Shadow Detection and Removal from Real Images: State of Art

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Shadow Detection and Removal from Real Images : State of Art

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ABSTRACT
Shadow detection and removal is used in various image processing applications like video surveillance, scene interpretation and object recognition. Ignoring the existence of shadows in images may cause serious problems like object merging, object lose, misinterpretation and alternation of object shape in various visual processing applications like segmentation, scene analysis and tracking. Many algorithms have been proposed in the literature, that deals with shadow detection and removal from images as well as videos. A comparative and empirical evaluation of the existing approaches in video has already been reported, but we lack a similar one in case of still images. This paper presents a comprehensive survey of existing shadow detection and removal algorithms reported in the case of still images. Evaluation metrics involved in shadow detection and removal techniques are discussed and the inefficiency of conventional metrics such as; per pixel accuracy, Precision, Recall, FScore etc in detection phase are also explored. Quantitative and qualitative evaluation of selected methods are also discussed. To the best of our knowledge this is the first article that exclusively discusses shadow detection and removal methodologies from real images.

Keywords
Shadow detection, Shadow removal, Per pixel accuracy, Precision, Recall, FScore, MCC.

1. INTRODUCTION
Methodology and purpose of shadow extraction in still image and video is fairly dissimilar. In videos, information from previous frames is also available for shadow detection, whereas in images we have to rely on the geometrical and statistical features of the shadow in a single image to exactly segment shadow.

Shadow detection is mainly used in video surveillance system as a pre-processing step to achieve better performance in applications such as object tracking[1] and automated driving [2]. Whereas in images depending on the type of input images such as indoor, outdoor or satellite; shadow detection and removal finds applications in object recognition[3] and scene interpretation[4]. For example, images are often analyzed, to infer the geometry of the objects causing the shadow, to obtain the 3D analysis of objects to extract geometry of object [4] or to find light source direction [5]. Other important applications include enhancing object localization and measurements, especially in aerial image for recognizing buildings [3],[6],[7] for obtaining 3D reconstruction of the scene [8], or detecting clouds and their shadows [9].

A comparative and empirical evaluation of existing shadow detection approaches in video has already been reported by Andrea Prati et al. in 2003[10], Al-Najwadi et al. in 2012[11] and Sanin et al. in 2012[12]. Shadow detection algorithms are classified into two-layer taxonomy, mainly statistical and deterministic by Andrea et al. [10] and four representative algorithms are described in detail. Al-Najwadi et al. [11] categorizes methods based on object/environment dependency and implementation domain. Sanin et al. [12] categorizes works reported till date into a feature-based taxonomy comprising of four categories: chromaticity, physical, geometry and textures. Authors of [10] [11] [12] provide quantitative and qualitative evaluation of the works reported at the time using benchmark set of videos available. Another interesting review by Dee and Santos [13] is an interdisciplinary discussion about cast shadow which throws light into the theoretical aspect of cast shadow formation. This review also discusses about, the perception of shadows in human and machine vision, and the ways in which the human perceptual system makes use of information from shadows. But the above reviews [10] - [12] are specific for videos and a similar one exclusively for images has not been reported so far. Such a review might be helpful to researchers, planning to work in the area.

1.1 Shadow
A shadow is formed when an opaque object obstructs the path of direct light. Physicists consider shadow as an optical illusion. A shadow doesnt possess any wavelength properties so it cannot be scientifically measured.

Generally, shadows are of two types: self shadow and cast

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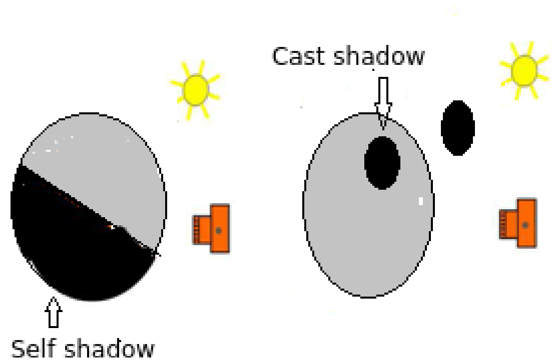

Figure 1: Self shadow and Cast shadow.

