Image with the Most Dynamic Screen Pixel Recovery Algorithm

***J.Saravanakumar*[1], *K.Sindhuja*[2]**

[1] Anna University, M.E Applied Electronics, II year,
Shree Venkateswara Hi-Tech Engineering College, Gobi
ecejsk@gmail.com
[2] Assistant Professor/ECE
Shree Venkateswara Hi-Tech Engineering College, Gobi
sindhuja.km@gmail.com

Abstract: *Image has editing applications such as security surveillance and warm rain that is very useful and important technique. Many rain removal instructions have optics, color and rain effect to demonstrate the ability to identify the characteristics of exploitation. The heavy rainfall and relatively mild conditions in general when dealing with static displays variable current methods and these methods are work well and give very poor visual results. The proposed algorithm is based on dynamic visual movement. Detection optics and color controls, rain and fire hazard after applying filters clues as to what is found in the rain dynamic property of their pixels are used. The spatial and temporal information has then adaptively used both during the rainy pixel recovery. It will be a good action scenes rainfall patterns show that the proposed algorithm is better than the results. Images have rain that causes a noise. The weather can affect Stereo consonance, make a feature of detection, segmentation and object tracking and recognition. Images surveillance is any problem with the product, if the weather is not well monitored. In this paper we only rain falling in the standard environment.*

Keywords: Rainfall removal, image decontrol, Morphological component analysis (MCA).

1. INTRODUCTION

Different of weather conditions are rainfall, dew, mist or steam will cause complex visual effects of spatial or temporal dominion in images. Such effects that are remarkably degrade the performances of outdoor scene systems relying on image feature extraction or visual attention modeling, such as image registration, occasion detection, device detection, tracking and identification, site analysis and assortment, image indexing and retrieval and image copy/near-duplicate detection. In a survey of detection approaches for outdoor territory factors such as rainfall and dew to enhance the accuracy of based automatic incident detection systems can be found. Removal of rain streaks has recently received much attention to the best of my knowledge in current approaches.

We propose an image-based rain streak removal framework by formulating rain streak removal as an image decomposition problem based on MCA. In this method, an image is first decomposed into the low-frequency and high-frequency parts using two-sided filter. Two-sided filter is edge preserving, noise reducing, smoothing filter for images. The high-frequency segment is then decayed into rain component and "non-rain component" by performing dictionary learning and sparse coding based on MCA. Instead of directly applying a conventional image decontrol technique, the proposed method first decomposes an image into the low- and high-frequency (HF) segments using two-sided filter. As a result, the rainfall component can be successfully removed from the image while preserving most original image details.

1.1. Visual Based Rain Identification and Riddance

A consciousness work on identification and riddance rain streaks in image was proposed in where the authors developed interaction model capturing the dynamics of rain and a physics-based moving shape model characterizing the photometry of rain. It was subsequently shown in that some camera parameters such as exposure time and depth of field can be selected to mitigate the effects of rain without altering the appearance of the scene.

Moreover, an improved video rain streak removal algorithm incorporating both temporal and chromatic properties was proposed. The method proposed in further utilizes the shape characteristics of rain streak for identifying and removing rain streaks from images. Furthermore, a model of the shape and appearance of rain or dew streak in the image space was developed in to detect rain or dew streaks. Then, the amount of rain or snow in the image can be reduced or increased.

In selection rules based on photometry and size are proposed to select the potential rain streaks in image, where a histogram of orientations of rain streaks, estimated with geometric moments, is computed.

Moreover, some research works focus on raindrop detection in images (usually on car windshields) that is different from the detection of rain streaks. A image-based raindrop detection method for improving the accuracy of image registration was proposed in where a photometric raindrop model was utilized to perform monocular raindrop detection in video frames. In addition, a detection method for detecting raindrops on car windshields using geometric–photometric environment construction and intensity-based correlation was proposed in which can be applied to vision-based driver assistance systems.

1.2. Image Noise Removal

Image noise removal or denoising problem is important and challenging. The major goal of image noise removal is to design an algorithm that can remove unstructured or structured noise from an image, which is gain in the appearance of an additive noise. Numerous contributions for image denoising in the past 50 years addressed this problem from many and diverse points of view. For instance, spatial alteration filters, random processes, partial differential derivatives, transform-domain methods, splines, approximation theory methods, and order statistics are some of the directions explored to address this drawback. In the use of sparse and unessential representations over learned dictionaries has become one specific approach toward image denoising, which has been proven to be effective and promising.

2. PROBLEM STATEMENT

In existing except from rain detection one shared short-coming of the existing methods is in the prediction of the rain covered pixel's original value where they simply compute its temporal mean. This causes serious corruption in areas where obvious motion is present; important information's are erased and an undesired ghost effect is often observed.

Rain removal is a complex task. In rainy images pixels exhibit small but frequent intensity alterations and this alteration could be caused by several other reasons besides rain fall namely world gleam change, camera move and object motion etc. In order to remove the rainfall effect, it is mandatory to detect the alterations that are caused by rainfall and then replace them with their original value. Some right algorithms have been proposed.

