oil spills had been observed many times. The oil slick in this study area was located at the edge of the cloud layer. It was distributed in a ribbon-like shape with local rainbow visual characteristics. The appearance was consistent with the typical characteristics of natural oil spills. In the thematic map of oil spill detection result, the oil slicks extracted by the ASDE method were marked in red. From the identification results, it could be found that the ASDE method accurately distinguished between marine oil spills and background seawater. Except for a small number of thin clouds that were mistakenly identified as oil slicks, most of the natural oil spills were correctly identified.

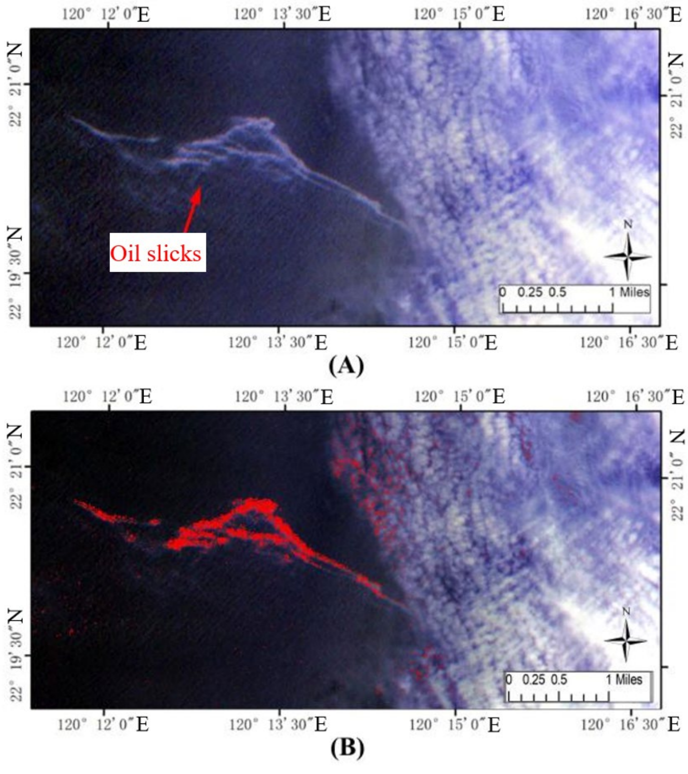

Figure 4. Oil spill detection result of the experimental data 1.

Figure 5 showed the true colour composite image of experimental data 2 (Figure 5.A) and its thematic map of oil spill identification results (Figure 5.B). The result was produced by the parameters of α=1.0, β=1.0, and δ=0.3. The study area (8.10 km × 7.51 km) was located in the Yinggehai Basin. It was surrounded by numerous oil production platforms. Oil slicks caused by accidental oil spills had been observed many times. In this satellite image, the oil slicks were converged in a black stripe. Some emulsified oil appeared white in the core area of oil spill, which only happened when large oil spill occurred. In the detection result, the identified oil slicks by the ASDE method were marked red. Since the surface oil slicks was located in the sun glint area, the seawater presented

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higher spectral signal and the shadow region of the waves presented lower spectral signal. In the detection result, only a small number of shadow areas were misidentified as oil slicks.

