

Shadow Detection and Removal in Real Images: A Survey

Li Xu, Feihu Qi, Renjie Jiang, Yunfeng Hao, Guorong Wu,

Computer Vision Laboratory,
Department of Computer Science and Engineering,
Shanghai JiaoTong University,
P.R. China
June 1st, 2006

Shadow Detection and Removal in Real Images: A Survey

Li Xu, Feihu Qi, Renjie Jiang, Yunfeng Hao, Guorong Wu

Department of Computer Science and Engineering,
Shanghai JiaoTong University, P.R. China

Abstract. Shadow detection and removal in real scene images is always a challenging but yet intriguing problem. In contrast with the rapidly expanding and continuous interests on this area, the authors are unaware of any comprehensive surveys on this topic. This paper aimed to give a comprehensive and critical survey of current shadow detection and removal methods. Algorithms are categorized into three sets by their different functions and assumptions about the scenes. A discussion of reasonable evaluation is given at the end of this survey.

1 Introduction

Shadows and shadings in images have long been disruptive to computer vision algorithms. They appear as surface features, when in fact they are caused by the interaction between light and objects. This may lead to problems in scene understanding, object segmentation, tracking, recognition, etc. Because of the undesirable effects of shadows on image analysis, much attention was paid to the area of shadow detection and removal over the past decades and covered many specific applications such as traffic surveillance [1, 2], face recognition [3, 4, 5] and image segmentation [6]. In spite of these extensive studies, more researches focus on providing a general method for arbitrary scene images and thereby obtaining “visually pleasing” shadow free images. In contrast with the rapidly expanding interests on shadow removal, no comprehensive survey is reported on this particular topic. A list of recent work on this area is reported in [7] but algorithm details are missed. A survey was conducted by A. Prati [8, 9] on the moving cast shadow detection, which is the part of current interests. This paper aims to give a relatively comprehensive study on the current methods of detecting and removing shadows in both still and moving images. Before going into the detailed algorithms, we first review some different kinds of shadows in natural scenes.

1.1 Shadows in Images

A shadow occurs when an object partially or totally occludes direct light from a source of illumination. In general, shadows can be divided into two major classes: self

and cast shadows. A self shadow occurs in the portion of an object which is not illuminated by direct light. A cast shadow is the area projected by the object in the direction of direct light. Fig 1 shows some examples of different kinds of shadows in images. Fig.1 (a) shows scene image with both cast and self shadows; Fig.1 (b) gives an example of cast shadow of two photographers on a grass field; Fig.1 (c) shows an example of self shadow. Cast shadows can be further classified into umbra and penumbra region, which is a result of multi-lighting and self shadows also have many sub-regions such as shading and interreflection. Usually, the self shadows are vague shadows and do not have clear boundaries. On the other hand, cast shadows are hard shadows and always have a violent contrast to background. Because of these different properties, algorithms to handle these two kinds of shadows are different. For instance, algorithms to tackle shadows caste by buildings and vehicles in traffic systems could not deal with the attached shadows on a human face. Accordingly, this survey attempts to classify various shadow removal algorithms by the different kind of shadows they focus on and in fact, by the different assumptions they made to the shadows.



Fig. 1. Different kinds of shadows in image: (a) an overview of different kinds of shadows in one image, (b) cast shadow in a natural scene image (courtesy of G. D. Finlayson et al [44]), (c) an example of attached shadow (courtesy of M. Tappen et al [39])

1.2 Scope and Organization

This paper presents a comprehensive survey of shadow removal for still and moving images. Algorithms are organized into two stages: shadow detection and shadow removal. Shadow removal is further divided into vague shadow removal and cast shadow removal.

The rest of the paper is organized as follows: Section 2 reviews the various methods of shadow detection and removal in images. Section 3 gives some discussion on performance evaluation. Section 4 concludes the paper.

2 Taxonomy of Shadow Suppression Algorithms

In this section, two categories of shadow suppression methods are reviewed. The first one is the shadow detection. By detecting and classifying shadow regions in an image, it is possible to segment the target object without shadows. The next one is the

shadow removal stage. In recent years, shadow removal is more likely to be an independent application to provide people a “visually pleasing” shadow free image.

