A Novel Shadow Detection Method using Fuzzy Rule based Model

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***Abstract*— Computer vision applications such as object classification, human detection, action recognition, gait recognition, etc. are often facing challenges in terms of improper segmentation and tracking due to shadow effect. However, conventional shadow detection algorithms highlight the shadow variant and invariant features. The limitation comes from the fact that many approaches are not applicable for both outdoor and indoor shadows. They fail to detect shadow in different illumination conditions as well as a different geometric position such as ground shadow, vertical shadow, self-shadow, etc. Moreover, the limitation includes shadow detection in video sequence, where different threshold values have been computed for each change of frames due to the dynamic nature of the video sequence. As a result the complexity of the system increases. To overcome the above challenges, this paper proposes a fuzzy rule based model for cast shadow and self-shadow detection using three premises, variant properties such as R-channel spectral ratio from RGB, invariant properties such as a difference in chromaticity color space, and average image intensity. Fuzzy rules are employed using some training data sets. Then, another validation data set is used to check how the application of fuzzy rules reproduces the threshold values for various illumination conditions, as well as different environments (indoor, outdoor) and different texture based background. The proposed framework has been compared with other state-of-the art methods.**

Keywords*— cast shadow; chromaticity; shadow detection; fuzzy rules.

I. INTRODUCTION

In realistic environments, cast shadow is a major factor to consider for the development of robust system in computer vision. In dynamic scene analysis, the accuracy for object segmentation degrades a lot due to the cause of cast shadow, as a result tracking algorithm fails. The main hindrance of computer vision algorithms is the preprocessing of image or video to get rid of from shadow. In gait recognition the shadow can affect the proper contour of the subject, similarly

for object detection shadow can affect the position, shape, as well as contour. Moreover in the moving object, shadow pixels are very adjacent to the object pixels. In some cases, both shadow pixels and object pixels are merged to form a common pixel. These cause two important drawbacks: both the pixel intensity of object and subject is falsified by shadow, and geometrical shape is distorted.

There are many literatures to give reviews on cast shadow. A deterministic model is proposed in [7] for eliminating the shadow of pedestrian. The paper uses two cameras for estimating objects height and employs manual registration for removing shadow. The literature in [8] describes reflection method for cast shadow removal but fails to remove the outdoor shadows. Elgammal and Harwood [5] define a color domain method, which uses normalized RGB color components and lightness. The paper in [9] proposes outdoor shadow removal techniques in traffic scene. The method employee's multi-gradient operation between current frame and background frame, which aim to find most likely shadow regions. But it fails to recognize those shadow regions which has no clear boundaries. Another literature [4] works on shadow detection based on texture information. The algorithm is developed for moving cast shadow detection using Gaussian Mixture Model (GMM) technique. But the limitation is, an object must be predefined. The literature in [6] combines both statistical model and texture effects to remove shadow. However, it fails in indoor environment with multiple illuminations and degrades its performance in daytime, where the distribution of light is non-uniform. Chcchiara et al. [1] carries out his analysis on shadow detection using Hue-Saturation-Value (HSV) color space. The paper determines the threshold value empirically and computes the changing of HSV values due to shadow effect. However, many object pixels are vanished in this method.

In this study, a hypothesis of shadow is discussed, which describes the variant and invariant properties of shadow. Next step to detect the shadow pixels by utilizing the above properties. The threshold values of each property is synthesized the results by Fuzzy rule based models. So that the threshold values are adaptive automatically in different types of shadow (both indoor and outdoor). Both quantitative as well as qualitative results are shown in the improvement of performance of the proposed method.

The layout of this paper is as follows. Section II describes the hypothesis of shadow. The proposed scheme is introduced in Section III. Experimental set up and results are shown in Section III, and the paper is concluded in Section IV.

