VOL. 11, NO. 10, MAY 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

A REVIEW OF RAIN STREAKS DETECTION AND REMOVAL TECHNIQUES FOR OUTDOOR SINGLE IMAGE

Samer Mahmoud Shorman and Sakinah Ali Pitchay
Faculty of Science and Technology, Universiti Sains Islam Malaysia, Bandar Baru Nilai, Nilai, Negeri Sembilan, Malaysia
E-Mail: shormansamer@gmail.com

ABSTRACT

The impact of rain weather in the images will make it complicated to distinguish in the environment surroundings using an outdoor camera. Moreover, single image plays important role in numerous areas such as in object recognition and detection, enhancement, noise removal and weather condition removal. Rainy weather of outdoor images and videos reduces the visibility, performance of computer vision algorithms and other outdoor activities, which use for extracting features and information from images. Most of the previous review papers focus on the video techniques and raindrops which adherent on the surface and in the images. This paper presents a review of restoration rain streaks detection and removal from single image which has different techniques used in video and includes the result of the implemented experiments using three images.

Keywords: raindrop, rain streaks, single image, outdoor images.

INTRODUCTION

Computer vision in weather conditions such as haze, fog and rain for the outdoor vision system is using in various area such as in image analysis, surveillance and navigation. Nevertheless, it can be more complicated and images are not clear. The vision systems are designed to perform in clear weather. Therefore, the weather condition has an undoubted impact on images and videos. Many applications have been effected via bad weather conditions such as intelligent transport systems (ITS) 1. Substantially, computer vision systems should include techniques which authorize them to function in the bad weather [2]. Gary and Nayar detected rain streaks using individual pixels [3, 4]. However, the detection of raindrops through local information is not consistent. Zhang detected rain streaks using chromatic properties in [5]. It is also a rain removal algorithm from video and may fail to detect in some gray color regions.

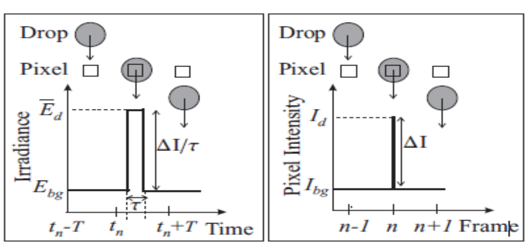

Figure-1. Effect raindrop on pixel intensity [2].

Figure-1 shows the effect raindrop on pixel intensity between successive frames. Using the method of spatiotemporal, it means that it changes pixels between frames will use to clean raindrops from video. The works [1-5] mentioned previously are video-based and could not perform on single image that are degraded by raindrops.

This paper will discuss rain detection and removal from single image. According to [6], they remove rain, snow and keep the details of the background in a single image are still quite challenging since it is hard to identify a pixel of rain and snow. The type of images and videos was studied by many researches. This can be classified into static scenes and videos that related into usage for each of them and algorithm processing. These differences are presented in Table-1.

Table-1. Comparison between single image and video.

Criteria	Single Image	Video
Accuracy	High	High
Time	Medium	High
Details	High	Medium
Spatio	Yes	Yes
Temporal	No	Yes

High and medium refer to the importance of these criteria for a single image, meanwhile Yes in Table-1 indicates that the criteria can implement on a single image or video and No is vice versa. This paper was organized as follows. Next section presents literature survey which studied twelve articles, extracting techniques, publication chronology, finding and experiments, conclude the results and comparisons discussion.

LITERATURE SURVEY

Single-image restoration of outdoor in bad weather conditions especially rainy weather, it was a good field research in the recently years. In this section will focus on works that related in raindrops and streaks removal from outdoor images as in Table-2.

The research was started on raindrop detection and removal in the end of 90s decade. Many researches were studied detection and removal of raindrop from videos extensively, while the detection and removal of raindrop from single image not got the same interest. Therefore this work focuses on single image.

ARPN Journal of Engineering and Applied Sciences

Table-2. Algorithms of detection and rain removal.