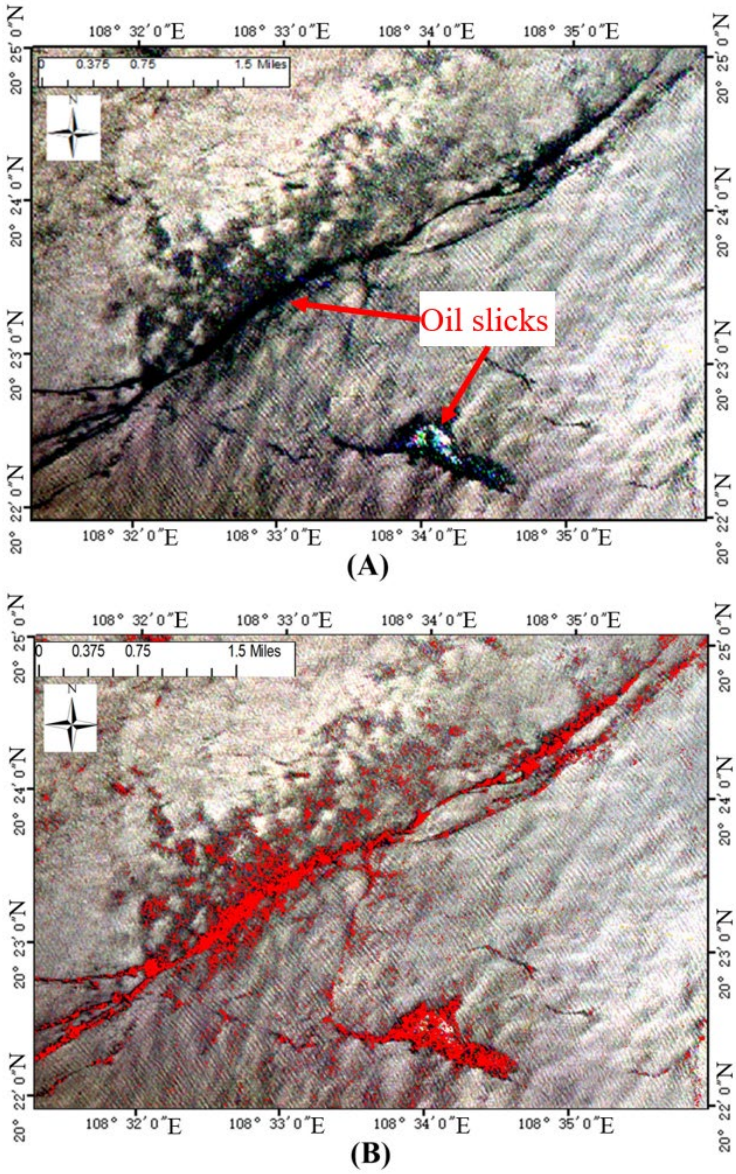

Figure 5. Oil spill detection result of the experimental data 2.

Figure 6 showed the true colour composite image of experimental data 3 (Figure 6.A) and its thematic map of oil spill identification results (Figure 6.B). The result was produced by the parameters of α=1.0, β=1.0, and δ=0.4. The study area (12.04 km × 8.91 km) was located in the Yinggehai Basin. The oil slicks in the study area were diffusive. Affected by the sea wind and ocean current, the oil slicks accumulated on the windward side and spread on the downwind side. In the detection result, the oil slicks were marked red. Since a part of the study area was covered by thick clouds and its shadows, oil slicks in the shadows were not identified. However, the ASDE method detected the oil slicks uncovered by the clouds accurately.