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II. Hypothesis Of Shadow

1. All Red-Green-Blue (RGB) values of shadow are lower than those in background.
2. In Hue-Saturation-Value (HSV) color space, the hue and saturation components of shadow pixels are a bit smaller than there points in background.
3. The shadow and the background have almost same texture.
4. Both shadow and the background are illuminated by different lights. Shadow illuminated by indirect lights while background illuminated by direct light.
5. A shadow and an object have same motion, but their locations are different.

III. The Proposed Model For Shadow Detection

The proposed model in *Fig. 1* depicts the shadow detection model. The features of each pixel of a frame are fuzzified and then defuzzified to give an absolute value which is compared to the pixel based intensity difference between a current frame and its background frame. The result is compared with a fixed threshold value to decide whether it is a shadow pixel or non-shadow pixel.

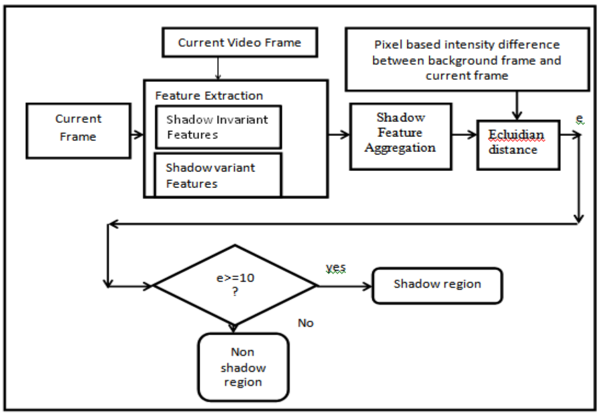


Fig. 1. The block diagram of the proposed model.

A. *Charecterization of shadow*

1) *Spectral properties of a shadow*

The spectral appearance of the shadow is the result of interaction among illumination, surface reflectance properties, and the responses of the chromatic mechanism as shown in *Fig. 2*. Dichromatic Reflection Model [8] gives an idea of physical interaction between illumination and object's surface. The radiance of light $L_r(\lambda,\vec{p})$, reflects at a given point $\vec{p}$ on a surface in the 3D space, given some illumination and viewing geometry, is formulated as

$$L_r(\lambda,\vec{p}) = L_a(\lambda) + L_b(\lambda,\vec{p}) + L_s(\lambda,\vec{p}), \quad (1)$$

where $L_a(\lambda)$, $L_b(\lambda,\vec{p})$, $L_s(\lambda,\vec{p})$ are the ambient reflection term, the body reflection term, and the surface reflection term respectively and λ is the wavelength. The ambient illumination term is assumed to account for all the light indirectly reflected among because an object is obstructing the direct light, then the radiance of the reflected light is

$$L_{r_{shadow}}(\lambda,\vec{p}) = L_a(\lambda), \quad (2)$$

which represents the intensity of the reflected light at a point in a shadow region.

Let $S_R(\lambda), S_G(\lambda)$, and $S_B(\lambda)$ be the spectral sensitivities of the red, green and blue sensors of a colour camera respectively. Three colour components of the reflected intensity reaching the sensors at a point (x,y) in the 2D image plane are

$$C_i(x,y) = \int_{\wedge} E(\lambda,x,y) S_{C_i}(\lambda) d\lambda, \quad (3)$$

where $C_i \in \{R,G,B\}$ are the sensor responses, $E(\lambda,x,y)$ is the image irradiance [3] at (x,y). Image irradiance is proportional to the scene radiance [8], for a pixel position (x,y) representing a point $\vec{p}$ in the direct light, the sensor measurements are

$$C_i(x,y)_{lit} = \int_{\wedge} \alpha(L_a(\lambda) + L_b(\lambda,\vec{p}) + L_s(\lambda,\vec{p})) S_{c_i}(\lambda) d\lambda \quad (4)$$

Giving a color vector $C_i(x,y)_{lit} = (R_{lit}, G_{lit}, B_{lit})$. α is the proportionality factor between radiance and irradiance. For a point in shadow the measurements are

$$C_i(x,y)_{shadow} = \int_{\wedge} \alpha L_a(\lambda) S_{c_i}(\lambda) d\lambda, \quad (5)$$

$C_i(x,y)_{shadow} = (R_{shadow}, G_{shadow}, B_{shadow})$. It follows that each of the three RGB color components decreases, when passing from a lit region (4) to a shadowed one (5), $R_{shadow} < R_{lit}$, $G_{shadow} < G_{lit}$, $B_{shadow} < B_{lit}$.