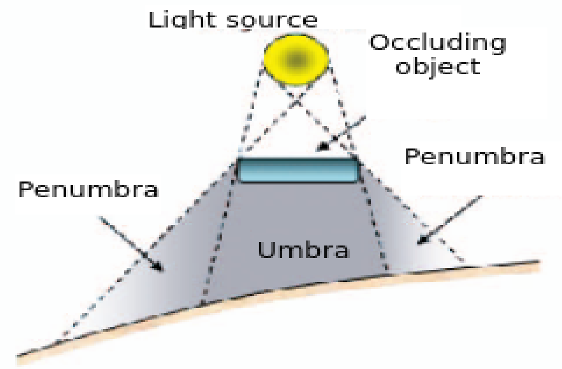

Figure 2: Umbra and Penumbra regions

shadow(See Fig.1). A self shadow is the part of the shadow where illumination is completely absent. Shadow cast by an object onto the background of a scene is called cast shadow. For a non-point source of light, a cast shadow is further sub-divided into umbra and penumbra regions. Umbra is the darker central part which gets no light at all. The rest of the shadow is lighter and is called the penumbra(see Figure 2). Union of the umbra and the penumbra region gives the shadow. Ambient light may be present in umbra and penumbra[14].

1.2 Shadow basic model

Barrow and Tanenbaum in 1978 proposed a model about the formation of image[15]. The model defines an image I(x,y) as composed of reflectance component R(x,y) and the illumination component L(x,y) as follows

$$I_k(x, y) = R_k(x, y) \bullet L_k(x, y) \tag{1}$$

where k ϵ R,G,B and '$\bullet$' denotes pixel-wise multiplication. In shadow regions illumination is reduced and image intensities are reduced by multiplicative scalars of $C_k(x, y)$. Thus, (1) can be rewritten as:

$$I_k(x, y) = R_k(x, y) \bullet L_k(x, y) \bullet C_k(x, y) \tag{2}$$

Hence in log domain, shadow implies an additive change in intensities. Many works have been reported in literature which tries to reduce the additive shadow component. However, separating shadow regions from near black regions needs intelligent shadow segmentation methods, and hence, it is not a trivial task. Self-shading, inter-reflection, non-uniform shadow, geometry of the object casting shadow and the artefacts involved in image capturing make the process of shadow detection more complicated.

The rest of the paper is organized as follows: Comprehensive review of major papers in the area of shadow detection and removal is carried out in Section 2. Evaluation metrics used, qualitative and quantitative evaluation of selected methods in the area of shadow detection and removal is discussed in Section 3. Finally the paper is concluded in section 4.

2. REVIEW OF SHADOW DETECTION AND REMOVAL APPROACHES

In the last fifteen years, several shadow detection and removal algorithms have been proposed in the literature for still images, satellite images and videos which make use of learning techniques, color models, invariant images etc for shadow detection and removal. Most of the works reported in the area of moving shadow detection are specific to a particular domain like traffic monitoring and video surveillance systems. Hence, they are not suitable for real images. Even certain works in shadow detection from still images consider soft shadow[16] and hard shadow[17] separately. A general method which can be commonly applied to all categories has not been devised till now. State of the art methods that use multiple images, video frames have given impressive results, but segmenting shadows accurately from a single indoor or outdoor image having various geometrical features and illumination constraints is extremely challenging. This is because the appearances and shapes of indoor and outdoor shadows depend on several factors such as direction, colour, geometry, shape and material properties of occluding object and surface onto which the shadows are cast.

Researchers have contributed various algorithms and we find it difficult to fit those methods to different approaches. Generally shadow removal involves two basic stages: detection of shadow regions, typically expressed in the form of shadow edges followed by removal of detected shadows. Shadow removal involving invariant image follows different approach. Here the main task is generating an invariant image, which is free from shadows. Depending on the methodologies involved we classify the shadow detection and removal works reported in the last few years into the following categories.

- Shadow detection and removal based on Invariant image
- Shadow detection based on feature extraction and learning
- Shadow suppression techniques
- Other approaches

2.1 Shadow detection and removal based on Invariant image

Invariant image formation uses the basic model discussed in Section 1.2 and aims to separate an image into its reflectance and illumination components. Reflectance component will be invariant to both color and intensity of the scene,

