SHADOW DETECTION AND COMPENSATION FOR COLOR AERIAL IMAGES

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ABSTRACT: This paper presents a property-based method defined on principal components for automatic shadow detection, called the PCA method. This method applies both RGB and HSI color models. In addition, some shadowed image patches still offer the brightness and color information for shadow compensation. This research compares the methods of histogram matching and local statistics method, and figures out the effectiveness of the two methods. Experimental results are evaluated in terms of subjective and objective evaluation figures. Test results demonstrate that the proposed PCA method with the input data of the four bands R, G, B, and NIR provides the best accuracy of shadow detection, e.g. with the overall accuracy of 93.7% and 92.2% in the test areas A and B, respectively.

1. INTRODUCTION

The illumination and ground reflection functions can be represented by means of the variable of the intensity value on each image pixel. The shadow is caused by light which casts through terrain raised objects such as buildings, towers, bridges, trees, or due to occlusion caused by clouds (Salvador, et al., 2004). On the one hand, shadow can illustrate additional geometric and semantic information, but it is more considered as nuisance in image interpretation (Polidorio, et al., 2003). On the other hand, image information in shadow areas is thus lost to some extent or totally. Shadowed images will cause some problems such as inaccurate image matching, misclassification of objects, wrong extractions of image features and false color tone. Also, they deteriorate the quality of image recognition and image classification. Thus the problems of shadow detection and shadow compensation must be solved somehow.

Methods for shadow detection and shadow compensation have been studied for many years, but it's still difficult to obtain a satisfied outcome. Approaches for shadow detection can be categorized as model-based and property-based method (Salvador, et al., 2001). A prior knowledge of the three dimensional geometry of scenes, objects, and the illumination is usually represented by using models (Thirion, 1992). The second approach takes advantages of attributes such as color, brightness, etc. to identify shadow. According to Dare (2005), thresholding, classification, region growing, and geometric modeling are four different techniques for extracting shadow pixels from images. Tsai (2006) used spectral ratioing to classify shadow images by hue and intensity which can increase the tone in shadow with low luminance.

Images for remote sensing applications would require images with optimum light conditions and minimize shadows. Histogram matching is to produce an image with a specified histogram, i.e. it brings the brightness of a given image to an assigned one. Histogram has become one of the classic approaches with better result on local rather than on global since the variation of radiometry of an image is quite considerable (Dare, 2005). Local statistics method assumes a linear relationship between radiance of shadow and non-shadow areas (Sarabandi, et al., 2004). It provides useful information even the signals in shadow areas are weak. This research compares the methods of histogram matching and local statistics and then figures out the effectiveness of the two methods.

2. METHOD

2.1 Principal Component (PC) Differential Method for Shadow Detection

Principal component analysis is a statistical data-analytic technique that linearly transforms a set of signals of possibly correlated variables into a smaller set of values of uncorrelated variables called principal components

(PCs). PC can describe a number of images that are registered spatially with different values on their corresponding image pixels. For an image with n bands, the vector will be n-dimensional and described as follows:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad (1)$$

The Hotelling transform can be expressed by (Hotelling, 1933):

$$y = A\,(X - m_X) \quad (2)$$

where m_X is the mean vector for a number of sample vectors X, C_X is the covariance matrix of X, and the row vectors of the matrix A are the eigenvectors matrix of C_X in the form of descending power of value,

In this research, R, G, B, and NIR channels are taken as input data. Four principal component images are computed by Eq. 2. Then, the differential images are obtained by subtracting first principal component image from each input band respectively.

$$Input\ band - First\ principal\ component\ image = differential\ image \quad (3)$$

Since differential processing improves the contrast between shadow and nonshadow areas, the Otsu's method is applied to the differential images over the histogram to determine the threshold for segmentation. Threshold is an issue of statistic problem in which the main goal is to minimize errors from assigning pixels to two or more classes. In 1979, Otsu introduced a nonparametric and unsupervised method for automatically selecting threshold value for image segmentation. It is quite simple, and needs only the gray level histogram. The Otsu's method can be briefly described as follows:

$$\sigma_B^2(k) = \frac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1 - P_1(k)]} \quad (4)$$

where

$$m_G = \sum_{i=0}^{L-1} ip_i\ ,\ P_1(k) = \sum_{i=0}^{k} p_i\ ,\ m(k) = \sum_{i=0}^{k} ip_i\ ,$$

and p_i is the probability of the i-th gray level in the image. For example, L=256 for a color image with 8-bit digital numbers per each channel.