2.1 Shadow Detection

In some applications, especially traffic analysis and surveillance system [8], the existence of shadows may cause serious problems while segmenting and tracking objects: shadows can cause object merging. For this reason, shadow detection is applied to locate the shadow regions and distinguish shadows from foreground objects. In some cases, shadow detection is also exploited to infer geometric properties of the objects causing the shadow (“shape from shadow” approaches). In spite of the different purposes, invariably the algorithms are the same and can extend to any of these applications.

A. Prati et al [9] conducted a survey on detecting moving shadows; algorithms dealing with shadows are classified in a two-layer taxonomy by the authors and four representative algorithms are described in detail. The first layer classification considers whether the decision process introduces and exploits uncertainty. *Deterministic approaches* use an on/off decision process, whereas *statistical approaches* use probabilistic functions to describe the class membership. As the parameter selection is a crucial problem for statistical methods, the authors further divided statistical methods into *parametric* and *nonparametric* methods. For deterministic approaches, algorithms are classified by whether or not the decision can be supported by *model-based* knowledge. The authors reviewed four representative methods for these categories of his taxonomy and argued that *Deterministic Model-based* methods [10] rely so much on models of the scene that they inevitably become too complex and time-consuming.

T. Horprasert et al’s method [11] is an example of the statistical nonparametric approach and the authors denote it with symbol **SNP**. This approach exploits color information and uses a trained classifier to distinguish between object and shadows. I. Mikic et al [12] proposed a statistical parametric approach (**SP**) and utilized both spatial and local features, which improved the detection performance by imposing spatial constraints.

R. Cucchiara et al’s method (**DNM1**) [13] and J. Stauder et al’s work (**DNM2**) [14] were representatives of deterministic non-model based method. **DNM1** is based on an assumption that shadows in image do not change the hue of surfaces. The reason why the author reviewed **DNM2** is that it is the only work that handles the penumbra regions in image.

The survey of A. Prati et al mainly focuses on the moving shadow detection and most of the papers they reviewed do not examine the self-shadow and typically they concentrate the attention on umbra, considering the penumbra as a particular case of umbra. It is because the distance between the objects and the background is negligible compared to the distance of illumination sources to the objects in a highway scene and most or all of the shadows are umbra or strong shadow.

S. Nadimi and B. Bhanu [15, 16] proposed physical model based method to detect moving shadows in video. They used a multistage approach where each stage of the algorithm removes moving object pixels with knowledge of physical models. Input

video frame is passed through the system consists of a moving object detection stage followed by a series of classifiers, which distinguish object pixels from shadow pixels and remove them in the candidate shadow mask. At the end of the last stage, moving shadow mask as well as moving object mask is obtained. Experimental results demonstrated that their approach is robust to widely different background surface, foreground materials and illumination conditions.

E. Salvador et al proposed an approach to detect and classify shadows for still images [17]. They exploit invariant color features to classify cast and self shadows. In the first level, the authors utilize edge detection followed by a morphological operation to extract object and cast shadow regions. A dark region extraction process is then applied to identify shadow candidates in the segmented regions. In the second level, an edge detector is also applied first to the invariant color features proposed in [18] to obtain an edge map which does not contain the edges corresponding to shadow boundaries. The obtained edge map is used, together with the dark region map, to distinguish between self and cast shadows. Experimental result for single images is showed in Fig.2: images in column (a) are the original images and column (b) and column (c) are the segmented cast shadow and self shadow respectively. Although the method can be used to detect shadows in still images, the constraint of the algorithm such as uniform colored object, non-textured surfaces may hinder the applications of the method.

