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REMOTE SENSING IMAGE SEGMENTATION BASED ON AN IMPROVED 2-D GRADIENT HISTOGRAM AND MMAD MODEL

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ABSTRACT

A novel remote sensing image segmentation algorithm based on an improved 2-D gradient histogram and minimum mean absolute deviation (MMAD) model is proposed in this letter. We extract the global features as a 1-D histogram from an improved 2-D gradient histogram by diagonal projection and subsequently use the MMAD model on the 1-D histogram to implement the optimal threshold. Experiments on remote sensing images indicate that the new algorithm provides accurate segmentation results, particularly for images characterized by Laplace distribution histograms. Furthermore, the new algorithm has low time consumption.

***Keywords:* Gradient histogram, image segmentation, minimum class mean absolute deviation, remote sensing.**

I. INTRODUCTION

The problem of recovering patterns and structures in images from corrupted observations is encouraged in many engineering and science applications, ranging from computer vision, consumer electronics to medical imaging. In many practical image processing problems, observed images often contain noise that should be removed beforehand for improving the visual pleasure and the reliability of subsequent image analysis tasks. Images may be contaminated by various types of noise. Among them, the impulse noise is one of the most frequently happened noises, which may be introduced into images during acquisition and transmission. For example, it may be caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware or transmission in a noisy channel.

Automatic extraction of information from remote sensing images has been a notably active topic of research in recent years. One important approach to perform feature extraction is image segmentation, which divides the image into distinct and self-similar pixel groups [3], [4]. Due to the large quantity of texture information in remote sensing images, it is difficult and time-consuming to segment objects from the backgrounds in remote sensing images.

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For segmentation of remote sensing images, many algorithms have been proposed. Thresholding based on a histogram is the most simple and effective one among them [5]. Otsu applied the maximum between-class variance criteria into a gray scale histogram [6]. By using the relative distance and average distance, Hou *et al.* proposed minimum class variance thresholding (MCVT) [9]. In addition, a median minimum error thresholding (MMET) was proposed by Xue and Titterington [7] along with the expanding maximum log-likelihood estimation. All algorithms are based on a 1-D grayscale histogram. To take advantage of spatial information, many researchers construct 2-D histograms for threshold selection. However, 2-D algorithms lead to the exponential increase of computation time. To address this computational burden, by using an iterative process, Chen *et al.* [10] derived an improved 2-D Otsu fast algorithm. In addition, a fast algorithm that uses MCVT into a 2-D grayscale histogram was presented by Nie *et al.* [11]. Nie *et al.* also proposed a 2-D thresholding algorithm based on variance analysis of a grayscale histogram to improve the performance.

II. EXPERIMENTS USING MMAD MODEL

The MMAD model can obtain an accurate optimal threshold based on the global features. Experimental results indicate that this algorithm performs well for remote sensing images, not only for those characterized by Gaussian distribution histograms but also for those characterized by Laplace distribution histograms. In addition, the time consumption of our algorithm is acceptable.

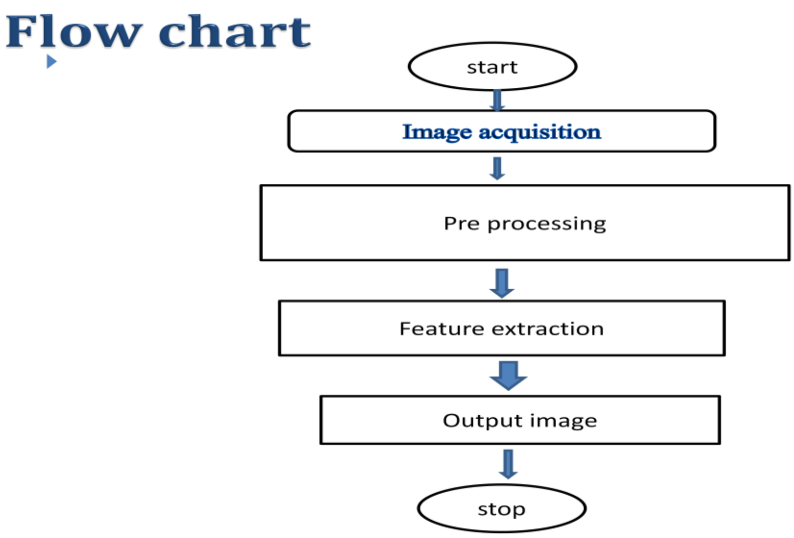

Fig 1: Flow chart for MMAD model

III. RESULTS AND DISCUSSION

A. Improved 2-D Gradient Histogram

Without losing generality, let I denote a grayscale image with L gray levels of size $M \times N$. The 2-D histogram is composed of two parameters of the image: one is the grayscale image, which is denoted by $f(x, y)$, and the other is the gradient image. For the given function $f(x, y)$, the gradient of f at the location (x, y) is defined as the 2-D column vector.

B. Transformation from the 2-D Histogram to the 1-D Histogram

The GF pairs of remote sensing images are mainly concentrated on the diagonal of 2-D histograms. Therefore, we project GF pairs in the 2-D histogram on the diagonal to construct a 1-D histogram. From Fig. 2(b), passing through point (i, j) in the 2-D histogram, line AB is defined to be the line perpendicular to the principal diagonal in the 2-D histogram. The geometric equation of AB is $h(i, j) = i + j$, where $0 \le h(i, j) \le 2(L - 1)$.If we regard the principal diagonal OC of the 2-D histogram as a projection axis and the function $h(i, j)$ as a new variable r,a 1-D histogram of r is constructed. Each bin r in this histogram contains a contribution only from a unique line in the 2-Dhistogram matrix.

C. MMAD Model

In the 1-D histogram, let k be an assumed threshold for binary segmentation. For binary segmentation, pixels in the images are divided into two classes: one class of pixels corresponding to bins $r \in \{0, 1, 2 . . . k\}$. in the 1-D histogram and the other class corresponding to bins $r \in \{k + 1, k + 2, . . . , 2(L - 1)\}$ in the 1-D histogram.

A: Input image

B: Output image

THEORETICAL INTERPRETATION

Our algorithm performs well for remote sensing images, and it is more suitable when the histograms correspond to the Laplace distribution. We provide the theoretical interpretation to this phenomenon. For roads and residential areas and for vegetation areas, the gradients and grayscales are similar within one type of scene and different between them. Thus, in the 1-D histogram, two scenes each can appear as a bell-shaped mode, and the threshold can be selected as the valley between modes.

IV. CONCLUSION

In this letter, we have proposed and validated a novel algorithm to segment the roads and residential areas from vegetation areas in remote sensing images. The features of the input image are extracted from an improved 2-D gradient histogram as a1-D histogram. Next, the MMAD model is used on the 1-D histogram to obtain the optimal threshold. Generally speaking, the segmentation results of our algorithm are visually and statistically satisfactory. This algorithm not only expands thresholding segmentation into remote sensing images characterized by Laplace distribution histograms but also meets the time requirements.

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