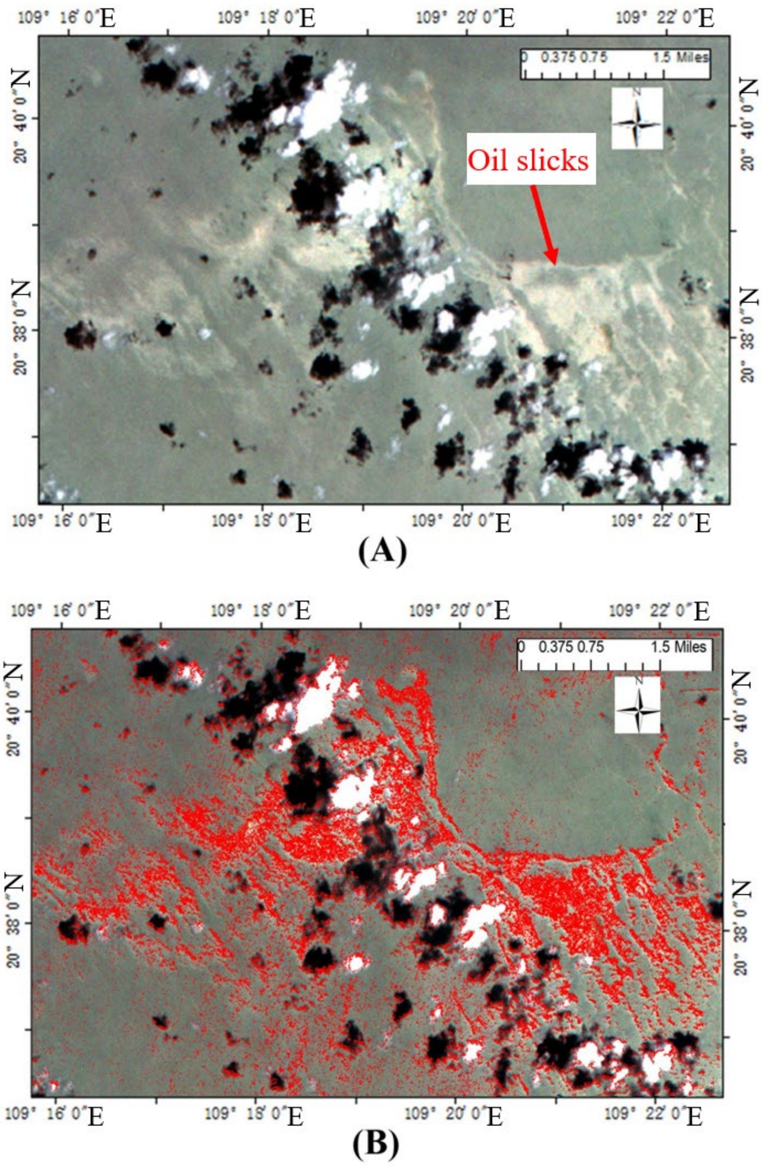

Figure 6. Oil spill detection result of the experimental data 3.

4. Discussion

The proposed oil spill detection method based on the ASDE method had 2 kinds of spectral gene extraction strategies: LIS and LID (formula 7 and 8). Selecting proper spectral gene extraction strategy was vital for identifying oil slicks in satellite imagery. In addition, the parameters of the spectral amplitude encoding and spectral shape encoding processes would affect oil spill detection accuracy directly. Thus, the spectral gene extraction strategy and the parameters were discussed in this section.

4.1. Discussion on Spectral Gene Extraction Strategy

When extract spectral genes using LIS strategy, high frequency code words (> δ) of training samples would be extracted as spectral genes. The size of spectral genes was controlled by the frequency parameter δ. Figure 7 showed the oil spill detection results of experimental data 1 with different frequency parameters by LIS strategy ($\alpha = 1$, β=1). In the detection results, the clouds were marked white, the background seawater was marked blue, and the detected oil slicks were marked red, respectively. From the detection results, it could be found that the oil slicks could be detected correctly when frequency parameter δ was at a low level (0.3~0.5). Although some seawater was misidentified as oil slicks, the scope of the oil spill was fully identified. It indicated that the ASDE

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method could describe the spectral details of oil slicks and seawater in Zhuhai-1 satellite data with LIS strategy.

In the contrast experimental results, when the frequency parameter δ increased from 0.3 to 0.6, the oil spill detection performance improved distinctly. It meant that the spectral genes extracted by LIS strategy could differentiate oil slicks from seawater accurately. In addition, when frequency parameter δ increased from 0.6 to 0.8, the oil spill detection performance deteriorated obviously. It indicated that the ASDE method with LIS strategy needed optimizing frequency parameter. Selecting proper spectral gene frequency was important for detecting oil spills in different study areas. The best spectral gene frequency was around 0.6 usually.