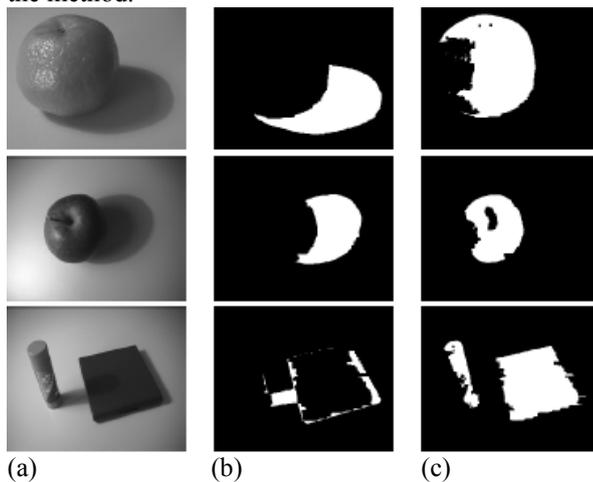


Fig. 2. Shadow detection and classification results of E. Salvador et al.(courtesy [17]) (a) original image, (b) cast shadow map, (c) self shadow map.

E. Salvador et al [19] then present an enhanced version also using invariant color features to segment cast shadows in both still and moving images. For videos, analysis performs only in areas that identified by motion detector. Still, an initial hypothesis is tested to identify candidate shadow regions and a verification stage is then applied based on color invariance and geometric properties. The authors also conducted a comparison between their method for videos and some other moving shadow detectors reviewed in the [9]. The performances are evaluated by the moving object segmentation accuracy (good moving shadow detection rate lead to high

accuracy on object segmentation). In a test sequence named *Hall Monitor*, the authors' method achieved an average accuracy about 0.86. Results on some other methods reviewed in [9] are also given: **SP** [12] 0.59; **SNP** [11] 0.63; **DNM1** [13] 0.78 and **DNM2** [14] 0.60.

2.2 Shadow Removal

The following algorithms are classified based on their assumptions of world. The first category of method is the canonical retinex problem separating illumination images (also called shadow images) from reflectance images. These methods intended to enhance images for human vision but can also remove vague shadows and suppress cast shadows. The Retinex model was motivated by E. H. Land's Mondrian world [20] and assumes that reflectance is piece-wise constant. Contrary to this, some algorithms to remove cast shadows are based on different assumptions (Weiss's sparse derivative outputs [35], for example), which gives them different behaviors.

2.2.1 Vague Shadow Removal, Retinex

Vague shadows are those shadows which do not have clear boundaries and usually have a gradually changed intensity. Such shadows could be removed by separating the gradually changed illumination from the reflectance; that is the classical problem called retinex.

The retinex model was first proposed by E. H. Land et al [20] and aimed to calculate the sensory response of lightness. Consider the case of two faces of a white cube, one is illuminated by direct light source and the other is not (self shadow). The appearances of the two faces of the cube are different due to the different illumination while the properties of reflectance are physically identical. The goal of retinex is to separate the illumination from the reflectance and obtained a uniform-colored image.

E. H. Land and his colleagues have described several variants on the original method [21-24, 26] and most of them address to improve the efficiency of the previous version. Generally, the model can be described as follows: given an image S , which is the pixel-wise multiplication of two images, the reflectance R and the illumination L , i.e. $S = R \cdot L$. A first step taken by most algorithms is the conversion to the logarithmic domain: $s = \log S$, $l = \log L$, $r = \log R$, and thereby $s = l + r$. By recovering l from s , the result images may possibly remove illumination effects.

Land and McCann's first version of retinex was of random walk type [20, 22]. The random walk algorithm begins at initializing a large number of walkers at random locations of an input image and assigns them the gray-value of their initial position. An accumulator image of the same size as the input image is initialized to zero. As the walkers walk around, they update the accumulator image by adding their values to each position they visit. Finally, the illumination image is obtained by normalizing the accumulator image, i.e., its value at each location divided by the number of walkers visited it. D. H. Brainard [25] presented that in the case of long path length, the dependence on the surfaces in the image is strong. That is, if enough walks with long paths are adopted, estimated illumination pixels would converge to a Gaussian average of its neighbors, which is a low-pass filter of the logarithmic input image.

