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Zhao, Chunhui
Qi, Bin
Youn, Eunseog
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Use of neighborhood unhomogeneity to detect the edge of hyperspectral spatial stray light region

Chunhui Zhao^a, Bin Qi^{a,*}, Eunseog Youn^b, Guisheng Yin^c, Christian Nansen^d

^a College of Information and Communication Engineering, Harbin Engineering University, Harbin, Heilongjiang Province, 150001, China

^b Department of Computer Science, Texas Tech University, Lubbock 79409, USA

^c College of Computer Science and Technology, Harbin Engineering University, Harbin, Heilongjiang Province, 150001, China

^d The University of Western Australia, School of Animal Biology, The UWA Institute of Agriculture, Crawley, Perth 6009, Australia

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ABSTRACT

Since hyperspectral images contain fine spectral information of the target objects, there is continuous demand for the detailed analysis about such images. A somewhat neglected but critically important challenge regarding hyperspectral image is the presence of “spatial stray light” – a phenomenon caused by scattering of photons from target objects. In this study, neighborhood unhomogeneity method is used to detect the edge of spatial stray light region in hyperspectral images. Analyses were conducted on reflectance datasets of standard card, potato leaf, and corn kernels from three inbred lines. By using neighborhood unhomogeneity method, the edge of spatial stray light region could be detected obviously and experimental results show the effectiveness of the proposed method.

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1. Introduction

Hyperspectral remote sensors can provide fine spectral information by simultaneously capture hundreds of narrow and contiguous spectral bands from a wide range of electromagnetic spectrum [1–3]. Images acquired by these hyperspectral sensors provide greater details on the spectral variation of the targets than those acquired by conventional multispectral systems [4–6]. Despite these significant improvements broadened the potential of spectral-based applications, it still has challenges associated with this technology, including those associated with “spatial stray light”, which is also referred to as lens flare or veiling glare [7,8].

Spatial stray light is a phenomenon caused by scattering of photons from target objects, and is mainly generated among adjacent objects. The intensity and radiometric composition of spatial stray light depends on the light source properties and chemical and physical properties of the objects being imaged. For satellite based remote sensing, it has been estimated that, due to spatial stray light, less than half of the signal recorded by the Landsat’s multispectral scanner system originates from the imaged pixel itself, while the remainder of the reflectance signal is derived from surrounding pixels [9]. Du, et al. further reported that less than half of the total signal

from a point light source actually acquired from the central pixel; about 60% of the source is spread elsewhere and 3.7% difference can be generated between the radiance of two plaques of different size with the same illumination [10]. Consequently, a special kind of region exists in the hyperspectral images, referred to as spatial stray light region, which has two characteristics: (1) it can be regarded as a boundary between different objects; (2) the size of the region is not zero. In this study, neighborhood unhomogeneity method is used to detect the edge of this special region. Experiments are designed to validate the performance of the proposed algorithm. The remainder of this paper is organized as follows. In Section 2, we proposed neighborhood unhomogeneity for the edge detection of hyperspectral spatial stray light region. After a brief introduction of our hyperspectral imaging system and experimental data in Section 3, experiments are carried out to assess the performance of the proposed method, which are presented in Section 4. Finally, we end this paper with conclusions in Section 5.

2. Methods and concepts

Suppose that X is a hyperspectral dataset with n observations $x_k \in R^{M \times N}$, $k = 1, 2, \dots, n$. Each observation could be represented as a fuzzy matrix ϕ , such as

$$\phi_k = \begin{bmatrix} \mu_{11}(x_k(1, 1)) & \dots & \mu_{1N}(x_k(1, N)) \\ \dots & \dots & \dots \\ \mu_{M1}(x_k(M, 1)) & \dots & \mu_{MN}(x_k(M, N)) \end{bmatrix}, \quad k = 1, 2, \dots, n \quad (1)$$

* Corresponding author at: Room 511, Building 21, Harbin Engineering University, Nangang District, Harbin, China. Tel.: +86 451 82519802x601; fax: +86 451 8256 9810.

E-mail address: zhaochunhui@hrbeu.edu.cn (B. Qi).