Table 1: Shadow detection and removal based on invariant image-Highlights

Author, Year	Detection/ Removal	Remarks
Salvador, Cavallaro 2001 [18]	Detection	Applicable to indoor environment. Restrictions : Shadow should cast on flat and non-textured surfaces. Light source must be single and strong.
Finlayson, Hordley, Drew. 2002[19]	Detection and Removal	Requires calibrated camera. Do not deliver photo quality images.
Finlayson, Hordley, Drew 2006 [20]	Removal	3D representation is more complex. Produces good quality output image. Post- processing :inpainting.
Finlayson, Drew, C. Lu 2009 [21]	Removal	No need of camera calibration and prior assumption of image. Works for colour images
Yang, Tan and Ahuja.2012[22]	Removal	Uses bilateral filtering to recover 3D intrinsic image. Works for colour images
Zhu, Chen, Xia and Zhang 2015 [23]	Removal	Based on YCbCr colour space and concept of bilateral filtering. Works for colour images

and hence it will be shadow free. The main problem in recovering an invariant image from intrinsic scene characteristics of a digital image is that a single intensity value contains all the characteristics of the corresponding pixel. Earlier, intrinsic image formation requires a calibrated camera or a sequence of images. Later many other authors worked on the idea and came up with methods that exploit physical and natural constraints so as to form an invariant image. This section provides a brief idea about shadow detection and removal methodologies making use of invariant image.

Salvador et al.[18] proposed a method to identify and classify the shadows in colour images using invariant color models. Luminance and colour information are used to detect shadows. This method also classifies the shadow as self or cast shadow. But the algorithm sets much restrictions, that makes the method limited for a certain set of images where environment is simple and shadows should fall on flat, nearly flat or non-textured surfaces. Other restrictions are objects must be uniformly colored and there should be a single strong light that illuminates the scene. Once these conditions are satisfied result will be satisfactory.

A good number of work in the area of shadow detection and removal using invariant image has been proposed by Finalyson along with his colleagues and students [19] -[21] In general,many of these methods are based on forming an invariant image free from shadow followed by shadow removal. The most difficult part in this approach is to generate an invariant image.

Finlayson et al. [19] proposed a method to locate the shadows by generating an illumination-invariant image, in which the shadows do not appear. The illumination-invariant image is used with the original colour image to locate the shadow edges. The edge representation is reintegrated and edges are set to zero to get the shadow-free image. This method requires images acquired using a calibrated camera to generate an illumination-invariant image.

In another work reported by Finlayson et al. [20], shadow removal procedure involves three phases. A one dimensional shadow free gray scale illumination invariant image is formed in first phase from which an equivalent 2D chromaticity shadow free representation is derived in phase 2. In phase three, a 3D shadow-free full color image representation is recovered. A number of parameters are involved in the recovery algorithm which makes the method more complex.

Finlayson et al. [21] proposed that the shadows can be removed by minimizing quadratic entropy. Producing a 1D projection, in the correct invariant direction will result in a 1D distribution of pixel values that have smaller entropy than projecting in the wrong direction. The detection of shadows is more complicated in the case of monochromatic images, than colour images. The algorithm works fine if strong shadow edges are present in the image.

Yang et.al.[22] proposes a method to remove shadow using bilateral filtering and the 2-D intrinsic image. The input RGB image and the intrinsic image is decomposed into a base layer and a detail layer. Final shadow-free image is obtained by combining the base layer from the input RGB image and the detail layer from the intrinsic image. The reduction in luminance in the derived 3-D intrinsic image is corrected by transferring the details of the intrinsic image. The author doesnt provide a quantitative evaluation but resulting images are visually pleasing.

A method to remove shadow using the concept of bilateral filtering and narrowband camera sensors was presented in [23]. The method is based on the assumptions of Lambertian reflectance and Planckian lighting. Here shadow removal is a secondary procedure and primary goal was to find an intrinsic reflectivity image. The result of shadow removal as given in the paper is not up to the marks and the paper lacks a quantitative evaluation of the results.

Discussion

The higlights of works [18]-[23] reviewed in this section are summarized in Table 1. The main requirement of this approach is the formation of an invariant image which requires a calibrated camera or a sequence of images. Illumination invariant image formation results in the loss of photo quality of image. As a post processing many works are depending on image in-painting for visual clarity.

