A New Algorithm of Rain (Snow) Removal in Video

Chen Zhen
College of Automation, Harbin Engineering University, Harbin 150001, China,
College of Information Technology, Beihua University, Jilin 132013, China
E-mail: fred61111@sina.com.cn

Shen Jihong
College of Science, Harbin Engineering University, Harbin 150001, China,
E-mail: shenjihong@hrbeu.edu.cn

***Abstract*—The images acquired by outdoor vision system in the rain or snow have low contrast and are blurred, and it can cause serious degradation. Traditional rain (snow) removal method is restricted with the intensity, so the effect is not ideal. According to the characteristic of vision system acquiring multiple different degraded images in a short time, the paper processes multiple images to realize restoration. Snow and rain have the dynamic characteristic that the direction, intensity and shape of rain and snow are unfixed, which makes it difficult to establish unified physical model in the spatial domain. But analyzing them in the frequency domain doesn't affected by the dynamic characteristic. From the perspective of frequency domain, the paper uses the method of wavelet multi-level decomposition and wavelet fusion to determine the number of layers of rain (snow) noise, formulates a fusion rule based on rain (snow) noise pollution, and makes wavelet fusion on specific layer of multiple continuous degraded images for achieving the objective of rain (snow) removal. Simulation results indicated that the method in the paper not only has ideal restoration results, but also is not restricted by noise intensity.**

***Index Terms*—rain (snow) removal, image restoration, wavelet multi-level decomposition, wavelet fusion, fusion rule, rain (snow) noise pollution**

I. INTRODUCTION

With the rapid development of computer technology, outdoor vision system is being more and more widely used, and it plays a critical role in traffic surveillance, remote sensing monitoring and military surveillance. However, robustness and practicability of outdoor vision system in adverse weather conditions are influenced greatly. Especially the images acquired in the rain (snow) have high pollution levels and are blurred, and the ambiguous recognition of detail content makes it impossible to make application process including feature extraction and target recognition. So it has important significance to process the images acquired in the rain or snow, which can make outdoor vision system have greater reliability and adaptability.

There are two main methods of restoring rain ore snow images. The first method is based on hardware. In 2005, Garg [1, 2] reduced the degree of rain and snow of the video by setting the parameters of camera. But it is difficult for this method to be applied to outdoor vision system, and the clear effect on the condition of greater degree of rain and snow is not ideal. So there are few studies on hardware methods. The other method is based on software. Proper digital image processing algorithm is used to process one or multiple degraded images for achieving the objective of rain and snow removal. It includes the method based on image spatial domain and the method based on image frequency domain. The first method started early and the study on it is deep. In 1999, Hase [3] proposed a method of reducing the visibility of snowflake of the video in real time, in which each pixel is for Median filtering processing in the direction of time axis. In 2004, Garg [2, 4] studied the optical and motion characteristics of raindrops and constructed the optical model and dynamic model of raindrops to detect and remove the raindrops, which is called frame difference. In 2006, Zhang [5] made k-means cluster on all pixels with the same coordinates in the direction of time axis in the video to detect and remove raindrops, which is called cluster method. The later method of rain and snow removal based on image spatial domain is the improvement on frame difference and cluster method. In 2008, Zhao Xudong [7] studied the distribution range of brightness of the rain to determine if the pixel is covered by the raindrops. The method based on image frequency domain started late. In 2009, Barnum [8, 9] constructed the frequency domain model of raindrops to recognize the raindrops, and made filtering operation to realize rain removal, but the process of constructing frequency domain model of raindrops is very complicated. In 2011, Fu[10] made decomposition of sparse coding on single degraded image and rain removal was realized by filtering operation. As the clear process is made on single image, it inevitably makes the details of images lost.

According to the characteristic of vision system acquiring multiple different degraded images in a short time, the paper processes multiple images for realizing restoration. And snow and rain has the dynamic

doi:10.4304/jmm.8.2.168-174

characteristic that the direction, intensity and shape of rain and snow are unfixed, which makes it difficult to establish unified physical model in the spatial domain. But analyzing them in the frequency domain doesn't affected by the dynamic characteristic. From the perspective of frequency domain, the paper uses the method of wavelet multi-level decomposition and wavelet fusion to determine the number of layers of rain (snow) noise, formulates a fusion rule based on rain (snow) noise pollution, and makes wavelet fusion on specific layer of multiple continuous degraded images for achieving the objective of rain (snow) removal. Simulation results indicated that the method in the paper not only has ideal restoration results, but also is not restricted by noise intensity.