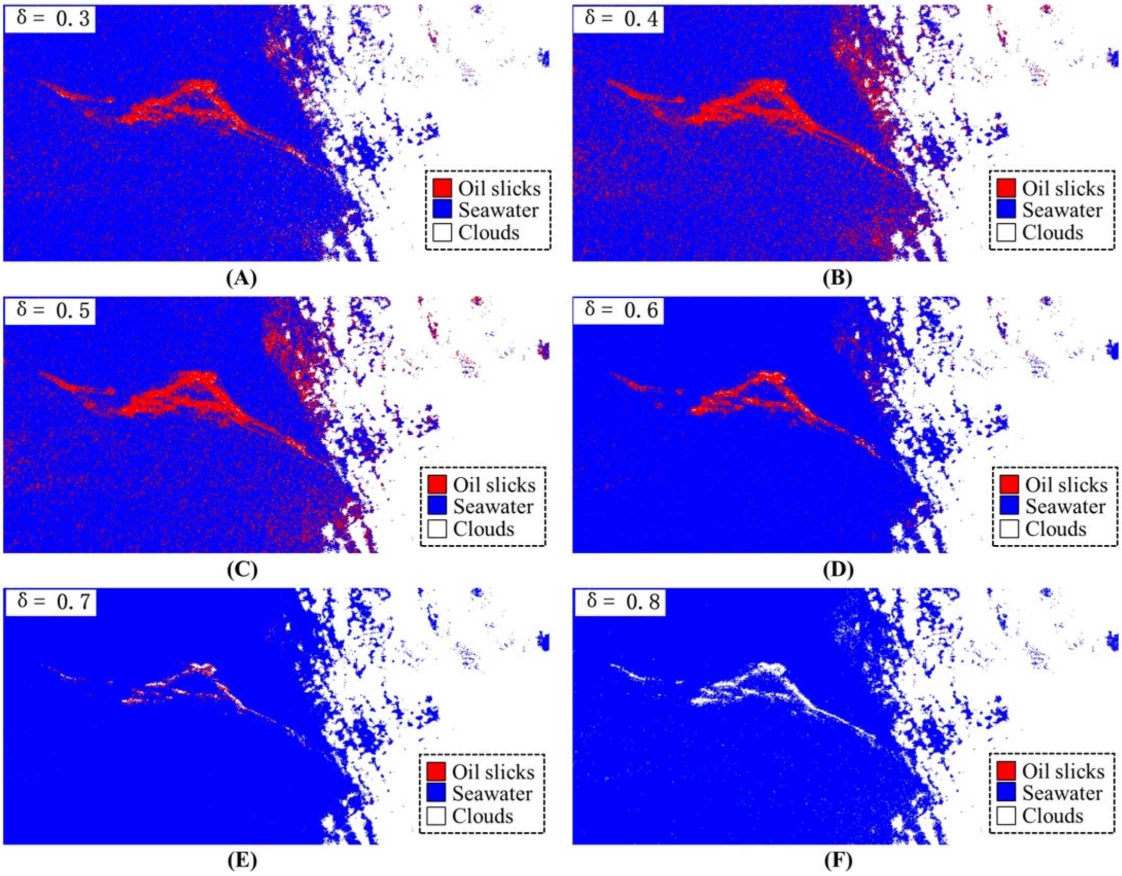

Figure 7. Oil spill detection results produced by the LIS strategy with different δ.

When extract spectral genes using LID strategy, unique code words of oil slicks (spectral gene frequency < δ in seawater samples) were extracted as spectral genes. The size of spectral genes was controlled by optimizing the spectral gene frequency δ. Figure 8 showed the oil spill detection results of experimental data 3 with different spectral gene frequency by LID strategy ($\alpha = 1$, β=1). When the frequency parameter δ was at a low level (0.2~0.4), the extracted spectral genes were the most unique. It could be found from the results that the oil slicks were identified best when spectral frequency parameter δ was 0.3. It indicated that the ADSE method with LID strategy could extract abundant spectral genes from Zhuhai-1 satellite to identify oil slicks.