2.2 Shadow detection based on feature extraction and learning

Learning based methods require feature extraction followed by training and classification. Features include geometrical, statistical and colour features to correctly segment

Table 2: Shadow detection using feature extraction and learning: Highlights

Author , Year	Detection/ Removal	Features used and Classifier	Highlights	Evaluation Metrics and Datasets
Gijsenij et.al 2009 [24]	Detection	**Features**:Geometric- SIFT, Local Binary Pattern, Grey-level Co- occurrence Matrix Photometric- Physics-based invariants, Color constancy at a pixel, Normalized-rgb **Classifier**: Nearest neighbour classifier	Geometric features consider edge information also.	Accuracy=82% Own dataset
Zhu et al. 2010 [25]	Detection	**Features**: shadow invariant, shadow variant and near-black features. **Classifier**: Boosted decision tree along with Conditional Random Field (CRF).	Applicable to indoor and outdoor monochromatic image.	Accuracy= 87.3% Dataset[a]
Lalonde et al. 2010 [26]	Ground Shadow Detection	**Features** : Intensity, texture and colour features on both sides of edges. **Classifier** :Decision tree classifier and CRF.	Outdoor ground shadows only. Fails in detecting thin structure shadow.	Accuracy=80.5% Dataset[b]

[a] \http://www.cs.ucf.edu/k̃egan/shadows.html
[b] \http://vision.gel.ulaval.ca/ jflalonde/projects/shadows/

shadow region.

Shadow edge detection using geometric and photometric features is proposed in [24]. Initially, thousands of patches are annotated and labelled as either containing a shadow edge or not. Then, the geometric features of these patches are analyzed and a classifier is trained to distinguish between shadow and non-shadow patches. The combination of photometric and geometric features is exploited for classification of shadow edges in addition to using either photometric or geometric features. The authors provide accuracy evaluation using Area under Receiver operating characteristics(ROC) curve(AUC) using their own dataset.

A learning based method was proposed in [25] to detect the shadows from monochromatic image using a shadow variant, shadow invariant and near-black features. This method is based on boosted decision tree classifier along with a Conditional Random Field (CRF). To learn the CRF parameters, they used a Markov Random Field (MRF) model for labelling. When applied, BDT and CRF together provide an accuracy of 87.3%.

Lalonde et.al [26], uses a trained decision tree classifier to detect ground shadow edges in outdoor images. The shadow edges are then grouped by CRF based optimization. This method mainly focuses on the shadows cast by objects onto the ground plane hence the type of materials on the ground in outdoor scenes is limited to mud, grass, brick etc. for the method.

Discussion

Table 2 summarizes the highlights of learning based shadow detection approaches reviewed in this section [24] - [26]. Feature based techniques detect shadows using its features. The most noticeable feature of a shadow is that it darkens the surface it cast on, hence shadows usually have lower pixel values. But pixels that have lower values may not be shadows. Computer vision techniques cannot directly judge that a dark region is a shadow or a black object. Therefore, most methods combine more than one features like edge, texture, geometry property, histograms and color ratios. Feature-based approaches are more flexible and can be applied to a wider class of scenes.

2.3 Shadow suppression techniques

Shadow suppression involves interactive and automatic techniques.

2.3.1 Interactive shadow suppression approaches

Many applications demand high quality images after shadow removal. Once shadows are manually/interactively detected many algorithms produce high quality shadow free images. Hence, these methods come under semi-automatic approaches.

In Bayesian approach of shadow detection proposed by Wu and Tang [27], user supplies a quadmap. These user supplied hints are encoded and employed in the effective likelihood and prior functions for Bayesian optimization. To solve the optimization, a decent estimation of the shadowless image is obtained by solving the associated Poisson equation with the necessary boundary conditions. Bayesian extracts smooth shadows while preserving texture appearance under the extracted shadow.

Pyramid based shadow detection and removal by Y. Shor et al.[28] requires user assistance to identify shadowed and lit areas. These areas are used to estimate the parameters of an affine shadow formation model. Pyramid-based restoration process is then applied to produce a shadow-free image. For varying shadow intensity inside the shadowed region they process it from the interior towards the boundaries. To ensure a seamless transition between the original and the recovered regions they apply image inpainting along a thin border.

An interactive approach to extract shadow from an image is proposed by Miyazaki et al.[29]. The image is segmented and the user is allowed to specify shadow, non shadow and background regions. This method performs shadow removal by graph cut algorithm.

Eli Arbel and Hagit proposes a method to remove shadow using intensity surfaces and texture anchor points[30]. Shadow detection part requires user input for shadow region labelling. This method preserves the original texture in shadow free regions and wide penumbra areas and is applicable in shadows cast on flat or curved surfaces. Post-processing further enhance the visual clarity and reduce the effects of noise.