II. Rain (Snow) Removal Methods of Multiple Images

A. Digital Image and Wavelet Analysis

Digital image is essentially a two-dimensional discrete signal and has limited resolution. Fourier transform was used in the early days to realize the conversion of images in spatial domain and frequency domain for removing the needless frequency in mage. But as the study on digital images goes deeper, the limitation of Fourier transform solving problems arises, that is, it is a global transformation and the whole spectrum of images is obtained, so it is unable to express the local quality of spatial domain for images, and it can't find out accurate frequency of rain (snow) in the images. But wavelet analysis is a quantitative image analysis method, and wavelet multi-layer decomposition can determine the frequency range of rain (snow) in the images.

Wavelet analysis is a signal analysis tool which was proposed in the mid-1980s, and it has good space—frequency localization feature. And it can decompose the signals into eeg sub-bands with different resolutions, frequency characteristics and directional characteristics, so it is called mathematic microscope. With the inspiration of image decomposition and reconstruction pyramid algorithm of of Burt and Adelson, Mallat proposed Malla algorithm based on wavelet analysis. The projection $A_j f(x,y)$ of V_j^2 space can be used to express two-dimensional images:

$$f(x,y) = A_j f(x,y) = A_{j+1} f + D^1{}_{j+1} f + D^2{}_{j+1} f + D^3{}_{j+2} f \tag{1}$$

$$A_{j+1} f = \sum_{m_1,m_2 \in Z} C_{j+1,m_1,m_2} \phi_{j+1,m_1,m_2} \tag{2}$$

$$D^{\varepsilon}{}_{j+1} f = \sum_{m_1,m_2 \in Z} D^{\varepsilon}{}_{j+1,m_1,m_2} \psi^{\varepsilon}{}_{j+1,m_1,m_2} \ (\varepsilon = 1,2,3) \tag{3}$$

If the filter coefficient matrix of scale function $\phi(x)$ and wavelet function $\psi(x)$ are H and G, the decomposition formula of Mallat algorithm with j scale is

$$C_j = H_c H_r C_{j-1}$$

$$D^1{}_j = G_c H_r C_{j-1}$$

$$D^2{}_j = H_c G_r C_{j-1}$$

$$D^3{}_j = G_c G_r C_{j-1} \tag{4}$$

C_j, $D^1{}_j$, $D^2{}_j$ and $D^3{}_j$ respectively corresponds to low-frequency component of image C_{j-1}, high-frequency component in vertical direction, high-frequency component in horizontal direction and high-frequency component in diagonal direction. And Mallat reconstruction algorithm corresponding to it is:

$$C_{j-1} = H^*{}_r H^*{}_c C_j + H^*{}_r G^*{}_c D^1{}_j + G^*{}_r H^*{}_c D^2{}_j + G^*{}_r G^*{}_c D^3{}_j \tag{5}$$

In the algorithm, H^* and G^* is respectively conjugate transpose matrix of H^* and G^* .

Wavelet analysis can respectively make line and high and low filtering operation on images. Rows and columns low filtering on the original image can get low-frequency coefficient of myopia C1 of the first layer including the background and color of the images. Rows, columns, rows and columns high filtering on the original images can obtain high-frequency detail coefficient $D^H{}_1$, vertical high-frequency detail coefficient $D^V{}_1$ and diagonal high frequency-detail coefficient $D^D{}_1$ including the information of texture and edge in difference directions. The above operations are made on C1 repeatedly to get C2, $D^H{}_2$, $D^V{}_2$ and $D^D{}_2$ which is respectively the low-frequency coefficient of the second layer and high-frequency coefficients in three directions. If the low-frequency coefficient in the m-1layer is continued to be filtered, Cm, $D^H{}_m$, $D^V{}_m$ and $D^D{}_m$ can be obtained. And size relation of the frequencies is Cm < C m-1 < Dm <Dm-1.

