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A SURVEY OF RAIN REMOVAL ALGORITHMS FROM VIDEO

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Abstract:

Objective. This article presented a review of current rain removal algorithms from video that widely used nowadays. For comparative analyzing algorithms, excremental researches were carried and according to results of these researches given the conditions and requirements for the application, advantages and disadvantages of these algorithms.

Methods. We are trying to compare the performance of methods which discussed above by PSNR (peak-signal-to-noise ratio) [8], SSIM (structure similarity) [9], VIF (visual quality) [10] and FSIM (feature similarity) metrics. The implementation environment is Windows10, Matlab (R2018b), PyTorch (version 1.0.1) [77], and Tensorflow (version 1.12.0) with an Intel (R) Core(TM) i7-8700K at 3.70GHZ, 32GM RAM, and two Nvidia GeForce GTX 1080Ti GPUs.

Keywords: rain removal algorithms, model-driven methods, data-driven methods, rain streaks, exposure time, raindrops, rain detection, rain map, recurrent convolutional networks.

Introduction.

Quality of image is one of the important parameter in the image processing sphere. Capturing conditions might to cause appearing various noises in the image. Images shot in weather conditions such as rain, snow and fog can cause divers problems in further processing steps, such as object recognition, classification, and extracting features. Typically, raindrops, or rain streaks bring situations like fog or blurring the image, resulting in distortion of the content of the image scene. The researches on rain removal from video or a single image has thus been attracting much attention in computer vision and pattern recognition sphere, and many algorithms have been developed for this kind of problems recently. In this article, we aim to describe several rain removal methods, their overall structures, performance process, application conditions and possibilities.

Rain removal methods can divided into two groups: removing the rain from single image and video stream. There are differences and similarities in the methodologies

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developed for these two issues. Both issues adopt conventional methods based on the model-driven methodology. By using the physical properties of rain, a model of raindrops is created then rain streaks' layer extracted from the image. In addition, neural network technologies, which have been widely used in recent years, are being used to solve both problems. Many of these methods focus on specific aspects of the problem, and there are its own suitability and advantages. These algorithms can be mainly divided into four categories: time domain based ones, frequency domain based ones, low rank and sparsity based ones, and deep learning based ones. Algorithms belonging to the first three groups can be seen as a model-based methodology because they are designed to manually create a rain context model. The algorithms in the fourth group are algorithms that automatically learned features pre-collected training data (rainy/clean frame pairs). Therefore, we can see the algorithms belonging to this category as data-driven methodologies [1].

2. Review of current rain removal methods.

Initially, Garg and Nayar [1] tried to develop rain removal method from video and proposed detecting and eliminating rain streaks without changing scene of the video by directly extending the exposure time or reducing the depth of the camera area. They have developed a comprehensive model of rain visual appearance. Due to each raindrops acts refracts and reflects light from a large field of view towards the camera spherical lens create sharp intensity patterns in images. This kind of falling drops causes appearing complex space and time-varying signals in images. Additionally, because of the long exposure time of camera, the intensities produced by rain are motion-blurred and hence affected to background. Authors modeled these effects by developing separate photometric and dynamic models of rain. Together these models depict the complete visual appearance of rain streaks.

Based on appearance models, they had designed a simple algorithm for detection and removal of rain in videos. This algorithm uses the photometric and dynamic constraints extract from the appearance models to distinguish rain from other types of signals. This causes it powerful in detecting and removing rain even in the appearance of complex scene motions and time-varying textures. Based on analysis on visibility, they had developed a method that sets the camera parameters to remove or reduce the effects of rain streaks without any kind of changes the appearance of the scene.

However, this method does not work well in heavy rain and fast-moving objects near the camera. Also, camera settings cannot be made without significantly degrading the video stream.

Jin-Hwan Kim and Jae-Young Sim developed novel rain removal algorithm using temporal correlation and low-rank matrix completion [2]. If the adjacent frame distorted by the optical current differs from the current frame only in the areas of the rain lines, then the initial rain map is generated using this difference. Then, the initial

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rain map is represented using sparse basis vectors, which are dichotomized into rain streak ones and outliers using a support vector machine (SVM). By clearing the outliers, the rain map is refined and the rain lines are detected. Finally, the detected rain pixels are replaced using a matrix completion algorithm. This algorithm is performed using the expectation maximization (EM) iterations for the low-rank approximation.

