"PERFORMANCE ANALYSIS OF SINGLE IMAGE SHADOW DETECTION AND REMOVAL TECHNIQUE"

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Abstract
Shadows can either aid or confound scene interpretation, depending on whether we model the shadows or ignore them. In addition, shadows are also responsible to degrade the image quality. Therefore, shadow detection and removal is an important pre-processing step for computer vision and image enhancement. This thesis presents a chromaticity based method for detection and removal of shadows in aerial images. In our proposed method a modified hue over intensity ratio is taken as the base parameter for shadow detection. The proposed shadow removal is an intensity based approach which results a more clear and understandable aerial image. Our proposed framework consistently performed better than the state-of-the-art on all major shadow databases collected under a variety of conditions.

IndexTerms: Self-Shadow, Shadow Detection, Image Processing, Hue, Accuracy.

I. INTRODUCTION

The Shadows in images are typically affected by several phenomena in the scene, including physical phenomena such as lighting conditions, type and behaviour of shadowed surfaces, occluding objects; etc. Human vision system is very immune to shadows. We do not find any difficulty in recognizing, tracking objects even with shadows [1-3]. But in the case of computer vision, shadows create problems and reduce the reliability of the system. In addition, shadows are also responsible to degrade the image quality. Therefore, shadow removal is an important pre-processing step for computer vision and image enhancement algorithm.

High-resolution satellite images contain a huge amount of information. Shadows in such images generate real problems in classifying and extracting the required information. Although signals recorded in shadow area are weak, it is still possible to recover them. Significant work is already done in shadow detection direction but, classifying shadow pixels from vegetation pixels correctly is still an issue as dark vegetation areas are still misclassified as shadow in some cases. In this letter, a new image index is developed for shadow detection employing multiple bands. Shadow pixels are classified from the index histogram by an automatic threshold identification procedure [4].With the observation distance of the radar increasing, the multichannel high-resolution synthetic aperture radar system may suffer from the reduction of the target signal-to-noise ratio, which leads to degradation in the detection performance for ground moving target indication (GMTI). Fortunately, the shadow feature, apart from the amplitude and interferometric phase of a moving target, may be available to improve the performance for target detection. In this letter, according to the geometric relationships between the moving object and its shadow in position and size, a shadow-aided method for GMTI is proposed. In addition, an efficient shadow detection method based on multi feature fusion is discussed to improve the shadow detection performance. Finally, numerical simulation results show that the shadow-aided method has a better detection performance, compared with the traditional detection algorithms [5].

Fig.1. Image showing self-shadows and cast shadow

Tsai presented an efficient algorithm which uses the ratio value of the hue over the intensity to construct the ratio map for detecting shadows of color aerial images by using the global thresholding process. The input image can be first transformed into the *HSI*; hue, saturation, and value (*HSV*); luma, blue-difference chroma, and red-difference chroma (*Y CbCr*); hue, chroma, and value (*HCV*); or luminance, hue, and saturation (*YIQ*) colormodels. Under the transformed invariant color model, Tsai first

calculated the ratio of the hue over the intensity for each pixelto construct the ratio map, and then, a global threshold of the constructed ratio map is determined to identify shadows. Experimental results show that Tsai's algorithm has better shadow detection accuracy when compared to the previous works [6].
The rest of the paper is organised as follows. The second section contains the previous work. The third section contagions the proposed method. in the fourth section, the result analysis is performed. And the last section concludes the paper.

II.PREVIOUS WORK

Khan et al. [1], said that their framework automatically learns the most relevant features in a supervised manner using multiple convolutional deep neural networks (ConvNets). The features are learned at the super-pixel level and along the dominant boundaries in the image. The shadow detection framework is shown in fig. 2.