Year	Author	Algorithm / Technique	Drawbacks
2011	Fu, Yu-Hsiang et. Al [7]	Analyze an image into low frequency and high frequency via a bilateral filter and performs dictionary learning with sparse coding.	Remove some of image details and time of complexity.
2012	Jing Xu et. Al [8]	Refined guidance image.	Detection and remove some of raindrops and blue of edges, better than [20].
2012	Li-Wei Kang et.al [9]	Framework based on morphological component analysis (MAC), bilateral filter, dictionary learning and sparse coding.	Long execution time. And remove some details from original image, and using gray images.
2012	Huang, De-An, *et al* [10]	Dictionary learning-based framework	Still lost details and complexity time.
2012	Xu, Jing *et al* [11]	Guided filter	Remove raindrops with blue image and edges, has less performance of [39]
2012	Chen, Duan-Yu *et al* [16]	Guided image filter, then performing dictionary learning and sparse coding	Using gray images, and better than [17]. However, it still lost some of the image details.
2013	Kim, Jin-Hwan, *et al* [12]	Adaptive nonlocal means filter.	It does not remove all raindrops and remove some of the image details.
2013	Eigen, David *et al* [13]	Neural network	It does not deal with large raindrops and heavy rain.
2013	Zheng, Xianhui *et al* [17]	Using low frequency for single image and guided filter.	Lost some details and does not preserve the edges.
2014	Sun, Shao-Hua *et al* [14]	Incremental Dictionary learning-based method	Time consuming and delete some of the details.
2014	Pei, Soo-Chang *et al* [6]	Framework Merge Saturation and Visibility, High Pass Filter, Orientation Filter, Threshold.	Consume most of execution time and remove some of the details.
2014	Chen, Duan-Yu *et al* [15]	Framework guided image filter, low-frequency and a high frequency dictionary learning with sparse coding.	Long execution time and remove some details. It is better than works in [9].

According Fu, Yu-Hsiang [7] which used rain removal from single image based on morphological component analysis. This method used image decomposition technique depends on low frequency and high frequency using a bilateral filter, dictionary learning with sparse coding. The result shows remove rain streaks without perceiving of the original image details.

In contrast with Jing Xu *et al* [8] perform rain and snow removal by refined guidance image that to reduce the degradation image and maintains some the details, the method is similar with guidance image which proposed by Kaiming He [19].

Li-Wei Kang *et al* [9] proposed an image analyses based on morphological component. Instead applying a conventional image a technique, the proposed method first decomposes an image into the low and high frequency (HF) parts using a bilateral filter, and applying dictionary learning with sparse coding, the cons preserving some original image details.

According to Huang, De-An, *et al* [10] proposed a method to implement context-constrained image segmentation, and using dictionaries for the high frequency components in different context categories via sparse coding for reconstruction the image. The disadvantage is lost details and complexity time.

In Xu, Jing *et al* [11] proposed a guided filter method suitable for removing rain and snow in video because that our method has good visibility and greatly reduces degradation, however the output sill blue and not perceive the details and edges. While Chen, Duan-Yu *et al* [16] proposed a method based by decomposed the image into low-frequency part and high-frequency part, by using guided image filter and performing dictionary learning and sparse coding. Some details were lost and not all raindrops removed.

In addition Kim, Jin-Hwan, *et al* [12] proposed algorithm using the adaptive nonlocal means filter. We first identified the locations of rain streak regions by investigating the shape and the orientation of the elliptical kernel at each pixel location, can remove rain streaks than the conventional algorithms [9].

Eigen, David *et al* [13] proposed a method deal with dataset of clean/corrupted image pairs which are then used to train neural network, the cons not good work in rain very heavy. This method is able to remove most of the water droplets.

In Zheng, Xianhui *et al* [17] proposed a method using low frequency of a single image, and the high frequency as input image of guided filter. According to Sun, Shao-Hua *et al* [14] proposed a method learning-

ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

based method for rain removal from single image to exploit the structural similarity of the image bases for solving this task. Then synthetic and real-world denoising and rain removal, while the detailed image information can be preserved. The result based on PSNR, SSIM is better than K-SVD [22], BM3D [21], and Huang *et al* [20].

Pei, Soo-Chang *et al* 6 proposed framework merge saturation and visibility, high pass filter, orientation filter, thresholds. On the other hand the guided results related to edge-preserving smoothing operator better than bilateral filter. In this technique is computationally effective taking approximately 2 seconds (Matlab code) for a 400×400 image. Kang *et al* [9] takes approximately 66 seconds and Xu *et al* [11] method taking approximately 0.3 seconds. Although Xu *et al* [11] method use the shortest time, this method simultaneously removes other image detail and blurs.

