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RESEARCH ARTICLE

High spatial resolution remote sensing image segmentation using marker based watershed algorithm

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Abstract

We propose an edge embedded marker based watershed algorithm for high spatial resolution remote sensing image segmentation. Two improvement techniques are proposed for the two key steps of maker extraction and pixel labeling, to make it more effective and efficient for high spatial resolution image segmentation. Moreover, the edge information, detected by the edge detector embedded with confidence, is used to direct the two key steps for detecting objects with weak boundary and improving the positional accuracy of the objects boundary. It performs well in retaining the weak boundary and reducing the undesired over-segmentation.

Keywords: High spatial resolution, image segmentation, marker based watershed, remote sensing.

Introduction

In recent years, more and more high spatial resolution remote sensing images are available for earth observation. However, how to mine information from high resolution remote sensing images efficiently has always been one of the key issues for its application, in which image segmentation is a fundamental work (Pal and Pal, 1993; Ma and Manjunath, 2000; Freixenet *et al.,* 2002; Juan *et al.,* 2006; Chen and Chen, 2009). The initial region of the segmentation is the expression of the shapes of the image objects; therefore, segmentation quality has a direct influence on the following-up image analysis and understanding. Because of the complexity of remote sensing image and the uncertainty of the image segmentation of its own, getting high accuracy in remote sensing image segmentation is difficult and very important as well.

Marker-based watershed algorithm is an improvement to the traditional watershed algorithm (Sun, 2008). It firstly extracts the regional minima locations which are relevant to the objects from the morphological gradient image and makes them constitute a binary marker image; then using minima imposition to extract the partial minima of the original gradient image as the marker, reducing the segmentation areas produced by all the original partial minima in the gradient image; Finally the watershed algorithm divides the modified gradient image. This method produces good results and efficient satellite images. We apply this method to segment Quick bird image, which is a kind of high-resolution remote sensing image (Trias-Sanz *et al.,* 2008). The quality of the extracted object boundaries plays a key role for the overall efficiency of the feature extraction or classification.

It is needed to develop effective and efficient image segmentation approach to extract accurate object boundaries from High Spatial Resolution Remote Sensing Image (HSRI). This correspondence follows the edge integration strategy and proposes an Edge Embedded Marker-based Watershed Algorithm (EEMW) for high spatial resolution remote sensing image segmentation. Edges detected by the edge detector embedded with confidence are integrated into the two steps of marker-based watershed segmentation, namely the extraction of markers and the labeling of pixels. Moreover, an adaptive maker extraction method is proposed and implemented. This method takes into account the complexity of grey level distribution of different objects on HSRI. The extracted makers are more coincide with the inner regions of ground objects. To meet the application requirement of efficient large HSRI processing, the scheme of labeling pixels in literature is implemented. It was developed based upon the pixel labeling scheme of Meyer's algorithm. Instead of using the hierarchical circular queues, a data structure with one queue and one stack is used in the pixel labeling process. Therefore, it can largely save memory cost and be applied to large size images.

A. Edge detection with embedded confidence

The edge information is detected by the confidence embedded edge detection method (Canny, 1986). In the method, (Karantzalos and Argialas, 2006) an independent measure of confidence is estimated in the presence of the employed edge model. The widely used three-step edge detection procedure: gradient estimation, non-maxima suppression, hysteresis thresholding is generalized to include the information provided by the confidence measure.