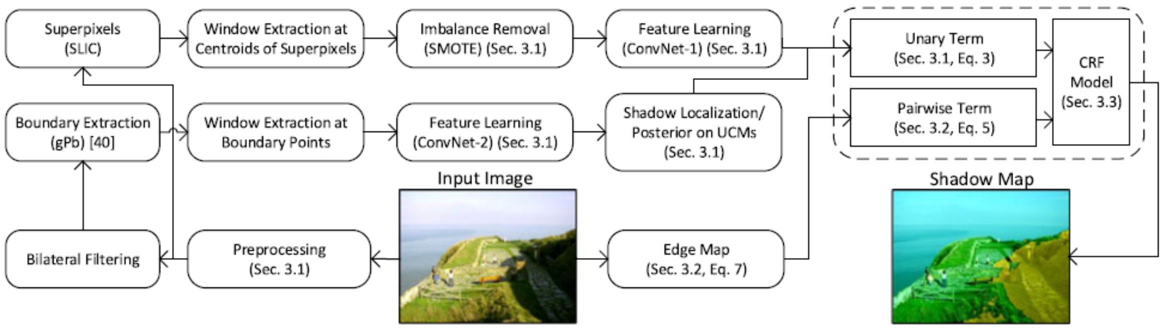

Fig. 2.Shadow detection framework of Khan's model [1]

The predicted posteriors based on the learned features are fed to a conditional random field model to generate smooth shadow masks. Using the detected shadow masks, we propose a Bayesian formulation to accurately extract shadow matte and subsequently remove shadows. The Bayesian formulation is based on a novel model which accurately models the shadow generation process in the umbra and penumbra regions. The model parameters are efficiently estimated using an iterative optimization procedure. The shadow removal framework is shown in fig. 3.

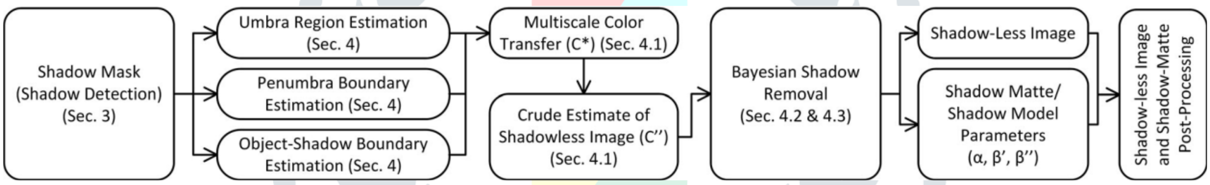

Fig. 3.Shadow removal framework of Khan's model [1]

Rough Estimation of Shadow-Less Image: The rough shadow-less image estimation process is based on the one adopted by the color transfer techniques in [7, 8]. As opposed to [7, 8] we perform a multilevel color transfer and our method does not require any user input. The color statistics of the shadowed as well as the non-shadowed regions are model using a Gaussian mixture model (GMM). For this purpose, a continuous probability distribution function is estimated from the histograms of both regions using the Expectation-Maximization (EM) algorithm. The EM algorithm is initialized using an unsupervised clustering algorithm (k-means in our implementation) and the EM iterations are carried out until convergence. We treat each of the R, G and B channels separately and fit mixture models to each of the respective histograms. It is considered that the estimated Gaussians, in the shadow and non-shadow regions, correspond to each other when arranged according to their means.

III. PROPOSED METHOD

The proposed method work on the color features of the shadow region in the image. The value of hue is high and the saturation value is low in the shadow region. The hue over saturation ratio provides the more clear characteristics for the shadow detection.
In this method, sometimes the non-shadow region is detected as shadow region. In order to overcome the above problem the modified ratio map is used to improve the shadow detection accuracy. Based on HSI color model, the intensity-equivalent Image I_e and the hue-equivalent ImageH_e used in the modified ratio map are calculated by

$$I_e = \frac{1}{3}R+\frac{1}{3}G+\frac{1}{3}B \qquad (1)$$

$$H_e= \left(\tan^{-1}\left(\frac{V_1}{V_2}\right)+\pi\right)\times\frac{255}{2\pi} \qquad (2)$$

