Research Article

An Effective Framework Using Region Merging and Learning Machine for Shadow Detection and Removal

Mohankumar Shilpa[a], Madigondanahalli Thimmaiah Gopalakrishna[b], and Chikkaguddaiah Naveena, Sharathkumar Y H[c]
[a]Department of ISE, BIT, Affiliated to Vivesvaraya Technological University,
Bangalore , India
[b]Department of CSE, SJBIT, Affiliated to Vivesvaraya Technological University , Bangalore , India
[c]Department of ISE, MITM, Affiliated to Vivesvaraya Technological University ,Mysuru , India

Article History: Received: 11 January 2021; Accepted: 27 February 2021; Published online: 5 April 2021

Abstract: Moving cast shadows of moving objects significantly degrade the performance of many high-level computer vision applications such as object tracking, object classification, behavior recognition and scene interpretation. Because they possess similar motion characteristics with their objects, moving cast shadow detection is still challenging. In this paper, the foreground is detected by background subtraction and the shadow is detected by combination of Mean-Shift and Region Merging Segmentation. Using Gabor method, we obtain the moving targets with texture features. According to the characteristics of shadow in HSV space and texture feature, the shadow is detected and removed to eliminate the shadow interference for the subsequent processing of moving targets.

Finally, to guarantee the integrity of shadows and objects for further image processing, a simple post-processing procedure is designed to refine the results, which also drastically improves the accuracy of moving shadow detection. Extensive experiments on publicly common datasets that the performance of the proposed framework is superior to representative state-of-the-art methods.

Keywords: moving cast shadow; feature extraction; Region Merging, Gabor, Meanshift

1. Introduction

Shadow is a ubiquitous natural phenomenon in our daily life. Although shadows can provide useful clues for illumination estimation, scene depiction and object shapes, shadows also degrade the performance of some applications, such as object recognition, object tracking and intrinsic image decomposition. Therefore, it is a fundamental problem to detect and remove shadows from single images and will definitely be beneficial for computer vision and graphics communities. Shadow removal involves three main challenges. First, for the image with complex shadows like a surface with both soft and hard shadow, accurate shadow detection is challenging. Second, there are usually texture details losing on hard shadow boundaries, which will induce visual artifacts on these boundaries during shadow removing. Finally, to obtain visually consistent shadow removal results, the shading information should be preserved in the shadow-free image. To overcome the above challenges, we propose an automatic shadow detection and removal method by jointly exploring color cues as well as depth information. First, based on the observation that shadows essentially appear as smooth and continuous regions, we develop a shadow-preserving. Our visualization results of shadow detection and removal.

2. Literature Review

Moving shadow detection has been investigated for years, and many researchers and scientists are working together in the shadow removing domain to reduce processing time and improve the quality of the segmentation result to deliver appropriate object tracking applications. However, shadow detection remains one of the most important and challenging issues in the areas of computer vision, object detection, and machine learning. Detecting shadow regions by the human eye may be a somewhat easy task, but it is a relatively challenging problem for a computer, as shadow pixels also simultaneously move as an object region. For these reasons, most contemporary studies concern detecting and removing shadows.Yanli Wan et al. [1] introduced a shadow removing technique for moving objects to eliminate ghosting artifacts. In their approach, the ghosting area is rearranged to avoid removing the moving shadow pixels in the scene. However, this method is relatively difficult to use in urban surveillance and in multiple noise environments. Cucchiara et al. [2] utilized shadow features in the hue, saturation, value (HSV) color space to recognize shadow pixels where the object of interest is in motion. These properties demonstrate that cast shadows obscure the background in the luminance component, whereas the saturation and hue spaces change inside specific limits. The HSV color space was utilized because it provides a superior separation of chromaticity and grey level than other color spaces. In [3], the authors reviewed several shadow detection methods, each of which proved their efficiency in detecting and removing shadow pixels in indoor and outdoor environments. Several other research works were proposed for dynamic image sequences [4,5,6]. The scientists investigated the concept of including a multi-frame differencing system to enhance the division in situations where the shadows may not be effectively removed. Stauder et al. [7] suggested a new physics-based method that used luminance and intensity values to describe physical illumination changes.Recently published articles are different in terms of productivity and reliability [8,9]. They try to overcome the modern problems in moving shadow detection, such as those in smart city and intelligence-building frameworks. Today, applying computer vision tasks to machine learning and neural networks is becoming a very important research area. Dong Seop Kim et al. [10] employed a convolutional neural network (CNN) in their study, for shadow detection in images using a visible light camera sensor. The researchers presented a shadow detection and removal algorithm that used a 21 × 21 sliding window-based visual geometry group (VGG) "Net-16" CNN and showed a high accuracy, even in a high-definition surveillance condition. A new method for dynamic object and shadow detection based on motion prediction was proposed by Jong Taek Lee et al. [11], solving the shadow problem by using deep learning. In addition, applying a Markov random field enables a system to refine shadow detection results to improve its performance. In [12], a novel approach is presented for versatile shadow removal by consolidating four distinct filters in a neuro-fuzzy structure. The neuro-fuzzy classifier has the capacity for real-time self-adaptation and training, and its execution has been quantitatively surveyed with both indoor and outdoor video streams.