A fundamental concept behind Land's retinex computation at a given image pixel is the comparison of the pixel's value to that of other pixels. The main difference between such kinds of retinex algorithms is the way in which they are chosen. Land's original version randomly picked up a neighboring pixel as the next position. Many variants of retinex modified the way in which the next position is determined to achieve computational efficiency. McCann et al [26] proposed a modified version of retinex also via changing the comparison method. They create a multi-resolution pyramid from the input by averaging image data. The algorithm begins the pixel comparisons at the most highly averaged, or top level of the pyramid and then, after computing lightness at a reduced resolution, the result lightness values are propagated down, by pixel replication, to the pyramid's next level as initial lightness estimation. This process continues until lightness has been estimated for the pyramid's bottom level. Another improvement introduced by McCann is to apply a nonlinear Max operator in the *reset* stage and thereby adding a constraint that l must be greater than s , which is a physical property of the real scenes. A detailed implementation in matlab is addressed in the work of B. Funt et al [27].

A low-pass filter is directly applied on input image s to estimate the illumination l under the name of *homomorphic filtering* [24, 28, 29]. The motivation behind the homomorphic filtering is that the reflectance image corresponds to the sharp details in the image whereas the illumination image is expected to be spatially smooth. Usually, the low pass is usually obtained as a convolution with a wide Gaussian kernel.

B. K. P. Horn introduced poisson equation type retinex in [30] and an improvement was made by Blake et al [31]. The method is also based on the assumption that illumination is spatially smooth and its derivative should be close to zero everywhere. By clipping out the high derivative peaks, the authors assume that the remained derivative signal only corresponds to the illumination. The algorithm can be divided into three parts: a) apply the Laplacian b) clip out the high peaks via a threshold and c) estimate l by solving the standard poisson equation. Note that the poisson type retinex and most retinex algorithms rely on Land's Mondrian world model and assume that the reflectance is piece-wise constant.

R. Kimmel et al [32] proposed a variational framework for the conventional retinex and turned the generally ill-posed problem into a mathematically well-posed problem by formulating it as a Quadratic Programming problem:

$$\text{Minimize: } F[l] = \int_{\Omega} |\nabla l|^2 + \alpha(l-s)^2 + \beta|\nabla(l-s)|^2 dx dy$$

$$\text{Subject to: } l \geq s \text{ and } \langle \nabla l, \bar{n} \rangle = 0 \text{ on } \partial\Omega$$

where $\langle \nabla l, \bar{n} \rangle = 0$ on $\partial\Omega$ was the boundary conditions, α and β are free non-negative real parameters. In the function $F[l]$, the first penalty term forces spatial smoothness on the illumination image. The second penalty term $(l-s)^2$ forces a proximity between l and s . The difference between these images is exactly r , which means that the norm of r should be small. The authors added this term as a regularization of the problem in order to make it better conditioned. The last term of the function forces r to be spatially smooth. The authors also discussed that with specific parameters, this method could be identical to other algorithms such as homomorphic filtering [30], McCann's walk algorithm [26] and so on. Although the problem is well-defined, the solving procedure is time consuming and several improvements are made on this

framework. M. Elad et al. [33] made a compromise between the full fledged solutions to the model and efficient yet limited computational methods to achieve better efficiency. Still, M. Elad [34] proposed a new penalty function via bilateral filters. The proposed method could deploy a non-iterative solver and force both illumination and reflectance to be piece-wise smooth, thus preventing hallows. Fig.3 gives an example of the variant of retinex: (a) is the input image and (b) is its retinex result using method in [34]. Note that the result of the algorithm is adjusted by returning part of the illumination L' (Gamma correction of L) to the reflectance image R .

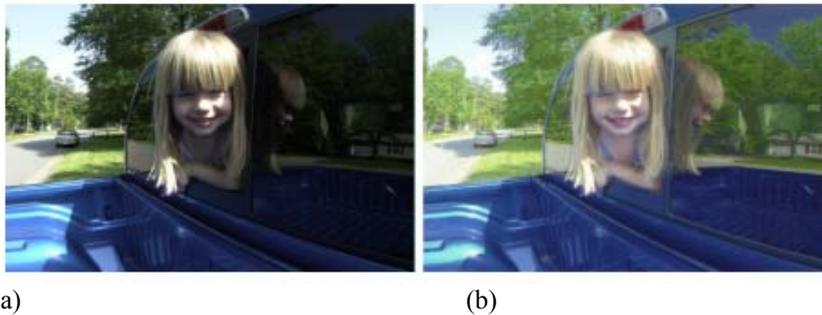


Fig. 3. Example of a variant of retinex (courtesy [34]): (a) original image, (b) retinex result