Except from rainfall identification, one shared short-coming of the existing methods is in the prediction of the rain covered pixel's original value where they simply compute its secular mean. This causes serious corruption sin areas where obvious motion is present; important information erased and an undesired ghost effect is often observed.

The algorithm is based on motion segmentation of dynamic scene. After applying photometrical and flashy constraints for rainfall identification, rain removal filters are applied on pixels such that their dynamic property as well as motion occlusions clue are considered; both spatial and temporal information are then adaptively exploited during rain pixel recovery. Experiment results show that our algorithm outperforms existing ones in highly dynamic scenarios.

3. PROPOSED METHOD

The proposed system, several rain showers optics, color and position to find properties for removal instructions to remove the effect of the probability of rain this year proposed exploited. These methods are better in the rain, light rain, and relatively static scenes, usually very poor visual results when dealing with work and are dynamically displays the current methods.

3.1. Technique: MCA-based image decontrol via dictionary learning and sparse coding:

The proposed system, image based rain band removal structure in which rain band removal is formulated as an image decontrol problem. In this method, the input rainfall image is first roughly decay into the low-frequency (LF) part and the high-frequency (HF) part using the bilateral filter, where the most basic information will be retained in the LF part while the rain streaks and the other edge information will be included in the HF part.

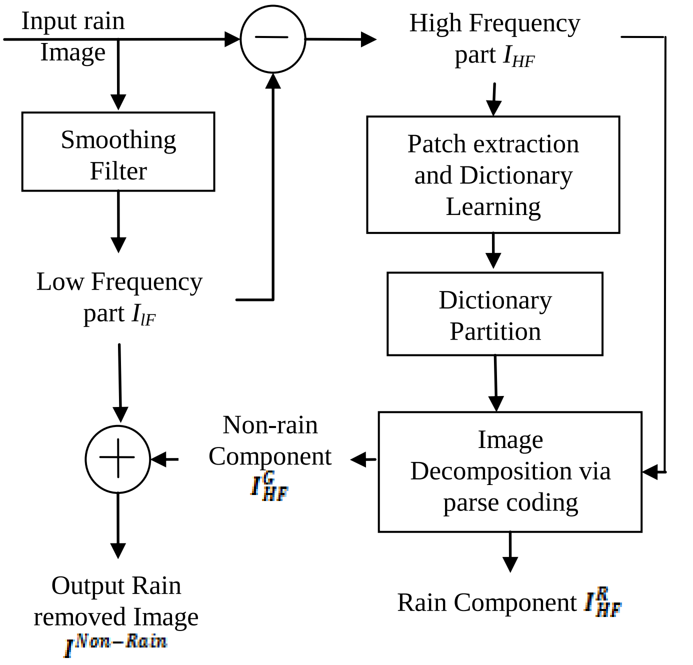

Figure 1: Block for Removal Method

Suppose that image have I of N pixels is a superposition of layers (called morphological components), denoted by I = ΣIs, where Is denotes the s-th component. To decompose the image I into $\{I_S\}_{S=I}^{S}$.The MCA iteratively minimize the following energy function:

$$E(\{I_s\}_{s=1}^S, \{\theta_S\}_{s=1}^S) = \frac{1}{2}\left\| I - \sum_{S=1}^{S} I_S \right\|_2^2 + \tau \sum_{S=1}^{S} E_S(I_S, \theta_S), (1)$$

where $\theta \in R^{M_s}$denotes the sparse coefficients corresponding to I_s with respect to dictionary D_s, τ is a regularization parameter and is the energy defined according to the type of D_s (denoted by D_{gs} for a global dictionary or by D_{Is} for a local dictionary). For a global dictionary $D_{gs} \in R^{N\times M_s}, N \leq M_s$ energy function is E_s defined as

$$E_s(I_s, \theta_s) = \frac{1}{2}\left\| I_S - D_{gs}\theta_s \right\|_2^2 + \lambda \left\| \theta_s \right\|_1, (2)$$

where τ is a regularization parameter. Usually, to decayed an image into its geometric and textural components traditional basis functions such as wavelets or curvelets are used as the dictionary for representing the geometric component, whereas global discrete cosine transform (DCT) basis functions are used as the dictionary for representing the textural component of the image.

Usually, a nearby meaning for representing the textural component of an image is either composed of traditional basis functions, such as local DCT or constructed from the dictionary learning procedure.

The MCA algorithms solve (1) by iteratively performing for each component I_S the following two steps: 1) update of the sparse correlation i.e., this blow achieve performs sparse coding to solve θ_S or $\{\theta_S^k\}_{k=1}^N$to minimize E_S (I_S, θ_S) while fixing I_S and 2) update of the components, i.e., this step updates I_S or while fixing θ_S or$\{\theta_S^k\}_{k=1}^N$.

