ISPRS Journal of Photogrammetry and Remote Sensing 123 (2017) 104–113

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Raft cultivation area extraction from high resolution remote sensing imagery by fusing multi-scale region-line primitive association features

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ARTICLE INFO

Article history:
Received 16 July 2016
Received in revised form 4 October 2016
Accepted 28 October 2016
Available online 8 December 2016

Keywords:
Region-line primitive association framework
Raft cultivation
High resolution remote sensing
Information extraction
Multi-scale
Object-based image analysis

ABSTRACT

In this paper, we first propose several novel concepts for object-based image analysis, which include line-based shape regularity, line density, and scale-based best feature value (SBV), based on the region-line primitive association framework (RLPAF). We then propose a raft cultivation area (RCA) extraction method for high spatial resolution (HSR) remote sensing imagery based on multi-scale feature fusion and spatial rule induction. The proposed method includes the following steps: (1) Multi-scale region primitives (segments) are obtained by image segmentation method HBC-SEG, and line primitives (straight lines) are obtained by phase-based line detection method. (2) Association relationships between regions and lines are built based on RLPAF, and then multi-scale RLPAF features are extracted and SBVs are selected. (3) Several spatial rules are designed to extract RCAs within sea waters after land and water separation. Experiments show that the proposed method can successfully extract different-shaped RCAs from HR images with good performance.

1. Introduction

High spatial resolution (HSR) remote sensing (RS) images are commonly used in the current field of RS applications. The superiority of HSR images lies in the possibility of extracting fine earth surface details. However, widespread spectral diffusion and noise within these detailed spatial objects are commonly found in HSR images. These deficiencies challenge traditional pixel-based image analysis (PBIA) techniques, which offer very limited feature availability (basically pixel spectra). Unlike in PBIA, the minimum analyzing units in object-based image analysis (OBIA) are generally regions (or segments given that they are often obtained by image segmentation; in the following sections, we use these terms alternately according to the context) that are composed of mutually related pixels. Thus, OBIA can utilize more abundant features than PBIA, including region shapes and relationships. In addition, it facilitates the fusion of knowledge rules in image processing and analysis. Thus, OBIA may be a better choice than PBIA for extracting information from HSR images. As a result, it has become the paradigm techniques for HSR image analysis technique after decades of development (Benz et al., 2001, 2004; Blaschke, 2010; Blaschke et al., 2014).

Currently, representative business OBIA software systems include Trimble eCognition and the ENVI Feature Extraction Module. Hot OBIA topics include optimizations of image segmentation and feature selection (Anders et al., 2011; Drăguţ et al., 2010, 2014; Tong et al., 2012; Laliberte et al., 2012), new segmentation algorithms (Chen et al., 2012; Yu et al., 2012; Wang and Li, 2014; Wang et al., 2015; Wang et al., 2016), and applications on thematic information extraction, classification and change detection (Sebari and He, 2013; D'Oleire-Oltmanns et al., 2014; Rasi et al., 2013; Hebel et al., 2013; Qin et al., 2015; Du et al., 2015). More comments on OBIA methods and applications can be found in (Blaschke et al., 2014; Cheng and Han, 2016).

Despite implementation differences, mainstream OBIAs generally follow the technical route of "segment and then classify." The minimum analyzing units are determined once images are segmented. Feature extraction and classification are then based on regions. Thus, image segmentation is the most crucial step for OBIAs. Several OBIA studies have combined image segmentation and classification in flexible schemes, thereby weakening the role

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http://dx.doi.org/10.1016/j.isprsjprs.2016.10.008
0924-2716/

of initial segmentation. For example, in Tiede et al. (2010, 2011), segmentations were tailored at a later stage for specific classes or regions in the image when required in the classification process. Despite these improvements, however, the region-based analysis framework has been completely adopted in the aforementioned studies.

Although OBIA has shown strong capabilities in HSR image analysis, it still has limitations in a segmentation-driven, region-based technical framework. Typically, image edge lines, which are composed of a group of highly related pixels with strong semantic connotations, have not obtained primitive-level attention as regions in OBIA. In mainstream region-based OBIA systems such as eCognition, image edges function only as an auxiliary feature in image analyses. In fact, image edge lines, typically straight-edge lines, can be useful and deserve a primitive-level role in OBIA. Straight lines have distinctive features, such as length, direction, and density. After building the relationships between regions and lines, abundant new features can be derived, thereby enriching the OBIA feature set. In (Wang et al., 2015), a specific region-line relationship, known as IPSL-neighborhood, was used for image segmentation refinement. Furthermore, in (Wang and Wang, 2016), we proposed a novel OBIA technical model, namely, the region-line primitive association framework (RLPAF), based on region-line relationship modeling. In this framework, straight lines are called line primitives and are the basic analyzing unit for OBIA along with regions. A suite of RLPAF concepts were used successfully for impervious surface and road network extraction from HSR images (Wang and Wang, 2016).