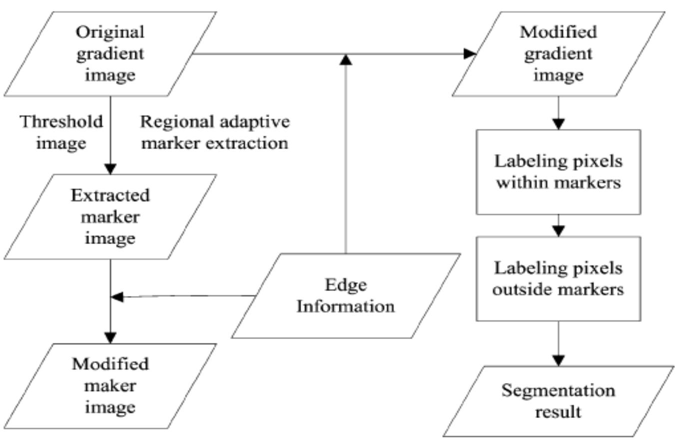
B. Marker based watershed segmentation

Watershed algorithm is usually applied to the gradient image (Vincent and Soille, 1991). Imagine the gradient image is a topographic surface, a hole is drilled in each minimum of the surface, and water is flooded into different catchment basins from the holes. As a result, the water starts filling all catchment basins, which have minima under the water level. If two catchment basins would merge as a result of further immersion, a dam is built all the way to the highest surface altitude and the dam represents the watershed lines. This flooding process will eventually reach a stage when only the top of the dam is visible above the water line. The result is a tessellation of the input image into its different catchment basins; each one characterized by a unique label. The method is a two-stage process, including the extraction of marker image and the labeling of pixels (flooding). Markers are a set of components marking flat regions of an image, i.e., each marker indicates the presence of an object. If the object interiors (markers) are set to 1, and the uncertainty areas are set to 0, we get a binary marker image. It contains a set of components (markers) marking the core regions and a large number of pixels may remain unassigned. The next step is then to label the unassigned pixels by the extended watershed algorithm dealing with markers to get the final partition. It has the advantage that segmented results can have coherent regions, link edges, no gaps due to missing edge pixels. However, applying this method to HSRI segmentation, the noises or textures on the image are usually labeled as the pseudo-local minimum regions and result in over-segmentation. To reduce over-segmentation, we make some improvements to the marked-based watershed segmentation algorithm.

C. Scheme of integrating edge information

The edge information should be tracked before using them to guide the segmentation. It is time-consuming and efficiency. With consideration that object edges cannot pass through the markers, the marker image is rectified according to the edge information to get the final marker image.

Fig. 1. Framework of EEMW segmentation.



In labeling pixels, pixels are more possible to become the pixels on watershed line if they are lastly labeled. Therefore, we assign pixels on the edges the lowest priorities and processed lastly. Since the processing priority of pixel is defined as the reciprocal of its gradient magnitude, the gradient image is rectified according to edge information in advance. In the process, the pixels within markers are labeled by the region growing method first and then the other pixels outside the markers are labeled according to the rule that two pixels must not be labeled with same region ID if their common neighboring pixels are all the edge pixels. The overall framework is shown in Fig. 1.

Materials and methods

The proposed method

A. Marker extraction

The GM of pixels within the homogenous object is commonly lower than that of the boundary pixels. This makes it possible to set a threshold to binarize the gradient image to get makers. However, the GM of pixels in the object with complex texture may be comparable or ever higher than that of the boundary pixels. It will fail to extract correct marker image with a single threshold in binarization. We propose a regional adaptive marker extraction method, instead of using a single threshold, a threshold image (TI) is estimated. Let GI represent the gradient image, then the marker image is defined as a binary image (BW) that is the result of the logical operation. The estimation of TI is the key for extracting good markers. Finally, the pixels of markers should be within the objects, the edge pixels should not be within markers. Under the direction of edge information, we assign value 0 to each edge pixel on BW. The updated BW is taken as the final marker image.

B. Labeling pixels

The labeling of pixels is the process of assigning each pixel a unique identity (ID). There are two often-used pixel labeling methods. 1) The first method uses the individual markers as the local minima in the gradient image. It filters out the undesired minima of the gradient image, and applies the traditional watershed segmentation on the revised gradient image. 2) The second method suppresses unwanted minima during labeling process. The hierarchical circular queues are a set of queues with different priorities; each queue is a first-in first-out data structure. The priority of each pixel in the gradient image is defined as the reciprocal of its gradient value. This implies that a high (low) priority is assigned to a pixel with low (high) grey-level value. To save memory cost for large image segmentation, we proposed to use a data structure of only one queue and one stack to store the temporary data in image labeling. It can largely reduce the memory cost. The pixels are first sorted in descending order of priority. Then the possible neighbor labeled pixel of each unlabeled pixel is searched by seed tracing to identify the label ID for the current processing pixel.

C. Labeling pixels within markers

The labeling of pixels is the process of assigning each pixel a unique identity (ID). There are two often-used pixel labeling methods. The first method uses the individual markers as the local minima in the gradient image. The second method suppresses unwanted minima during labeling process. This step is realized by seed tracing in the eight compass directions. Each connected region on the marker image is labeled with a unique ID with the following rules.

i. Pixels in the same region are labeled with the same unique ID.
ii. Different regions are labeled with different ID.