In [13], Dong et al. proposed method to detect the penumbra shadow edge form a single image of outdoor scenes. In the proposed method, based on three parameters center position, orientation, and width of the penumbra shadow an intensity model has been developed using intensity change rate, intensity variation of the penumbra shadow. By adjusting the intensity model the initial umbra and penumbra shadow edge segment is identified then the continuous complete boundary is optimized globally with the level set method. The proposed method, gives good accuracy for the even surface, outdoor based single images but inconsistent, asymmetric casting background is still the problem. As the future work other parameters as color and gradient should be considered for the performance improvement. In [14], Wang et al. proposed a method by combining two methods of shadow detection color based and model based. First moving region of the shadow is detected using property-based method and then coarse region is obtained by model-based method, then this coarse region is used in the shadow detection approach based on HSV color-space. Proposed method performed well in moving shadow detection, especially for the shadow which lies in the boundary of the vehicle. However, this method is not found suitable for the shadow which lies under the vehicle or the shadow which is covered by the vehicle. In [15], Yang et al. proposed an approach to remove the shadow in work piece. The method first converts the RGB image to HSV color model, according to the association between the variation of values (V)-elements and the shadow of the image, the elements of the corresponding shadow is obtained. Then a homomorphic filter is designed, which is used to filter the elements of shadow in the image and a new image is incorporated without having the shadow. The quality is further improved by subsequent image processing. Their method effectively, completely removes the shadow in the outer region of the workpiece but shadow in the inner region is not effectively removed it is reduced to some extent. In [16], Asaidi et al. proposed an approach to automatically detect and extract shadow based on various properties acquired by the spectral, temporal and geometric analysis of shadow, which detects the shadow region using time and direction of shadow. Using the spatial analysis, method analyzed the candidate shadow region using the direction of the shadow according to the time of the day. And then colorimetric is used to verify the hypothesis of the detected region. Proposed method is evaluated through various real environment videos.

In [17], Russell et al. proposed a method for detection of moving cast shadow based on spatial and temporal color constancy among the pixels. The method uses the texture information of the different sub regions, then spatial constancy is obtained to determine the similar texture regions and temporal constancy is obtained for the classification of shadow. The proposed method is efficient for both indoor and outdoor sequences and for both chromatic and achromatic shadows. Proposed approach also resolves the problem of foreground and background camouflage. In [18], Pan et al. proposed a method for shadow detection of remote sensing images using the actual edge features rather than the arbitrary pixels of the images region based on WGER (Weighted Gradient Edge Region). To show the edge intensity of a region a feature edge gradient is proposed, further for improvement of detection of shadow edge texton texture analysis is used to determine the weight (number of pixels) of each region [26]. Method gives good accuracy and better result in comparison to the methods of Liu et al. [27] and Chung et al. [28]. In [19], Khan et al. proposed a method for automatically detection and removal of shadow from a single image. Method automatically learns the features by using Convolutional Deep Neural Networks (ConvNets) and then using detected shadow mask. Bayesian formulation is proposed for the automatically removal of shadow. The proposed method gives good performance for both umbra and penumbra shadows.

In [20], Shen et al. proposed a efficient learning based framework for shadow detection from single image using structured Convolutional Neural Network(CNN). Method uses CNN to extract local structure of shadow edges to improve the local consistency throughout pixel labels. Shadow and bright measure are computed by the detected shadow edge and subsequently least square optimization problem will be solved efficiently for the shadow recovery. The proposed method can be further extended to object edge detection and smoke region detection. In [21], Russell et al. proposed a method for shadow detection for real time moving vehicle and traffic sequences. The method is works on two aspects; (a) it performs image-line analysis. (b) illumination direction of the light source, to detect the intervals with a decreasing function in the scanned images of the method extracts two feature, namely, Intensity and Spatial relationship among the points. Method gives good performance when there is foreground-background and background –foreground camouflages and for real time outdoor vehicles and traffic sequences.In [22], Qi et al. presented an efficient cascade method for the cast shadow detection. Method works in very systematic way firstly, it extracts the initial moving frames from the Gaussian Mixture model (GMM) then to separate a portion of moving object from the initial moving pixels Local Binary pattern(LBP) is applied. Subsequently for the improvement intensity ratio is acquired and then by post processing techniques the spurious pixels will be corrected. Their proposed method gives good performance comparatively but for some of the outdoor scenes misclassified the pixels.

Recently, various shadow identification techniques have been announced in science-related literature. They can be divided into two areas. The first area generally concerns static images, while the second concerns image sequences and specifically video contents [23]. Static shadows are shadows cast by immobile objects such as buildings, parked vehicles, and trees. In that regard, moving object identification methods do not suffer from static shadows because these shadows are classified as a piece of background. In contrast, dynamic shadows, the subject of interest for this manuscript, are harmful to moving object recognition algorithms. Shadows can be smoothly stitched to an object in action or can be disconnected from it. In the first case, the shadows usually cause the shape of the original object to look different, making the utilization of subsequent shape recognition strategies less reliable. In the second case, the shadows might be incorrectly categorized as an object in the scene. The work performed in this study concerns the second case, where, in this way, it addresses the issue of the detection and removal of moving shadows cast from objects in video surveillance. This is done to improve the process of moving object identification. Moving shadows are often recognized as foreground objects, and this degrades the expected execution of object tracking and accurate segmentation, as depicted in Figure 1.