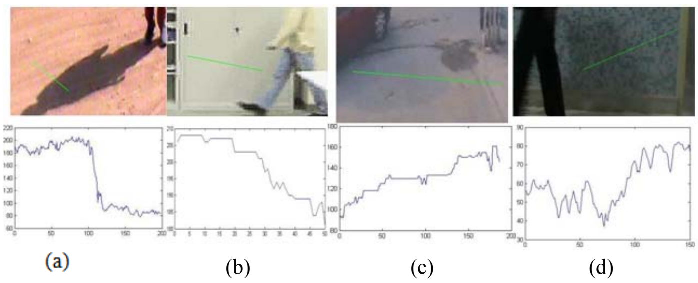


Fig. 2. First row: Shadow images. Second row: Pixel intensities difference of cross-section in the R-color channel of images shown by green lines. It gives sharp transition between shadow region and its neighborhood background region. (a) It is known as uniform shadow, (b) and (c) gives smooth transition between shadow and background is known as non-uniform shadow, (d) gives shadow transition on a texture based background.

2) *Shadow variant properties*

In *Fig. 3*, shadow variant features are shown. It describes different characteristics in shadow and in non-shadow regions. The first two hypotheses belong to shadow variant feature. The assumption is made to detect the cast shadow where the shadow regions are blocked from illumination effect. As a result, a sharp transition is made in the intensity level between the shadow and non-shadow region. These assumptions can be used to predict the range of intensity reduction of a region under shadow. Shadow variant cues are getting from luminance, R-channel or G–channel or B-channel from RGB, V-channel from HSV [5].

(a) (b) (c)

Fig. 3. Shadow variant features are shown by taking ratio between current frame and its background model frame, using Red-channel from RGB, luminance and V-channel from HSV on two sets of images in column a, b and c respectively.

Three different methods of separation of luminance from RGB channel is in (6), (7), (8).

$l = \sqrt{0.299R^2 + 0.587G^2 + 0.114B^2}$, where $l = luminance$

$$\zeta^{l}_{ratio} = \frac{C^{l}_{k}(x,y)}{C^{l}_{r}(x_r,y_r)} \tag{6}$$

$$\zeta^{R}_{ratio} = \frac{C^{R}_{k}(x,y)}{C^{R}_{r}(x_r,y_r)} \tag{7}$$

$$\zeta^{v}_{ratio} = \frac{C^{v}_{k}(x,y)}{C^{v}_{r}(x_r,y_r)} \tag{8}$$

(6), (7), (8) are spectral ratio in terms of luminance, red channel (R), V (intensity) from HSV. k and r represent the current frame and the background frame respectively.

3) Shadow invariant properties

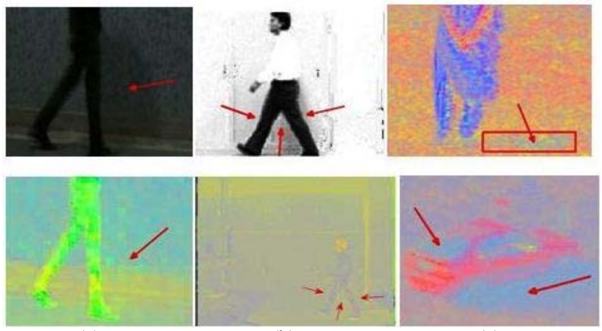
Shadow invariant features describe similar characteristics of shadow and its corresponding non-shadow regions. Chromaticity and saturation are two invariant cues. The difference of chromaticity in terms of hue, or normalized rgb or $c_1c_2c_3$ color space in between shadow region and its corresponding background region is quite small. Shadow region contains same color information as its background. But this behaviour of shadow shows only in indoor environment, it is quite different for outer shadow. In outdoor shadow region, the shadow is little bit bluish in color due to sky [6].