Respectively, where V_1 and V_2 have been defined as

$$\begin{bmatrix} I \\ V_1 \\ V_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{-\sqrt{6}}{6} & \frac{\sqrt{6}}{6} & \frac{\sqrt{6}}{3} \\ \frac{1}{6} & \frac{-2}{\sqrt{6}} & 0 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (3)$$

The value of I_e and H_e are bounded in the range[0, 255]. The ratio value argument used in modified ratio map is given by

$$r(x,y) = \text{round}\left(\frac{H_e(x,y)}{I_e(x,y)+1}\right) \quad (4)$$

Where the term $I_e(x,y) + 1$ can avoid dividing by zero and value of r(x, y) can be bounded in the range [0, 255]. The modified ratio map R' is defined by

$$r'(x,y) = \text{round}\left(\frac{H_e(x,y)}{I_e(x,y)+0.1}\right) \quad (5)$$

The relation has the modified ratio in the above formula divides by$I_e(x,y) + 0.1$, to increase the ratio range for the shadow identification. It is then normalized to maintain the energy of the signal.

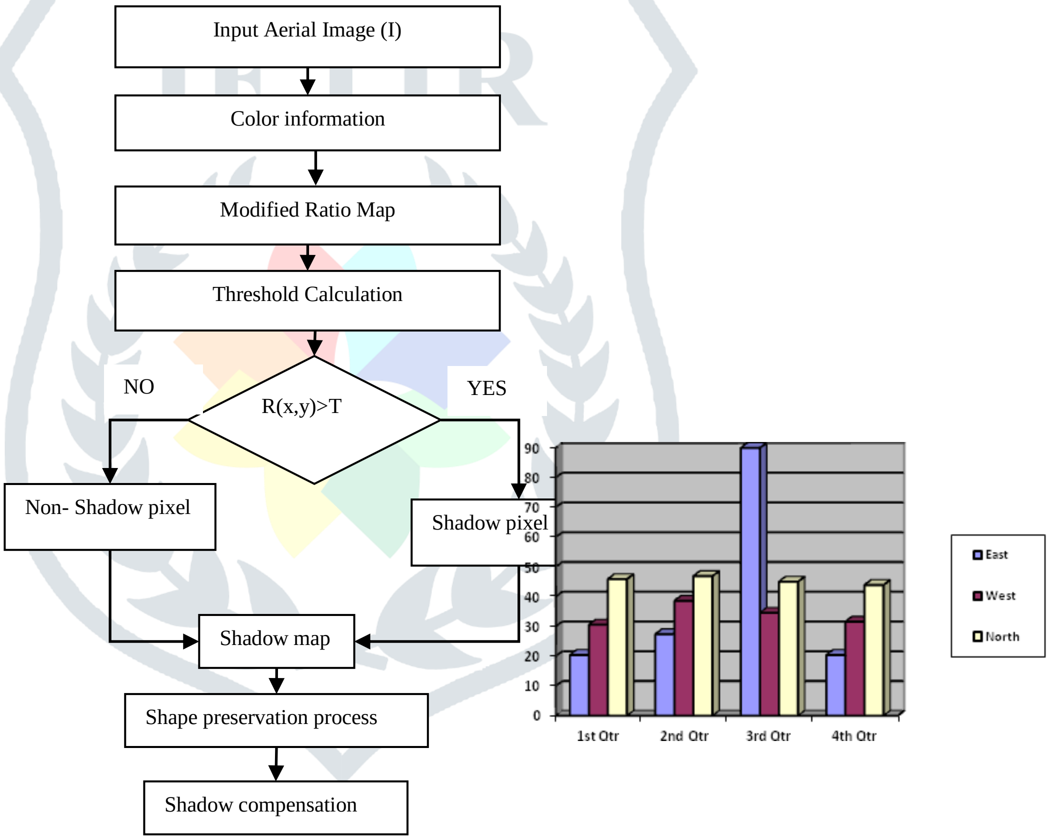

Fig.4 The flow chart of proposed algorithm

The flowchart of Tsai's algorithm is shown in Fig. 1. To detect shadows in the color aerial image, Tsai transforms the input *RGB* image *I* into an invariant color model, i.e., *HSI*, *HSV*, *HCV*, *YIQ*, or *Y CbCr* color models. For each pixel, the ratio of the hue over the intensity is used to determine whether the pixel is a shadow pixel or not. For easy exposition, the *HSI* color model is used as the representative. Note that, among these five invariant color models, Tsai's algorithm has the best shadow detection performance for the *HSI* model. Later, Kuo-Liang Chung,Yi-Ru Lin, and Yong-Huai Huang have developed a new thresholding scheme, which is based on successive thresholding scheme (STS) [9]. Flowchart of the STS-based algorithm is shown in fig.2.
STS-based algorithm is applied to detect shadows for color aerial images. Instead of using the ratio map obtained by Tsai's algorithm, they implemented the modified ratio map to distinguish the candidate shadow pixels from non-shadow pixels. From the modified ratio map, the global thresholding process is first performed to obtain the coarse-shadow map, which separates all the pixels of the input image into candidate shadow pixels and non-shadow pixels. Furthermore, the local thresholding process is applied to each candidate shadow region in the coarse-shadow map iteratively to distinguish true shadow pixels from candidate shadow pixels. Finally, the fine-shadow determination process is applied to determine whether each pixel in the remaining candidate shadows is a true shadow pixel or not.