Boolean operation is considered as a constraint condition for binary images which is calculated by the Otsu's method. In the research, it only retains pixels with value zero and the rest all set as nonshadow pixels. Morphological operation is then used to eliminate the holes in binary images. Dilation and erosion are two basic morphological operations. Opening and closing are formed by these two primary operations.

2.2 Shadow Compensation

Both histogram matching and local statistics methods are two approaches for shadow compensation. In this research, it only used RGB for shadow compensation, and NIR band is only applied in shadow detection. In order to compensate for image information in shadow areas, grey levels in nonshadow areas are served as reference data for each band respectively. The reference data is given by the largest nonshadow area in the image to obtain as more image information as possible.

2.2.1 Histogram Matching

Histogram matching, which is also named as histogram specification, is developed from histogram equalization algorithm (Gonzalez and Woods, 2008). It is desirable to convert a histogram of one image to match another image or a specified functional form. For image processing, histogram matching is used to match two brightness distributions as close as possible. We used it to recover the digital numbers in shadow areas by fixing the brightness in nonshadow area as a reference histogram and matching the histogram of shadow areas to the reference one.

2.2.2 Local Statistics Method

The local statistics method (Lee, 1980) utilizes the minimum square error criterion, and also refers as mean and variance transformation. Although the signals recorded in shadow area are weak, it assumes that the signals can still provide valuable image information for shadow compensation. The linear function can be defined as follows (Lee, 1980):

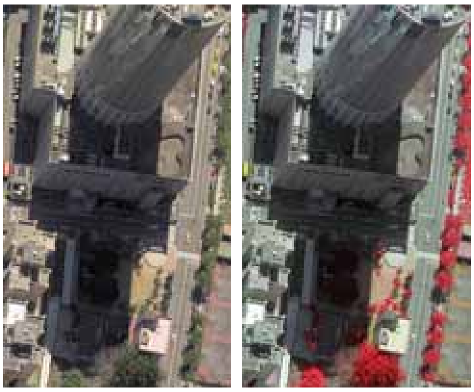
$$DN_{recovered} = \frac{\sigma_{nonshadow}}{\sigma_{shadow}}\left(DN_{shadow} - m_{shadow}\right) + m_{nonshadow} \qquad (5)$$

where m is the mean value, σ_{shadow} and $\sigma_{nonshadow}$ are the root mean square difference (RMSD) in the shadow and nonshadow areas, respectively.

3. EXPERIMENTAL RESULTS AND ANALYSIS

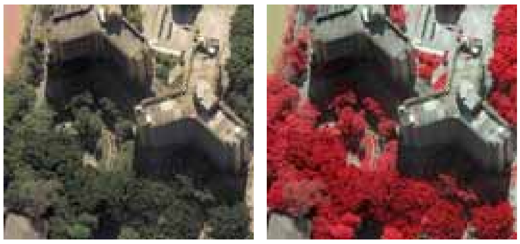
3.1 Study Areas

In the research, the test data are the color aerial images with four bands taken with the camera UltraCamD by GroForce Technologies Co., Ltd in 2005 in the area of the campus of National Cheng Kung University. Figure 1 and figure 2 illustrate both the RGB image and the NIR-R-G image in the test areas A and B, respectively. As shown in Figure 1, the texture in the shadow area is complex and includes the image information of buildings, trees, and high reflective mirrors. The most portion of the test image in the test area B is the texture of trees.



(a) RGB image (b) NIR-R-G image

Figure 1 Images of the test area A



(a) RGB image (b) NIR-R-G image

Figure 2 Images of the t**est** area B

3.2 The Result of Shadow Detection

Figure 3 and figure 4 illustrate the results of shadow detection in the test areas A and B, respectively. Figures 3(a) and 4(a) show the binary images of the so-called true shadow denoted by black pixels. The true shadow images are manually interpreted and are used to evaluate the quality of shadow detection results. Figures 3(b) and 4(b) are the results of shadow detection by means of the PCA method using the input data of R, G, B, and NIR bands. To contrast with the results from R, G, B, and NIR bands, figure 3(c) and 4(c) illustrate the results of shadow detection by means of the PCA method using the input data of H, S, and I bands.