$\mu_{ij}(\mathbf{x}_k(i, j))$ is the membership of $\mathbf{x}_k(i, j)$, which is defined as

$$\mu_{ij}(\mathbf{x}_k(i, j)) = \frac{1}{1 + |\mathbf{x}_k(i, j) - m_k|}, \quad i = 1, 2, \dots, M, j = 1, 2, \dots, N \quad (2)$$

For each observation $\mathbf{x}_k$, a centroid m_k is identified, which is the mean value of the reflectance of each band. Subsequently, higher membership is assigned to the pixels near the centroid and lower membership is assigned to the pixels away from the centroid. Since fuzzy entropy could represent the uncertainty of the target information, it is used to detect the variance of the reflectance value, which is given as follows

$$\text{Fuzzy entropy}(\mathbf{x}_k(i, j)) = -u_{ij}(\mathbf{x}_k(i, j))\log_2 u_{ij}(\mathbf{x}_k(i, j)) - [1 - u_{ij}(\mathbf{x}_k(i, j))]\log_2 [1 - u_{ij}(\mathbf{x}_k(i, j))] \quad (3)$$

In hyperspectral images, overall fuzzy entropy could reflect the variance of the reflectance value. However, the spatial distribution information of the pixels is not considered in it that the variance of local region could not be measured. So overall fuzzy entropy is extended to regional fuzzy entropy that the fuzzy entropy of a small rectangle area $\Omega_{p,k}(i, j)$ with the size of $M_p \times N_p$ is calculated, which is given as follows

Regional fuzzy entropy ($\Omega_{p,k}(i, j)$)

$$\begin{aligned} &= \frac{1}{M_p N_p} \sum_{m = -\text{fix}(M_p/2)}^{\text{fix}(M_p/2)} \sum_{n = -\text{fix}(N_p/2)}^{\text{fix}(N_p/2)} \text{fuzzy entropy}(\mathbf{x}_k(i + m, j + n)) \\ &= \frac{1}{M_p N_p} \sum_{m = -\text{fix}(M_p/2)}^{\text{fix}(M_p/2)} \sum_{n = -\text{fix}(N_p/2)}^{\text{fix}(N_p/2)} \{-u_{ij}(\mathbf{x}_k(i + m, j + n))\log_2 u_{ij}(\mathbf{x}_k(i + m, j + n)) \\ &\quad - [1 - u_{ij}(\mathbf{x}_k(i + m, j + n))]\log_2 [1 - u_{ij}(\mathbf{x}_k(i + m, j + n))]\} \end{aligned} \quad (4)$$

where $\text{fix}(\cdot)$ is integral function and it produces the integral part of the quotient (e.g. $\text{fix}(13/5) = 2$). And $\Omega_{p,k}(i, j)$ is defined as

$$\Omega_{p,k}(i, j) = \left\{ \mathbf{x}_k(m, n) \mid i - \text{fix}\left(\frac{M_p}{2}\right) \leq m \leq i + \text{fix}\left(\frac{M_p}{2}\right), j - \text{fix}\left(\frac{N_p}{2}\right) \leq n \leq j + \text{fix}\left(\frac{N_p}{2}\right) \right\} \quad (5)$$

Neighborhood unhomogeneity is used to describe the variance of the regional fuzzy entropy, which is given as follows

$$\text{Neighborhood unhomogeneity}(\Omega_{p,k}(i, j)) = \max_{\theta_t} |R_{t1}(\Omega_{p,k}(i, j)) - R_{t2}(\Omega_{p,k}(i, j))| \quad (6)$$

where θ_t is the angle of the separating line that divides $\Omega_{p,k}(i, j)$ into two parts S_{t1} and S_{t2} . R_{t1} and R_{t2} are the regional fuzzy entropy of S_{t1} and S_{t2} respectively, which are given by

$$R_{t1}(\Omega_{p,k}(i, j)) = \sum_{(m, n) \in S_{t1}} \text{fuzzy entropy}(\Omega_{p,k}(i, j)) \quad (7)$$

$$R_{t2}(\Omega_{p,k}(i, j)) = \sum_{(m, n) \in S_{t2}} \text{fuzzy entropy}(\Omega_{p,k}(i, j)) \quad (8)$$