To construct a dictionary D_S for sparsely representing each patch $\{\theta_S^k\}$ extracted from the component I_S of the image I, one may use a set of available training exemplars y^k, $k=1,2,\ldots,K$ to learn a dictionary D_S and solve the following optimization problem:

$$\min_{D_x,\, \theta^k} \sum_{k=1}^{k} (\frac{1}{2} \| y^k - D_s \theta^k \|_2^2 + \lambda \| \theta^k \|_{1,} \quad (3)$$

3.2. Discussion

Removal of rain as security monitoring, images editing, vision-based navigation, and image indexing / retrieval is a very useful and important technique in such applications.
Imaging system of visual effects of rain and the various factors that affect it and they create the proper instruction in computer vision, computer graphics and optical system to handle rain shower.

Removal of rain showers after removal of the image camera motion stabilized and destabilized recover. It can handle both light rain and heavy rain conditions.

An efficient, simple and rain removal algorithm based on the probabilistic model. This method is good for the differences in the intensity of the rain. The probabilistic approaches have automatically adjusting the threshold and effectively differentiate between the pixels of rain moving object pixels.

4. CONCLUSION

A novel, efficient and probabilistic model based rain removal algorithm is proposed for images. The advantage of this proposed approach is that it automates the algorithm and reduces the user intervention. Here, it is assumed that the image capturing camera is static. There is a significant difference in time evolution between the rain and non-rain pixels in images. This difference is analyzed with the help of the skewness and Pitman test for symmetry. Proposed algorithm uses these properties to separate the rain pixels from the non-rain pixels. Lower values of variance show that proposed algorithm effectively inpaints the rain affected pixels. Qualitative results reveal that proposed algorithm outperforms other rain removal algorithm by achieving good perceptual image quality. Proposed algorithm does not assume the shape, size and velocity of raindrops and potency of rain, which makes it rugged to different rain conditions. As the proposed algorithm works only on the intensity plane, it helps to reduce the complexity and execution time of the algorithm.

In summary, the proposed algorithm has outperformed all the existing algorithms in all respect. We have proposed a single-image-based rain streak removal framework by formulating rain removal as an MCA-based image decomposition problem solved by performing sparse coding and dictionary learning algorithms. The dictionary learning of the proposed method is fully automatic and self-contained where no extra training samples are required in the dictionary learning stage. We have also provided an optional scheme to further enhance the performance of rain removal by introducing an extended dictionary of non-rain atoms learned from non-rain training images. Our experimental results show that the proposed method achieves comparable performance with state-of-the-art image-based rain removal algorithms without the need of using temporal or motion information for rain streak

5. References

[1] Jie Chen and Lap-Pui Chau, "A Rain Pixel Recovery Algorithm for Videos With Highly Dynamic Scenes," IEEE. Trans. Image Processing. Mar. 2014 pp. 1097-1104.

[2] K. Garg and S. K. Nayar, "Detection and removal of rain from videos," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., vol. 1, Jul. 2004, pp. 528–535.

[3] X. Zhang, H. Li, Y. Qi, W. K. Leow, and T. K. Ng, "Rain removal in video by combining temporal and chromatic properties," inProc. IEEE Int. Conf. Multimedia Expo, Jul. 2006, pp. 461–464.

[4] A. Verri and T. Poggio, "Motion field and optical flow: Qualitative properties," IEEE Trans. Pattern Anal. Mach. Intell., vol. 11, no. 5, pp. 490–498, May 1989.

[5] A. Ogale, C. Fermuller, and Y. Aloimonos, "Motion segmentation using occlusions," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 6, pp. 988–992, Jun. 2005.

[6] H. Stark and J. W. Woods, Probability and Random Process with Applications to Signal Processing, 3rd ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2002, pp. 589–601.

[7] J. Fan, D. Yau, A. Elmagarmid, and W. Aref, "Automatic image segmentation by integrating color-edge extraction and seeded region growing,"IEEE Trans. Image Process., vol. 10, no. 10, pp. 1454–1466, Oct. 2001.

[8] A. K. Tripathi and S. Mukhopadhyay, "A probabilistic approach for detection and removal of rain from videos,"IETE J. Res., vol. 57, no. 1, pp. 82–91, Mar. 2011.

[9] A. Tripathi and S. Mukhopadhyay, "Video post processing: Low-latency spatiotemporal approach for detection and removal of rain,"IET Image Process., vol. 6, no. 2, pp. 181–196, Mar. 2012.

[10] M. Shen and P. Xue, "A fast algorithm for rain detection and removal from videos," in Proc. IEEE Int. Conf. Multimedia Expo, Jul. 2011, pp. 1–6.

Author Profile

Mr.J.Saravanakumar, Received Bachelor of Engineering in Electronics and Communication Engineering, Anna University in 2010 at Muthyammal Engineering College, Rasipuram. PG Scholar Currently perusing his M.E Applied Electronics degree in shree Venkateshwara Hi-Tech Engg College, Gobi, TamilNadu, India.

Miss.K.Sindhuja, Studied Electronics and Communication Engineering in Vivekanadha College of Engineering for Women from 2005 – 2009, September 2009 to April 2012 having two years 8 months work experience in The Kavery Engineering College Maechiri, Studied M.E. Applied Electronics in SSM College of Engineering from 2012 – 2014 and Now currently working as Assistant Professor in Shree venkateswara HI-Tech Engineering College, Gobi.