Jiang and Huang proposed a new tensor-based method to remove the rain from the video, fully considering the discriminatively intrinsic features of rain streaks and clean videos [3]. This method does not require any rain detection or time consuming dictionary learning period. (Fig. 1). Here analysis specifically spatial and temporal, global and local prior knowledge. In the spatial aspect directional properties of the raindrop affects to rainy video by two direction: along the raindrops' direction (Fig. 3 c-1,2,3) and perpendicular to it (Fig. 3 d-1,2,3). Temporal aspect, the graph of the rainy part of the video (a-2 and b-2) produces the tighter correlation along the time axis than the graph of the rainless video and the rain streaks (a-1,3 and b-1,3). Therefore, a tensor nuclear norm and the time direction difference operator are used to simultaneously increase the global and local dependence of the main rainless video along the time direction. The rarity of rain streaks is then calculated and the l_1 norm is used to guarantee it.

This method also has its drawbacks. If the rain direction is far from that axis, it can be controlled by video / image reflection. But reflection in digital data can lead to many distortions.

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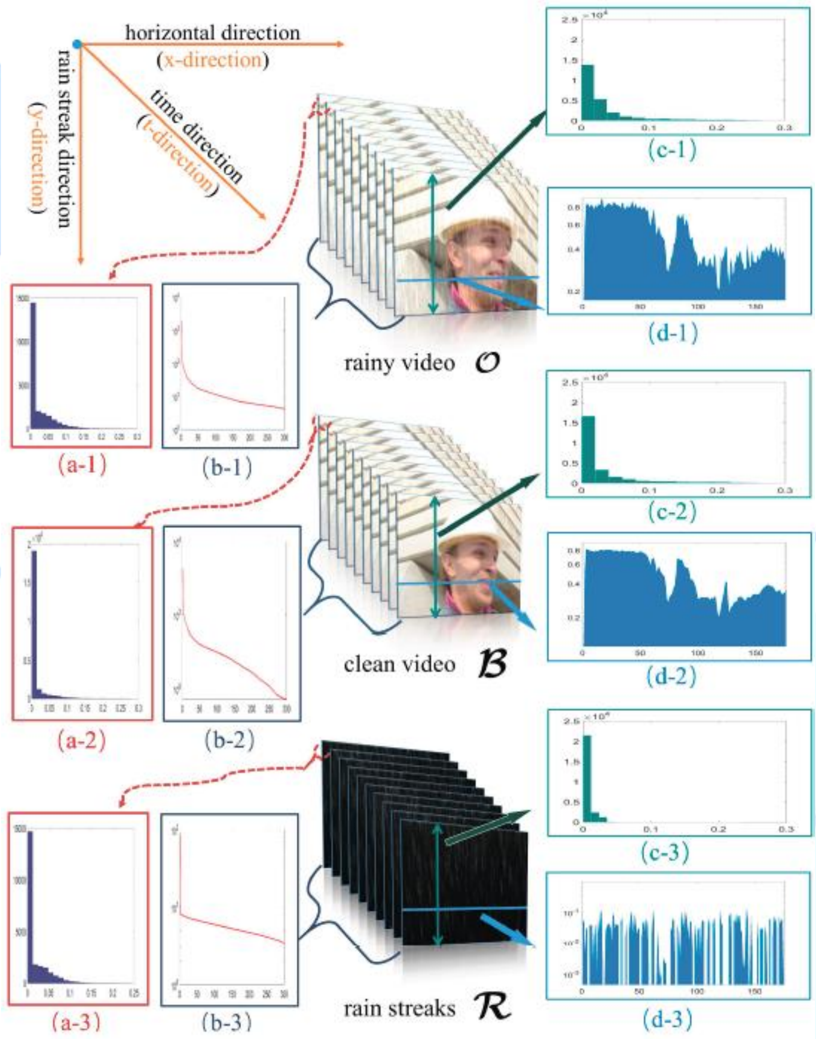

Figure 1. From left to right: 1) the histograms of difference of the 1st and 2nd frame from the rainy video, clean video and rain streaks, respectively; 2) the singular values of O $_{(3)}$, B $_{(3)}$ and R in decreasing order, severally; 3) some example frames of rainy video, clean video and rain streaks; 4) the histograms (c-1,2,3) of rain directional difference of the 10th frame, and the intensities of a row (d-1,2,3) of the rainy video, clean video and rain streaks, respectively.