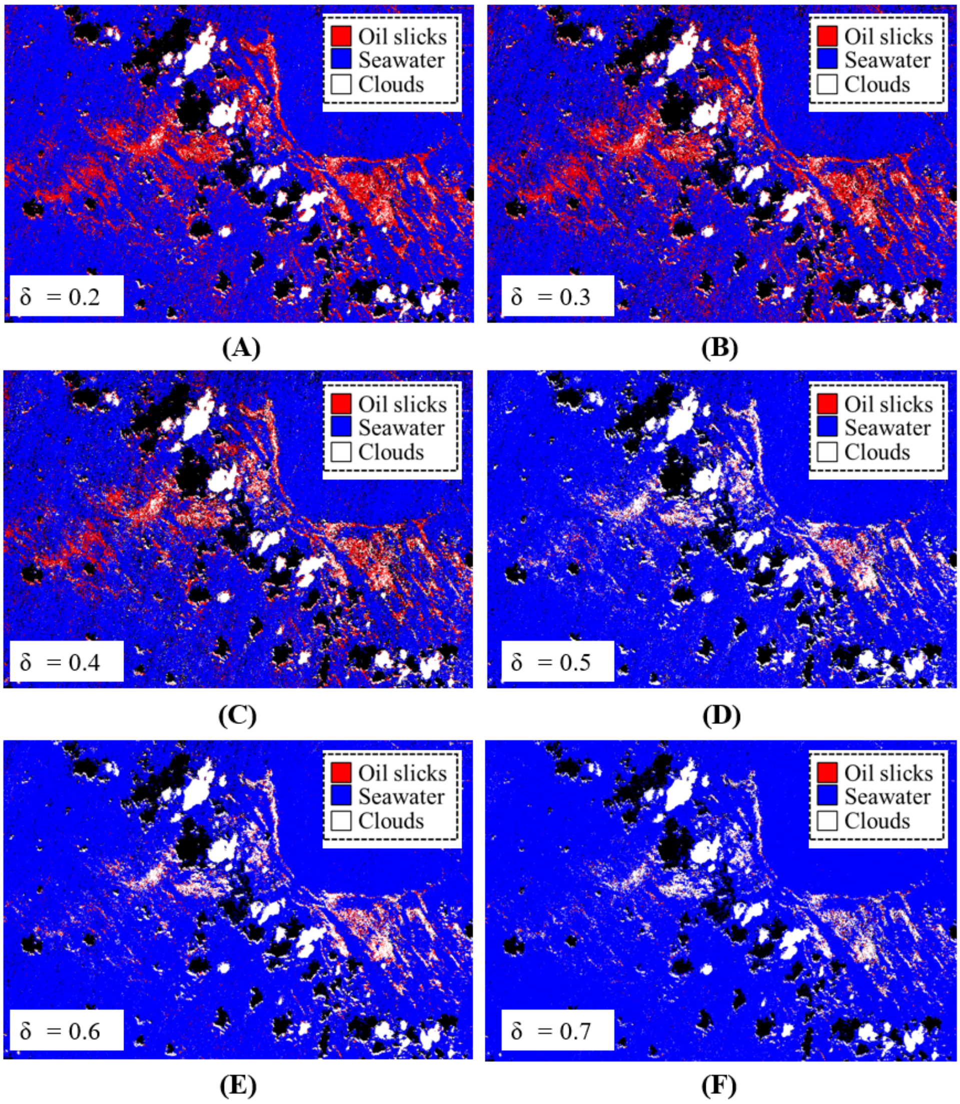

Figure 8. Oil spill detection results produced by the largest inter-class difference strategy with different δ.

However, in the contrast experimental results, the oil spill detection results got the best performance when the parameter δ was around 0.2. It indicated that although the spectral gene extraction rule was rigorous. Zhuhai-1 satellite data could provide abundant spectral information for differentiating oil slicks from seawater. With the parameter δ increasing, the spectral gene extraction rule became relaxed, more and more nongenetic spectral codewords would be extracted for identifying oil slicks. Thus, the oil spill detection performance became worse. From the contrast experimental results, it could be found that the ASDE method could detect oil slicks from Zhuhai-1 satellite data accurately. The ASDE method with LIS strategy should use high frequency parameter (δ = 0.6) and ASDE method with LID should use low frequency parameter (δ = 0.2).