In *Fig. 4* there are two sets of outdoor and indoor images given in terms of $c_1c_2c_3$ spaces. $c_1c_2c_3$ spaces [6] are supposed to fulfil color constancy through using only chrominance color components. In indoor images the shadow regions are not visible in terms of color components due to invariant characteristics, whereas outdoor shadow regions are visible due to the nature of sky as shown in *Fig. 4(c)*.

Invariant property can be described as,

$$\psi_i(s) = C^{color}_{k}(s) - C^{color}_{r}(s) \tag{9}$$

where i is the index of invariant features, s is the shadow.



(a) (b) (c)

Fig. 4. Invariant properties of shadow at indoor and outdoor scene. In coloms (a), (b) of first row gives indoor rgb images and second gives $c_1c_2c_3$ color space shadow is not visible, in colom (c) gives outdoor images in $c_1c_2c_3$ color space where shadow pixel looks bluish.

B. Algorithm

Input: Reference pixel (x_r, y_r), current pixel (x, y)

Output: Shadow pixel $S_c(x, y)$

for *k =2: total no of frames*

for *x = 1:size of image in row*

for *y =1:size of image in column*

Compute color vector of current frame $\vec{C}_k(x,y) = (R(x,y), G(x,y), B(x,y))$

Compute color vector of reference frame $\vec{C}_r(x_r,y_r) = (R(x_r,y_r), G(x_r,y_r), B(x_r,y_r))$

Compute ratio in terms of R spectral component

$$\zeta^{R}_{ratio} = \frac{C^{R}_{k}(x,y)}{C^{R}_{r}(x_r,y_r)}$$

If $\zeta^{R}_{ratio} <= th_1$, *(where* th_1 *(threshold) <1 for shadow region)*

$S_c(x,y) = 1$; *Candidate shadow pixel*

else

$S_c(x,y) = 0$; *Non shadow pixel*

end

Compute color invariant property

Compute $c_1c_2c_3$ invariant color features

$$c_1(x,y) = \arctan\frac{R(x,y)}{\max(G(x,y), B(x,y))}$$

$$c_2(x,y) = \arctan\frac{G(x,y)}{\max(R(x,y), B(x,y))}$$

$$c_3(x,y) = \arctan \frac{B(x,y)}{\max(R(x,y), G(x,y))}$$

$$\psi_{chromaticity}(x,y) = (|c_1(x_r,y_r) - c_1(x,y)|, |c_2(x_r,y_r) - c_2(x,y)|, |c_3(x_r,y_r) - c_3(x,y)|)$$

if $\psi_{chromaticity_{(i)}}(x,y) <= f_i, for\ i = 1,2,3$

$S_c(x,y) = 1$

else

$S_c(x,y) = 0$

end

end

end

end

C. Design a Fuzzy Rule based System for Shadow Detection

Shadow detection can't be possible using a constant threshold value for different environment. The thresholding values change by changing luminance, brightness, scene characteristics, e.g. (indoor, outdoor). Fuzzy Rule Based system for shadow detection is constructed with a collection of related rule sets. The aim is to employ a fuzzy rule to automatic detect shadow.

The shadow region is exactly determined by the three set of thresholds which are described in the above section. To express the concept of "shadow" in fuzzy terms, we consider the intensity difference between the pixel of shadow to its corresponding pixel of background. To establish 'IF-THEN' rules, we take some sample data from selected shadow region and find out its relation between output and input.

D. System Overview

It is a three inputs and single output fuzzy inference system. The features of shadow of an image are analyzed using fuzzified technique and implemented based on fuzzy inference method. The fuzzy inference system consists of four basic parts; Fuzzifier, Inference system, rule base, defuzzifier [10]. In fuzzification step the inputs are processed to determine the degree of its fuzzy sets using membership functions. A membership function defines the mapping between each point in the input space x to a membership value or degree of membership $\mu(x)$. The threshold features of shadow are selected as inputs from section 2.1, each input is described by its linguistic variables.

