RAIN STREAK REMOVAL VIA MULTI-SCALE MIXTURE EXPONENTIAL POWER MODEL

Xiaofen Wang[1,2,3], *Jun Chen*[1,3,4,*], *Zhen Han*[1,3], *Mingfu Xiong*[5], *Chao Liang*[1,3], *Qi Zheng*[1,3], *and Zhongyuan Wang*[1,3]

[1]National Engineering Research Center for Multimedia Software, School of Computer Science, Wuhan University, China
[2]School of Electronics and Information Engineering, Hubei University of Science and Technology, China
[3]Hubei Key Laboratory of Multimedia and Network Communication Engineering, Wuhan University, China
[4]Collaborative Innovation Center of Geospatial Technology, Wuhan, China
[5]School of Mathematics and Computer Science, Wuhan Textile University, China

ABSTRACT

Rain streaks severely hamper the visible performance of the outdoor surveillance videos, which becomes an attractive issue in recent computer vision research. Existing methods usually encode rain streaks into Gaussian Mixture Model (GMM). However, the limited number of Gaussian components in the GMM compromises the ability of the model in fitting real noise, such as sparse noise, which is exactly the characteristic of the rain streaks. In this paper, a novel model named Mixture Exponential Power Model (MEPM) is exploited. It sets multiple Laplace noise components and expands the representation capability for the sparse noise. Moreover, considering that the rain streaks in a video occur in different distances from the camera, we encode rain streaks into Multi-scale Mixture Exponential Power Model. The model is optimized by expectation-maximization (EM) algorithm and Lagrange multiplier strategy. Experiments are implemented on synthetic and real rain videos and verify the superiority of the proposed method, compared with state-of-the-art methods.

***Index Terms*—** Rain streaks, video, sparse noise, Mixture Exponential Power Model, Multi-scale.

1. INTRODUCTION

Rain removal is an important problem in computer vision, and it may degrade performance of video processing, like person tracking [1], recognition [2], detection [3] and re-identification [4, 5]. The performance of outdoor surveillance videos often degrades when videos contain rain streaks. Therefore, it is essential to remove rain streaks from the surveillance videos in bad rainy conditions which attracts wide attention in recent years.

In 2004, the characters of the nature rain streaks was firstly analyzed by Garg and Nayar. They [6] presented the comprehensive analysis of the visual effects of rain streaks, and detected the rain streaks based on a correlation model. Garg and Nayar [7] further proposed to reduce or even remove the effects of rain streaks by setting parameters of the camera, such as exposure time and depth of field. Afterwards, more intrinsic properties of rain streaks and algorithms of rain streak removal were explored. Recently, Jiang *et al.* [8] considered the sparsity of rain streaks and proposed a tensor-based rain streaks removal approach in video. To deal with heavy rain streaks in dynamic scenes, Ren *et al.* [9] divided rain streaks into dense layer and sparse layer, and they assumed that the dense ones obeyed Gaussian distribution. Later Wei *et al.* [10] firstly encoded the rain streaks in video into a patch-based mixture of Gaussians and proposed 3DTV to regulate moving objects. However, the limited number of Gaussian components in the GMM compromises the ability of the model in fitting real noise, especially the sparse noise. It has been investigated in [11], Mixture Exponential Power Model (MEPM) performs better than GMM in the sparse noise case.

In view of the limitation of GMM, we adopt the novel model named MEPM in this paper. This model sets multiple Laplace noise components, which expands the representation ability for the sparse noise. Taking the rain streaks as an example, the sparsity of rain streaks has been investigated in [8, 12].

In addition, the multi-scale strategy has attracted much attention and achieved impressive performance for low-level vision tasks, *e.g.*, image super-resolution, noise removal, image segmentation, visual tracking. According to [7], the rain streaks near the camera are dynamic with large shapes, while the rain streaks away from the camera are with small shapes. Considering that we encode the rain streaks in MEPM from different scales. The parameters of the Multi-scale Mixture Exponential Power Model (MMEPM) can be optimized by expectation-maximization (EM) algorithm.

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2. MMEPM FOR RAIN REMOVAL IN A VIDEO

2.1. Problem formulation

In general, video with rain streaks is constituted with background information, rain streaks and moving objects, such that

$$O = B + R + M, \tag{1}$$

where $O \in \mathbb{R}^{w\times h\times n}$, $B \in \mathbb{R}^{w\times h\times n}$, $R \in \mathbb{R}^{w\times h\times n}$ and $M \in \mathbb{R}^{w\times h\times n}$ respectively represent the input video, the background, the rain streaks and the moving objects. w, h and n respectively represent the width, height and the frame number of a video. Our goal is to remove the rain streaks R from the video O and get a non-rain video.

