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Efficient sea–land segmentation using seeds learning and edge directed graph cut

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ABSTRACT

Separating sea surface and land areas in an optical remote sensing image is very challenging yet of great importance to the coastline extraction and subsequent inshore and offshore object detection. The state-of-the-art methods often fail when the land and sea areas share complex and similar intensity and texture distributions. In this paper, we propose a graph cut (GC) based supervised method to segment the sea and the land from natural-colored (red–green–blue, RGB) images. Firstly, an image is pre-segmented into superpixels and a graph model with the superpixels as its nodes is constructed. Then each superpixel node is encoded by a multi-feature descriptor, and a probabilistic support vector machine (SVM) is trained for automatic seed selection. These seeds will be used to build the prior model for GC. When modeling boundary term in GC, we incorporate edge information between neighboring superpixels to get finer results for some thin and elongated structures. Experiments on a set of natural-colored images from Google Earth demonstrate that our method outperforms the state-of-the-art methods in terms of quantitative and visual performances.

1. Introduction

For remote sensing images, sea–land segmentation is aimed to separate the sea from the land exactly. The segmentation results will provide helpful information for coastline extraction and ship detection.

As for ship detection [18,27], the boundary accuracy of the sea–land segmentation results can directly influence inshore ship detection. In addition, the segmentation errors in the land area will increase the complexity of the detection process for offshore ship detection. As for coastline extraction [6,15,4,5], the results of sea–land segmentation is of great significance to coastline navigation, resource management and protection.

There are three factors that make sea–land segmentation a challenging task. Firstly, the situations in the land area are diverse and complicated, which can be broadly divided into harbors and islands. The various distribution of intensity and texture on the land makes it difficult to get spatially consistent results. Secondly, compared with natural images, there exists a more complicated distribution of the border between sea and land in remote sensing images. The shadows near the borders often make the segmentation results break at the boundary. Finally, the disturbance of cloud, wave and shallow water further makes it challenging to obtain an accurate position of the coastline.

Most of the existing methods [3,26] for differentiating between sea and land regions are based on threshold selection and edge detection. In addition, methods vary in accordance with the differences of the processed remote sensing images.

For multispectral imagery, normalized difference water index (NDWI) is an important metric for sea–land segmentation and coastline extraction, which takes advantage of the fact that the reflectance of water areas is near to zero in near-infrared (NIR) band and high in green band. By calculating the NDWI map of the multispectral image, we can enhance the water areas while suppress the green land and soil areas.

Lots of efforts have been made on the sea–land segmentation and coastline extraction for multispectral images derived from different geographical positions and satellite sensors. Kuleli et al. [16] computed automatic threshold for the NDWI map based on Otsu [21] method to segment water and land, and detected shoreline changes on coastal Ramsar wetland of Turkey. Di et al. [13] merged pixels in the sea and the land by mean shift [11], and interactively refined the shoreline in a geographic information system (GIS) environment by manually picking the correct boundaries and replacing the corresponding part of the initial shoreline. Zhang et al. [26] identified the water body by evaluating the intensity of the NIR band, and refined the edge by merging small pre-segmented regions according to a proposed object merging index (OMI). The method was used for extracting

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shoreline of the aquaculture coast. Aktas et al. [3] presented a similar approach which used a different merging method integrating intensity differences and edge information. Aedla et al. [2] modified the histogram of the NIR image according to the mean plateau value to erase local maximum values. The automatic threshold was decided by calculating the mean and variance of the equalized histogram.

Compared with researches on multispectral images, there is limited literature on the methods of sea–land segmentation for panchromatic and natural-colored imagery. Most of them are based on the thresholding method, accompanied with morphological operations to eliminate errors in the results. Liu and JEZEK [19] proposed an approach to determine the thresholds for local regions by fitting a bimodal Gaussian curve. The method is suitable for images with coarse spatial resolution, while the convergence of the fitting process to a global optimum is not guaranteed. You and Li [25] computed the maximum area of the sea based on Otsu results and built a statistical model for the sea area to decide the segmentation threshold. Zhu et al. [27] enhanced the original image with Sobel operator and segmented the enhanced image by Otsu method. The final result was refined by level-set methods.

