Shadow Detection and Removal Techniques in Aerial Images

Komal Prasad Kanojia, Bharti Chourasia

***Abstract*: One of the complicated tasks is to detect & remove Shadow from single images of aerial images. Significant research is being carried out on various techniques of shadow detection. Over past decades, many shadow identification & removal approaches have been applied. Shadows are optical effects that arise when a region in the scene occurs when the primary light. Shadows are all over around us, so there is no confusion by their appearance. In this paper we provide an overview of the different methods used in the aerial images to identify & eliminate shadows & also provide their comparative study.**

***Keywords:* Shadow detection; Shadow removal; Aerial images;.**

I. INTRODUCTION

There has been vast growth from the last decade or more, in analyzing high resolution imagery as various applications due to the availability of high spatial satellites for earth reflection & rapid development of air platforms such as airships or unmanned air vehicles. The surface features of urban areas are quite complex, with a large array of artifacts & vegetation, like high buildings, bridges & woodlands, creating high objects. The shadow regions are the area produced by the darkening of an object light source. The shadow regions can either help or complicate the interpretation of the scene, depending on whether they model the shadow or neglect it. It can help identify objects & recognize their appearance if the shadows are identified & eliminated. It helps to determine the boundaries of objects & ground contact[1] as shown in fig.

Reflections are divided into two that are reflections of themselves & cast shadows[2] as shown in fig 2. There are two forms of cast shadows-umbra & penumbra as shown in fig[3]. Such regions are formed because of multiple lighting. The umbra is created because it completely blocks the direct light. Yet penumbra is produced by blocking the direct light partially. Shadows degrade the image segmentation & pattern recognition accuracy when remote sensing images are decoded & analyzed. Shadow detection & removal plays an vital role in aerial camera applications.

Revised Manuscript Received on February 28, 2020.
***** Correspondence Author
Komal Prasad Kanojia*, Department of EC, Sarvepalli Radhakrishnan University, Bhopal, India. Email: komal44@gmail.com
Dr. Bharti Chourasia, Associate Proff, HOD, Department of EC, Sarvepalli Radhakrishnan University, Bhopal, India. Email: bharti.chourasia27@gmail.com

The purpose of removing the shadow is to get a shadow-free image. Shadow reduction is a crucial function for further analysis and image recognition. Shadow reduction is particularly important to Earth's remote sensing. Due to shadowed field collection, the quality of satellite & aerial photographs can be significantly improved. The artefacts are becoming more evident in the shadowed area.

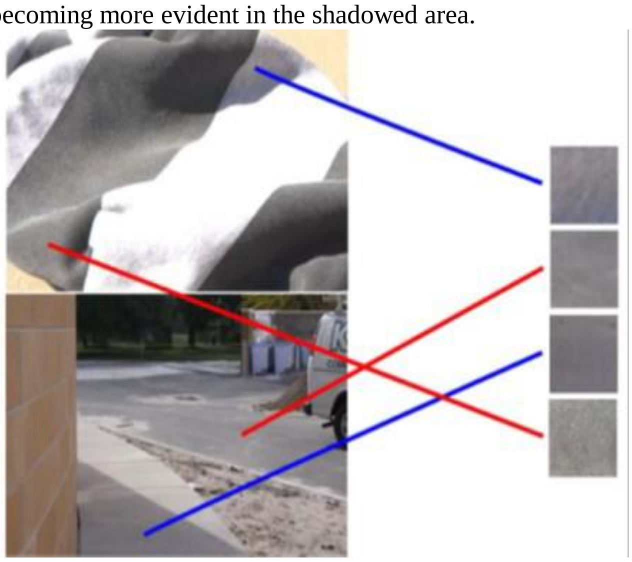

Fig. 1 The local region appears with vague features, contrasting the surfaces of the same substance to locate outlines. [1].