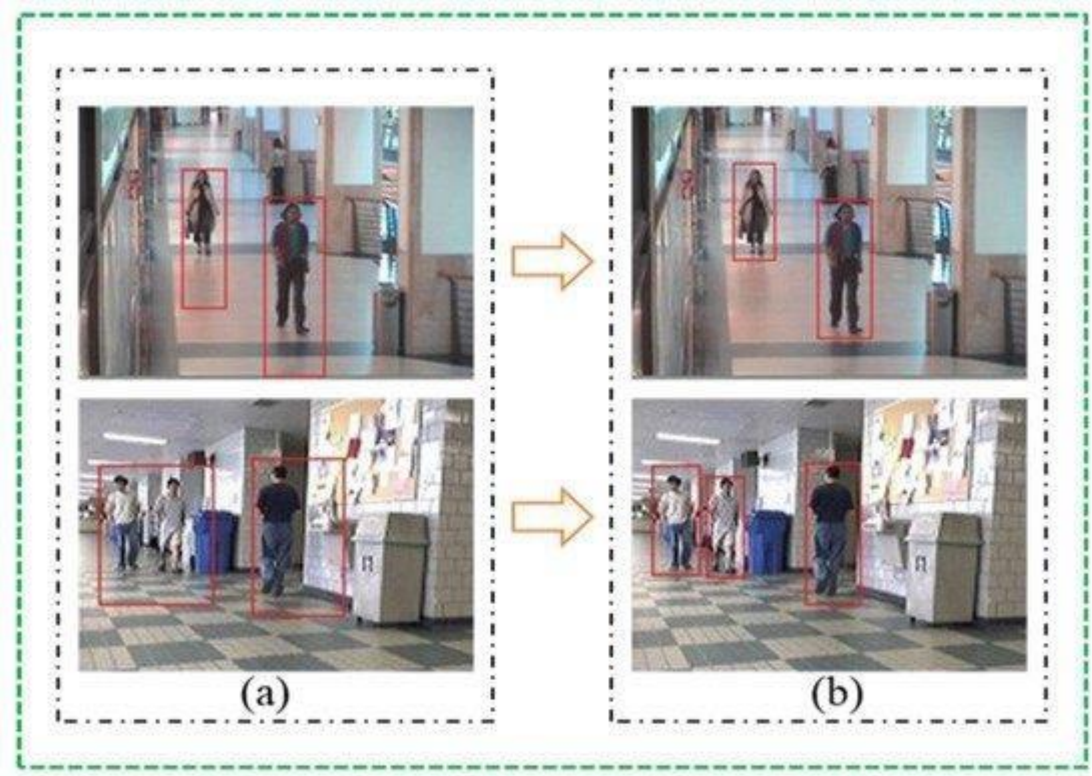


Figure 1. Tracking process on indoor video surveillance: (a) Object tracking with shadow region. (b) Object tracking without shadow region.

The main contribution of this manuscript is that we present a simple, reliable, and automatic shadow removal method that is robust against background surface similarity and ghost problems. The method requires a small amount of computational time to detect the presence of moving objects for indoor video surveillance and is based on geometry features. Existing geometry-based methods do not adequately process shadow removal with objects having multiple shadows or where several objects are recognized as a single foreground mask. Our suggested algorithm is comprised of the following steps:

Shadow Detection
- Mean shift segmentation
    -Dynamic Region merging
    Shadow Removal
    - Processed in HSV color space
    -Gabor Filter

The rest of the paper is partitioned into section as follows: Section 2 shows a survey of some related shadow detection strategies. Section 3 provides a brief discussion of the Proposed Method. Section 4 provides conclusions based on the experimental results and future directions for study.

3. Proposed Work

The flow of the Proposed method is shown in Figure 2 contains following stages like Keyframe Extraction, Shadow Detection and Shadow Removal.

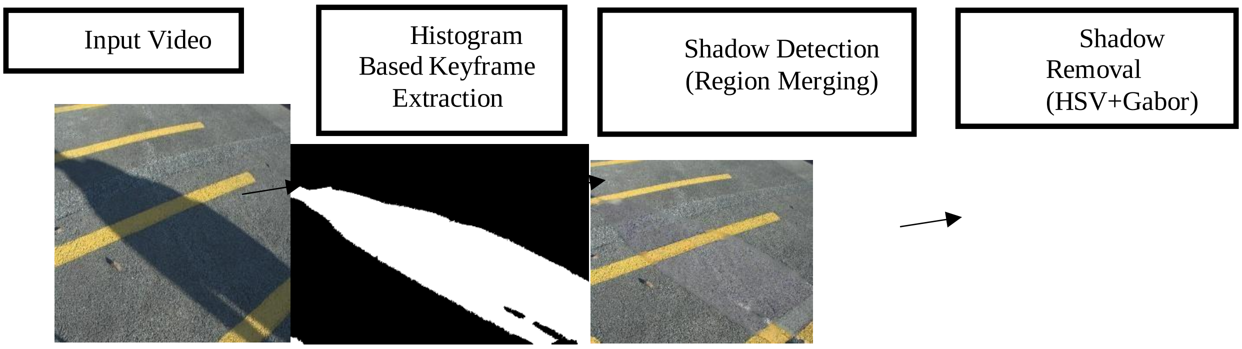


Figure 2: shows the Stages of Proposed Method

Keyframe Extraction

This section explores a method of key-frame extraction algorithm based on absolute difference of histogram of consecutive image frames. It is a two phase method in which first phase compute threshold using mean and standard deviation of histogram of absolute difference of consecutive image frames. Second phase extract key –frames comparing the threshold against absolute difference of consecutive image frames. The algorithm starts by extracting video frames one by one. After preprocessing each video frames histogram difference between two consecutive frames are calculated. The mean and standard deviation of absolute difference of histogram is calculated to fix a threshold point.

Once thethreshold is obtained next phase determine the key-frames by comparing the absolute difference of histogram against threshold. The proposed algorithm is given below.

Step.1 Extract frames one by one
Step. 2 Histogram difference between two consecutive frames
Step. 3 Calculate mean and standard deviation of absolute difference
Step. 4 Compute threshold
Step. 5 Compare the difference with T and if it is
>Tselects it as a key-frame else go to step 2
Step. 6 Continue till end of video

Shadow Detection

In this work, the Mean shift segmentation is used to Partition the image into similar areas to combine the images. The cluster of pixels in joint color and spatial dimensions is identified in a RGB image. RGB image is segmented using algorithm. The segments which are superpixels can be utilized as a source for additional processing.