The Color Aerial Image Detection requires the thresholding for image segmentation [10]. Under some testing images, experimental results show that, for the first three testing images, both Tsai's and STS-based algorithms have better detection performance than that of the algorithm of Huang *et al.*, and the shadow detection accuracy of STS-based algorithm is comparable

to Tsai's algorithm.[6] For the other testing images, which contain some low brightness objects, STS-based algorithm has better shadow detection accuracy when compared with the previous two shadow detection algorithms proposed by Huang *et al.* and Tsai.

IV RESULT ANALYSIS

The evaluation matrices used inTsai's model is adopted to evaluate the accuracy of the concerned shadow detection algorithms. Based on the concept of the error matrices [11, 12] and terminologies defined in [13, 14] three types of accuracy, namely the producers accuracy, the users accuracy and the overall accuracy, are used in objective evaluation. The three types of accuracy are described as follows. The first type of accuracy is the producers accuracy, which contain two parameters P_S and P_N and they are defined by Producer's accuracy:

$$P_S = \frac{TP}{TP+FN}$$

$$P_N = \frac{TN}{FP+TN}$$

where true positive (TP) denotes the number of true shadow pixels which are identified correctly; false negative (FN) denotes the number of true shadow pixels which are identified as non-shadow pixels; false positive (FP) denotes the number of non-shadow pixels which are identified as true shadow pixels; and true negative (TN) is the number of non-shadow pixels which are identified correctly. The parameter $P_S(P_N)$ denotes the ratio of the number of correctly detected true shadow (non-shadow) pixels over that of total true shadow (non-shadow) pixels. The second type accuracy is the user's accuracy in terms of and which are defined as User's accuracy:

$$A_S = \frac{TP}{TP+FP}$$

$$A_N = \frac{TN}{TN+FN}$$

The parameter A_S (A_N) denotes the ratio of the number of correctly detected true shadow (non-shadow) pixels over that of the total detected true shadow (non-shadow) pixels and thus the user's accuracy can be used to measure the precision of the shadow detection algorithm. Combining the accuracies of user and the producer, the third type of accuracy τ defined as follows can be used to evaluate the correctness percentage [15] of the algorithm:

$$\text{Overall accuracy } \tau = \frac{TP+TN}{TP+TN+FP+FN}$$

Where $TP + TN$ denotes the number of correctly detected true shadow and non-shadow pixels; $TP + TN + FP + FN$ is equal to the number of total pixels in the image.