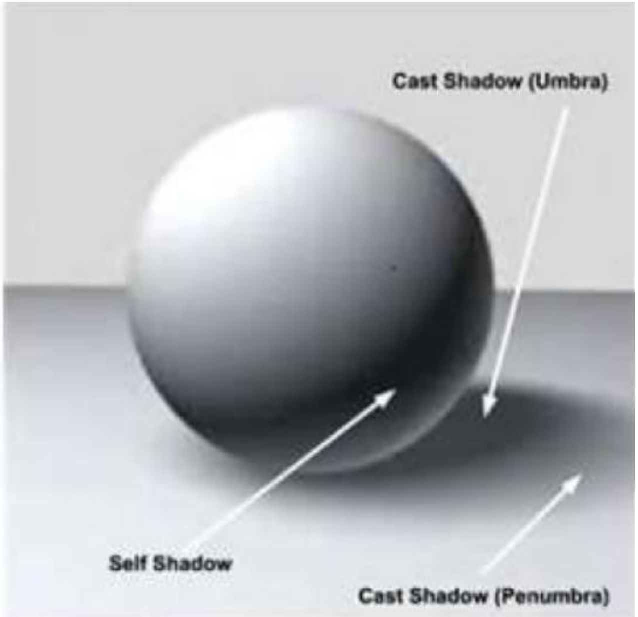

Fig 2. Different types of shadow

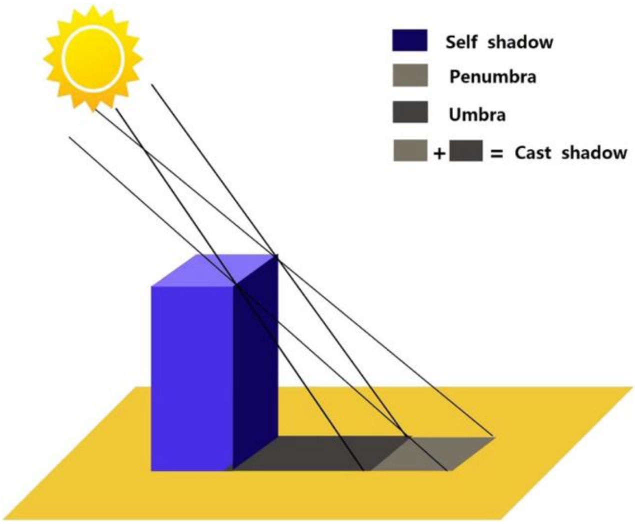

Fig 3. Principle of shadow formation[10].

II. LITERATURE SURVEY

A lot of work has been devoted to the identification & elimination of shadows. Many effective algorithms have been developed to process single images of natural scenes. Classification of current shadow detection techniques into two classes[3] is loosely possible: model-based & shadow-based approaches. In order to create shadow models[4],[5] the first group uses prior information including situation, moving targets, and camera altitude. In certain unique scene settings, such as aerial image analysis & video tracking, this group of methods is often used. The second set of approaches describes shadow areas with details like gray scale, light, contrast. The two approaches incorporate an enhanced algorithm[6]. Next, the shadow regions will be measured on the basis of the space coordinates of buildings determined from computer models & the sun's altitude & azimuth. The threshold value is then calculated from the shadow area's average gray value in order to accurately describe a shadow. Nonetheless, data such as scene & camera height is typically not readily accessible. Therefore, most algorithms based on shadow detection are color-based. For example, the shadow region has a low gray picture, and a threshold can be used to differentiate between shadow and the shadow area from two pinnacles within the histogram of gray frame data[6][8].Shadows have been detected by a light-filled invariance model which, through some neutral interfsace, can obtain a comparatively complete shading pattern from a complex scene & draw the shadowless image[9],[10].

In the corresponding study[11] multiple methods for improving shadows, such as gamma correction, LCC, & histogram correction, were studied. An analysis based on the study of this relationship was developed based on a linear relationship between shadow classes and the corresponding non-shadow classes[12]. A combined region-based approach is also used to measure the disparity between shadow and non-shadow of the same kind in order to identify and remove the shadow in a single image[13]. Apart from the above techniques, multisource data can be used to extract shadows. For example, from the area of concern of a picture & from some other image at a unlike time shadow pixels can be identified. Non shadows are then used to remove the shadow in the corresponding area. For images of low-closure[7],[14] and[15], this latter method is useful.

Authors[16] present this like the question of image region labeling where every area represents with a super pixel group. We train the Last-Squares support vector (LSSVM) kernel for the detachment of shadow & non-shadow regions to forecast each region's name. In combination with kernel / classifier parameters, the validation error is reduced from start to finish. Optimizing the validation failure is usually difficult, but can be done effectively under our umbrella. Two challengeous shadow datasets, UCF & UIUC, have been tested to show that the approaches in our area are more complex.

A recent extensive Generative Adversarial Networks (GAN) is being presented for authors in [17] to address the challenging issue of image shadow detection. Prior shadow detection methods are designed to understand the local presence of shadow areas while using limited local context reasoning in a conditional random field as pair-like ability. The suggested opposing approach is in comparison capable of modeling higher levels of relationships & global scene characteristics. Authors in[18] examined satellite images of high resolution provide an enormous amount of information. Shadows in such pictures cause real detection & extraction problems. While the signals reported in the shadow area are low, they can still be recovered. Significant work has already been done in the direction of shadow detection, but accurate classification of vegetative pixel shadow pixels remains a problem since dark vegetation areas in some cases are still not identified as shadows. A new image index for shadow detection using multiple bands is established in this document.