B. Determination on the Layer of Rain (snow) Noise

The frequency of rain (snow) noise is different from that of degraded images scene. The frequency of rain (snow) is higher. And the frequency of the texture and edge of the scene information is also has higher and may be higher than that of rain (snow), but the frequency of background and color information of images is low. So the frequency of a image including rain (snow) noise is as follows: the frequency of background and color information of images is the lowest, the frequency of rain (snow) noise is higher, and the frequency of detail information including texture and edge is the highest. From the multi-layer decomposition of wavelet analysis on a degraded image, we can find that rain (snow) noise should be included in high-frequency coefficients in the low layer. The greater decomposition layer-number is usually selected to ensure that the detailed information of images after decomposition have less rain (snow) noise. And the concrete layer of rain (snow) noise, detail information, background and color information of images is respectively determined.

Next, we make wavelet multi-layer decomposition on an image in the rain, in which the decomposition layer-number is 10, as shown in Figure 1a. Figure 1b is the image of low frequency restructure of the 10th layer. And the images of high frequency restructure from the 10th layer to the 1st layer are shown from figure 1c to figure 11. Figure 1m is the image of high frequency restructure from the 10th layer to the 5th layer, and the high-frequency coefficients of the 1st layer, which includes less rain noise. Figure 1n is the image of high frequency restructure from the 4th layer to the 2nd layer, which includes most rain noise.

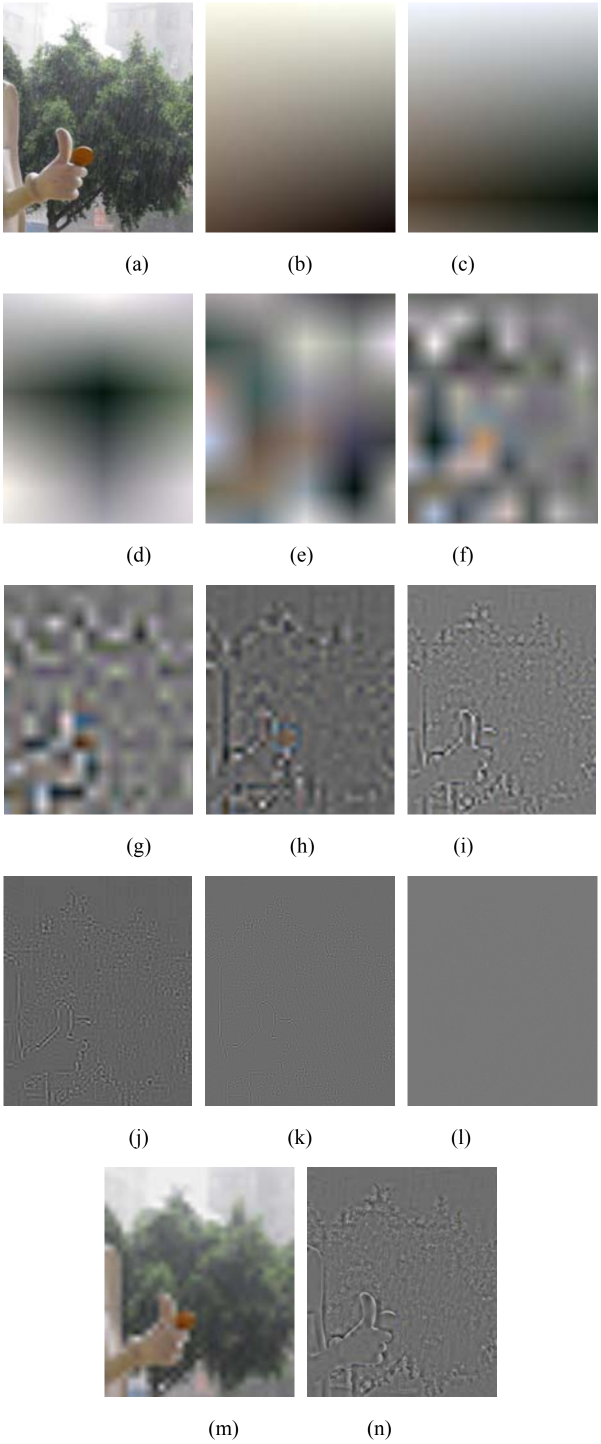


Figure 1. (a-n)Wavelet multi-layer decomposition on images in the rain (a) Image in the rain, (b) Low frequency restructure of the 10th layer, (c) High frequency restructure of the 10th layer, (d) High frequency restructure of the 9th layer, (e) High frequency restructure of the 8th layer, (f) High frequency restructure of the 7th layer, (g) High frequency restructure of the 6th layer, (h) High frequency restructure of the 5th layer, (i) High frequency restructure of the 4th layer, (j) High frequency restructure of the 3rd layer, (k) High frequency restructure of the 2nd layer, (l) High frequency restructure of the 1st layer, (m) Image without rain, (n) Image with rain