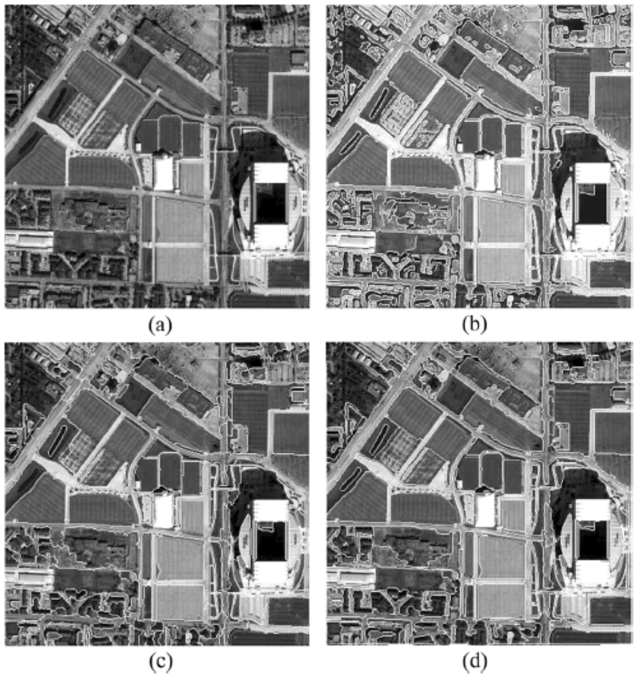
D. Labeling pixels outside markers

During labeling, the pixels outside the markers and the pixels labeled lastly are more possible to be on the watershed line. To make sure that the edges are labeled as the object boundaries, the gradient image is rectified by assigning the largest gradient magnitude value to the edge pixels first. For each priority level, there are two steps. In the first step, only pixels with priority higher than the current processing priority are processed. These pixels can be divided into two groups. The first group includes pixels with higher priority but not labeled in the previous labeling process, and they are stored in Queue (QU). The second includes all the unlabeled pixels with priority. The first groups of pixels are processed in advance to the second one. After the first step, if the pixel cannot be labeled, it is stored in Stack (ST) and processed in reverse order in the second step. If after the second step, the pixel still cannot be labeled, it will be stored in QU and processed together with the pixels.

Results and discussion

In this experiment, two Quick Bird images are used to demonstrate the added value of integrating edge information. In Fig. 2(a), there are seven main landmarks: road, green belt, play ground, farm, bush, lake and house roof. Fig. 2(a) Original image (b) Edge map detected by the confidence embedded method (c) Segmentation result by the improved marker based watershed algorithm (d) Segmentation result by the improved algorithm integrating the edge information. Fig. 2(b), show the edge map detected by the confidence embedded method. Fig. 2(c) show the segmentation without the edge information integrated. Fig. 2(d) and show the results integrating the edge information. In Fig. 2(c), road and the green belts nearby it are segmented into one region. In the play ground, we only get a whole region which includes running track and stadium turf. To conclude, there is under segmentation in Fig. 2(c) and the objects with weak boundaries cannot be extracted correctly. Meanwhile, Fig. 2(d) show better segmentation results than those in Fig. 2(c) In Fig. 2(d), the road is segmented out from its neighbor objects and there is a clear boundary between them. The play ground is partitioned into two parts: running track and stadium turf. The small objects, such as single tree, can be extracted correctly. The forest is segmented into a region. With assumption that the edge detection embedded with confidence can get accurate edges. We can compute the number of boundary pixels that have the same location as the detected edge pixels and estimate the geometric accuracy of boundary pixels.

Fig. 2(a) Original image; (b) Edge map detected by the confidence embedded method; (c) Segmentation result by the improved marker based watershed algorithm; (d) Segmentation result by the improved algorithm integrating the edge information.



Conclusion

An edge embedded marker-watershed image segmentation method is developed for segmenting images with precise objects boundaries and without spurious boundaries. With the edge information detected by the confidence embedded method, the proposed method can be divided into two stages. In the first stage, we extract marker image by binarization. To get good marker image, the threshold of each pixel is defined according to the histogram statistical estimation instead of a single fixed threshold for the whole image. In addition, the edge information is integrated into the extraction of markers with the rule that edges cannot cut through a marker. In the second stage, we improve the Meyer's method to label the pixels with only one queue and one stack data structure. The edge information is integrated into the labeling process with the edge pixels assigned the lowest priority and lastly labeled. It can be concluded that the method has good generality for integrating edge information into segmentation, and can get good result for images with diverse objects distribution and structure characteristics.

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