From the above equations, it could see that neighborhood unhomogeneity is generally small within the interior of the objects or the spatial stray light region and changes to be big near the boundary of adjacent objects. Consequently, the edge of spatial stray light region could be detected by the neighborhood unhomogeneity of regional fuzzy entropy. Another challenge associated with the detection of this edge is the determination of the size of $\Omega_{p,k}(i, j)$. Through vast amount of experiments, 5×5 was selected as the suitable size

of window. The angles ($\theta_1, \theta_2, \dots, \theta_8$) of the separating line that divides $\Omega_{p,k}(i, j)$ into two parts are shown in Fig. 1

From the above analysis, the edge detection of spatial stray light region can be put forward as the following steps:

- 1) Suppose X is a hyperspectral dataset with n observations $\mathbf{x}_k \in R^{M \times N}$, $k = 1, 2, \dots, n$. Set the size of selected window Ω_p and the angles of the separating line θ_t .
- 2) Apply principal component analysis (PCA) to hyperspectral dataset X to produce the maximum component $\mathbf{X}_m$.
- 3) Calculate fuzzy matrix ϕ of $\mathbf{X}_m$ according to Eq. (1).
- 4) Apply Eq. (4) to ϕ to produce regional fuzzy entropy ($\Omega_p(i, j)$).
- 5) Calculate neighborhood unhomogeneity ($\Omega_p(i, j)$) with Eq. (6) and give the final edge detection result.

3. Experimental data and hyperspectral imaging system

To testify the validation of the proposed method, experiments with three different actual hyperspectral images were conducted. The hyperspectral image data used in this study were obtained from Texas Agrilife Research (Texas A&M University). Hyperspectral images were acquired with a line-scanning hyperspectral camera (PIKA II, www.resonon.com), which has 640 sensors

producing hyperspectral images with 160 wavelength channels within the wavelength range from 405 to 907 nm (wavelength resolution of 3.1 nm). The objective lens has 35 mm focal length optimized for the visible and near-infrared (NIR) spectra and the angular field of view is 7° [11]. Hyperspectral image acquisition was conducted inside a darkroom with four halogen lamps (<http://www.resonon.com/scanning-systems-and-accessories.html>) as only light source in order to keep unwanted light from contaminating the signal. To ensure consistent acquisition conditions, the hyperspectral camera and lighting system were turned on at least 30 min prior to image acquisition. Dark calibration was conducted at the beginning of the data acquisition (covering the lens of the camera with its cap), and white Teflon was used for

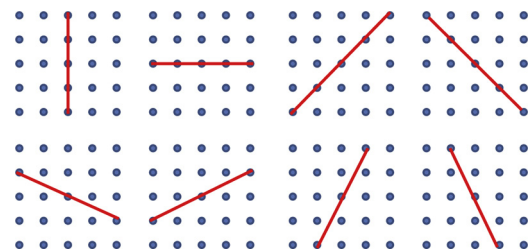


Fig. 1. The angle of the separating line.

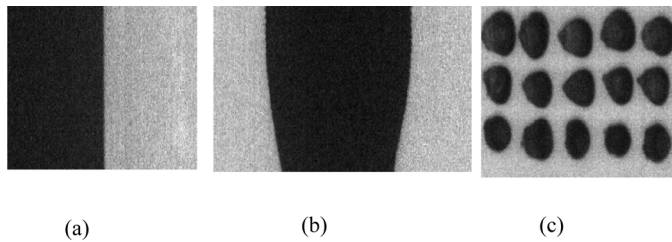


Fig. 2. Experimental dataset, (a) card dataset, (b) leaf dataset, (c) corn kernel dataset: wild type (top line), mutant 1 (center line), and mutant 2 (bottom line).

white calibration immediately before image acquisition. Based on dark and white calibration, reflectance values from hyperspectral image cubes were converted into proportions (denoted relative reflectance) ranging from 0 to 1. A software program automatically operates the camera and records the raw data into the hard drive.