Mean shift Algorithm

The mean shift algorithm is a clustering technique which is non parametric and neither require prior knowledge of the number of clusters nor constrain the shape of the clusters. This algorithm is use for the initial segmentation.

The algorithm is:
Step 1: Fix a window around each data point.
Step 2: Compute the mean of data within the window.
Step 3: Shift the window to the mean and repeat till convergence.

Dynamic Region Merging algorithm

The DRM algorithm is used for an Image Segmentation as dynamic region merging process, which is proposed to minimize an objective function with the merging predicate P.the proposed work is started from a set of oversegmented regions, because a small region can provide more stable statistical information than a single pixel, and using regions for merging can improve a lot the computational efficiency. There are many regions to be merged for a meaningful segmentation. By taking the region merging as a labeling problem, the goal is to assign each region a label such that regions belong to the same object will have the same label, some global properties of thesegmentation can be obtained. It can be noted that the proposed DRM algorithm produces a segmentation which is neither over merged nor undermerged according to the proposed predicate P. Figure 3 shows the shadow detection results.

.

Thealgorithm is summarize in the steps:
Step 1: Take input image file.
Step 2: Read image file.

Step 3: Extract width and height of image file.
Step 4: Apply segmentation.
Step 5: Extract the regions from segmented output.
Step 6: Build pairing of segmented region.
Step 7: Generated pair get merged.
Step 8: Generate boundary around the region obtained aftermerging.
Step 9: Generate image.
Step 10:Show result

Shadow Removal

HSV Color Space

The HSV (hue-saturation-value) system is a perception oriented non-linear color space. Color information is represented by hue and saturation values in HSV color space. The extent of the color's brightness of an image is described by value, which is determined by the amount of the light. Hue represents basic colors, and is determined by the dominant wavelength in the spectral distribution of light wavelengths. It is the location of the peak in the spectral distribution. Saturation refers to the color depth, which is measured in percentage, ranging from 0 to 100%, and signifies the amount of white light mixed with the hue. It is the height of the peak relative to the entire spectral distribution. Value is the color brightness, and also indicated in percentage, ranging from 0 to 100%. Human vision system can distinguish different hues easily, whereas the perception of different intensity or saturation does not imply the recognition of different colors. The HSV color space is more intuitive to human vision for its good capability of representing the colors of human perception. The HSV coordinates can be transformed from the RGB space easily.

Gabor Filter Responses

Texture analysis using filters based on Gabor functions falls into the category of frequency-based approaches. These approaches are based on the premise that texture is an image pattern containing a repetitive structure that can be effectively characterized in a frequency domain, such as the Fourier domain. One of the challenges, however, of such an approach is dealing with the tradeoff between the joint uncertainty in the space and frequency domains. Meaningful frequency based analysis cannot be localized without bound. An attractive mathematical property of Gabor functions is that they minimize the joint uncertainty in space and frequency. They achieve the optimal tradeoff between localizing the analysis in the spatial and frequency domains. Using Gabor filters to analyze texture appeals from a psycho-visual perspective as well. The texture analysis is accomplished by applying a bank of scale and orientation selective Gabor filters to an image (Newsam and Kamath, 2004). These filters are constructed as follows. A two-dimensional Gabor function g(x; y) and its Fourier transform G (u; v) can be written as:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi iWx\right] \tag{3.1}$$

and

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \tag{3.2}$$

Where $i=\sqrt{-1}$, $\sigma_u = 1/2\pi\sigma_x$ and $\sigma_v = 1/2\pi\sigma_y$ control the tradeoff between spatial and frequency resolution, and W controls the modulation. A class of self-similar functions referred to as Gabor wavelets is now considered. Let g(x, y) be the mother wavelet. A filter dictionary can be obtained by appropriate dilations and translations of g(x, y) through the generating function.

$$g_{rs}(x,y) = a^{-s}g(x',y'),\ a>1, s\in 0,......S-1, r\in 1,....R \tag{3.3}$$

$x' = a^{-s}(x\cos\theta + y\sin\theta)$ and $y' = a^{-s}(-x\sin\theta + y\cos\theta)$

where $\theta = (r-1)\pi / R.$

The indices r and s indicate the orientation and scale of the filter respectively. R is the total number of orientations and S is the total number of scales in the filter bank. While the size of the filter bank is application dependent, experimentation has shown that a bank of filters tuned to combinations of 0, 2, 4, 6, 8, 10 scales, and different orientations, at 22.5 degree intervals is sufficient for flower analyses. Figure 3.2 displays the real components of a bank of Gabor filters tuned to the combinations of different scales and orientations.

Combine HSV and Texture Features to Remove Shadows. Traditionally, the background subtraction method builds the background which is an image or a combination of multiple images as the background image by video frames and extracts the foreground. (e shadow of the moving object is detected by the HSV color space model. (ecolor detection method detects almost the whole shadow pixels. However, the luminance ratio of α and β generally depends on the circumstances. Some changes lead to relative dark area in the moving object or a region with similar chrominance information in the background area, which is mistaken for the shadow. (erefore, when the process of the shadow detected only use color information, it cannot obtain satisfactory results. To overcome the above disadvantages of the HSV color space model, we combine HSV and texture features to remove shadows. First, the extracted background is, respectively, processed by the Gabor method. Since the Gabor method can not only get some moving objects, but also eliminate the shadow basically, the moving target is obtained by OR operating on the processed results of Gabor methods. When the HSV color space model detects the shadow, we can make the brightness ratio select a fixed value and then the shadow is detected as much as possible. When the shadow is combined with the foreground which is extracted from a video frame by background subtraction method, there is a loss in some areas of the moving object. But if it is matched with the moving object which is extracted by the Gabor, the completed moving target can be obtained.