Chen Duan-Yu *et al* [15] proposed a framework to color image is first analyse into a low-frequency and a high frequency via using the guided image filter so that the rain streaks would be in the high-frequency part with no rain textures/edges. While image to decompose into a rain and a non-rain by using high-frequency, and apply dictionary learning with sparse coding which will used to restore image.

EXTRACTING TECHNIQUES

Extraction procedure is selecting techniques from the literature survey, to be more structured. Table 3 shows extracting techniques of single-image restoration, and taking in the account the next terms was used in the following Table-3.

Table-3. Extracting techniques which used in the algorithms.

Author / Method	HF	LF	SC	DL	NN	BF	MAC	GF	NF
[7]	*	*	*	*		*			
[8]								*	
[9]			*	*		*	*		
[10]				*					
[11]								*	
[12]									*
[16]	*	*	*	*				*	
[13]					*				
[17]	*	*						*	
[14]				*					
[6]	*								
[15]	*	*	*	*					

HF: high frequency, LF: low-frequency, SC: sparse coding, DL: dictionary learning, NN: neural network, BF: bilateral filter, MAC: morphological component analysis, GF: guided filter, NF: nonlocal filter. Note: * Indicate techniques in the papers.

PUBLICATION CHRONOLOGY

In The following Figure-2 shows the distribution of the selected publications from 2010 to 2014.

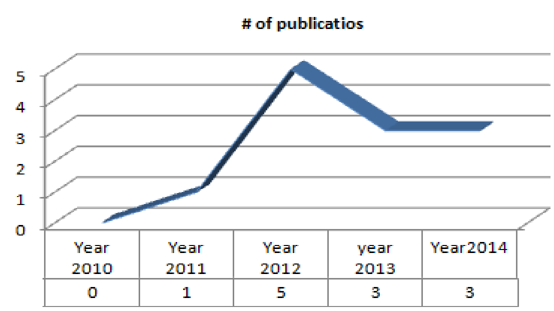

Figure-2. Chronology of publications.

Figure-2 shows the most publication was in 2012, in contrast one paper in 2011, 3 papers in 2013 and 2014 respectively.

FINDING AND EXPERIMENTS

In this section different experiments have been implemented using four techniques which are Bilateral filter [23], Guided filter [11], MCA [9] and Chen Duan-Yu [15] based on four measurements starting from mean square error (MSE) [24], peak signal-to-noise ratio (PSNR) [26] structural similarity index method (SSIM) [25], and VIF. All of these images used in the experiments are in size 256 × 256. Images used in this experiment are taken from dataset which is available online in [18].

Table-4. Experiment result using images in figure-3 [15].

Method / Measurement	MSE	PSNR	SSIM	VIF	Type of image
Bilateral filter [23]	0.0238	64.4046	0.9987	0.1070	Color
Guided filter [11]	0.0229	64.5582	0.9986	0.1082	Color
MCA[9]	0.0211	64.9279	0.9993	0.0969	Gray scale
Chen Duan-Yu [15]	0.0237	64.4142	.9987	0.1096	Color

(a) (b)

Figure-3. [15] (a) Rainy image (b) Clean image.

Table-5. Experiment result using images in Figure-4.

Method /Measurement	MSE	PSNR	SSIM	VIF	Type of image
Bilateral filter [23]	0.0125	67.1871	0.9982	0.4177	Color
Guided filter [11]	0.0140	66.7109	0.9981	0.4148	Color
MCA [9]	0.0113	67.6280	0.9985	0.3683	Gray scale
Chen Duan-Yu [15]	0.0133	66.9166	0.9982	0.4099	Color

(a) (b)

Figure-4. [15] (a) Rain image (b) Clean image.

ARPN Journal of Engineering and Applied Sciences

Table-6. Experiment result using images in Figure-5.