Similarly, we make 10 layers of wavelet decomposition on an image in the snow, as shown in Figure 2a. The image without snow is obtained by the coefficients from the 10th layer to the 5th layer, and high frequency restructure, as shown in Figure 2b. The high-frequency coefficient reconstruction from the 4th layer to the 2nd layer can get the image with snow, as shown in Figure 2c. And we can draw the conclusion that rain (snow) noise is included in high-frequency coefficients from the 4th layer to the 2nd layer in a degraded rain (snow) image, the background and color information is mainly in the coefficients form the 10th layer to the 5th layer, and the high-frequency coefficients of the 1st layer include major texture and edge information.

(a) (b) (c)

Figure 2. (a-c)Wavelet multi-layer decomposition of images in the snow (a) Image in the snow, (b) Image without snow, (c) Image with snow,

C. Fusion on Multiple Continuous Degraded Images

The rainy (snowy) day is dynamic and adverse weather, which is easy for outdoor vision system to acquire multiple continuous different degraded images. Next, we make wavelet fusion on continuous degraded images for achieving the objective of rain (snow) removal. According to the frequency structure of degraded rain (snow) images, the background and color information, rain (snow) noise, and texture and edge information is respectively fused. And appropriate fusion rules are made based on different characteristics of them.

Fusion of rain (snow) noise means the fusion on high-frequency coefficients from the second layer to the fourth layer. The fusion rules on the coefficients play a critical role in removing rain (snow) noise of degraded images. Next, we analyze the characteristics of raindrops. As raindrops move rapidly, they are like thin line with high light in video images. The image of raindrops we see is the result of the reflection of light on surface and internal reflection, which is the reason why the light intensity of raindrops is high.

As shown in Figure 3, the surrounding light is acquired by visual system after spherical reflection and internal refraction of raindrops. And the maximum angle of the light acquired by the visual system is 165 degrees [4]. And there is enough light being collected through the raindrops, which makes the brightness of raindrops improve greatly. Although, the raindrop is transparent, the brightness doesn’t depend on the brightness of the covered background. The further experiment indicates that the intensity of the raindrops not only has no relationship with the covered background, but also is the same. As shown in Figure 1, the left side is raindrops and background, and the background consists of 5 horizontal stripes with different brightness. And the right side is the function image of pixel brightness and time. When the background is covered by the raindrops, the brightness increases and the brightness value is consistent (about 200). Therefore, raindrops have two important characteristics, high brightness and uniform brightness.

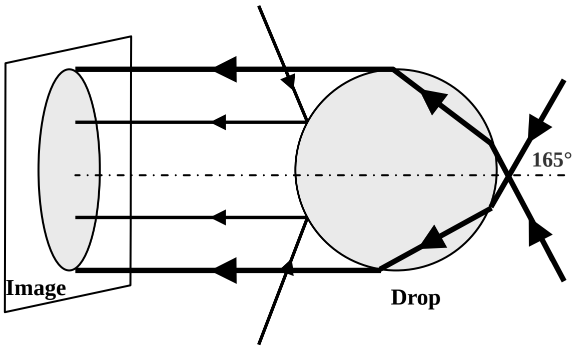


Figure 3. Reflection of light on surface and internal refraction through raindrops

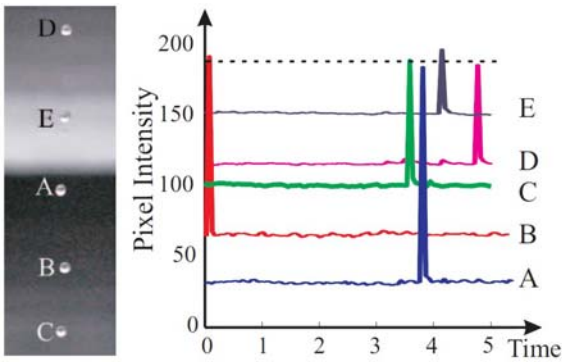


Figure 4. Relation between brightness of raindrops and background

The following is an analysis on the features of snowflake. Compared with the raindrops, snowflake is not transparent and the motion velocity is slow, snowflake and raindrops have similar features. Firstly, the brightness of snowflake is high. Secondly, all snowflakes have the same brightness.