Average image intensity (I): The first input is to classify the image according to its intensity levels. It has five linguistic values, very low intensity (vl); low intensity (l); low medium intensity (lm); medium high intensity (mh); high intensity (h). Ratio of pixel of current frame to its corresponding background of Red-channel (ζ^R_{ratio}): It has six linguistic values, very low ratio (vl); low ratio (l); Low medium ratio (lm); medium high ratio (mh); high (h); very high ratio (Vh). Difference of $c_1c_2c_3$ color space based illumination between current frame and background ($\psi_{chromaticity}$): It is described by its three linguistic variables such as *low* , *medium* , *high* .

IV. EXPERIMENTAL RESULTS AND DISCUSSION.

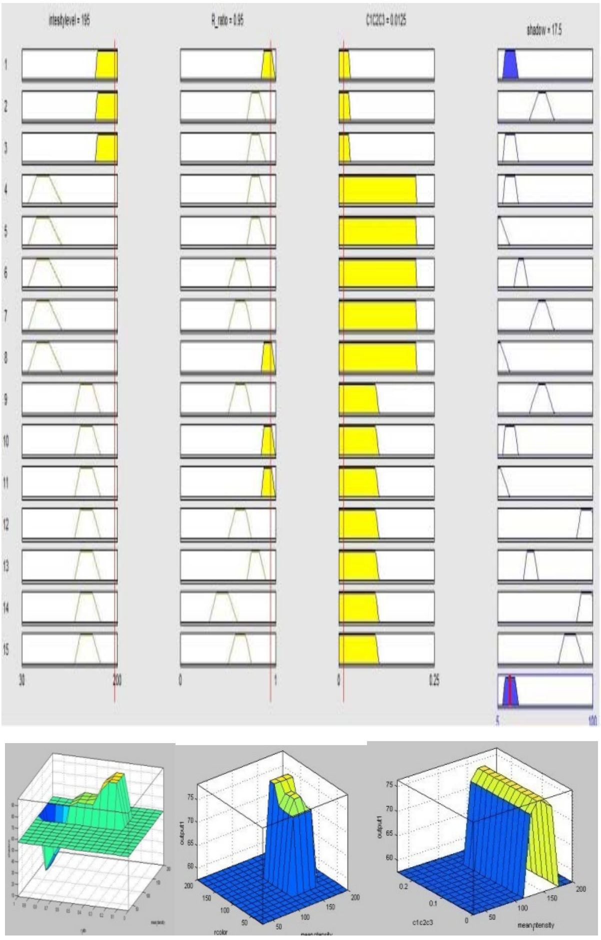
A. Test Set

In this section we explore the performance of our approach and discuss the parameters which are involved in the above methods and estimation. The experiments have been carried out on different test video sequences such as Campus, Laboratory and Intelligent video sequences, and own made database of outdoor and indoor video sequences. We manually select both outdoor and indoor shadow regions and calculate the value of spectral ratio ζ^R_{ratio} and difference of $c_1c_2c_3$ color parameter $\psi_{chromaticity}$, and also find mean intensity of overall image. Because the illumination is directly proportional to the light intensity (luminance intensity), i.e. $I = L/r^2$, where I is the illuminance, L is the luminance intensity of light, r is the distance between source of light and surface. So the first input of FIS system is divided into five different set of intensity levels, from low to high, which makes the system adaptive for shadow detection at different illuminance conditions. The average intensity of campus_raw, laboratory video, outer video, and indoor video (less illumination) are 123, 173, 135, 81, 138 intensity level respectively. The second input is ζ^R_{ratio} having range 0-1. So we divide the overall range into 5 different spectral range. The last input is having range 0-.25. We divide the range into three sets according to outdoor and indoor regions. The chromaticity difference of shadow in indoor region is almost '0', but the outdoor region is having little-bit higher value.