4.2. Discussion on Spectral Encoding Parameters

Spectral amplitude encoding parameter α and spectral shape encoding parameter β were used to adjust the encoding result of the ASDE method. The parameters affected the oil spill detection performance directly. In order to reveal the effect of spectral amplitude parameter α on oil spill detection, experimental data 1 was used to conduct contrast experiments (LIS strategy, δ = 0.6, β = 1.3). Figure 9 showed the oil spill results produced by the ASDE method.

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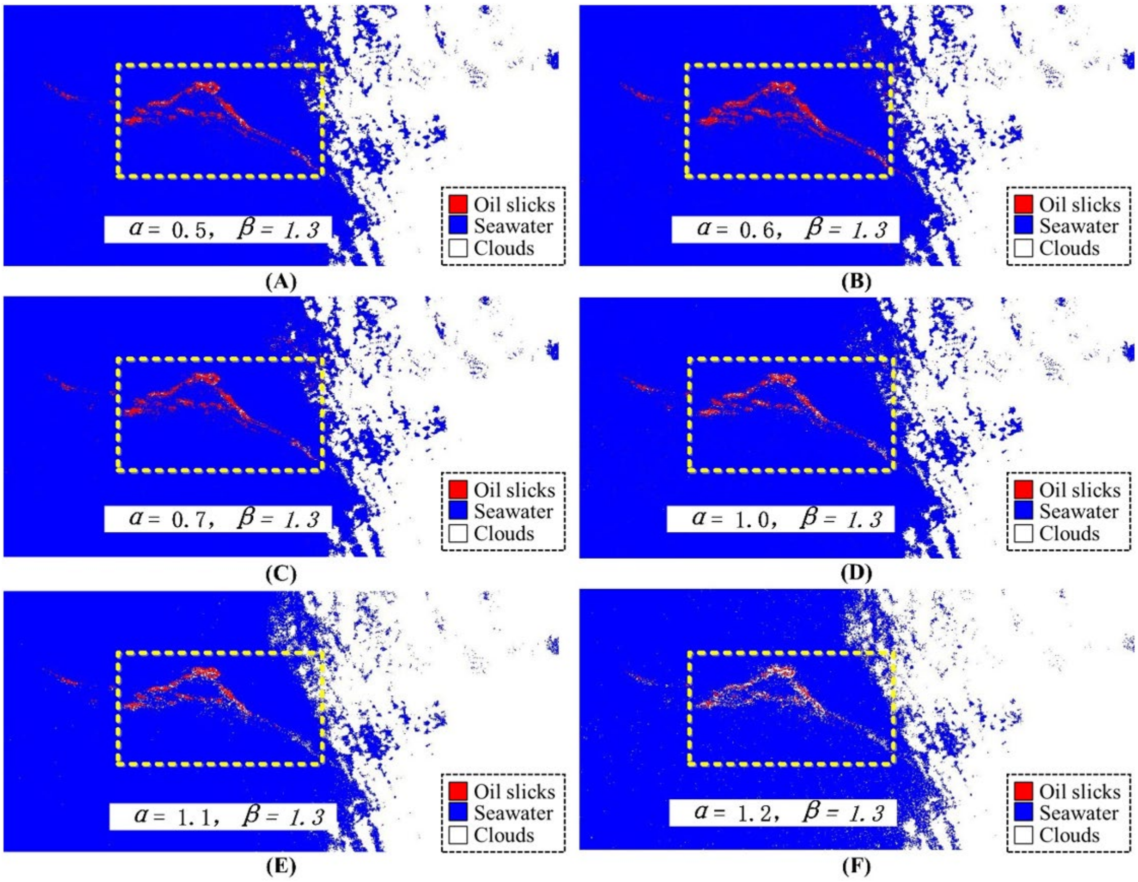

Figure 9. Oil spill detection results produced by different amplitude parameter.