According to the characteristics of rain (snow) noise, the layers including rain (snow) noise are for wavelet fusion, and specific fusion rules are made. As the brightness of rain (snow) is higher than that of the surrounding background, the degree of gray scale for pixels being covered by the rain (snow) and background pixels is great, which can produce better edge effect. The local gradients can be used to measure the variations of gray, and the definition is

$$G = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{\Delta xf(i,j)^2 - \Delta yf(i,j)^2} \qquad (6)$$

G is local gradients, $\Delta xf(i,j)$ and $\Delta yf(i,j)$ is respectively the gradient value of point (i ,j) in horizontal and vertical direction, and M and N are the side length of the local area. As the bright of rain (snow) is essentially unchanged, the pixels covered by rain (snow) have higher and more stable energy compared with the background pixels. The local energy can be used to measure the energy of pixels, and the definition is

$$E = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j)^2 \qquad (7)$$

E is local energy, f(i, j)is the gray value of pixels, and M and N are the side length of the local area. The local gradients are directional and the local energy is stable. The two parameters can reflect that the bright of rain (snow) noise is high and same. Multiplying G and E can get new parameter S which is called rain (snow) noise pollution. It can make the characteristic of rain (snow) noise expand, which is conductive to removing rain (snow) noise.

Rain (snow) noise pollution S means the degree of images being polluted by rain (snow), which can effectively differentiate the rain (snow) and background area in the images. Therefore, the paper proposes wavelet fusion based on rain (snow) noise pollution. And the procedures are as follows.

(1) Wavelet decomposition. The degraded images are for 10 layers of wavelet decomposition, which can get high-frequency coefficients from the 4th layer to the 2nd layer, and rain (snow) noise is included.

(2) High-frequency coefficients including rain (snow) noise are for fusion. The coefficient matrix corresponding to each direction of the 4th layer and the 2nd layer is figured out, and the pollution degree S matrix corresponding to these coefficients matrix is solved. S matrix are made unitization processing, which can get the new S matrix. The greater the value corresponding to S matrix in the same position is, the more serious the position is polluted by rain (snow) noise.

So each coefficient matrix and each S' matrix are for inverse weighted arithmetic, which can get the fused coefficient matrix in which rain (snow) noise reduces greatly. In order to reduce rain (snow) noise, a weight less than 1 can be set on the fused coefficient matrix (0.9 is selected in the paper).

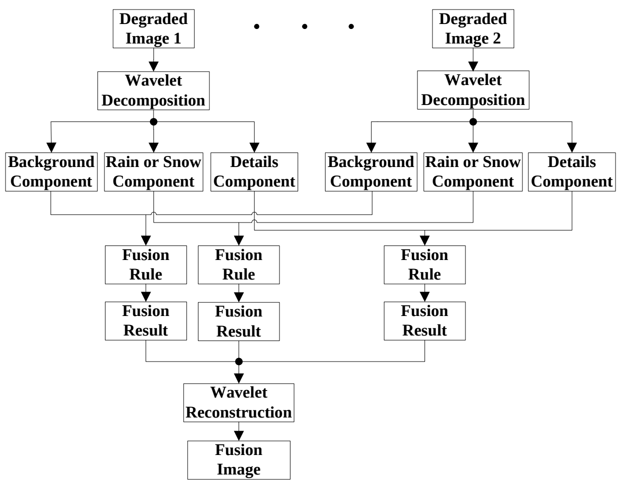


Figure 5. Flow chart of fusion method

(3) The coefficients not including rain (snow) noise are for fusion, which means the fusion on the coefficients from the 10th layer to the 5the layer and the high-frequency coefficients of the 1st layer. The coefficients include major effective information of images, so the weight greater than 1 can be set on the fused coefficient matrix, which can show the color area and details of the images.

(4) Wavelet reconstruction. The coefficients after fusion are for restructure, which can get the image of rain (snow) removal after fusion.

The concrete flow chart of fusion methods based on pollution is shown in Figure 5.