4. Experimentation

The proposed method is carried out in handling the video frame on the computer with 2.70 GHz dual core CPU and 4 GB RAM. The shadow elimination algorithm is tested in the CVPR-ATON standard video library with video (Intelligent Room, Campus, and Laboratory), CAVIAR standard video library (caviar_eecp2c) and our own Videos. The four popular and widely tested scenes, which is summarized as follows. Moreover, the details of the popular dataset are listed in Table 1.

Intially, we select the key frames using histogram Equalization. And in the HSV model shadow detection, the threshold of the hue and the saturation select largely and the brightness ratio of the threshold select 0.7 to 1.

The target can be detected accurately because the HSV color space model detects shadow better. The proposed algorithm firstly uses the shadow detection method which uses the HSV color space model to eliminate the shadow as much as possible. But the moving target extracted has much loss. Then, the proposed algorithm makes use of Gabor. The proposed algorithm extracts the accurate moving target and obtains the shadow which is basically eliminated. In order to evaluate the performance of the shadow detection method, Prati et al. [6] proposed two evaluation indicators, i.e., the shadow detection rate η and shadow discrimination rate ξ, which are defined as

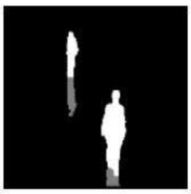
$\eta = (TPS/\ TPS+FNS)\ X100\%$ $\qquad\qquad$ $\xi = (TPF/\ FNF + TPF\ )\ X100\%$

where the subscripts S and F, respectively, represent the shadow and the target; TPS and TPF, respectively, represent the number of shadow pixels and target pixels which is detected correctly; and FNS and FNF, respectively, represent the number of shadow pixels and target pixels which is detected falsely. Obviously, η and ξ are the evaluation of the shadow and target detection performance, but they cannot comprehensively reflect the performance of the shadow detection algorithm. Joshi and Papanikolopoulos [30] combined η with ξ and presented an evaluation index avg, which was the average of the shadow detection rate and the shadow discrimination rate. It is defined as follows:

$Avg = (\eta + \xi)/2$

The quantitative results obtained by the proposed method and nine comparative methods are given figure 4. Some quantitative results of comparative methods refer to literature. It can be observed that the proposed method has the highest shadow detection rate η on CAVIAR, Laboratory and Intelligent Room and has the best shadow discrimination rate ξ on Campus. From the aspect of the mean value Avg, the proposed method performs well on Campus, CAVIAR, , Highway and Intelligent Room compared with the existing state-of-the-art methods. In particular, the mean value Avg of the proposed method is higher than the literature. Moreover, the proposed method is slightly lower than the literature about 0.14% on Laboratory.

Table 1: The detailed information of a popular dataset.

Scene	Laboratory	CAVIAR	Campus	Intelligent Room
Video Frame				
Ground Truth				

Scene Type	Indoor	Indoor	Outdoor	Indoor
labelled Frames	14	164	53	100
Total Frames	887	2725	1181	300
Shadow strength	Weak	Weak	Weak	Weak
Object Type	People	People	People/Vehicle	People
Size	Medium	Variable	Large/ Medium	Medium