Method /Measurement	MSE	PSNR	SSIM	VIF	Type of image
Bilateral filter [23]	0.0090	68.6252	0.9988	0.4276	Color
Guided filter [11]	0.0112	67.6708	0.9985	0.4572	Color
MCA [9]	0.0090	68.6322	0.9988	0.3477	Gray scale
Chen Duan-Yu[15]	0.0096	68.3533	0.9988	0.4295	Color

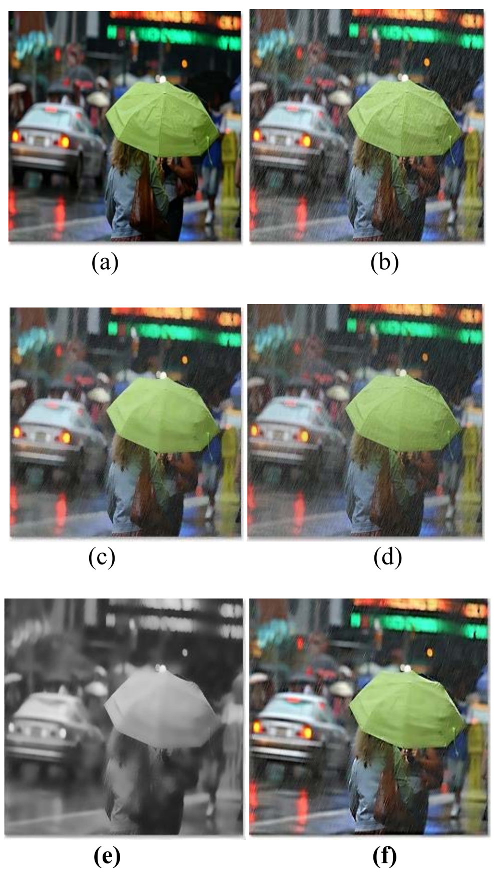

Figure-5. [15] (a) Rain image (b) Clean image (c) Bilateral filter (d) Guided filter (e) MCA (f) Chen Duan.

Figure-5 shows images using in the experiment for all methods. Based on the findings, the measurement value that is large such as, VIF, SSIM and PSNR is better, whereas, small value using MSE measurement is better. All the experiments show the fluctuation between the techniques depend on the details and colors in the images. Previous methods in Figure-5 (c,d,f) are dealing with color images but MAC [9] used the gray color images. Therefore, the comparisons will be between color images techniques which are bilateral filter, guided filter and Chen Duan-Yu [15]. Tables 4-6 show guided filter is better in MSE, PSNR and VIF measurement. However, bilateral filter and Chen Duan-Yu improved in SSIM. We note some different in VIF Guided filter work when comparing images and measurement values. It shows that not all measurements are accurate.

CONCLUSIONS

In this paper, review methods for a detection and removal of rain from single images, which are frameworks and algorithms for the detection and removal of rain have been presented. Those algorithms in this paper have been discussed in details, to present major aspects of tradeoffs raindrops detection and removal such as accuracy and perceiving details and edges. The best method was found based on measurement values and eye view which Chen Duan-Yu [15] because this method contains more than one process to execute the algorithm. In the future work, the research will concentrate on the designing the algorithm, which requires to detect the rain and non-rain components, then remove the candidate pixels with higher accuracy and the same time perceive the details.

ACKNOWLEDGEMENT

This research is supported by Universiti Sains Islam Malaysia (USIM) funds.

REFERENCES

[1] Sugimoto, M., Kakiuchi, N., Ozaki, N., Sugawara, R. A. 2012. Novel Technique for Raindrop Detection on A Car Windshield Using Geometric-Photometric Model. In: 15th International IEEE Conference. IEEE Press, New York 740-745.

[2] Nayar, S. K., Narasimhan, S. G. 1999. Vision in Bad Weather. In: the Seventh IEEE International Conference Computer Vision. IEEE Press, New York 820-827.

[3] Garg, K., Nayar, S. K. 2007. Vision and Rain. International Journal of Computer Vision. 75(1), 3-27.

[4] Garg, K., Nayar, S. K. 2004. Detection and Removal of Rain from Videos. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE Press, New York I-528.

[5] Zhang, X., Li, H., Qi, Y., Leow, W. K., Ng, T. K. 2006. Rain Removal in Video by Combining

ARPN Journal of Engineering and Applied Sciences

Temporal and Chromatic Properties. In: IEEE International Conference on Multimedia and Expo. IEEE Press, New York 461-464.

[6] Pei, S. C., Tsai, Y. T., Lee, C. Y. 2014. Removing Rain and Snow in a Single Image Using Saturation and Visibility Features. In: IEEE International Conference on Multimedia and Expo Workshops (ICMEW). IEEE Press, New York 1-6.