Shadows, created by clouds, trees, & buildings, degrade the precision of many remote sensing tasks including image recognition, improvements in detection, identification of objects, etc. Authors explore the shadow detection of complex scenes in this article. In contrast to traditional methods that only use pixel information, this approach combines model with observational indications. First, to model and extract the occulption map in a picture, we improve our previous bright channel (BCP). Method[19] for both natural & satellite images is appropriate

Shadows may occlude objects in highly resolution panchromatic satellite images, particularly in urban scenes, to reduce or lose their detail. Shadow removal is an important processing method for the analysis & application of the images[20] to recover the occluded details of objects. Authors in [21] suggested an approach to shadow removal focused on a subregion that suits the transition of illumination. The HSI color model is used to identify the shadows with a ratio chart. The Otsu method for obtaining a coarse shadow mask was applied over the histogram of the ratio plot. Then the segmentation is carried out of the shadowed & lit regions & the subregion based on the textural & spatial distance of each segment.

A 3-band color image processing method was suggested by authors in[22]. Next, they find a single scalar image feature that continually depends on light, color and intensity reflections & changes.

Using the mean shift algorithm, segment the image in[23]. Instead they measure the trust that each area is in darkness, using a qualified classifier.

Categorization results are used to construct a section table and segmentation is used to solve the classification of shadow and non-shadow areas. The shadow reduction approach is based on a simple shadow model where lighting consists of direct light & light setting.

A new method is proposed in[24] to remove shadows from a single image, based on the affine shadow formation model. The model parameters are estimated by a mask of shadowed & lit regions. Instead, to create a shadow-free image, a pyramid-based restore process is implemented. Shadow reduction algorithms have been applied in recent years to data received from multiple spacecraft from remote sensing. Auhtors in[25] suggested an approach to shadow elimination in dynamic color remote sensing photographs of urban areas based on HSV color model. Shadows are observed using a generic index of difference & corresponding thresholding based on the process of Otsu. Such buffer areas ' mean & variation is used to account for the shadow regions.

Authors in[26] suggested an internal profile outline (IOOPL) that fits the algorithm to eliminate satellite images from shadows. The characteristics of the shadow are evaluated through image segmentation. The authors in[27] suggested the following algorithm to obtain a shadow-free aerial image. First, to evaluate a coarse shadow map, they use the hue-to-intensity ratio. Better transformation is then applied in order to obtain a precise shadow mask. The pixel-wise function of each image pixel extracts the shadow from the image by a scaling factor.

III. DISCUSSION

Both approaches have pros & cons, except physical information-fixing mechanisms. Figure 4 depicts the comparison of various methods use for shadow detection .

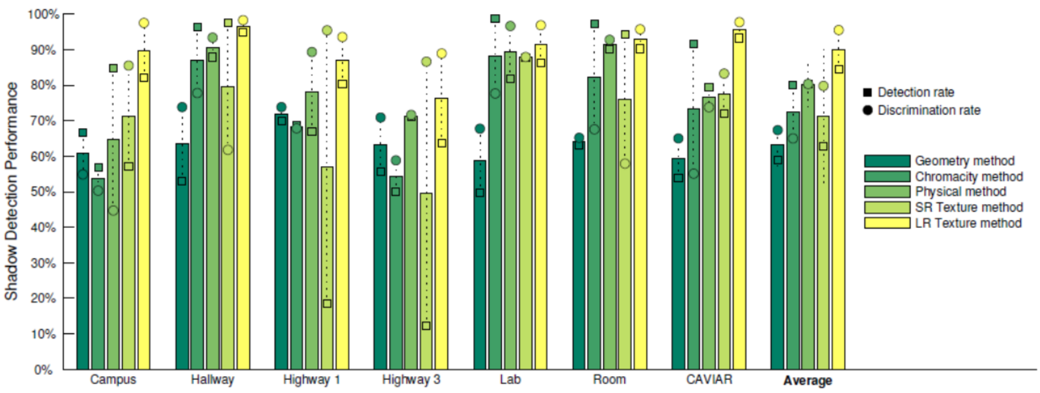

Fig 4. Comparison of shadow detection results[28]

Sr. No.	Technique	Idea	Pro	Cons
1	Intensity	Standard deviation is computed for ratio value. terms are set for a shadowed pixel.	Pixel intensity function without any other assumptions is calculated directly from the data	The pixel intensity value is fictile to classification changes.
2	Threshold	Predefined threshold histogram-based threshold standard used for evaluating white and dark pixels.	Simple & fast.	Post-processing is important as the results could be incoherent or distorted, and holes, noise etc.
	Classification	Classification techniques like SVM are used based on the properties possessed by shadow pixels.	Can detect probable shadow boundaries accurately. Simple and easy to implement.	There are chances of misclassification. Shadows of small objects are missed sometimes.
3	Geometric Properties	Sets of geometric features are matched.	Effective detection under simulated and controlled environment.	Method will be ineffective when geometric representation of object will change.
4	Chromaticity	Hue & saturation combined together are known as chromaticity.	Highly accurate. Can select proper features for shadow.	Tends to misclassify .