Multi-scale decomposition. Considering the calculation cost and experiment results, the number of scales is set to be 2. Laplace pyramid is proposed to decompose the video into multi-scale. At each pyramid level, rain streaks are progressively simulated by MEPM. Simulating the rain streaks in multiple scales can extract detail structures better.

$$O = O_1 + O_2, \tag{2}$$

Modeling rain streaks by MMEPM. It is a traditional method to stimulate rain streaks with GMM. As we have analyzed in the introduction, a novel model is exploited to simulate the rain streaks. However, rain streaks in video are generally with multi-scale characteristic since they are captured from different distances by camera. To better characterize the features of rain streaks, Multi-scale Mixture Exponential Power Model (MMEPM) is utilized to simulate the rain streaks. The MMEPM can be formulated as follows:

$$P(e_{ij}) = \sum_{k=1}^{K} \pi_k f_{pk}(e_{ij}; 0, \mu_k), \tag{3}$$

where π_k is the distribution weights with $1 \geq \pi_k \geq 0$, K is the number of the mixture components and $f_{pk}(e_{ij}; 0, \mu_k)$ denotes the k_{th} EP distribution.

The density function of the EP distribution (p $>$ 0) with zero mean is

$$f_{pk}(e_{ij}; 0, \mu_k) = \frac{p\mu^{\frac{1}{p}}}{2\Gamma(\frac{1}{p})} exp\left\{-\mu|e|^p\right\}, \tag{4}$$

where μ is the precision parameter, p is the shape parameter and $\Gamma(\cdot)$ is the gamma function. By changing the shape parameter p, we can get different Exponential Power distribution [11]. In particular, when p=1, it is a Laplace distribution, when p=2, it is a Gaussian distribution. Therefore, GMM is a special case of MEPM.

Modeling the background with low-rank decomposition. In order to initialize the background, the video information is converted into matrix information, and the column pixel values of the matrix represent the pixel values of a frame in the video. The number of frames in the video is equal to the number of columns in the matrix. Under the condition of still camera, the pixel changes among the video image sequences are caused by the moving objects M and rain streaks R. Then low-rank decomposition of the matrix can be used to get the initialization background information. Here, we adopt SVD decomposition. The low-rankness of the reconstruction UV^T can infer the final background information.

$$B = UV^T, \tag{5}$$

Where $U \in \mathbb{R}^{d\times r}$, $V \in \mathbb{R}^{n\times r}$, and $r \leq min(d, n)$.

Modeling moving objects with Markov random field and graph cut method. A binary mask H is used to mark whether there are moving objects or not. When the binary mask pixel value is 1, it indicates that there is a moving object at that pixel, otherwise there is no [15, 16]. For moving object areas, there is such a formula:

$$H \circ O = H \circ M \tag{6}$$

here, the rain streaks on the moving objects are neglected. In section 2.3, a correction factor is used to reduce the influence of the rain streaks on moving objects. Inspired by Wei. *et al.* [10], to regularize the moving objects mask H, L_1-penalty and 3DTV penalty are used. The moving objects are labeled with graph cut algorithm and Markov random field (MRF). By integrating the aforementioned three models, the proposed MMEPM can be constructed as follows:

$$\begin{aligned} &min - \sum_{ij\in\Omega} log \sum_{k=1}^{K} \pi_k f_{pk}((1-H)\circ R; 0, \mu_k) \\ &+ Q_1||H||_{3DTV} + Q_2||H||_1 \\ &s.t.(1-H)\circ R = (1-H)\circ(O-B), B = UV^T, \end{aligned} \tag{7}$$

The number of Exponential Power in the model can be solved by the method proposed by Huang *et al.* [17], and construct the following penalized MMEPM:

$$\begin{aligned} &min - \sum_{ij\in\Omega} log \sum_{k=1}^{K} \pi_k f_{pk}((1-H)\circ R; 0, \mu_k) \\ &- n\delta \sum_{k=1}^{K} D_k log \frac{\pi_k + \varepsilon}{\varepsilon} + Q_1||H||_{3DTV} + Q_2||H||_1 \\ &s.t.(1-H)\circ R = (1-H)\circ(O-B), B = UV^T, \end{aligned} \tag{8}$$

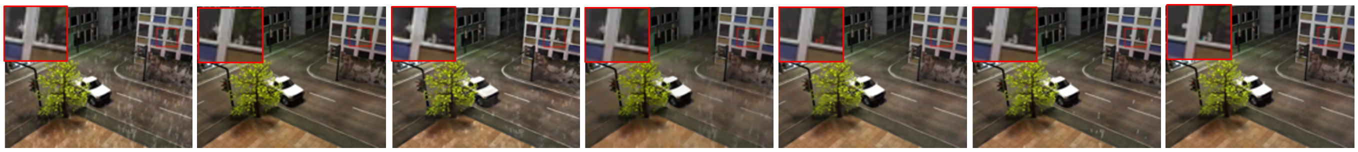
where ε is a very positive number. In this paper, we choose ε to be 10^{-6}, δ to be 0.1 and D^k is the free parameter for the k^{th} component. Then the parameters of the model can be optimized by EM algorithm.