[7] Fu, Y. H., Kang, L. W., Lin, C. W., Hsu, C. T. 2011. Single-Frame-Based Rain Removal via Image Decomposition. In: IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE Press, New York 1453-1456.

[8] Xu, J., Zhao, W., Liu, P., Tang, X. 2012. An Improved Guidance Image Based Method to Remove Rain And Snow in A Single Image. Computer and Information Science. 5(3), 49.

[9] Kang, L. W., Lin, C. W., Fu, Y. H. 2012. Automatic Single-Image-Based Rain Streaks Removal via Image Decomposition. Image Processing, IEEE Transactions. 21(4), 1742-1755.

[10] Huang, D. A., Kang, L. W., Yang, M. C., Lin, C. W., Wang, Y. C. 2012. Context-Aware Single Image Rain Removal. In: IEEE International Conference on Multimedia and Expo (ICME). IEEE Press, New York 164-169.

[11] Xu, J., Zhao, W., Liu, P., Tang, X. 2012. Removing Rain and Snow in a Single Image Using Guided Filter. In: IEEE International Conference Computer Science and Automation Engineering (CSAE). IEEE Press, New York 304-307.

[12] Kim, J. H., Lee, C., Sim, J. Y., Kim, C. S. 2013. Single-Image Deraining Using An Adaptive Nonlocal Means Filter. ICIP.914-917.

[13] Eigen, D., Krishnan, D., Fergus, R. 2013. Restoring an Image Taken Through a Window Covered with Dirt or Rain. In: IEEE International Conference on Computer Vision. IEEE Press, New York 633-640.

[14] Sun, S. H., Fan, S. P., Wang, Y. C. 2014. Exploiting Image Structural Similarity for Single Image Rain Removal. IEEE. 978-1-4799-5751-4.

[15] Chen, D. Y., Chen, C. C., Kang, L. W. 2014. Visual Depth Guided Color Image Rain Streaks Removal Using Sparse Coding. IEEE transactions on circuits and systems for video technology. 24(8), 1430-1455.

[16] Chen, D. Y., Chen, C. C., Kang, L. W. 2012. Visual Depth Guided Image Rain Streaks Removal via Sparse Coding. In: International Symposium on Intelligent Signal Processing and Communications Systems. IEEE Press, New York 151-156.

[17] Zheng, X., Liao, Y., Guo, W., Fu, X., Ding, X. 2013. Single-Image-Based Rain and Snow Removal Using Multi-Guided Filter. In Neural Information Processing. Springer Berlin Heidelberg. 258-265.

[18] Rain Image Dataset, http://www.ee.nthu.edu.tw/cwlin/Rain_Removal/Rain_Removal.html.

[19] He, K., Sun, J., Tang, X. 2010. Guided Image Filtering. In Computer Vision–ECCV. pp. 1-14. Springer Berlin Heidelberg.

[20] Huang, D. A., Kang, L. W., Wang, Y. C., Lin, C. W. 2014. Self-Learning Based Image Decomposition with Applications to Single Image Denoising. Multimedia, IEEE Transactions. 16(1), 83-93.

[21] Dabov, K., Foi, A., Katkovnik, V., Egiazarian, K. 2009. BM3D Image Denoising with Shape-Adaptive Principal Component Analysis. In: SPARS'09-Signal Processing with Adaptive Sparse Structured Representations.

[22] Elad, M., Aharon, M. 2006. Image Denoising via Sparse and Redundant Representations over Learned Dictionaries. Image Processing, IEEE Transactions on, 15(12), 3736-3745.

[23] Tomasi, C., Manduchi, R. 1998. Bilateral Filtering for Gray and Color Images. In: Sixth International Conference on Computer Vision. IEEE Press, New York 839-846.

[24] Sheikh, H. R., Bovik, A. C. 2006. Image Information and Visual Quality. Image Processing, IEEE Transactions. 15(2), 430-444.

[25] Garg, K., Nayar, S. K. 2006. Photorealistic rendering of rain streaks. ACM Transactions on Graphics (TOG), 25(3), 996-1002.

[26] Huynh-Thu, Q., Ghanbari, M. 2008.Scope of validity of PSNR in image/video quality assessment. In: Electronics letters, 44(13), 800-801.