5	Textu re	Takes in account the similarity between background and shadow texture as well as the difference in foreground and background textures.	Accurate results under stable illuminatio n conditions.	Poor performance for outdoor scenes as texture capturing is difficult. Difficult to implement.
6	Color	Color tune value of shadow & background same but different Intensity. Color differences of shadowed pixel & background pixels as well as illumination Invariance are used.	Reliable technique for Colored images.	It takes more time for computation. Fails when saturation of shadow & background is same.
7	Regio n Growi ng	Standard deviation and Mean are calculated.	Shape matching results are good.	Region growing failed when the pixel intensity varied widely in the shadow region.
8	Susan Algori thm	Video highway data with avi format, Edge is detected from Susan method.	Speed is enhanced. Method is simple, Convenient .	Less Efficient than Harris Algorithm.

In the analysis the methods of shadow detection are grouped into a taxonomy based on characteristics. Methods using mainly spectral characteristics are known as either chromacy-based or physical methods. Methods using primarily spatial characteristics are categorized either as methods based on geometry or texture. We selected a popular approach from each group for the comparative assessment, except for the category based on texture, where we selected two: one using small regions & one using large regions for the texture correlation. Using a wide range of test sequences, we compared the shadow detection efficiency of these approaches. Furthermore, it is observed the effect of low saturation on the performance of shadow detection & assessed the practical connection between shadow detection & tracking.

IV. RESULTS

The main objective of identifying shadow pixels is to compensate them so that shadow-free images can be achieved.

The results of the studied system are shown in below table.

Table 1: Result analysis

Methods	Accuracy
SDI INDEX	96.73
NSVDI INDEX	92.71
C*3 INDEX	93.21

V. CONCLUSION

In this article, we provided an extensive survey of aerial shadows, shadow detection & removal from a single image with different geometric characteristics and texture with different reflection parameters remains an extremely difficult problem shadow detection and deletion. It is known that Shadows are all around us & their existence never confuses us. Tracking or detecting moving objects is at the heart of many image sequence applications.