TABLE I Shadow Detection Accuracy for Image of Highway

Method	Producer's accuracy		User's accuracy		Overall Accuracy
	P_S (%)	P_N (%)	A_S (%)	A_N (%)	τ(%)
Proposed	94.61	97.84	81.79	96.59	89.19
Khan's method [1]	37.73	82.97	30.50	91.17	60.84
Kuo-Liang Chung [23]	37.73	82.79	40.59	94.32	67.46

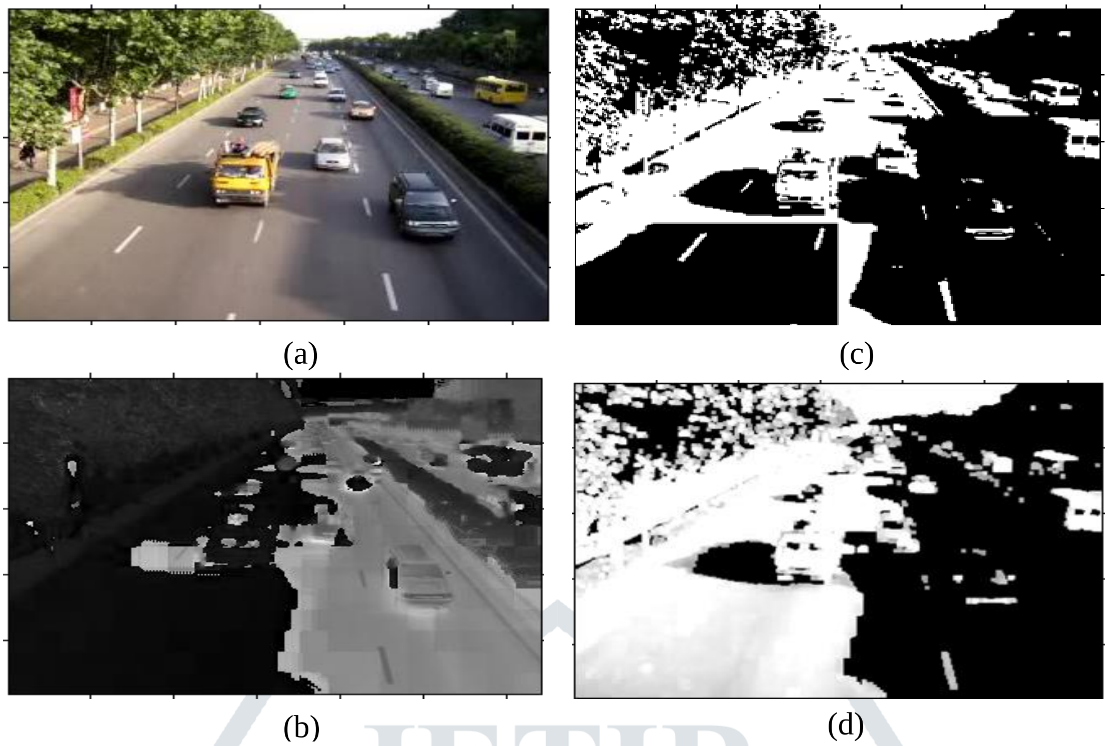

Fig. 5 (a) Original Image of Highway, (b) Shadow Detected Image of Khan's Model [1], (c) Shadow Detected Image using Chung [23] Method and (d) Shadow Detected Image Using Our Modified Ratio of Hue over Intensity.

V. CONCLUSION

In this paper, we present a novel scheme for effective shadows detection using both colour features. Since in any shadow removal algorithm, misclassification errors often occur, resulting in distorted object shapes. We presented a modified color ratio based shadow detection and removal approach to learn the most relevant features for the detection of shadows from a single image. We demonstrated that our framework performs the best on a number of databases regardless of the shape of objects casting shadows, the environment and the type of scene. We also proposed a shadow removal framework which extracts the shadow matte along with the recovered image. The proposed framework has a number of applications including image editing and enhancement tasks. The proposed method gives better performance as compared to the existing methods.

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