D. Rain (snow) Fog Removal

The obtained single fusion image can remove multiple continuous rain (snow) noise effectively, but rain (snow) fog in the area without rain (snow) can't be removed. And there is mist when its rain which makes the image fuzzy and the contrast low, the mist needs to be processed. Based on dark channel priority [11], the paper proposes an improved mist removal algorithm for single image which can remove the mist fast of single mist figure after rain (snow) removal. The paper uses rapid bilateral filtering method to figure out the clear dark channel of edge. And transmission figure can be estimated according to physical model of fog images. Bilateral filtering just can dispose the details fuzzy generated with median filtering, which makes the image after defogging is more natural. Bilateral filtering is defined as :

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_d}(\| p-q \|) G_{\sigma_r}(|I_p - I_q|) I_q \quad (8)$$

Ip and Iq are the brightness value of pixels, p and q. Wp is as follows:

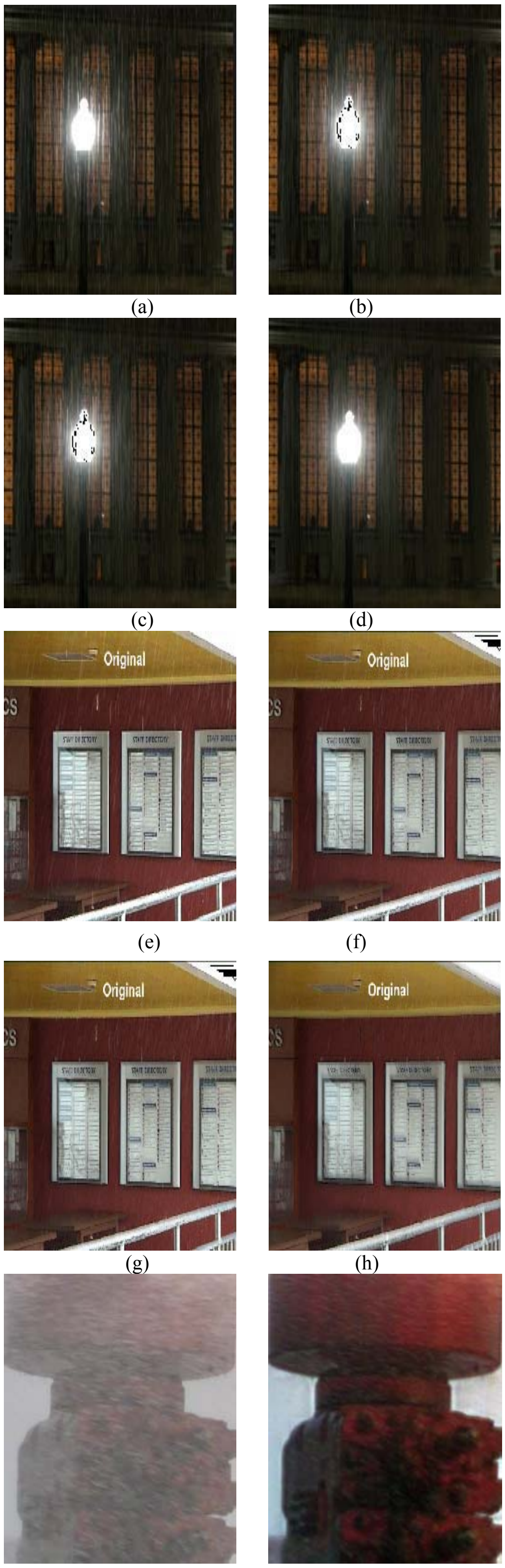
$$W_p = \sum_{q \in S} G_{\sigma_d}(\| p-q \|) G_{\sigma_r}(|I_p - I_q|) \quad (9)$$

Formula 9 is normalization coefficient. G_{σ_d} and G_{σ_r} is respectively gaussian kernel with σ_d and σ_r as standard deviation on static airspace D and dynamic range R. $\|\;\|$ represents euclidean distance. So bilateral filtering not only considers spatial relationship of pixels, but also takes similarity relation of brightness value for pixels into consideration. It can smooth images and make images clear.