In the contrast experiments, the spectral amplitude parameter was from 0.5 to 1.5 with the step length of 0.1. Figure 9 showed the most representative results. It could be found from the results that the performance of the ADSE method was satisfying when the spectral amplitude parameter was small (0.5~0.7). In these results (Figure 9.A-C), the identified seawater, oil slicks, and clouds were visually separable. When the spectral amplitude parameter became large (1.0~1.2), the encoding results of oil slicks and clouds were similar. As a result, oil slicks would be misidentified as clouds (Figure 9.D-F). Since floating oil slicks had many low spectral reflection signals in Zhuhai-1 hyperspectral images (Figure 10) and small spectral amplitude parameter contributed to describing the low spectral reflection signals, small spectral amplitude parameter could highlight the spectral differences of oil slicks, seawater and clouds. Thus, it was concluded that the ADSE method could produce excellent oil spill detection result with small spectral amplitude parameter.

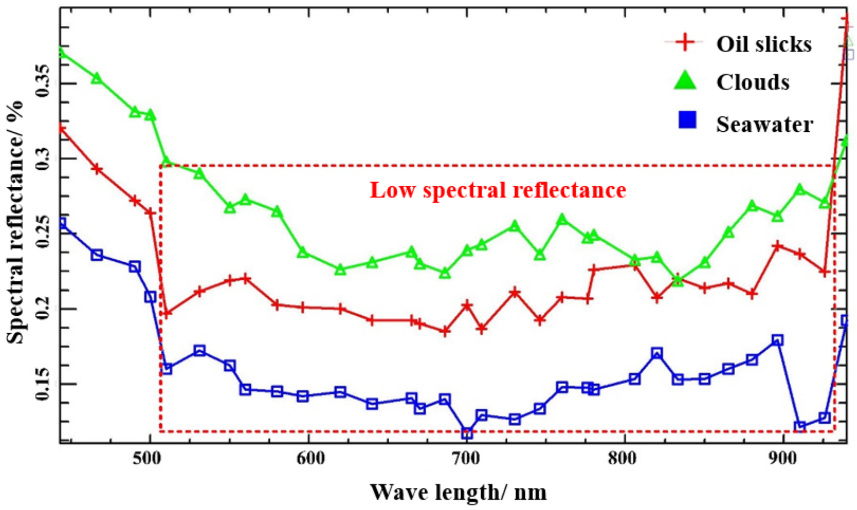

Figure 10. Spectral curves of the oil slicks, seawater, and clouds in experimental data 1.

In order to reveal the influence of spectral shape parameter on oil spill detection, experimental data 1 was used to conduct contrast experiments (LIS strategy, $\delta = 0.6$, $\alpha = 0.5$). Figure 11 showed the experimental results. In the contrast experiments, the spectral shape parameter was from 0.5 to 1.5 with the step length of 0.1. Figure 11 showed the most representative results. It was found from the results that the clouds could not be differentiated from the oil slicks when the spectral shape parameter was small (0.5~0.7). When the spectral shape parameter was large (1.0~1.2), ADSE method could distinguish oil slicks and clouds accurately. Since marine objects were influenced by seawater usually, their spectral signals appeared random noises, the oil slicks and clouds existed unstable spectral signals. Small spectral shape parameter would strengthen the interference to spectral signals. On the contrary, large spectral shape parameter could filter the instability to some extent. Thus, detecting oil spills in Zhuhai-1 satellite data by the ASDE method should use large spectral shape parameter.