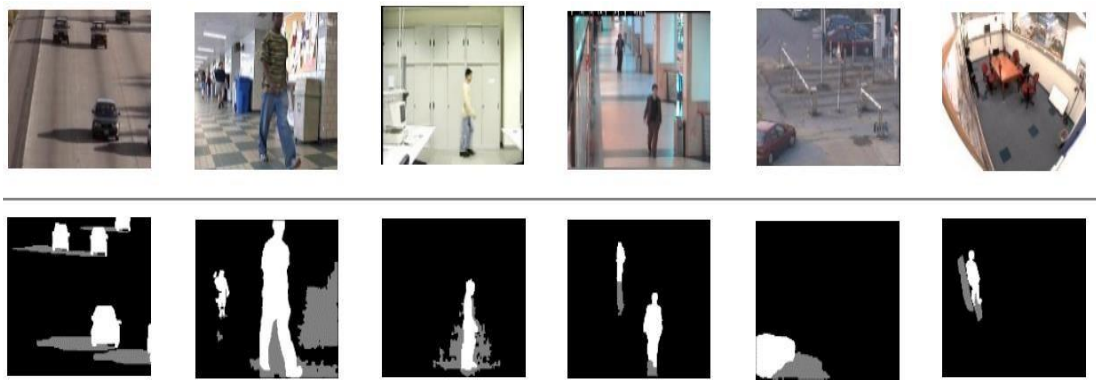
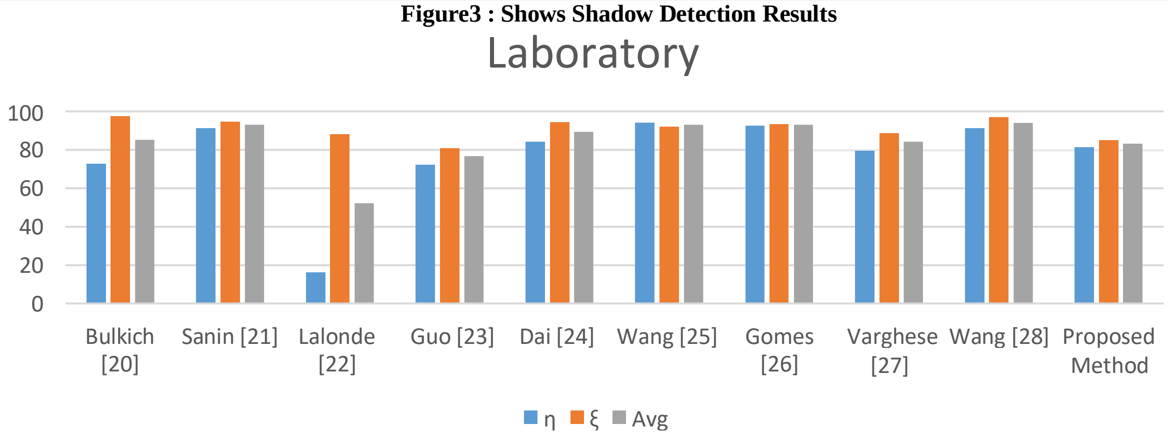
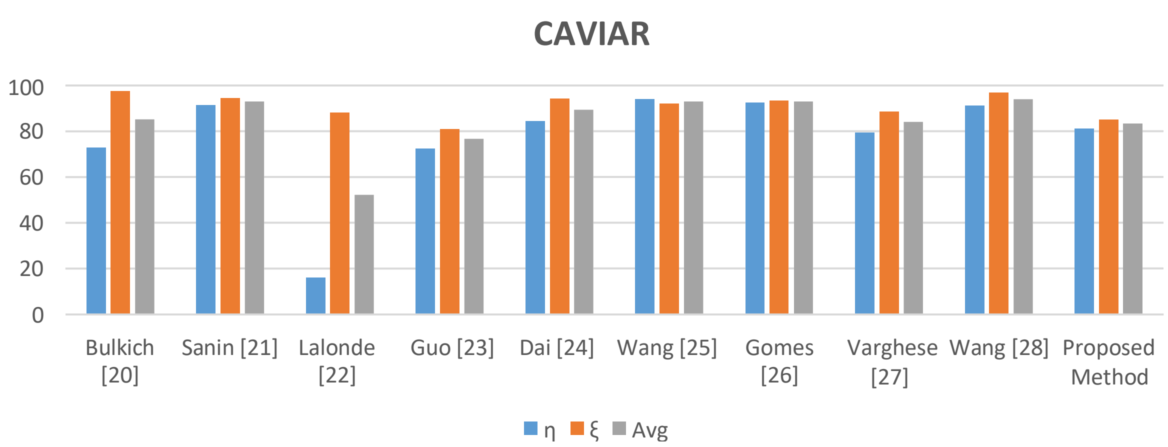
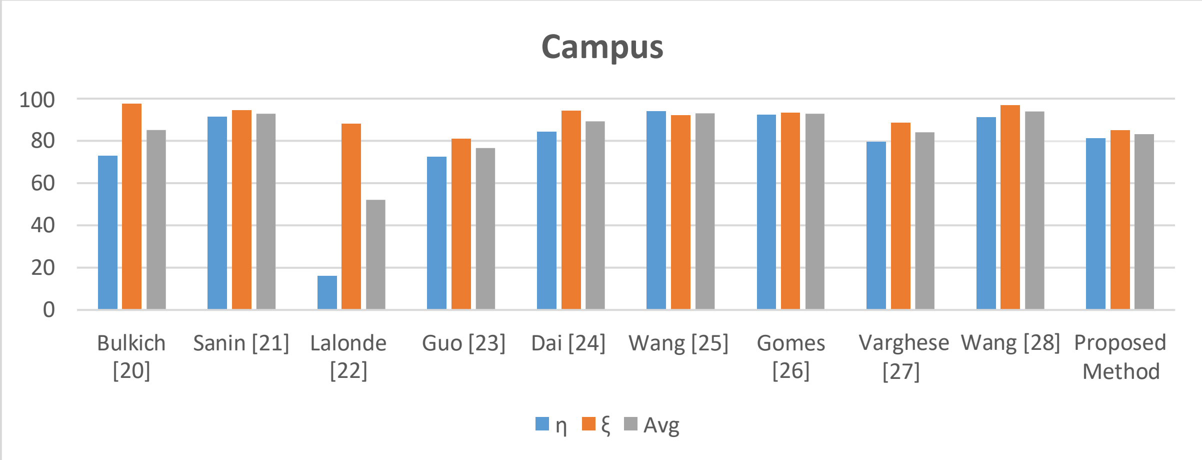