This study applies RLPAF in raft cultivation area (RCA) extraction from HSR images. RCAs are generally composed of belts with rope-linked floats. The belts are fixed on the shallow seafloor with aquaculture hung below. Several raft belts are densely arranged into a portion of sea with waterways inside. An investigation on RCA distributions and quantities is necessary for aquaculture planning. However, RCAs are generally widely and sparsely distributed, thereby resulting in expensive, difficult, and imprecise field survey and measurement (Liu et al., 2013; Fan et al., 2015). By contrast, RCA extraction using HSR images has good efficiency and precision, and is the necessary choice for a large-scale survey of sea use.

Existing aquaculture water extraction techniques can be grouped into visual interpretation, texture analysis, and spectrum-dominated image analyses, among which spectrum-based classification methods are common (Fan et al., 2015; Lu et al., 2015). However, because of the complexity of the sea environment, RCAs may have spectral confusion with surrounding waters on HSR images. Furthermore, raft belts are sometimes arranged into different-shaped RCAs. These unfavorable factors challenge accurate RCA extraction from HSR images. To address this problem, we first construct several new RLPAF features, create a suite of RCA extraction rules, and then propose the RCA extraction algorithm. Unlike the previous studies (Wang et al., 2015, 2016; Wang and Wang, 2016), the contributions of this paper are as follows: (1) several new RLPAF features, (2) a concise scale selection scheme, and (3) an accurate RCA extraction algorithm.

The rest of this paper includes the following parts: Section 2 introduces the new RLPAF features and RCA extraction algorithm, Section 3 presents the experiments, and Section 4 concludes the paper and introduces future work.

2. Methods

2.1. RLPAF profile

RLPAF involves two kinds of primitives, namely, regions and lines. In addition to the region-based features in common OBIA, line-based features, including line direction, length, and density, are utilized in RLPAF. In addition, the direction and topology relationships between region and line primitives are built in RLPAF, which thereafter derives abundant region-line association relationships. In RLPAF, the direction relationships of a region to a line are classified as "above," "bilateral," and "below." These classifications indicate that the region is located above the line, on the two sides of the line, and below the line, respectively (for a vertical straight line, "below" denotes the left side of the line). The topology of a region to a line includes separation, intersection, tangent, and inclusion. The last is regarded as a special case of intersection. Numerous region-line association concepts are then established for regions along with their contacting or neighboring straight lines on the basis of the different combinations of the topology and direction relationships.

Several RLPAF features and operations were designed and utilized in our previous studies. These features include the IPSL-neighborhood, PLSL-neighborhood, PPSL-neighborhood, line-based length-to-width ratio, and operators on region-line mutual conversions (Wang et al., 2015, 2016; Wang and Wang, 2016). In this study, new RLPAF features are proposed to extract RCAs, which are a typical manmade object, from the sea background. Generally, manmade objects have regular shapes, e.g., with straight boundaries, unlike natural objects. Furthermore, straight lines in natural objects are often cluttered, whereas those within manmade objects are more regularly distributed. An image object is confidently assumed to be manmade if it contains straight lines with specific configurations typically in the parallel or perpendicular direction. On the basis of such observations, the following RLPAF features are designed for RCA extraction.

2.2. RLPAF features based on line statistics

Let regions Q be a subpixel set within image I. $Q = \{q_i = (x_i, y_i) | i \in [1, k], k = |Q|\}$ where x and y are the pixel coordinates, and $|\cdot|$ is the cardinality of a set. Let straight line segments L be a pixel set in I: $L = \{l_i = (x_i, y_i) | i \in [1, k], k = |L|\}$. Let B_Q be the boundary pixels of Q defined by four connected neighborhoods. In this case, L needs to contact region Q:

$$Q \cap L \neq \varnothing. \quad (1)$$

We define the topology operator set as follows:

$$Top(L, Q) = \{In(L, Q), Touch(L, Q), Out(L, Q), Proj(L, Q)\}. \quad (2)$$

The first three operators denote a subset extracted from L, which is contained by, touched by, or outside Q. For example, operator $Touch(L, Q)$ is defined as follows:

$$Touch(L, Q) = \{l_i | l_i \in B_Q, l_i \in L\}. \quad (3)$$

Operator $Proj(L, Q)$ denotes the straight line segment obtained by vertically projecting Q onto L, as shown in Fig. 1(a) and (b).

When the line and the region form a tangent relationship, the line should be long, and the projected length of the region should not considerably exceed those of the parts of the line that fall within and touch the region to extract the meaningful region and line relationship. That is,

$$|L| \geqslant T_a, \text{ and } \frac{|Proj(L, Q)|}{|In(L, Q)| + |Touch(L, Q)|} \leqslant T_b, \quad (4)$$

where T_a and T_b are two user-defined thresholds.

We let all the contacting lines of Q satisfying Eqs. (1) and (4) be $\{L\}$. In this case, the region-to-line conversion (Wang & Wang, 2016) is defined as extracting a parallel line subset $\{L^*\}$ from $\{L\}$ whose direction is the main direction plus the perpendicular direction to the main direction within $\{L\}$. To accomplish this