Gong et.al.[31] proposes a shadow removal method that

Table 3: Interactive shadow suppression approaches:Techniques used and highlights

Author,Year	Method	Remarks
Wu and Tang 2005 [27]	**User input** : Quadmap **Removal**: User supplied hints are encoded and employed in the effective likelihood and prior functions for Bayesian optimization which is further solved using the associated Poisson equation with the necessary boundary conditions.	Bayesian extracts smooth shadows while preserving texture appearance under the extracted shadow
Yael Shor and Dani Lischinski 2008 [28]	**User input**: User selects seed points of shadowed areas. **Removal**: Pyramid-based restoration process is then applied to produce a shadow-free image.	Post processing- inpainting
Miyazaki et.al. 2010 [29]	**User input**: Shadow, non-shadow and back ground regions. **Removal**: Graph cut energy minimization	Applicable to soft and hard shadow
Eli Arbel and Hagit Hel-Or 2011 [30]	**User input** : Labelled shadow region **Removal**: Each image channel is considered as an intensity surface and approximates the shape of the intensity surface in shadow regions .	Preserves the original texture in shadow-free regions and wide penumbra areas. A high quality shadow-free image is obtained.
Han Gong and Darren Cosker 2014 [31]	**User input** : Pixels of the shadow and the lit area. **Removal**:Registering the penumbra to a normalised frame which allows to efficiently estimate non-uniform shadow illumination changes and thereby remove shadow.	Texture preserved. Works fine for colour images.

Table 4: Automatic shadow suppression approaches:Techniques used and highlights

Author,Year	Method	Remarks
Finlayson et al. 2002 [32]	Follows retinex paths. **Removal**: Multiplying with scale factor.	Pixel based. Computationally expensive.
Fredembach and Finlayson 2004 [33]	Follows hamiltonian paths but enters and leaves shadow region only once. **Removal**:Shadow and non shadow regions are reintegrated separately	Coloured noise is present
Fredembach and Finlayson 2005 [34]	Follows Hamiltonian paths. **Removal**: By setting gradient value in shadow region to zero.	Computationally less complex than [18] Visual artefacts exist after shadow removal.
Fredembach and Finlayson 2006 [35]	**Removal**: The constant for R, G and B channels are calculated separately and added to shadow region.	Simple, fast. Computationally less complex and less artefacts than [18] [25]. Post- processing inpainting.
Arbel and Hel-Or 2007 [36]	**Removal**: Calculate different scale factors for umbra and penumbra regions.	Texture preserved, Applicable for curved surfaces and outdoor images

takes as input two rough user inputs for the pixels of the shadow and the lit area. Using this they derive a fusion image that magnifies shadow boundary intensity change due to illumination variation. After detection, shadow removal is performed by registering the penumbra to a normalised frame which allows to efficiently estimate non-uniform shadow illumination changes, and to perform removal.

Discussion

Table 3 summarizes the advantages and disadvantages of the interactive shadow suppression approaches reviewed in this section[27] -[30]. Applications that demand high quality shadow free image can depend on interactive shadow removal approaches. Since they demand user assistance it cannot be listed under fully automatic methods.

2.3.2 Automatic shadow suppression approaches

There are many other methods which nullify the effect of shadow. It can be based on reintegration or multiplying shadow pixels using a scale factor.

Suppression of shadows using multiple Retinex paths was proposed in [32]. Reintegration by solving Poisson equation and using a large number of random paths in retinex method are both computationally expensive. Instead of retinex paths averaging the results of reintegration along a selected Hamiltonian paths in the image was proposed in [34] .

Fredembach and Finlayson [33] proved that by closing the shadow edges before reintegration the error propagation can be reduced . This algorithm is based on the observation that shadows in images are closed regions and if they are not closed artefacts can result during reintegration. To reduce artefacts, shadow and non shadow regions are reintegrated almost separately. Reintegration is done along Hamiltonian paths in the image that enters and leaves the shadow region only once. But reintegration using Poisson equation [30] gives better results.

Fredembach and Finlayson [35] proposed that the shadow and non-shadow regions differ by a single constant, which can be calculated easily for R, G and B channels separately. The constant when added to the shadow region will reduce the difference between the shadow region and the background. Proposed method is simple, fast and efficient once the location of shadows has been given.

A method to remove the shadows from curved areas is proposed in [36]. The effect of shadows cancels each other by calculating different scale factors for penumbra regions and shadow regions. This method also takes surface geometry when computing the scale factors.