Figure3 : Shows Shadow Detection Results







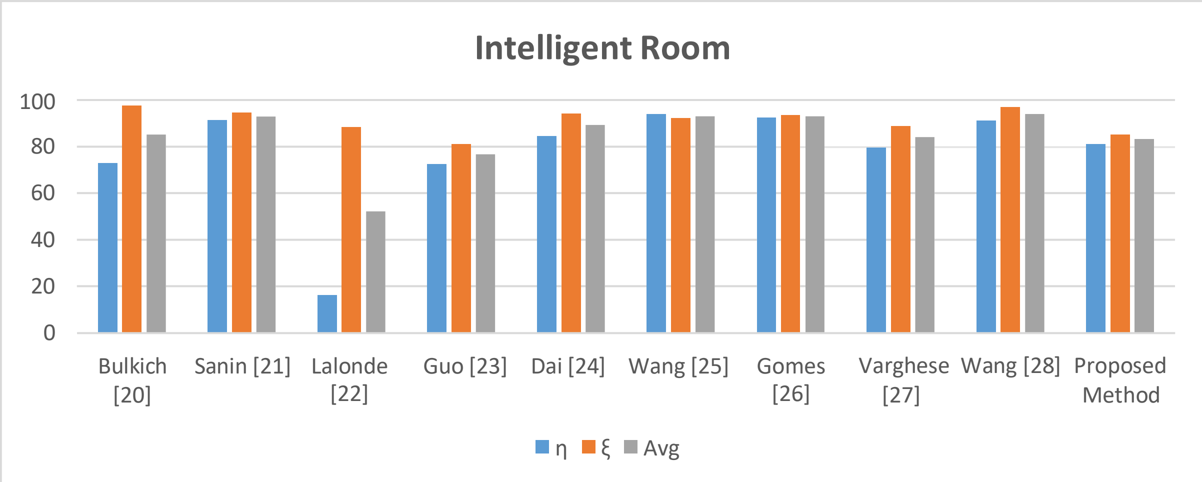
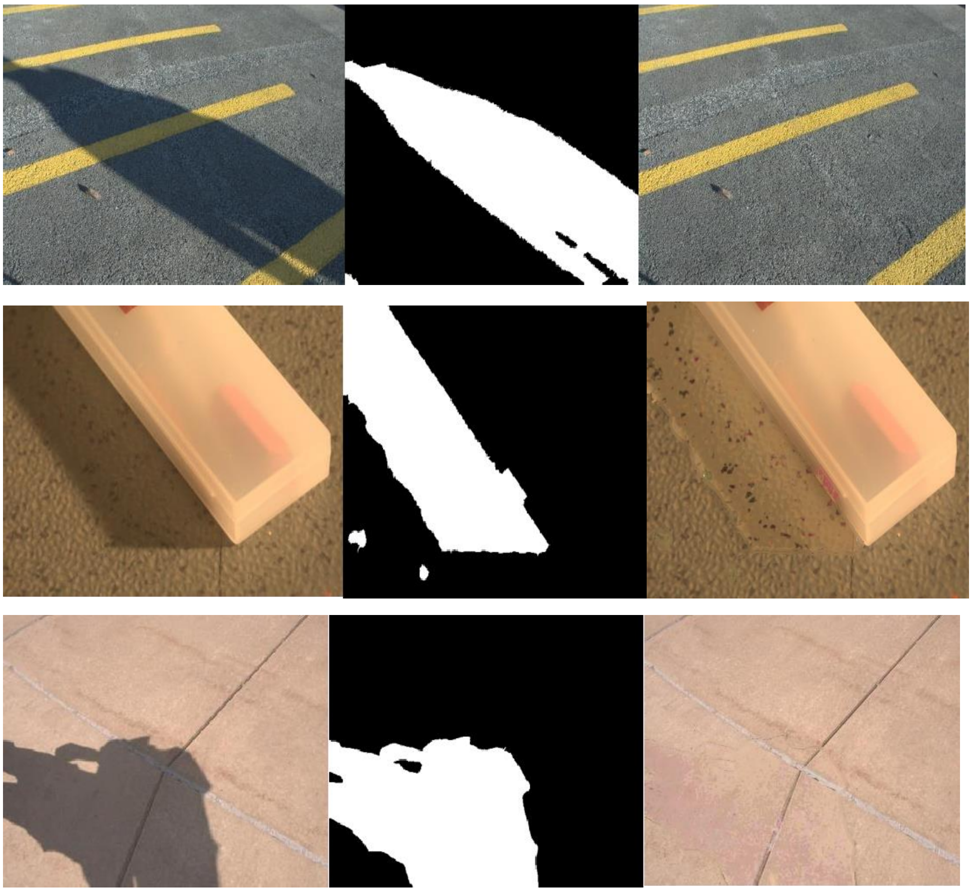


Figure 4: Shadow-detection results of the proposed method and compared methods on the popular dataset.



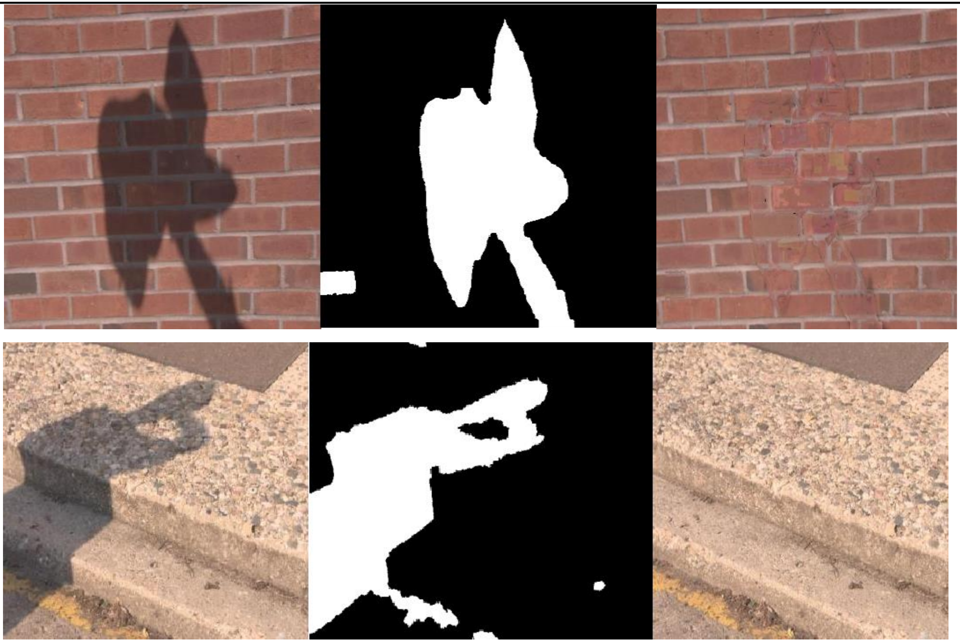


Figure 5: Shows Shadow Removal Results

5. Conclusion

In this study, we have proposed a novel moving cast-shadow detection method using the sregion merging. In contrast to the conventional methods, the proposed method not only incorporates pixel-level features but also explores region-level features according to the correlations among neighboring pixels to form input data for constructing the model. On the one hand, the proposed model only needs to turn one parameter which has little effect on the accuracy and can automatically determine one pixel whether it is a shadow or not. On the other hand, the post-processing operation can further improve the classification performance and guarantee the integrity of moving cast shadows and moving objects. We have evaluated the performance of the proposed method on publicly available datasets. Compared with some representative state-of-the-art methods, the extensive experimental results indicate the effectiveness and robustness to noises of our method.