2.2.2 Cast Shadow Removal

The area of cast shadow removal has made great progress in recent years and many of the algorithms works on the gradient domains by identifying strong shadow edges and removing those shadow edges. Unlike vague shadow removal, the Mondrian world assumption is not hold in some of them and more specific assumptions are made.

Y. Weiss [35] proposed a method for deriving intrinsic images from image sequences and also based on a decomposition of images into reflectance and illumination. In his paper, Weiss used the term “intrinsic images” introduced by Barrow and Tenenbaum [36] to refer to such kind of decomposition. Unlike previous algorithms on estimating illumination form a single image, Weiss focuses on a slightly easier version and derives intrinsic images from a sequence of images in which the reflectance is constant over time and the illumination changes. Based on the assumption that derivative filters applied to illumination L will tend to be sparse, the author applies two derivative filters to the image sequence and estimates the filtered reflectance image by exploiting the median operator on the filtered images. The estimated reflectance image is obtained by a pseudo-inverse on the estimated filtered reflectance. At last we get, for each sequence, one reflectance image and several illumination images corresponding to each image in the original sequence. Weiss’s method is quite effective for natural sequence since he made little assumptions on the scenes (unlike Land’s Mondrian world). Moreover, Weiss’s method could also be utilized in scene reconstruction: first, a) estimate the reflectance image for sequence and then, b) blend target objects into reflectance image and, c) add back illumination image.

Y. Matsushita et al [37] made an extension on Weiss's method. For each image sequence, they derive time-varying reflectance images instead of a single reflectance proposed by Weiss. They first employed the Weiss's algorithm to estimate a single filtered reflectance image and a set of filtered illumination images for a sequence. Then, for each filtered illumination image, they added strong responses back to the filtered reflectance image and obtained time-varying reflectance images. The pseudo-inverse operation is also the same as Weiss. The theory behind time-varying reflectance images is the time-varying reflectance properties of the object, i.e., the surface is non-Lambertian. Matsushita also described an illumination normalize scheme which can potentially run in real time, utilizing the illumination eigenspace and shadow interpolation.

Tappen, Freeman and Adelson [39, 40] proposed a method to recover intrinsic images from a single image. They aimed to separate intrinsic images by classifying their derivatives and then recover them from the classified derivatives using Weiss's method. Both color and gray scale information is used in their classifiers. Color classifier is based on a Lambertian assumption. Like their previous work [38], they trained a classifier using a set of oriented first and second derivative of Gaussian filters for gray scale information. After combined the both information, a Markov Random Field with brief propagation is applied to propagate information from areas where the correct classification is clear to areas where it is ambiguous. The method is effective for extracting illumination from a single image, but the stage of computing local evidence is time-consuming and the large training set of real scene is hard to obtain.

M. Baba et al [41, 42] proposed shadow removal algorithms from another aspect. They remove shadows via a two stage system: shadow detection and color correction. In the old version [41], they detect shadows by a K-means clustering method on color distribution. A darker cluster is classified as shadow region. In the later version [42] shadow region is detected based on the shadow density, which is defined as a measure of brightness. Then, both of the two versions remove the shadows by modifying the brightness and color. Finally, a smooth filter to correct the boundary discontinuity is applied to correct boundaries between sunshine and shadow regions. Despite many constraints of the surfaces the algorithm imposed, the method provides a new way to remove shadows in image.