When any video sequence is given to the system it first models its background frame. Each time current frame is compared to its background frame on a pixel basis manner in terms of ζ^R_{ratio} and $\psi_{chromaticity}$. If any pixel has either the value of ζ^R_{ratio}>1 or $\psi_{chromaticity}$>.25 then it consider as non-shadow pixel. If not, then this pixel is showing the shadow property as well as background property. It is in the form of uncertainty. So we use Fuzzy inference system (FIS) system to detect the shadow pixel. In *Fig.5* shows feature rule evaluation. FIS system is based on human intuition. Outer shadows are darker as compared to indoor shadow. By doing experiments we came to know that ζ^R_{ratio} is quite low for darker shadow and is high for light shadow. The value of difference of chromaticity component $\psi_{chromaticity}$ is very low to 0 for indoor shadow region, The difference of chromaticity component $\psi_{chromaticity}$ for outer shadow is little-bit higher than indoor, because shadow looks bluish having more color components due to sky. This chromaticity component $c_1c_2c_3$ space basically used for self-shadow detection.

B. *Fuzzy Based Thresholding Results*

The fuzzy based thresholding comprises input processing of features based on fuzzy rules and the threshold value is processed as an output. *Fig.5* shows the fuzzy rule base for the inference system, where fifteen rules are there for calculation of fuzzified pixel intensity. From the fuzzy output, centre of gravity deffuzification has been arriving at crisp output. When a new input frame comes with some shadow region, each pixel of its two features are fed into the FIS to calculate the fuzzified intensity range of shadow. Each pixel is classified as shadow pixel if its fuzzified value lies between a specific range. The specific range is the addition and subtraction of a constant numeric value 5 to the intensity difference between shadow pixel and the background pixel. Otherwise it is known as non-shadow pixel.



(a) (b) (c)

Fig. 5. Fuzzy rule evaluation for feature of shadow aggregation shows above. A three dimensional simulative sketch map of fuzzy inference plotting, (a) shadow vs. I, (b) shadow vs ζ^{R}_{ratio} , (c) shadow vs $\psi_{chromaticity}$.

C. *Quantitative Performance Evaluation*

In order to systematically evaluate a shadow detection algorithm, it is useful to identify the following two important quality metrics: shadow detection rate η and shadow discrimination rate ν

$$\eta = \frac{TP_S}{TP_S + FN_S} \text{ and } \nu = \frac{T\overline{P}_F}{TP_F + FN_F} \tag{10}$$

where S denotes shadow and F denotes foreground. $T\overline{P}_F$ is the number of ground-truth points of the foreground objects minus the number of points detected as shadows, but belonging to foreground objects. Based on the metrics of (10), Table I and Table II provide a quantitative and qualitative comparison of the proposed algorithm and comparisons with state-of-the-art methods. Extensive experiments have been carried out on different test sequences. Among the test sequences, two indoor and one outdoor scene with different illumination are shown in *Fig. 6*.