Weihong Ren et al. proposed a model based on matrix decomposition to remove rain and snow from the video. According to this method, rain streaks and snowflakes are divided into sparse and dense categories. Using background vibrations and optical flow data, moving objects are detected, and sparse rain lines (snowflakes) are formed as multi-labeled Markov Random Fields (MRFs). Dense rain streaks (snowflakes) are considered to obey Gaussian distribution [5].

In their methods, Minhan Li et al. focused on two internal features that are characteristic of rain streaks. Firstly, the rain streaks in the video include repetitive local patterns that are sparsely scattered across different positions in the video. Secondly, rain streaks are multiscale due to they appear at different distances from the camera. Based on these features, the authors developed the model MS-CSC (multiscale convolutional sparse coding) [6]. Specifically, they used multiple convolutional filters

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convolved on the sparse feature maps to deliver the former characteristic, and further use multiscale filters to represent different scales of rain streaks. Using this new method of coding, the proposed model effectively separates the rain lines in the video, thereby increasing the efficiency of removing rain effects

In the method Jiaying Liu et al. were used deep recurrent convolutional networks for removing the rain from video. They proposed the idea of taking into account the areas of rain occlusion (i.e., areas with low light transmittance of rain streaks) when extinguishing rain [7]. Different from normal rain streaks, there are completely losses occur in the background images in the occlusion areas. Therefore, the proposed model is intended to represent both rain lines and rain occlusion. Based on the wealth of temporal redundancy, a general recurrent network (J4R-Net) that removes and restores rain has been developed. This overall network combines networks that classification rain degradation, spatial texture appearances based rain removal, and temporal coherence based background details reconstruction. Rain degradation classification refers to the representation of a binary map describing whether an area is degraded by additive rain streaks or by rain occlusion. Based on the information obtained from it, the GRU (Gated recurrent unit) learns to make a trade-off between removal of rain streak and the restoration of background details (Fig. 3). This hybrid rain model to depict both rain streaks and occlusions as:

$$O_t = (1-\alpha_t)(B_t + R_t) + \alpha_t A_t, t = 1,2,\ldots,N,$$

where t and N signify the current time-step and total number of the frames in a video. $O_t \in \mathrm{R}^{h\times w}$, $B_t \in \mathrm{R}^{h\times w}$, and $R_t \in \mathrm{R}^{h\times w}$ are the rainy image, background frame, and rain streak frame, respectively.