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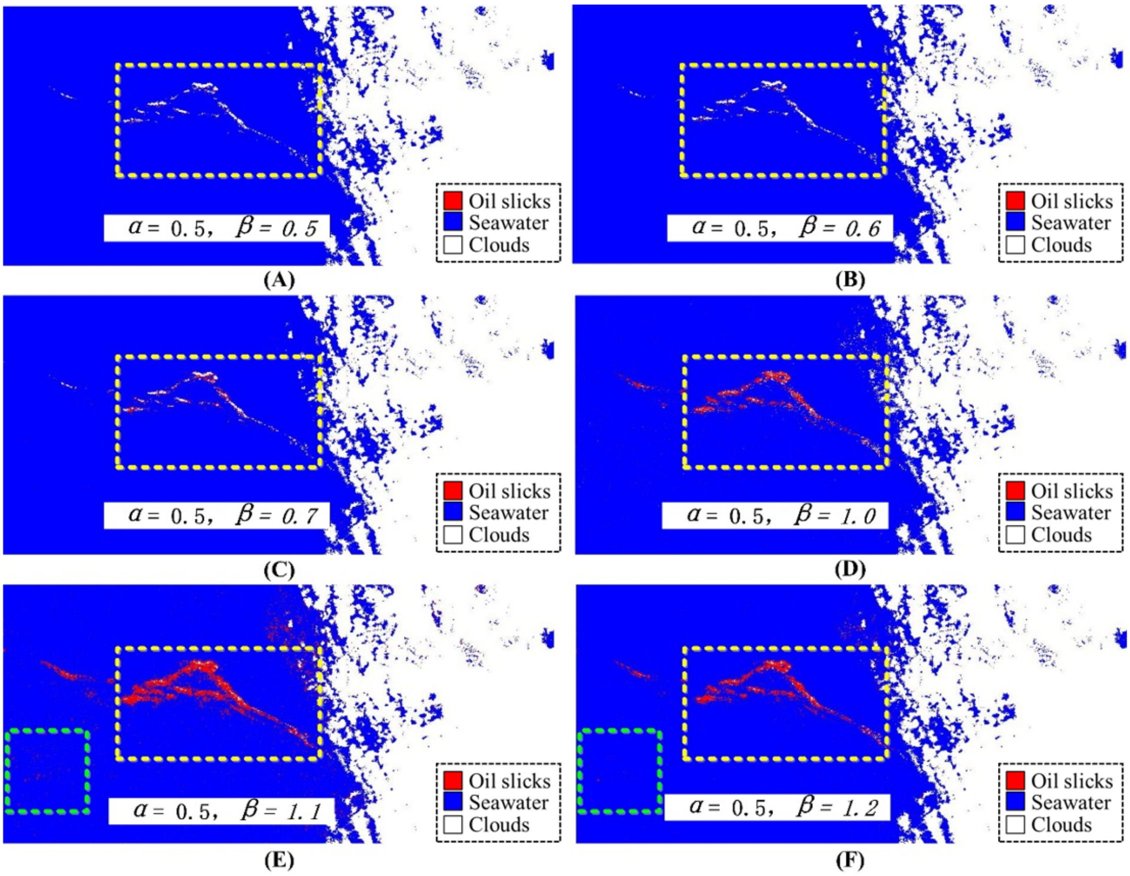

Figure 11. Oil spill detection results produced by different shape parameter.

5. Conclusions

Detecting oil spills is important for monitoring marine oil/gas resources and pollutions. In order to explore accurate methods for identifying marine oil slicks on hyperspectral satellite imagery, the ADSE method based on Zhuhai-1 satellite data was proposed in this research. The proposed method aimed at the fuzziness and ambiguity problems of traditional spectral DNA encoding method. It could describe the spectral details of floating oil slicks. In addition, two kinds of spectral gene extraction methods were used to extract the key spectral differential code words of oil slicks. The extracted spectral genes were used to detect oil slicks by pattern recognition. Experimental results indicated that the ADSE method could detect oil spills in Zhuhai-1 satellite imagery accurately. The ASDE method with LIS should use frequency parameter δ around 0.6 and ASDE method with LID should use frequency parameter δ around 0.2 could detect oil spills accurately. In addition, the spectral amplitude parameter should be small (around 0.5) and the spectral shape parameter should be large (bigger than 1.0) for Zhuhai-1 satellite data to detect marine oil spills.

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Data Availability Statement: The data that support the findings of this study are commercial. They are not open dataset. The data can be bought from Aero-Chips (www.myorbita.net).

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Conflicts of Interest: The authors declare that they have no conflict of interests in the work reported in this paper.

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