For panchromatic and natural-colored images, the traditional methods, which are based on threshold selection and edge detection, only employ the spectral information of individual pixel and ignore the local relationship of neighboring pixels. The results of them often contain misclassification, especially in the land area. With the improvement of the spatial resolution of satellite and aircraft sensors, more details of the intensity and texture are presented in remote sensing images, which makes the segmentation problem more challenging. For instance, the shadow and low reflectance regions in land areas may be classified as water, while waves and noises in water areas may be considered as land. In this case, how to effectively utilize the spatial and texture information is critical to the segmentation accuracy.

In this paper, we propose a supervised approach integrating multi-feature encoding and graph cut [24,17,7] to solve the sea–land segmentation problem for natural-colored images of high spatial resolution (5 m per pixel). The problem of user-specific strokes needed in GC is addressed by providing an automatic seed selection scheme based on the outputs of a trained classifier. The robustness of the proposed multi-feature descriptor enables us to select reliable and sufficient seeds for GC. Compared with traditional methods, the proposed approach employs the spectral–spatial information in three aspects. Firstly, the superpixel method groups neighboring homogeneous pixels together. Then the descriptor extracts texture and spatial features in multi-scales. Finally, the edge constraints in GC employ local relationship among neighboring superpixels to make the segmentation results spatially consistent. The flowchart of the methodology is illustrated in Fig. 1.

Our work is distinguished by the following three contributions:

- We pre-segment the image into superpixels to extract training samples and construct the graph model for GC, which will reduce information redundancy in the training process and utilize the local relationship in GC.
- A multi-feature descriptor that fuses spectral, texture and spatial information is proposed to characterize the sea and the land, and a two-class probabilistic SVM is trained based on feature vectors encoded by the descriptor.
- Reliable and sufficient seeds are selected automatically to build prior models for GC based on the probabilistic outputs of SVM. When modeling the boundary term in GC, we incorporate Canny edge detection results to reduce the cost of separating superpixels located at two sides of the edges into different parts, which can help to avoid the under-segmentation for some thin and elongated structures.

The remainder of this paper is outlined as follows: Section 2 gives a description of the data used in this paper. We introduce the superpixel method and multi-feature descriptor in Section 3. Seeds learning and GC segmentation are described in Section 4. Experimental results and comparisons with the state-of-the-art methods are reported in Section 5. Finally, conclusions are drawn in Section 6.

2. Data description

Google Earth (GE) is a freely available version of Earth Viewer 3D that enables personal computer users to visualize superimposed landscapes derived from satellite and aircraft imageries. Images derived from GE have been used in mapping water depth and land cover [10]. In this paper, we use images obtained from GE to evaluate the effectiveness of our proposed methods.

We adjust the eye altitude of GE to match the spatial resolution of around 5 m per pixel and employ GETScreen software to take screenshots. 58 large images of different geographical locations are obtained in this way. We randomly select 20 large images to provide training set. The rest are used for testing and validation. We further crop all the large images by hand and select 122 representative sea–land images with the size ranging from 300×300 to 1500×1500 approximately to form the data set. The cropped images include scenes of both harbors and islands and have a complicated distribution of intensity and texture. All the 122 images are divided into three parts: training set, validation set

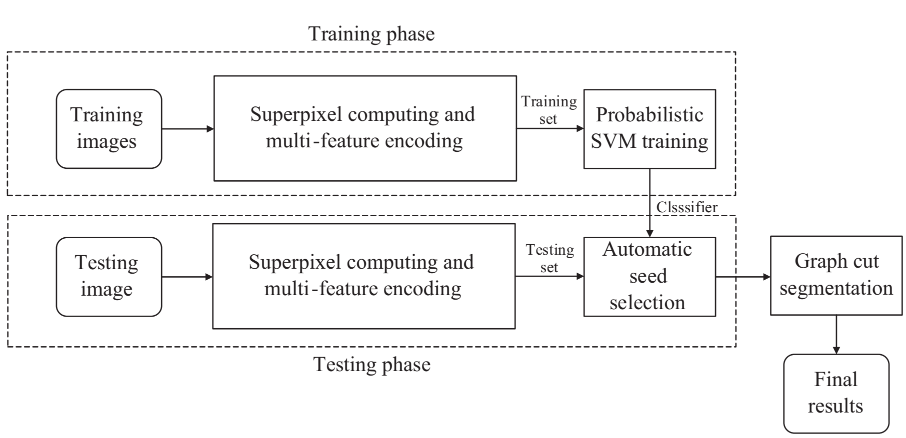

Fig. 1. Flow chart of the proposed segmentation algorithm.