Discussion

Table 4 summarizes the techniques, advantages and drawbacks of automatic shadow suppression approaches [32]- [36]. Many methods require manual intervention or need useful information like time zone and camera parameters to perform shadow detection.

2.4 Other Approaches

Some of the other prominent approaches in the literature are region based, color plane based, statistical, gradient domain based, and shadow matting. These are briefly reviewed in the following subsections.

2.4.1 Region based approach

A paired region-based approach to detect and remove the shadows from an image was proposed by Ruiqi et al. [37]. Using relative illumination and graph-cut, shadow and non-shadow regions are labelled. Detected shadows are later refined by image matting and-pixels relighting to recover an image free from shadow. The author provides quantitative and qualitative evaluation of the approach with standard dataset.

2.4.2 Colour plane based approach

Shadow detection method which works on the average value of a and b planes of an Lab image is proposed by Saritha and Govindan [38]. Those pixels having intensity values less than a threshold are classified as shadow pixels, and others as non-shadow pixels. The method works well only for images whose yellow to blue ratio is maintained within a range. The shadow removal is done by multiplying the shadow region by a constant. As a post processing step, shadow edge correction is performed to reduce the errors due to diffusion in the shadow boundary. The drawback of the approach is that the dark objects are likely to be misclassified as shadow areas.

2.4.3 Statistical approach

In [39] Germain et al. proposes a method based on a probability shadow map. Shadow detection method uses a near infra-red image along with a colour image for detecting shadows. Here, shadow removal is performed by illuminating the shadow region till it gets the same illumination as the surroundings. The texture is retained and it is able to successfully remove both umbra and penumbra shadows.

2.4.4 Fuzzy approach

Split and merge is a classical algorithm used in image segmentation. Remya and Govindan [40] proposed a method to detect shadow using fuzzy split and merge approach. The method follows a recursive approach of splitting an image into homogeneous quadtree blocks, followed by merging adjacent unique shadow regions.

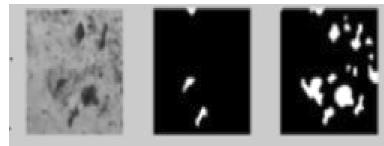

Figure 3: Left-Input Middle-Result Right-Ground truth

Table 5: Shadow detection confusion matrix of image in Fig 3

	Shadow	Non-shadow
Shadow(GT)	0.9552	0.0448
Non-shadow(GT)	0.8925	0.1075

Table 6: Perceptual quality metric values for image in Fig 3

PPA	Precision	Recall	Fscore	MCC
89.35	0.95	0.89	0.92	0.32

2.4.5 Shadow Matting

Wu et al. [41] proposed a method for shadow removal using shadow matting. The method finds shadow intensities based on shadow and non-shadow intensity ratios in the umbra and uses a Bayesian framework for regularization of shadow scale factors in the umbra and penumbra regions. The method removes soft shadows and preserves texture at shadow boundaries.

3. PERFORMANCE EVALUATION

This section discusses freely available datasets, various evaluation metrics and a qualitative and quantitative evaluation of selected methods in shadow detection and removal.

3.1 Datasets

Standard datasets for shadow detection research is available from University of Central Florida's database created by Zhu et al.[25] [1]. This dataset consists of 245 images, with manually labelled ground truth shadow masks useful for detection evaluation.

Gong et.al. [31] provides shadow removal dataset consisting of 186 test cases, which contains challenging categories for soft, broken, colour and shadows cast on strong textured surfaces as well as simpler shadows, plus 28 examples from [37] resulting in 214 test cases in total. The database is available in Bath university website and an to encourage the open comparison of single image shadow removal, they provide an online benchmark site. [2]

Ruiqi et al.[37] provide datasets for shadow detection as well as removal and is available in University of Illinois database.[3] This dataset consists of 108 indoor as well as outdoor image pairs, photographed under a variety of illumination conditions. This dataset provide shadow free image as well as ground truth of shadow region hence the dataset is useful for evaluating shadow detection and removal.