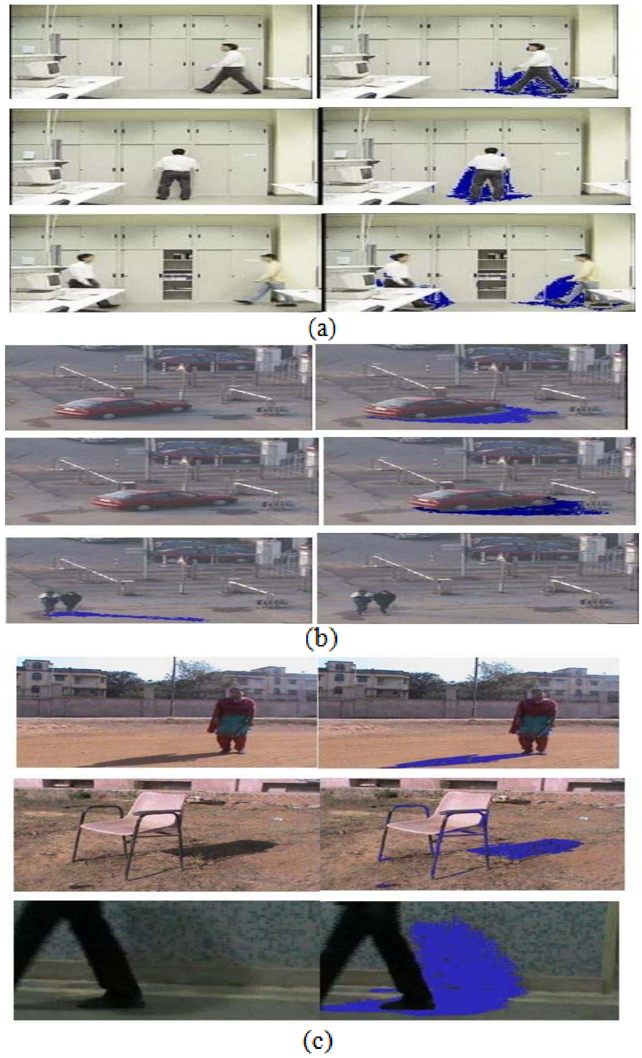


Fig. 6. Subjective comparison of proposed method of , the 100th, 150th, 485th and 150th , 165th and 300th Frames of laboratory and campus videos respectively in (a) and (b) and in (c) own made database.

TABLE I. QUANTITATIVE COMPARISON BETWEEN DIFFERENT ALGORITHMS AND DIFFERENT TEST VIDEO SEQUENCES.

Database	**Laboratory**		**Intelligent room**		**Campus**		**Own database (Outdoor)**		**Own database (Indoor)**	
Algorithms	η%	ν%	η%	ν%	η%	ν%	η%	ν%	η%	ν%
Cucchiara et al. [1]	65.4	92.4	79.9	87.8	78.4	71.4	90.8	90.8	85.6	76.4
Chung et al. [3]	87.7	88.3	85.1	76.6	69.6	76.3	**NA**		**NA**	
Yue Wang [5]	69.9	75.5	73.5	86.5	72.2	80.1	**NA**		**NA**	
Shoaib et al.[4]	84.8	86.1	83.2	88.2	86.3	79.6	**NA**		**NA**	
Lin et al. [11]	75.2	83.6	79.6	79.1	78.4	72.5	**NA**		**NA**	
Deb et al. [11]	81.5	83.5	83.2	85.3	89.5	91.7	88.7	90.4	82.6	76.8
Proposed Method	**89.3**	**92.6**	**88.6**	**88.9**	**88.0**	**97.7**	**88.9**	**86.5**	**85.8**	**91.5**

D. Qualitative Evaluation.

TABLE II. QUALITATIVE EVALUATION OF ALGORITHMS**.** THE INFORMATION HAS BEEN OBTAINED FROM [8].

Algorithm	**Robustness to noise**	**Flexibility to Shadow**	**Shadow Detection**	**Illumination Independence**	**Computational Complexity**
Cucchiara et al. [1]	High	Medium	Medium	Medium	Low
Chung et al. [3]	High	Medium	High	Low	High
Yue Wang [5]	Low	Low	Low	Low	Low
Shoaib et al.[4]	Low	Medium	Low	Low	Low
Lin et al. [11]	Medium	High	Medium	Low	Medium
Deb et al. [11]	Medium	Medium	High	High	Low
Proposed Method	**High**	**High**	**High**	**High**	**Medium**

V. CONCLUSION

In this paper, we proposed a novel approach for shadow detection both in outdoor and indoor scene. The shadow hypotheses are considered to give more focus on the properties of self-shadow and cast shadow. The analysis gives the inference that the chromaticity of both shadow and non-shadow regions are remain same and only differentiate in terms of brightness. The proposed method is demonstrated through a number of manually captured video sequence and test video sequences. The improvement has been quantified by means of an objective evaluation metric. The proposed algorithm gives high robust to noise, high level shadow detection on different illumination condition. So it is highly illumination independent. In future work the membership functions and rules are decided using optimized algorithms.

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