G.D. Finlayson et al [43, 44] proposed a shadow removal method for color images. They start from finding a 1-D illumination invariant image, which is a grey-scale shadow free image. Then, edge detection is applied to both the 1-D illumination invariant image and the three channels of the original color image. Next, three shadow edge maps can be obtained by selecting the edges that exist in the original image but not in the invariant image. The shadow edge maps can be either manually modified or automatically enhance with morphological operation to get a better result. At last, a shadow free color image can be obtained by removing the shadow edge from the original image derivatives and using a pseudo-inverse filter to reconstruct the shadow free image just like Weiss's method [35]. The authors also provide a retinex version to reconstruct shadow free images [45] and other reconstruction methods could be applied in this stage (poisson solution, for instance). In the journal version of the algorithm [46], the author described a 2-D illumination invariant representation which remains some color information in it. The key problem for the whole algorithm is the

illumination invariant image. To generate the invariant image, some constraints are required on the image: The lighting in the scene should be Planckian (like sun light) and the camera's sensors should be narrow-banded. Fig.4 shows the process of the work of Finlayson et al: Fig.4 (a) is the original color scene image with cast shadows; Fig.4 (b) is the generated 1-D invariant image and Fig.4 (c) is the result color image after shadow removal.

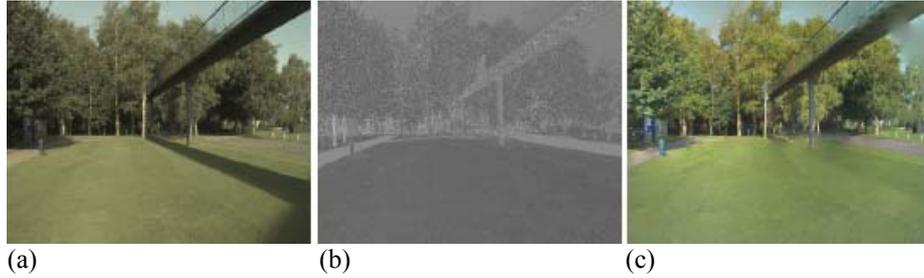


Fig. 4. Shadow removal from color image (courtesy [44]): (a) original color image, (b) 1-D illumination invariant image, (c) shadow-free color image

3 Discussion

Removing and suppressing shadows in images remains a difficult problem for computer vision systems and it is hard to measure the performance in this task. However, in the area of shadow detection, methodology used to evaluating object detection could be borrowed. A. Prati et al [9] modified the metrics *Detection Rate* and *False Alarm Rate*, which is widely used in the classification literature, to get a better evaluation for shadow detection. They ignore the errors of misclassifying shadow points as background points since it would not affect the result of object segmentation. Based on this point of view, shadow detection for object segmentation could also be evaluated by the segmentation accuracy [19]. For shadow removal, the performance evaluation is not an easy job, but there are still some methods to compare the algorithm results: a) for methods which remove shadows by separating the illumination from the reflectance (retinex, intrinsic images), observers describe the illumination images as “looking like marble status”, as would be expected from an illumination image [35]; b) for methods which remove shadows by clipping out shadow edges in the derivative map, a manually labeled ground truth of shadow edge could be employed to evaluate the performance.

4 Summary

In this paper, we have provided a comprehensive survey of shadow detection and removal in the natural scene images. The authors aimed to give a critical review of the current algorithms. Numerous representative techniques are studied and carefully

categorized into three sets based on their different functions and assumption of the scenes. At last, a discussion about reasonable performance evaluation is given.