[1]http://www.cs.ucf.edu/ kegan/shadows.html
[2]http://www.cs.bath.ac.uk/ hg299/shadow-eval/
[3]http://aqua.cs.uiuc.edu/site/projects/shadow.html

3.2 Evaluation metrics-Shadow detection

Most of the shadow detection works, reported in still images have not performed quantitative evaluation of the result. Very few works have reported evaluation in terms of Per pixel Accuracy [25] [26] [37] . Perceptual quality metrics which are applicable in shadow detection are; Accuracy(3), Precision(4), Recall(5), FScore(6) and Mathews Correlation Coefficient(MCC) (7). These metrics are computed in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) computed on per pixel basis.

$$Per\ pixel\ accuracy, PPA = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$FScore = \frac{Precision * Recall}{Precision + Recall} \quad (6)$$

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (7)$$

TP-Number of shadow pixels correctly classified as shadow
TN-Number of nonshadow pixels correctly classified as nonshadow
FP= Number of shadow pixels incorrectly classified as nonshadow
FN=Number of non-shadow pixels incorrectly classified as shadow

Metrics (3)-(6) are commonly used in Pattern recognition. MCC, defined in (7) is a balanced measure which returns a value between -1 and +1. A coefficient of +1 represents a hundred percent perfect prediction, -1 indicates total disagreement between prediction and observation. 0 means better than random prediction.

We performed experiments on the feasibility of applying above metrics in shadow detection area. From our experiments, it is observed that per pixel accuracy alone may not provide a better metric in case of shadow detection. This is noticeable especially in case of images where shadow occupies less pixel area. Figure 3 gives an example of such a result that better explains the failure of shadow detection when evaluated using per pixel accuracy. Figure 3 gives input image, ground truth and result of shadow detection and corresponding confusion matrix is given in Table 5. Though the result is not at all satisfactory PPA value of Figure 2 is computed as 89.35 whereas MCC value is 0.3293. We tried evaluation matrices like Precision(4), Recall(5), FScore(6) and Mathews Correlation Coefficient(MCC) (7) as an alternative evaluation metric for the same image and respective values are given in Table 6. Compared with other metrics MCC is a reasonable indicator of performance of result obtained in Figure 3. This rightly indicates the impairments in performance of MCC than accuracy.

We have further performed experiments on a set of six images whose results are given in figure 4. Respective perceptual quality metrics values for (3)-(7) are given in Table 7. Shadow detection result given in Figure 3 and Figure 4 are generated mainly for experimental purpose and it is not taken from any other work. On closely examining the metrics values in Table 7 we can conclude that MCC is better than Accuracy, Precision, Recall and Fscore.

Table 7: Perceptual quality metric values for images in Fig 4

Figure	PPA	Precision	Recall	Fscore	MCC
Fig 4a	0.9663	0.9844	0.9666	0.9754	0.5469
Fig 4b	0.5539	1	0.6787	0.8086	0.2459
Fig 4c	0.6721	0.9293	0.7281	0.8165	0.3032
Fig 4d	0.8686	0.9958	0.8773	0.9328	0.5126
Fig 4e	0.5090	1	0.6376	0.7787	0.3062
Fig 4f	0.8571	0.9014	0.8619	0.8812	0.3681

3.3 Evaluation metrics-Shadow removal

To the best of our knowledge Miyazaki et al.[29] and Guo et. al.[37] are the available works that provide quantitative evaluation in terms of Root mean squared error. Gong et. al[31] provides evaluation in terms of Error ratio. Other notable works provide only visual comparison. The quantitative evaluation on shadow removal can be performed only if shadow free ground truth is available.

3.4 Quantitative and qualitative evaluation

Perceptual quality metrics Accuracy and MCC are used to evaluate shadow detection. Table 8 compares the performance of Zhu et.al. [25] and Guo et.al.[37] quantitatively and qualitatively in shadow detection area. Table 9 gives a qualitative evaluation of four shadow removal algorithms [26],[29],[37],[41] and compare their performance using properties such as computational load and preservation of textures after shadow removal.

4. CONCLUSION

In this paper, we have provided a comprehensive survey of existing shadow detection and removal approaches arranged into useful categories. Evaluation metrics involved in shadow detection and removal techniques are also reviewed. Methods that use multiple images or methods that allows user intervention have given better results. Assumptions introduced in most studies increase the complexity of shadow removal from a single image and limit the class of shadow images which can be handled by these methods. Methods like reintegration and learning approaches are time intensive. Image inpainting method performs well for small-patch region, however the extension of inpainting to the large-patch hole brings about heavy computation. Also, dark objects are often mistaken as shadows. Many of the existing approaches that are applicable for video sequences are for specific application and cannot be used for still images. Shadow detection and removal from a single image having various geometrical features and textures exhibiting different reflection parameters remains an extremely challenging problem.