Comparing to the reference images of true shadow, both figures 3 and 4 show apparently that the PCA method using the input data of R, G, B, and NIR bands detects the shadow areas with better accuracy than the PCA method using the input data of H, S, and I bands in both test areas A and B. The shadow detection by means of the PCA method with HSI data results in the outcome full of holes and fragments, namely incomplete shadow areas. Many shadow pixels are misclassified into nonshadow ones.

Table 1 and Table 2 show the statistic accuracy figures of shadow detection results in both test areas A and B, respectively. The proposed PCA method with the input data of R, G, B, and NIR bands has the overall accuracy of 93.7% and 92.2% in both test areas, respectively, and both results are better than the ones by means of the PCA method with the input data of H, S, and I bands which have the overall accuracy of 83.8% and 72.3% in the test areas A and B, respectively.

(a) (b) (c)

Figure 3 Results of shadow detection in the test area A: (a) True shadow. (b) Shadow from the input R, G, B, and NIR bands. (c) Shadow from the input H, S, and I bands

Table 1 Accuracy figures of shadow detection results shown in Figure 3

Accuracy / Method	Producer's accuracy		User's accuracy		Overall accuracy (%)
	Shadow (%)	Nonshadow (%)	Shadow (%)	Nonshadow (%)	
Proposed PCA (R, G, B, NIR)	93.4	94.1	95.2	92.0	93.7
Proposed PCA (H, S, I)	90.7	97.9	97.7	74.1	83.8

(a) (b) (c)

Figure 4 Results of shadow detection in the test area B: (a) True shadow. (b) Shadow from the input R, G, B, and NIR bands. (c) Shadow from the input H, S, and I bands.

Table 2 Accuracy figures of shadow detection results shown in Figure 4

Accuracy / Method	Producer's accuracy		User's accuracy		Overall accuracy (%)
	Shadow (%)	Nonshadow (%)	Shadow (%)	Nonshadow (%)	
Proposed PCA (R, G, B, NIR)	93.8	90.8	89.9	94.4	92.2
Proposed PCA (H, S, I)	40.7	99.9	99.8	65.9	72.3

3.3 Results of Shadow Compensation

Figure 5 and figure 6 illustrate the original image and the compensated images by means of the histogram matching technique and the local statistics method in the RGB color space, respectively. Both figures show that the shadow compensation results of the histogram matching technique are a little better than the ones of the local statistics method, because the overall brightness and contrast of the compensated images by the histogram matching technique is better visually.

(a) (b) (c)

Figure 5 Results of shadow compensation in the test area A: (a) Original image, (b) Compensated image by histogram matching in RGB, (c) Compensated image by local statistics method in RGB

(a) (b) (c)

Figure 6 Results of shadow compensation in the test area B: (a) Original image, (b) Compensated image by histogram matching in RGB, (c) Compensated image by local statistics method in RGB..

4. CONCLUSIONS ANS SUGGESTIONS

The shadow detection method proposed in this research is developed based on the theory of principal component analysis (PCA) with the input data of a single color aerial image. It is expected to find out a better efficient algorithm for shadow detection and shadow compensation for color aerial images with better accuracy. The test results are assessed by using the proposed PCA method with the input data of different number of image bands and different color models as well.

In general, the result of the proposed PCA method is affected by the input bands. The input data of the four bands R, G, B, and NIR provide the best accuracy of shadow detection, e.g. with the overall accuracy of 93.7% and 92.2% in the test areas A and B, respectively. The shadow detection by the PCA method with the input data of HSI bands results in shadow pieces with fragments and holes with incomplete boundary due to misclassified pixels in shadow areas.

Moreover, test results show that the histogram matching technique for shadow compensation has a better performance visually than the local statistics method, because the overall brightness and contrast of the compensated images by the histogram matching technique is better visually.

The image of water body is not included in our test data. The property of water areas and the related issues on water body detection and color compensation should be further studied in the future. Besides, the umbra, penumbra and antumbra are also another study issues when considering the boundary.

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