WATERSHED-BASED RIVER REGION DETECTION IN LOW CONTRAST IMAGE

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ABSTRAC : In this paper, a novel river region detection method based on watershed for low contrast image is introduced. The watershed transformation is a popular image segmentation algorithm for grey-scale image, which finds "catchment basins" and "watershed ridge lines" by treating the image as a surface where light pixels are high and dark pixels are low. The original image is firstly preprocessed by finding its Local Binary Patterns (LBP) map and calculating a Euclidean Distance (ED) map for binary result of the LBP map. Then Watershed segmentation algorithm is exploited. Finally, a region merging is been applied and we get the river region. We have compared our method with the existing threshold-based algorithms. Experimental results with images from Google Earth demonstrate that the metric proposed in this paper can always achieve a better performance.

Keywords: River detection, watershed, low contrast image, region merging.

I. INTRODUCTION

The river region detection in low contrast image has important applications in many fields, since after segmenting the river region, we can easily do a series of detecting or tracking objects such as bridges over water [1], boats above river [2] and so on.

Traditional methods usually segment river using single or multi-threshold segmentation, this may works in some images with sample background like the situation in [3], and land regions are brighter than water region, so when the original image is segmented with an Ostu threshold, river region can be achieved easily.

However, optical images usually have a variety of scenes, in which rivers are not always darker or brighter than background, which means, it's not always effective to extract water region by using gray-level feature, especially for images whose contrast is low, since low contrast makes it more difficult to find a suitable threshold.

So in this paper, we use the texture feature rather than gray-level feature to detect river regions in low contrast image, since we know river usually has a uniform gray value, in other words, which has no apparent texture, so we can exploit this feature to achieve the river regions. An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image [4]. According to the low contrast, which means objects in the image do not have apparent boundaries, so watershed segmentation algorithm is applied because of its great performance in separate objects from each other which are almost connected together.

The method proposed is divided into three steps, which can be seen clearly in Fig.1. The paper is organized as follows. In section 2, we describe the way to segment the optical images with the improved watershed algorithm, and experiments and results are illustrated in Section 3. Finally, Section 4 gives conclusion.

Binarization image is obtained through a low threshold segmentation T_{LBP} when considering the river regions' texture value is low, statictics show that T_{LBP} ranging from 1 to 5 always have a satisfactory binarization result.

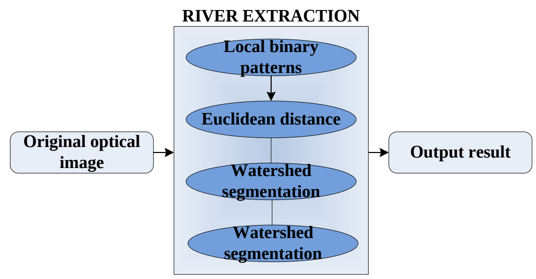


Figure 1. Diagram of the proposed method.

II. RIVER EXTRACTION

2.1. Local Binary Patterns

River is not always in a low gradation, but usually has a uniform gray value, in other words, which has no apparent texture, and we know that the local binary patterns (LBP) operator reflects this characteristics well [5], so local binary patterns with 8-neighbourhood is firstly used to transfer the original image to another gray image, LBP operator is implemented as Fig.2, and we just represent texture value instead of the center gray value:

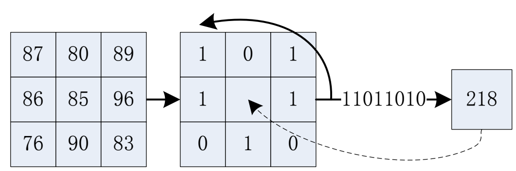


Figure 2. the LBP operator

2.2. Euclidean Distance Transform

Assuming that points which are far more away from flat regions are sharper, just like waterside hills, they should be merged together. So a distance transform (DT) is calculated to convert a digital binary image that consists of object (foreground) and non-object (background) pixels into another image in which each object pixel has a value corresponding to the minimum distance from the background by a distance function. Three distance functions are often used in digital image processing, they are: City-block distance, Chessboard distance, Euclidean distance [6].

Considering the complicated surroundings in optical images, Euclidean distance transform (EDT) was adopted in this paper. If there exist two points p=(x,y) and q=(u,v) in a digital image, the distance function is defined as

$$d_e(p,q)=\sqrt{(x-u)^2+(y-v)^2}$$

The result of Euclidean distance transform is to get a map which labels every pixel of the image with the distance to the nearest obstacle pixel, here we put pixels with 0 value as obstacles pixels. So the new value of point P=(u,v) can be represented as

$$f(u,v)=\min(\sqrt{(x-u)^2+(y-v)^2}),\forall f(x,y)=0$$

The result is implemented as Fig.3.

Figure 3. Diagram of Euclidean Distance Transform

2.3. Watershed segmentation algorithm

Objects like wetland and river in the optical images usually connected together, which makes it difficult to separate from each other. So watershed transform is then used to segment the Euclidean distance map.

The watershed transform finds "catchment basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low, classical watershed method of calculation is made by L.Vincent [7], in this algorithm, there are two steps, sorting and submerged.