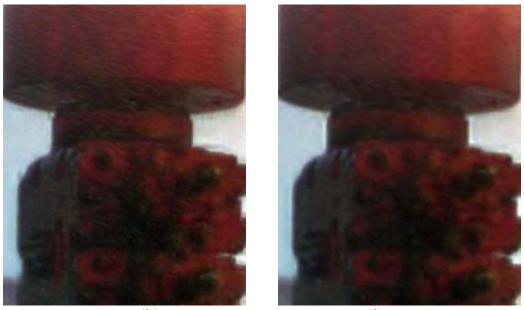
Compared with the traditional algorithm, the estimated transmission is clear, which not only overcomes the disadvantages of traditional algorithm using plenty of time to optimize the transmission, but also reduces the complexity of algorithm, which realizes rapid and high-quality mist removal on single image.

III. Simulation Analysis

In order to test the utility and validity of the algorithm, the common PC whose operation system is Windows XP, CPU is AMD quad 3.0GHz and memory is 4GB RAM is used for simulation experiment. The paper selects the heavy rain scene, moderate rain scene and heavy snow scene which are processed by using frame difference, cluster method and the method of the paper. The method of the paper fuses 9 continuous images and the clear images after fusion is used to replace th5th image for realizing the rain (snow) removal on the video. The experiment results are shown in Figure 6.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

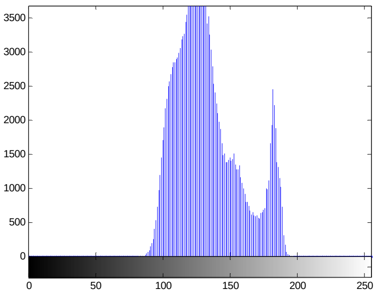


(k) (l)

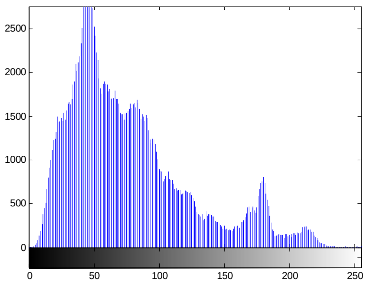
Figure 6. (a-l)Processing results of each scene and comparison (a)Image of heavy rain, (b)Reusltsof frame difference, (c) Results of cluster method, (d)Results of the paper, (e)Image of moderate rain, (f)Results of frame difference, (g)Results of cluster method, (h)Results of the paper, (i)Image of heavy snow, (j)Results of frame difference, (k)Results of cluster method, (l)Results of the paper

Figure 6 (a, e, i) is respectively the image of heavy rain, moderate rain and heavy snow. Figure 6 (b, f, j) is the results of frame difference method, Figure 6(c, g, k) is respectively the processing result of cluster method, and figure 6 (d, h, l) are the processing result of the paper. Seen from the experiment results, although the processing results of fame difference and cluster method are ideal, the processing results of heavy rain are not ideal. For degraded images with great intensity of rain (snow), the method of the paper also achieves ideal restoration results, the reason for which is that the direction, intensity and shape of rain (snow) are unfixed, it is difficult to establish unified physical model in the spatial domain. But analyzing them in the frequency domain doesn't affected by the dynamic characteristic. From the perspective of frequency domain, the paper uses the method of wavelet multi-level decomposition and wavelet fusion to process multiple continuous degraded images.

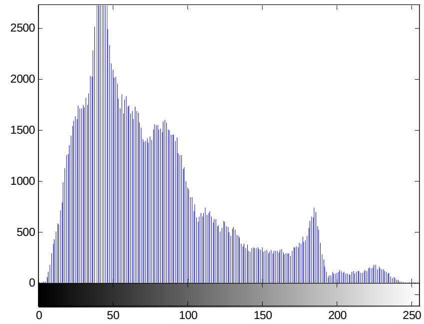
Next, various algorithms are compared objectively. And histogram, mean value, standard deviation and entropy of R channel from image 6(i) to (l) are calculated, and the results are shown in Figure 7 and Table 1.