Experimental analysis was organized with three hyperspectral datasets: card dataset, leaf dataset, and corn kernel dataset. A series of experiments were conducted to examine how reflectance data from either white Teflon or from objects were influenced by one another. In the first experiment, reflectance information of card dataset was collected from 8.5 cm × 5.5 cm plastic card (card code: 4288, www.boltaron.com). The control background was a 30 cm × 30 cm piece of white Teflon (Fig. 2(a)). In leaf dataset, the target object was a piece of potato leaf, which was placed on the white Teflon mentioned above (Fig. 2(b)). The corn kernel samples used in the third dataset were provided by Dr. Kolomiets at Texas A&M University. In brief, they represent three proprietary inbred lines: a wild type without genetic modification, and two mutants with suppression of one of two genes in the lipoxygenase pathway. Genetically, the homozygous corn mutants are near-isogenic to the recurrent wild type parent and share about 97.5% of the parent genome with one mutant (mutant 1) showing negligible visual/phenotypic difference from the wild type, and the other mutant (mutant 2) being slightly darker in color than the wild type (Fig. 2(c)).

4. Experimental results and analysis

Fig. 3 shows the variance of regional fuzzy entropy ($R_{t1}(\Omega_{p,k}(i, j)) - R_{t2}(\Omega_{p,k}(i, j))$, $t = 1, 2, \dots, 8$), obtained from card dataset with different separating line angles. With little difference could be observed from different sub-figures, Fig. 3(2) has a big difference with others. The difference in assignments of the variance of regional fuzzy entropy by θ_2 and other angles is attributed to the direction of θ_2 . Since θ_2 is perpendicular to the boundary, the corresponding R_{t1} and R_{t2} are nearly the same that the spatial stray light region might be hidden with this angle. However, with other angles, variance of regional fuzzy entropy could highlight the region of spatial stray light clearly.

For comparison, Figs. 4 and 5 show the variance of regional fuzzy entropy obtained from leaf dataset and corn kernel dataset respectively. In Fig. 4, careful evaluation reveals that part of the variance

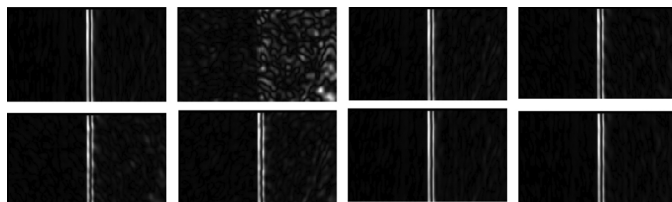


Fig. 3. Variance of regional fuzzy entropy with card dataset in different angle of the separating line.

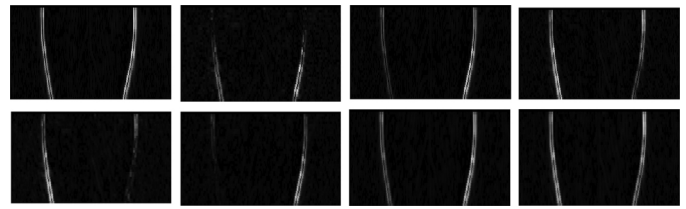


Fig. 4. Variance of regional fuzzy entropy with leaf dataset in different angle of the separating line.



Fig. 5. Variance of regional fuzzy entropy with corn kernel dataset in different angle of the separating line.

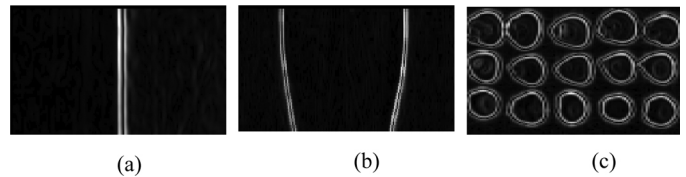


Fig. 6. Edge detection of spatial stray light region: (a) card dataset; (b) leaf dataset; (c) corn kernel dataset.

of regional fuzzy entropy could not show the region of spatial stray light in some angles. It is because the angles of the separating line in these parts are nearly perpendicular to the boundary of adjacent objects.

Fig. 6 shows the combined results from 8 different angles (Fig. 1) of the separating line. It can be seen that two edges are detected for each of the object clearly, which divides the images into three parts: (1) target objects region, (2) spatial stray light region, and (3) background region. The experimental results proved that fuzzy entropy neighborhood unhomogeneity method has powerful ability for hyperspectral images to detect the edge of spatial stray light region.

5. Conclusion

In conclusion, a simple, practical approach to detect the edge of spatial stray light region from spectrograph's measured reflectance signals is discussed based on the fuzzy entropy neighborhood unhomogeneity method. Examples for the edge detection of spatial stray light region from three actual hyperspectral images have been given to demonstrate the efficacy of this method.

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