Firstly, sort gray levels of each pixel from low to high to get the local minima, we call catchment basin CB(mi) of a regional minimum mi the set of points x∈supp(f) which are closer to mi than to any other regional minimum for the topographical distance, just similar with Euclidean distance:

$$\forall j\in I,\ j\neq i\Rightarrow TD(x,m_i)<TD(x,m_j)$$

Then label and judge each pixel from low to high using FIFO structure just like drowning process, producing many boundaries called watershed ridge lines, this step involves morphology operations, detailed solution process was given by Gonzalez and Woods [8].

Pixels in watershed ridge lines are grouped and small areas are merged to segment image well with the result above.

Taking into account the results of the watershed area are closed, we can easily calculate the area of each closed region, and label them with different value. Assume the regions which are connected with the pixel P to be grouped as R_i with the area S_i and labeled with L_i, while i represents the i-th area, then mark P with the label which has the greatest area S, indicating as follow.

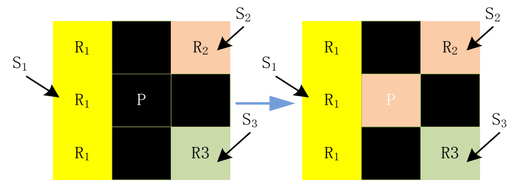


Figure 4. Schematic of grouping pixels (different colors means areas are marked with different value)

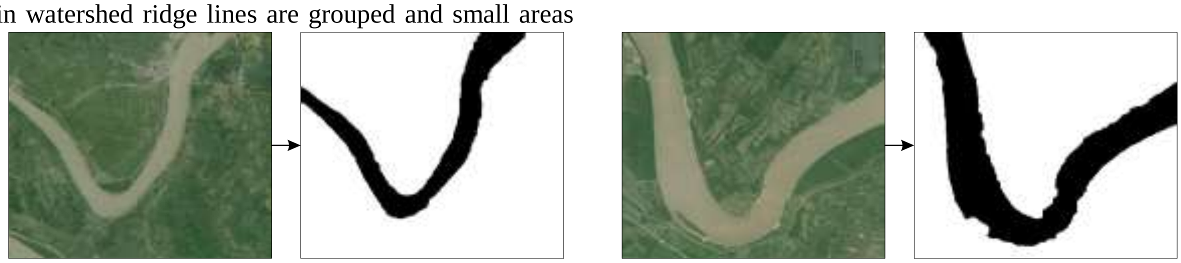
The center pixel P which is to be grouped has three adjacent areas R_1, R_2, R_3 with the area S_1, S_2, S_3 (i.e. $S_2 > S_1 > S_3$) respectively, then P will be marked with the same value as the region R_2.

If pixel P is located in the edge or a corner of the image, it will not have so many adjacent pixels, but this condition does not affect the research of adjacent regions according to the principle show above.

After grouping pixels in watershed ridge lines, small regions will be merged to complete the image segmentation. We make use of the area constraint to finish this process with the principle 'Retained large, combined small'.

The first phrase is to say regions meeting the condition $S_i>T_S$ are not subjected to any treatment, they are taken as the candidate river areas and treated as boundaries of subsequent processing; the latter two words meaning that small areas should be merged together to form a larger area. Considering that the river is always a large connected area, and it passes through the image, so the area of river sections can be estimate roughly, here we set the threshold value for one twentieth of the product of the width and height.

Small cavities may exist in the regions which have been retained, so a supplement step will be applied to this status, access every small cavity whose area is less than T_C, similar to the reason mentioned in the beginning of this section, find the area adjacent pixels maximum points and assign the cavity with its label.



(a) (b) (c) (d)

Figure 5. Result of the proposed approach. (a) Original image, (b) the result of image (a), (c) another image, (d) the detection result of image (c)

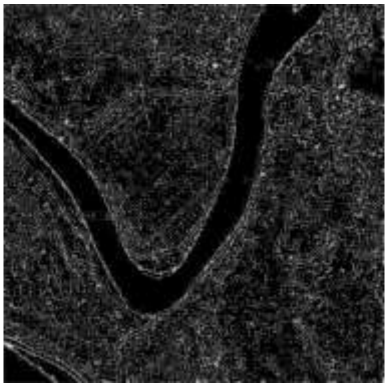


Fig.6 (a)

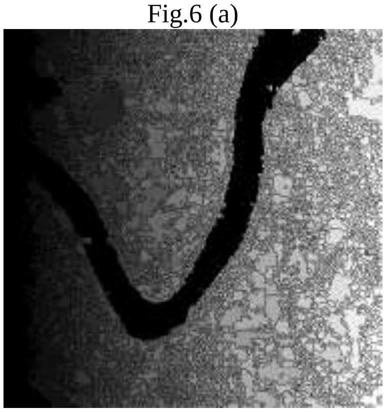


Fig.6 (b)

We have applied the method proposed by Gilvear [9] for the scene shown in Fig.5 (a), his approach can give the same result, but cannot detect the river in Fig.5 (c), while our method extracted all the whole river region in these complex background images.

VI. CONCLUSION

We have presented an approach for detecting river regions for low contrast images. The main contributions in the proposed method are an improved watershed segmentation algorithm combined with graph theory and a novel merger strategy. We don't use the sample threshold information, the experimental result we have obtained are very encouraging to show the effective of our proposed method.

V. REFERENCES

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