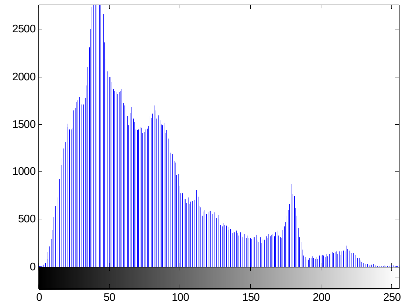
(a)



(b)



(c)



(d)

Figure 7 Histogram of R channel from image 6(i) to (l)

TABLE 1 HISTOGRAM, MEAN VALUE, STANDARD DEVIATION AND ENTROPY OF R CHANNEL FROM IMAGE 6(I) TO (L)

	Mean value	Standard deviation	Entropy
Figure 6(i)	133.0660	23.8748	6.3712
Figure 6(j)	76.8908	47.1843	7.2946
Figure 6(k)	77.2657	48.7048	7.3328
Figure 6(l)	75.4726	49.7910	7.4564

From Figure 7, we can see that the pixel stretch of histogram for the algorithm in the paper is greater and has evident spike, which indicates that the image is clear and there is high contrast. And we can see from Table 1 that the mean value of algorithm in the paper is the minimum, which shows that the interference of snow is the minimal. But it has maximal standard deviation and entropy, which indicates that the image includes the most information and the image, is the clearest.

IV. CONCLUSION

According to the characteristics of rain (snow) that the direction, intensity and shape of rain (snow) are unfixed, it is difficult to establish unified physical model in the spatial domain, but analyzing them in the frequency domain isn't affected by the dynamic characteristic, the paper applies the method of wavelet multi-level decomposition and wavelet fusion. Firstly, the layer of rain (snow) noise is determined, and fusion rules based on rain (snow) noise pollution are formulated. Specific layer of multiple continuous degraded images are for wavelet fusion to achieve the objective of rain (snow) removal. Simulation results indicate that the method of the paper is not restricted by rain (snow) intensity and has ideal restoration results, so the method is better than frame difference and cluster method.

REFERENCES

[1] K. Garg and S. K. Nayar, “When does a camera see rain”, Proc. ICCV, Oct. 2005, vol. 2, pp. 1067-1074.

[2] K GARG,S K NAYAR, “Vision and rain”, International Journal of Computer Vision, 2007, 75(1): 3-27.

[3] H HASE,K MIYAKE,M YONEDA, “Real time snowfall noise elimination”, IEEE Proceedings of 1999 International Conference on Image Processing. 1999, 406-409.

[4] K. Garg and S. K. Nayar, “Detection and removal of rain from videos”, Proc. CVPR, June 2004, vol. 1, pp. 528-535.

[5] X. Zhang, et al., “Rain removal in video by combining temporal and chromatic properties”, Proc. ICME, July 2006, pp. 461-464.

[6] Nbrewer, Liu Nian Jun, “Using the shape characteristics of rain to identify and remove rain from video”, Lecture Notes in Computer Science. 2008, 5342: 451-458.

[7] Zhao Xu Dong, Liu Peng, “The application of histogram on rain detection in video”,proceedings of the 11th Joint Conference on Information Science. 2008, 345-353

[8] P Barnum, T Kanade S Nar, “Spatio-temporal frequency analysis for removing rain and snow from videos”, Workshop on Photometric Analysis for Computer Vision. 2007, 14-21.

[9] P. C. Barnum, S. Narasimhan, and T. Kanade, “Analysis of rain and snow in frequency space” , IJCV, vol. 86, no. 2-3, pp. 256-274, 2010.

[10] Yu-Hsiang Fu, Li-Wei Kang, Chia-Wen Lin, ETAL, “Single-frame-based rain removal via image decomposition”, IEEE International Conference on Acoustics, Speech, and Signal Processing. 2011, 178-186

[11] He Kaiming, Sun Jian, Tang Xiaoou, “Single image haze removal using dark channel prior”, IEEE Conference on Computer Vision and Pattern Recognition, 2009:1956-1963

[12] Sun Yankui, “Wavelet Analysis and Application”, Beijing: Machinery Industry Press, 2005.

[13] Jean-Philipper Tarel, Nicolas Hauti`ere, “Fast Visibility Restoration from a Single Color or Gray Level Image” , International Conference on Computer Vision, 2009.

[14] J. M. Fadili, J. L. Starck, J. Bobin, and Y. Moudden, “Image decomposition and separation using sparse representations: an overview” , Proc. of the IEEE, vol. 98, no. 6, pp. 983-994, June 2010.

[15] G. Peyré, J. Fadili, and J. L. Starck, “Learning adapted dictionaries for geometry and texture separation”, Proc. SPIE, vol. 6701, 2007.

[16] M. Aharon, M. Elad, and A. M. Bruckstein, “The K-SVD: An algorithm for designing of overcomplete dictionaries for sparse representation”, IEEE Trans. Signal Process., vol. 54, 2006.