2.2. Optimization

EM algorithm is an iteration leaning processing. Calculating the log likelihood is the first step of the EM algorithm.

E step. Introducing a latent variable z_{ijk}. It is a random variable between zero and one, and $\sum_{k=1}^{K} z_{ijk} = 1$.

$$\gamma_{ijk}^{(t+1)} = E(z_{ijk}) = \frac{\pi_k^{(t)} f_{pk}((1-H)\circ R; 0, \mu_k)}{\sum_l^K \pi_l^{(t)} f_{pl}((1-H)\circ R; 0, \mu_k)} \tag{9}$$



(a) rain image (b) groundtruth (c) Fu [13] (d) Li [14] (e) Wei [10] (f) Li [12] (g) Ours

Fig. 1. Rain removal performance of different methods on a synthetic video .

(a) rain image (b) groundtruth (c) Fu [13] (d) Li [14] (e) Wei [10] (f) Li [12] (g) Ours

Fig. 2. Rain removal performance of different methods on a synthetic video with a moving truck.

M step. Then, we can get the final function Q, following EM algorithm theory.

$$
\begin{aligned}
Q = \sum_{ij}\sum_{k=1}^{K}\gamma_{ijk}^{(t+1)}[log f_{pk}((1-H)\circ R; 0, \mu_k) + log\pi_k] \\
- n\delta\sum_{k=1}^{K} D_k log\frac{\pi_k+\varepsilon}{\varepsilon} + Q_1||H||_{3DTV} + Q_2||H||_1
\end{aligned}
\tag{10}
$$

Update Q. Introduce a Lagrange multiplier λ and then maximum the Lagrange function

$$
\begin{aligned}
\sum_{ij}\sum_{k=1}^{K}\gamma_{ijk}^{(t+1)} log\pi_k - n\delta\sum_{k=1}^{K} D_k log\frac{\pi_k+\varepsilon}{\varepsilon} + \\
\lambda(\sum_k \pi_k - 1),
\end{aligned}
\tag{11}
$$

Update μ. To obtain the update equation of μ, take the first derivative of Q with respect to μ_k, and get the zero point:

$$
\mu_k^{(t+1)} = \frac{1}{p_k|(1-H)\circ R|^{p_k}} \tag{12}
$$

Update U, V. The updates for the unknown U, V as follows:

$$
\begin{aligned}
min\sum_{ij}\sum_{k=1}^{K}\gamma_{ijk}^{(t+1)}[log f_{pk}((1-H)\circ R; 0, \mu_k) \\
+ log\pi_k] + Q_1||H||_{3DTV} + Q_2||H||_1
\end{aligned}
\tag{13}
$$

Using Augmengted Lagrangian Multiplier strategy to solve Eq. (13).

2.3. Post processing

During the rain streaks removal processing, the algorithm neglects the effect of the moving objects on the rain. Then the post processing is necessary and solved with TV regularization [18, 19].

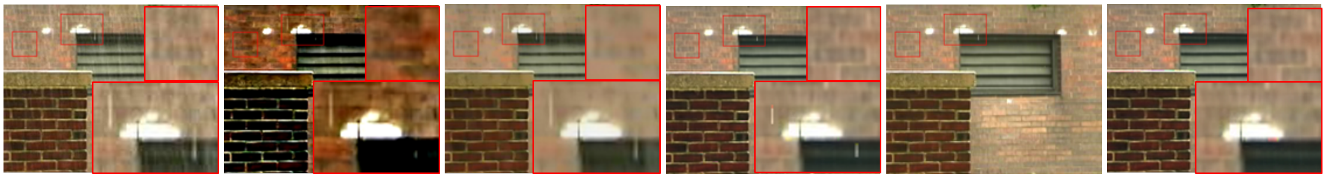
3. EXPERIMENTAL RESULTS

In order to prove the superiority of the proposed method, four current state-of-the-art methods are compared, including Fu *et al.* [13] (TIP's 2017) based on deep learning for a single image, Li *et al.* [14] (CVPR's 2016) based on GMM for a single image, Wei *et al.* [10] (ICCV's 2017) based on GMM for video and Li *et al.* [12] (CVPR's 2018) based on convolutional sparsely encoding for video. Due to the limited space, the experimental results are compressed to a small extent. In order to get better visual, please zoom in to see details.