REFERENCES

1. Guo, R., Dai, Q., & Hoiem, D. (2013). Paired regions for shadow detection & removal. IEEE transactions on pattern analysis & machine intelligence, 35(12), 2956-2967.
2. Avinash Kumar Singh1, Ankit Pandit2 “Shadow Detection & Removal Techniques: A Perspective View” International Journal of Trend in Scientific Research & Development (IJTSRD) Volume: 3 | Issue: 4 | May-Jun 2019
3. J. Yoon, C. Koch, & T. J. Ellis, “ShadowFlash: An approach for shadow removal in an active illumination environment,” in Proc. 13th BMVC, Cardiff, U.K., Sep. 2–5, 2002, pp. 636–645.
4. R. B. Irvin & D. M. McKeown, Jr, “Methods for exploiting the relationship between buildings & their shadows in aerial imagery,” IEEE Trans. Syst., Man, Cybern., vol. 19, no. 6, pp. 1564–1575, Dec. 1989.
5. Y. Li, T. Sasagawa, & P. Gong, “A system of the shadow detection & shadow removal for high resolution city aerial photo,” in Proc. ISPRS Congr, Comm., 2004, vol. 35, pp. 802–807, Part B3.
6. Y. Li, P. Gong, & T. Sasagawa, “Integrated shadow removal based on photogrammetry & image analysis,” Int. J. Remote Sens., vol. 26, no. 18, pp. 3911–3929, 2005.
7. P.M. Dare, “Shadow analysis in high-resolution satellite imagery of urban areas,” Photogramm. Eng. Remote Sens., vol. 71, no. 2, pp. 169–177, 2005.
8. R. Highnam & M. Brady, “Model-based image enhancement of far infrared images,” IEEE Trans Pattern Anal. Mach. Intell., vol. 19, no. 4, pp. 410–415, Apr. 1997.
9. G. Finlayson, S. Hordley, & M. Drew, “Removing shadows from images,” in Proc. ECCV, May 28–31, 2002, pp. 823–836, Vision-Part IV.
10. E. Salvador, A. Cavallaro, & T. Ebrahimi, “Shadow identification & classification using invariant color models,” in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2001, vol. 3, pp. 1545–1548.
11. P. Sarabandi, F. Yamazaki, M. Matsuoka et al., “Shadow detection & radiometric restoration in satellite high resolution images,” in Proc. IEEE IGARSS, Sep. 2004, vol. 6, pp. 3744–3747.
12. L. Lorenzi, F. Melgani, & G. Mercier, “A complete processing chain for shadow detection & reconstruction in VHR images,” IEEE Trans. Geosci. Remote Sens., vol. 50, no. 9, pp. 3440–3452, 2012.
13. R. Guo, Q. Dai, & D. Hoiem, “Single-image shadow detection & removal using paired regions,” in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2011, pp. 2033–2040.
14. W. Bin, O. Atsuo, K. Muramatsu et al., “Automated detection & removal of clouds & their shadows from Landsat TM images,” IEICE Trans. Inf. Syst., vol. 82, no. 2, pp. 453–460, 1999.
15. A. K. Shackelford & C. H. Davis, “A combined fuzzy pixel-based & object-based approach for classification of high-resolution multispectral data over urban areas,” IEEE Trans. Geosci. Remote Sens., vol. 41, no. 10, pp. 2354–2363, 2003.
16. Tomas F. Yago Vicente, Minh Hoai & Dimitris Samaras, “Leave-One-Out Kernel Optimization for Shadow Detection & Removal”, IEEE Transactions on Pattern Analysis & Machine Intelligence, Vol. 40, No. 3, March 2018.
17. Vu Nguyen, Tomas F. Yago Vicente, Maozheng Zhao, Minh Hoai & Dimitris Samaras, “Shadow Detection with Conditional Generative Adversarial Networks”, IEEE International Conference on Computer Vision, 2017.
18. Yasser Mostafa & Ahmed Abdelhafiz, “Accurate Shadow Detection from High-Resolution Satellite Images”, IEEE Geo Science & Remote Sensing Letters, Vol. 14, No. 4, April 2017.

19. Jiayuan Li, Qingwu Hu & Mingyao Ai, "Joint Model & Observation Cues for Single-Image Shadow Detection", MDPI Journal of Remote Sensing, 2016.
20. Nan Su, Ye Zhang, Shu Tian, Yiming Yan & Xinyuan Miao, "Shadow Detection & Removal for Occluded Object Information Recovery in Urban High-Resolution Panchromatic Satellite Images", IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing, Vol. 9, No. 6, June 2016.
21. C. Xiao, D. Xiao, L. Zhang & L. Chen, "Efficient shadow removal using subregion matching illumination transfer", Computer Graphics Forum, vol. 32, n. 7, pp. 421–430, 2013.
22. G. D. Finlayson, S. D. Hordley & M. S. Drew, "Removing Shadows from Images", Lecture Notes in Computer Science, vol. 2353, pp. 823–836, 2002.
23. R. Guo, Q. Dai & D. Hoiem, "Single-image shadow detection & removal using paired regions", in Proceedings of the IEEE Conference on Computer Vision & Pattern Recognition, 20–25 June, 2011, pp. 2033–2040.
24. Y. Shor & D. Lischinski, "The shadow meets the mask: pyramid-based shadow removal", Computer Graphics Forum, vol. 27, n. 2, pp. 577–586, 2008.
25. K. K. Singh, K. Pal & M. J. Nigam, "Shadow detection & removal from remote sensing images using NDI & morphological operators", International Journal of Computer Applications, vol. 42, n. 10, pp.37–40, 2012.
26. K. Prasad & B. Kiran, "An efficient method for shadow detection & removal in satellite images by segmentation", International Journal of Advanced Research in Computer & Communication Engineering, vol. 4, n. 6, pp. 97–101, 2015.
27. S. Tiwari, K. Chauhan & Y. Kurmi, "Shadow detection & compensation in aerial images using MATLAB", International Journal of Computer Applications, vol. 119, n. 20, pp. 5-9, 2015.
28. A. Prati, I. Mikic, M. Trivedi, & R. Cucchiara. Detecting moving shadows: algorithms & evaluation. IEEE Transactions on Pattern Analysis & Machine Intelligence, 25(7):918–923, 2003

AUTHORS PROFILE

Komal Prasad Kanojia* is a phd scholar in EC department, SRK University, Bhopal, India.

Dr Bharti Chourasia, Associate Proff, HOD,EC department, SRK University, Bhopal, India. She has published various papers in International journals. She gives his major contribution towards student guideline in their research work.