References

- [1] J.M. Wang, Y.C. Chung, C.L. Chang, S.W. Chen. Shadow detection and removal for traffic images, *Networking, Sensing and Control*, 2004 IEEE International Conference on Volume 1, 21-23 March 2004 Page(s):649 - 654 Vol.1
- [2] A. Bevilacqua. Effective Shadow Detection in Traffic Monitoring Applications. WSCG 2003
- [3] T. Chen, W. Yin, X.S. Zhou, D. Comaniciu, and T.S. Huang. Illumination Normalization for Face Recognition and Uneven Background Correction Using Total Variation Based Image Models. *CVPR (2) 2005*: 532-539
- [4] Y. Adini, Y. Moses, and S. Ullman. Face recognition: The problem of compensating for changes in illumination direction. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(7):721–732, 1997.
- [5] W. Zhao and R. Chellappa. Robust face recognition using symmetric shape-from-shading. Technical report, Center for Automation Research, University of Maryland, 1999.
- [6] G.J. Klunker, S.A. Shafer, and T. Kanade. A Physical Approach to Color Image Understanding, *Int'l J. Computer Vision*, vol.4, pp. 7-38, 1990
- [7] Shadow Removal - Seminar <http://cs.haifa.ac.il/hagit/courses/seminars/shadowRemoval/shadowRemoval.html>
- [8] A. Prati, I. Mikic, C. Grana, and M.M. Trivedi, Shadow Detection Algorithms for Traffic Flow Analysis: A Comparative Study, *Proc. IEEE Intelligent Transportation Systems Conf.*, Oakland, CA, Aug. 2001.
- [9] A. Prati, I. Mikic, M. Trivedi, and R. Cucchiara, Detecting moving shadows: Algorithms and evaluation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25, pp. 918--923, 2003.
- [10] D. Koller, K. Danilidis, H.-H. Nagel, Model-based object tracking in monocular image sequences of road traffic scenes, *Int. J. Comput. Vis.* 10 (3) (1993) 257–281.
- [11] T. Horprasert, D. Harwood, and L.S. Davis, "A Statistical Approach for Real-Time Robust Background Subtraction and Shadow Detection," *Proc. IEEE Int'l Conf. Computer Vision '99 FRAME-RATE Workshop*, 1999.
- [12] I. Mikic, P. Cosman, G. Kogut, and M.M. Trivedi, "Moving Shadow and Object Detection in Traffic Scenes," *Proc. Int'l Conf. Pattern Recognition*, vol. 1, pp. 321-324, Sept. 2000.
- [13] R. Cucchiara, C. Grana, G. Neri, M. Piccardi, and A. Prati, "The Sakbot System for Moving Object Detection and Tracking," *Video-Based Surveillance Systems—Computer Vision and Distributed Processing*, pp. 145-157, 2001.
- [14] J. Stauder, R. Mech, and J. Ostermann, "Detection of Moving Cast Shadows for Object Segmentation," *IEEE Trans. Multimedia*, vol. 1, no. 1, pp. 65-76, Mar. 1999.
- [15] S. Nadimi, B. Bhanu, Moving shadow detection using a physics-based approach, in: *Proc. IEEE Int. Conf. Pattern Recognition*, vol. 2, 2002, pp. 701-704. 16
- [16] S. Nadimi and B. Bhanu, "Physical models for moving shadow and object detection in video," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 8, pp. 1079–1087, August 2004
- [17] E. Salvador, P. Green, and T. Ebrahimi. Shadow identification and classification using invariant color models. In *Proceedings of ICASSP 01*, volume 3, pages 1545--1548. IEEE, 2001
- [18] T. Gevers and A. W. M. Smeulders, Color-Based Object Recognition, *Pattern Recognition*, (32): 453–464, 1999.