3.1. Results on synthetic videos

In this section, we show the experiment results on synthetic videos. We choose two videos with different types of rain streaks and background scenes. The frame number of each video is 100. Rain streaks in Fig. 1 are thin whereas that in Fig. 2 are thick. From Fig. 1, comparison methods proposed by Fu *et al.*[13], Li *et al.*[14] and Li *et al.*[12] fail to remove all rain streaks. Wei *et al.* [10] removes almost all rain streaks, while it generates a edge color problem. According to Fig. 2, methods of Fu *et al.* [13], Li *et al.* [14] can not remove all rain steaks. Wei *et al.* [10] causes serious color distortion problem. Li *et al.* [12] blurs the image. While our method can remove the majority of the rain streaks as well as maintain the feature details.

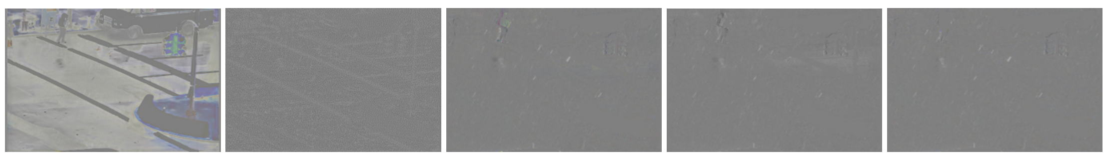
Quantitative comparisons are showed in Table 1 and Table 2. Here we choose three image performance metrics PSNR, SSIM and FSIM to verify the performance of the algorithms. We use average values of these performances metrics in videos. In the results of Fig. 1, it can be seen that our method outperforms other methods in objective parameters. In the results of Fig. 2, the PSNR is not particularly good, probably



(a) rain image (b) Fu [13] (c) Li [14] (d) Wei [10] (e) Li [12] (f) Ours

Fig. 3. Rain removal performance of different methods on a real video.

(a) rain image (b) Fu [13] (c) Li [14] (d) Wei [10] (e) Li [12] (f) Ours



(b) Fu [13] (c) Li [14] (d) Wei [10] (e) Li [12] (f) Ours

Fig. 4. Rain removal performance of different methods on a real video.

because our method not only removes the rain streaks in the video, but also removes the video noise.

3.2. Results on real videos

In this section, we show the experiment results on real videos. In the results of Fig. 3, we can see that the results of Fu *et al.* [13] have a severe color distortion. A severe detail texture distortion exists in the results of Li *et al.* [14]. Too many rain streaks remain in the results of Wei *et al.* [10] and Li *et al.* [12], and according to our statistic, there are respectively 35 and 51 frames in the 100 frames with rain streaks.

In Fig. 4, similar to above experiments, Fu *et al.* [13] and Li *et al.* [14] fail to protect the color or destroy the detail texture. What's more, in the results of Wei *et al.* [10], the color distortion problem of the passenger exists. Li *et al.* [12] removes the rain streaks at the expense of degrading the visual of moving objects. The rain streaks removed by each method in this scene are shown in Fig. 4. From the results of Fig. 3 and Fig. 4, the proposed method get a good visual effect in both rain streaks removal and detail preservation in real videos.

4. CONCLUSION

In this paper, considering the sparsity feature of rain streaks with scattered over different positions of the video, MMEPM is adopted to stimulate the rain streaks. The experiments on synthetic and real videos demonstrate that our algorithm can yield better results than other state-of-the-art methods. However, the proposed method exists a limitation that the images of the video must have a same background, which means it cannot be suitable for the scenarios of moving camera. Our further work will be devoted to address the background changes with the moving camera.

Table 1. Performance comparison of different methods on synthetic video in terms of PSNR, SSIM and FSIM in Fig. 1.

	Li [14]	**Fu [13]**	**Wei [10]**	**Li [11]**	**Ours**
PSNR	31.0354	28.5137	32.2509	34.3237	**34.6939**
SSIM	0.9039	0.8865	0.9691	0.96337	**0.9715**
FSIM	0.9310	0.9119	0.9799	0.9749	**0.9821**

Table 2. Performance comparison of different methods on synthetic video in terms of PSNR, SSIM and FSIM in Fig. 2.

	Li [14]	**Fu [13]**	**Wei [10]**	**Li [11]**	**Ours**
PSNR	24.1431	22.0278	25.8028	**26.2764**	26.1293
SSIM	0.9273	0.9217	0.9566	0.95615	**0.9572**
FSIM	0.9478	0.9519	**0.9805**	0.9795	0.9797

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