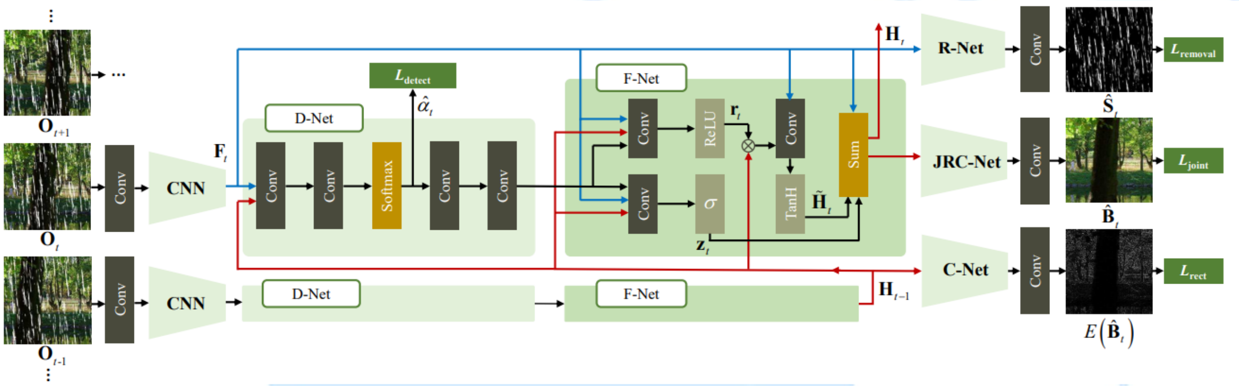

Figure 3. The framework of Joint Recurrent Rain Removal and Reconstruction Network (J4R-Net). D-Net is degradation classification network, F-Net is Fusion Network, R-Net is Removal Network, C-Net is Construction Network, JRC-Net is Joint Removal and Construction Network.

3. A Comprehensive Repository for Rain Removal.

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We are trying to compare the performance of methods which discussed above by PSNR (peak-signal-to-noise ratio) [8], SSIM (structure similarity) [9], VIF (visual quality) [10] and FSIM (feature similarity) metrics. The implementation environment is Windows10, Matlab (R2018b), PyTorch (version 1.0.1) [77], and Tensorflow (version 1.12.0) with an Intel (R) Core(TM) i7-8700K at 3.70GHZ, 32GM RAM, and two Nvidia GeForce GTX 1080Ti GPUs.

4. Experiments and analysis.

In order to determine the effectiveness of the analyzed methods, two videos were selected from the CDNET video database [13], including moving objects and background views in different scenes. Figure 8 presented frame of normal rainy video and images that consist of the results of the methods being analyzed. Figure 9 shows the results of rain removal in a video image of heavy rainfall.

Table 1. Performance comparisons of all competing video rain removal methods in synthetic rain.

Metrics	**Fig. 8**				**Fig. 9**			
	PSNR	SSIM	VIF	FSIM	PSNR	SSIM	VIF	FSIM
Input	28.22	0.637	0.935	0.927	23.82	0.766	0.970	0.929
Garg	29.83	0.661	0.955	0.946	24.15	0.611	0.960	0.911
Kim	30.44	0.602	0.958	0.952	22.39	0.526	0.932	0.886
Syan	31.93	0.745	0.971	0.974	24.32	0.713	0.966	0.938
Ren	28.26	0.685	0.970	0.962	23.52	0.681	0.966	0.927
Wei	29.76	0.830	0.992	0.988	24.47	0.779	**0.980**	0.951
Li	**33.89**	**0.865**	0.992	**0.992**	**25.37**	**0.790**	**0.980**	**0.957**
Liu	27.56	0.626	**0.995**	0.941	22.19	0.555	0.946	0.895