CVLAB, SJTU

- [19] E. Salvador, A. Cavallaro, and T. Ebrahimi. Cast shadow segmentation using invariant color features. In Proceedings of Computer Vision and Image Understanding 04, Volume 95, Issue 2 (August 2004) Pages: 238 - 259.
- [20] E. H Land, and J. J. McCann, Lightness and the Retinex Theory, J. Opt. Soc. Am., Vol. 61, pp. 1-11, 1971
- [21] E.H. Land, The Retinex Theory of Color Vision, Sci. Amer., Vol. 237, pp. 108-128, 1977.
- [22] E.H. Land, Recent Advances in the Retinex Theory and Some Implications for Cortical Computations: Color Vision and the natural Image, Proc. Nat. Acad. Sci. USA, Vol. 80, pp. 6163-5169, 1983
- [23] J. Frankle and J. McCann, Method and Apparatus for Lightness Imaging, US Patent no. 4,384,336 May 17, 1983
- [24] E. H. Land, An Alternative Technique for the Computation of the Designator in the Retinex Theory of Color Vision, Proc. Nat. Acad. Sci. USA, Vol. 83, pp. 3078-3080, 1986.
- [25] Brainard, David H. and Wandell, Brian A.. Analysis of the retinex theory of color vision. Journal of the Optical Society of America A, Vol. 3 No. 10, pp1651-1661, 1986.
- [26] J. McCann, Lessons Learned from Mondrians Applied to Real Images and Color Gamuts, Proc. IS&T/SID Seventh Color Imaging Conference, pp. 1-8, 1999.
- [27] B. Funt, F. Ciurea, and J. McCann, Retinex in Matlab, Proceedings of the IS&T/SID Eighth Color Imaging Conference: Color Science, Systems and Applications, 2000, pp 112-121.
- [28] D.J. Jobson, Z. Rahman, and G. A. Woodell, Properties and Performance of the Center Surround Retinex, IEEE Trans. on Image Proc., Vol. 6, pp.451-462, 1997
- [29] D.J. Jobson, Z. Rahman, and G. A. Woodell, A Multiscale Retinex for Bridging the Gap Between Color Images and the Human Observation of Scenes, IEEE Trans. On Image Proc., Vol. 6, 1997.
- [30] B.K.P. Horn, Determining Lightness from an Image, Computer Graphics and Image Processing, Vol, 3. pp. 277~299, 1974.
- [31] A. Blake and A. Zisserman. Visual Reconstruction, The MIT Press, Cambridge Massachusetts 1987.
- [32] R. Kimmel M. Elad D. Shaked R. Keshet I. Sobel A Variational Framework for Retinex International Journal of Computer Vision 52(1), 7-23, 2003
- [33] M. Elad, R. Kimmel, D. Shaked, and R. Keshet, Reduced Complexity Retinex Algorithm via the Variational Approach, JVCIR(14), No. 4, December 2003, pp. 369-388
- [34] M. Elad, Retinex by Two Bilateral Filters, The 5th international conference on scale-space and PDE in computer vision, Hofgeismar, Germany, 2005
- [35] Y. Weiss. Deriving intrinsic images from image sequences. In Proc. Int. Conf. Computer Vision, 2001.
- [36] H.G. Barrow and J.M. Tenenbaum. Recovering intrinsic scene characteristics from images. In A. Hanson and E. Riseman, editors, Computer Vision Systems. Academic Press, 1978.
- [37] Yasuyuki Matsushita, Ko Nishino, Katsushi Ikeuchi, Masao Sakauchi, "Illumination Normalization with Time-Dependent Intrinsic Images for Video Surveillance," IEEE Transactions on Pattern Analysis and Machine Intelligence 26(10):1336-1347, 2004
- [38] M. Bell and W.T. Freeman. Learning local evidence for shading and reflectance. In ICCV01, pages I: 670--677, 2001.
- [39] M. Tappen, W.T. Freeman, and E.H. Adelson. Recovering intrinsic images from a single image. Advances in Neural Information Processing Systems 15, 2002
- [40] M. Tappen, W.T. Freeman, and E.H. Adelson. Recovering intrinsic images from a single image. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 9, pp. 1459-1472, September, 2005
- [41] M. Baba N. Asada, Shadow Removal from a Real Picture, Proceedings of the SIGGRAPH conference on Sketches & applications, 2003

Shadow Detection and Removal in Real Images: A Survey

- [42] M. Baba, M. Mukunoki, N. Asada: Shadow Removal from a Real Image Based on Shadow Density, SIGGRAPH Posters, 2004.
- [43] G.D. Finlayson and S.D. Hordley. Color constancy at a pixel. J. Opt. Soc. Am. A, 18(2):253-264, Feb. 2001. Also, UK Patent application no. 0000682.5 Under review, British Patent Office
- [44] G.D. Finlayson, S.D. Hordley and M.S. Drew. Removing shadows from images. ECCV, 2002
- [45] G.D. Finlayson, S.D. Hordley and M.S. Drew. Removing shadows from Images Using Retinex. In Proc. of IS&T/SID, Tenth Color Imageing Conference: Color Science, Systems and Applications, 2002, 73-79
- [46] G.D. Finlayson, S.D. Hordley C. Lu and M.S. Drew, On the Removal of Shadows from Images, IEEE Transactions on Pattern Analysis and Machine Intelligence, Jan, 2006