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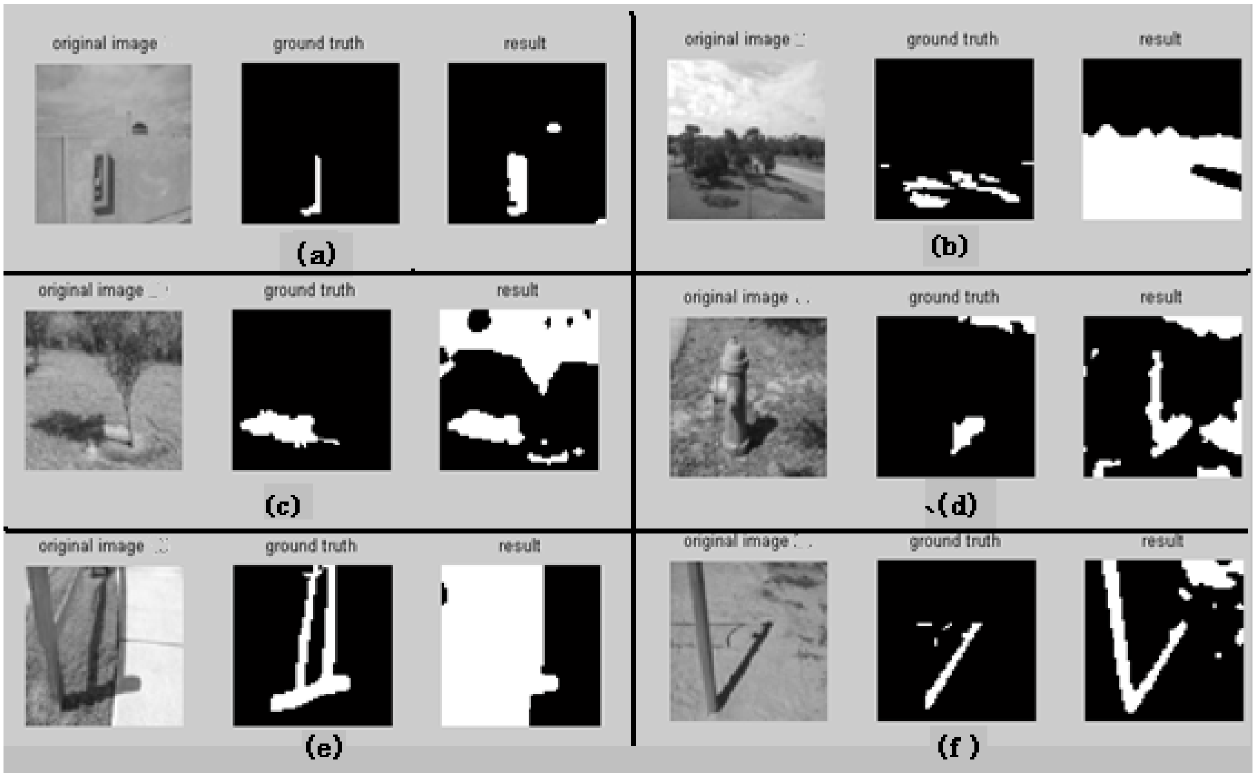

Figure 4: Shadow detection result for comparing perceptual quality metrics

Table 8: Qualitative and quantitative evaluation -Shadow detection

	Qualitative parameters			Quantitative evaluation			
				UCF Dataset[25]		ILLINOIS Dataset[37]	
Algorithm	Spectral	Spatial	Computational load	PPA	MCC	PPA	MCC
Zhu et al. 2010[25]	Monochrome	Pixel	High	0.887	0.599	-	-
Guo et.al. 2013[37]	Colour	Region	Medium	0.902	0.684	0.891	0.687

Table 9: Qualitative evaluation - Shadow removal

Author	Automatic/Interactive	Spectral	Preservation of Texture	Computational load
Wu et.al.2007 [41]	Interactive	Colour	Good	High
Lalonde et.al. 2010[26]	Automatic	Colour	Excellent	Low
Miyasaki et.al. 2010[29]	Interactive	Colour	Excellent	Low
Guo et.al. 2013 [37]	Automatc	Colour	Excellent	Medium

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