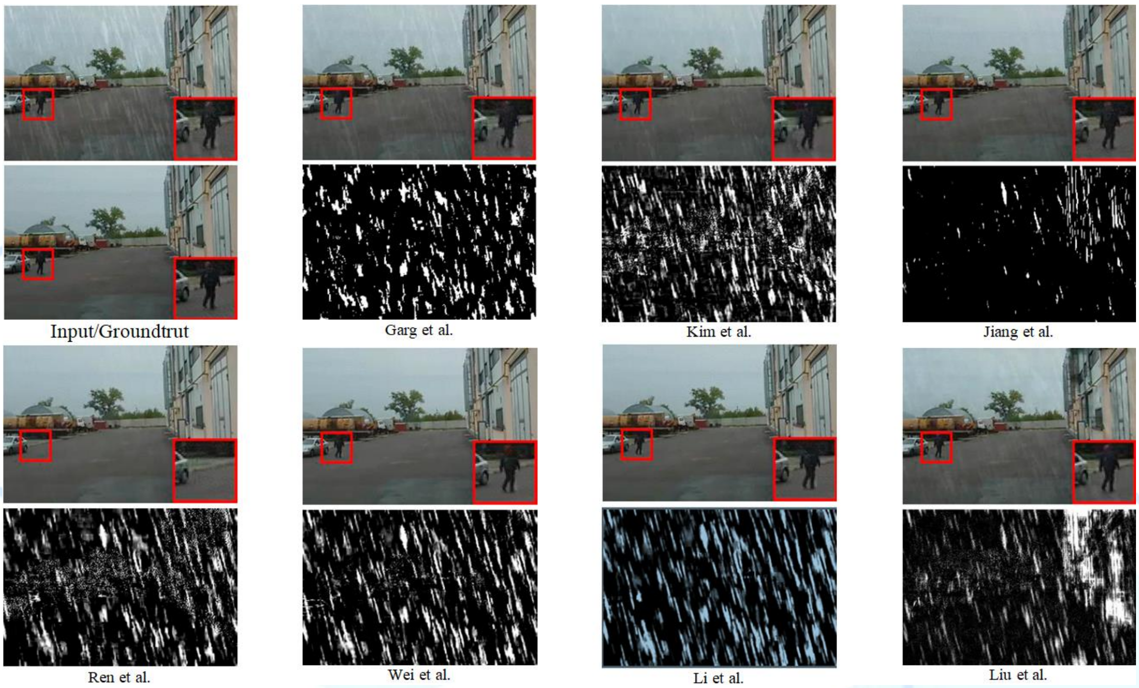

Figure 8. Results obtained using the methods being analyzed.

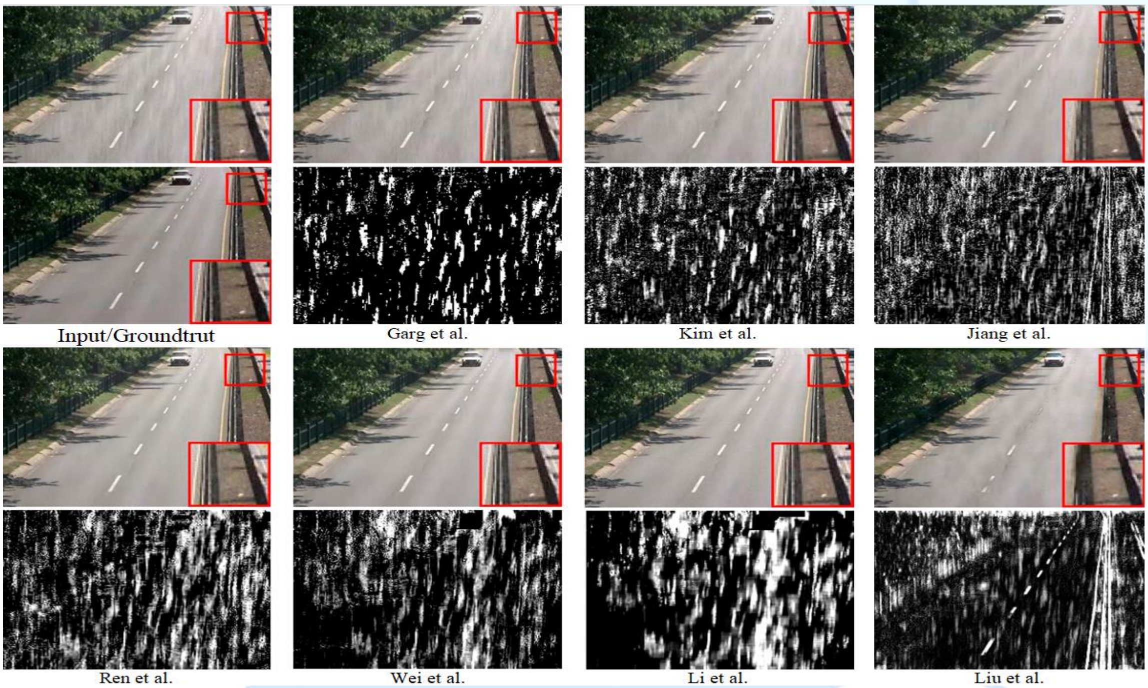

Figure 9. Results obtained using the methods being analyzed.

Conclusion

According to the results of an experiment conducted on a video image in normal rain conditions, the rain streaks were not clearly separated in the Garg, Kim, Qian, and Liu methods, as shown in Table 1. Also there are some errors appear when deleting moving objects and rain streaks in the Ren et al. method, (Fig. 8). The corresponding rain layers provided in the second row depict that apart from Li et al.'s method which can preserve texture details well, the rain layers extracted by the other methods contain different degrees of background information (Fig. 9).

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