6. References

1. Wan, Y.; Miao, Z. Automatic panorama image mosaic and ghost eliminating. In Proceedings of the International Conference on Multimedia and Expo, Hannover, Germany, 26 April–23 June 2008; pp. 945–948.
2. Cucchiara, R.; Grana, C.; Piccardi, M.; Prati, A.; Sirotti, S. Improving shadow suppression in moving object detection with hsv color information. In Proceedings of the IEEE Intelligent Transportation Systems, Oakland, CA, USA, 25–29 August 2001; pp. 334–339.
3. Abdusalomov, A.; Whangbo, T.K.; Djuraev, O. A Review on various widely used shadow detection methods to identify a shadow from images. Int. J. Sci. Res. Publ. 2016, 6, 2250–3153.
4. Horprasert, T.; Harwood, D.; Davis, L.S. A statistical approach for real-time robust background subtraction and shadow detection. In ICCV Frame-Rate WS. IEEE 1999, 99, 1–19.
5. Kim, K.; Chalidabhongse, T.H.; Harwood, D.; Davis, L.S. Real-time foregroundbackground segmentation using codebook model. Real Time Imaging 2005, 11, 172–185.
6. Yuan, C.; Yang, C.; Xu, Z. Simple vehicle detection with shadow removal at intersection. In Proceedings of the 2nd International Conference on Multimedia and Information Technology, Hong Kong, China, 28–30 December 2010; pp. 188–191.
7. Stauder, J.; Mech, R.; Ostermann, J. Detection of moving cast shadows for object segmentation. IEEE Trans. Multimed. 1999, 1, 65–76.
8. Amato, A.; Huerta, I.; Mozerov, M.; Gonsalez, J. Moving Cast Shadows Detection Methods for Video Surveillance Applications. In Wide Area Surveillance; Vijayan Asari, K., Ed.; Springer: Berlin/Heidelberg, Germany, 2014; pp. 23–47.
9. Katharavayan, R.S.; Nagarathinam, K. A Survey of Moving Cast Shadow Detection Methods. Int. J. Sci. Eng. Res. 2014, 5, 752–764.
10. Kim, D.; Arsalan, M.; Park, K. Convolutional Neural Network-Based Shadow Detection in Images Using Visible Light Camera Sensor. Sensors 2018, 18, 960.
11. Lee, J.T.; Kang, H.; Lim, K.T. Moving Shadow Detection using Deep Learning and Markov Random Field. J. Korea Multimed. Soc. 2015, 18, 1432–1438.
12. Lo, B.P.L.; Yang, G.-Z. Neuro-Fuzzy Shadow Filter; Imperial College of Science, Technology and Medicine: London, UK, 2014.

13. Q. Dong, Y. Liu, Q. Zhao, H. Yang, Detecting soft shadows in a single outdoor image:From local edge-based models to global constraints, published in Computer and Graphics, Vol. 38, pp. 310-319, 2014.
14. S.K. Wang, B. Qin, Z.H. Fang, Z.S. Ma, Fast Shadow detection According to the Moving Region, published in 6th International Conference on Machine Learning and Cybernetics, Hong Kong, pp 19-22 ,2007.
15. W.D. Yang, W. Gu, K. Peng, L.B. Liu, Research on Removing Shadow in Workpiece Image Based on Homomorphic Filtering, published in International Workshop on Information and Electronics Engineering (IWIEE), pp. 2360 – 2364 ,2012.
16. H. Asaidi, A. Aarab, M. Bellouki, Shadow Detection Approach Combining Spectral and Geometrical Properties, published in International Conference Multimedia Computing and System (ICMS), pp. 389-393, 2012.
17. A. Russell, J.J. Zou, Moving Shadow Detection Based on Spatial-Temporal Constancy, published in 7th International Conference on Signal Processing and Communication System, pp. 1-6, 2013.
18. B. Pan, J. Wu, Z. Jiang, X. Luo, Shadow Detection in Remote Sensing Images based on Weighted Edge Gradient Ratio, published in Geoscience and Remote Sensing Symposium (IGARSS) IEEE, pp.505- 508, 2014.
19. S.H. Khan, M. Bennamoun, Automatic Shadow detection and Removal from a Single Image, published in Transactions on Pattern Analysis and Machine Intelligence, IEEE, Issue 99, pp. 1-17, 2015.
20. L. Shen, T.W. Chua, K. Leman, Shadow Optimization from Structured Deep Edge Detection, published in Conference on Computer Vision and Pattern Recognition (CVPR),IEEE, pp. 2067 – 2074, 2015.
21. M. Russell, J.J. Zou and G. Fang, Real-time vehicle shadow detection, published in Electronics Letters, Vol.51, Issue 16, pp.1253-1255, 2015.
22. M. Qi, J. Dai, Q. Zhang, J. Kong, Cascaded Cast Shadow Detection Method in Surveillance Scenes, published in Optik - International Journal for Light and Electron Optics, Vol.125, Issue 3, pp. 1396-1400, 2014.
23. Amato, I.; Huerta, M.; Mozerov, M.G.; Roca, X.; Gonzalez, J. Moving Cast Shadow Detection Method for Video Surveillance Applications; Springer: Berlin/Heidelberg, Germany, 2012.
24. A. Prati, I. Mikic, M. M. Trivedi, and R. Cucchiara, "Detecting moving shadows: algorithms and evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 7, pp. 918–923, 2003.
25. A. J. Joshi and N. P. Papanikolopoulos, "Learning to detect moving shadows in dynamic environments," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 11, pp. 2055–2063, 2008.