International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.4, No.4, April 2015 DOI:10.15693/ijaist/2015.v4i2.212-216

Removing rain streaks from an image Using sparse coding

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***Abstract*—Image Rain streaks removal can be also treated as an image denoising task .The input image is first decomposed into a low-frequency part and a high-frequency part by using the guided image filter. By performing dictionary learning and sparse coding technique the high frequency part is decomposed into rain and non-rain component .To isolate the rain streaks from the high frequency part hybrid feature set, which consists of histogram of oriented gradients ,depth of field and Eigen vector techniques are adopted. With the help of hybrid feature set most rain streaks can be removed. Simultaneously non-rain component can be enhanced .DOF is helpful for identifying the main subjects to be preserved in a rain image. Here the rain streaks usually reveal neutral color in analyzing the atoms of rain.**

Keywords: Rain streaks removal, Depth of Field (DoF), Histogram of Gradient (HoG), Online Dictionary learning, Sparse representation

I.INTRODUCTION

Rain streaks removal is treated as an image denoising task because it affects the spatial and temporal characteristics of an image. Generally noise removal in an image is done to remove the structured and unstructured noise in an image. Such noise may be an additive noise also. Most of the image denoising algorithms can be effectively used to remove additive white Gaussian noise ,they does not give good result in rain removal because it does not have any property about rain streaks .so that some of the denoising methods are successfully employed as an preprocessing step in rain removal. The classical image denoising filter named bilateral filter which can smooth the image simultaneously preserves the edges by combining nonlinearly the nearby image values. The use of sparse over learned dictionaries becomes a specific approach towards denoising an image, which is proven effectively. Moreover, the algorithms such as NL-Means (nonlocal means) are base on the averaging of pixels of an image non-locally for image denoising, whereas the guided filter is used specifically as a pre-processing step to achieve the rain streaks removal.

A. Single Image Based Removal of Rain streaks

The most challenging task is the single image based rain streaks removal .The single rain image is based on the real requirement that a single image available, such kind of an image is captured from a camera or through camera-phone or may be a downloaded image. For rain removal the image decomposition problem based on sparse is used.

A rain image is divided into two parts namely low and high frequency part through guided filtering. The high frequency part (HF) are decomposed into rain and non rain components through learning the sparse based dictionary for rain and non rain components. Moreover rain streaks have same edge gradients or directions in an image; the dictionary is identified by computing the variance of gradient direction for each atom in the dictionary. The non rain component portions with similar direction of gradient to the rain component portion may be misclassified and simultaneously removed.

B. Proposed Method

The proposed framework for the rain removal is done by considering rain removal as a decomposing problem of an image based on sparse coding. First by using guided image filter [16], the input image is decomposed to low frequency part and high frequency part .The High frequency part consists of the textures and edges of a non rain component, and the rain streaks. This high frequency part is then further decomposed into non rain and rain component .This is done by dictionary learning and sparse coding. For the separation of rain streaks from the HF part (high frequency part), a hybrid feature set which includes histogram of oriented gradients (HOGs) [10], depth of field (DOF) [17], is employed. Rain streaks can be mostly removed by using the hybrid feature set.

The main contributions include 1) to facilitate the rain removal of a single image the property of photography is exploited, where DoF is calculated as an image feature. The rain streaks in an image are blurred than that of a focused subject their visual quality is weak and appears as fog. Therefore, employing the DoF is helpful in detecting the main subjects and used to preserve in a rain image. 2) The rain streaks usually have neutral color during analyzes of the rain atoms. So using these key features the rain removal can be done more effectively. 3) this method is fully automatic and also self-contained. That is it does not require any extra training samples in dictionary learning stage.

The DoF feature contribution to rain removal is the threshold 1) It enhance the low frequency part in the image .2) It enhance the learned dictionary quality of the atoms in the high

frequency part of an image.3)To recover some non-rain component with similar direction of gradient with the rain streaks. To achieve rain removal result with betterment guided filtering us used as a preprocessing step. Guided filter is more efficient than bilateral filter.

II. EXTRACTION OF DOF

A professional photographer makes the subject(s) of a photo clear and the background or the other unfocused scenes/objects in the photo blurred. The blurred images such as rain streaks,fog,haze ,etc., Therefore, the visual effect of rain streaks in an image would be relatively weak . As a result, the feature, named DoF which is used for extracting the region of interest (ROI) in a rain image to improve the performance of rain removal, and enhancing the perceived visual quality of rain-removed images. The distance between the nearest and farthest objects in a scene is known as DOF, it appears acceptably sharp in an image. This paper employs shallow DoF. It is used to emphasize the Region Of Interest in an image. DoF is used to measure local correlative information in an image.

Let I be an input image. The blurring kernels are first applied on the luminance component of *I* and the vertical and horizontal derivatives are calculated by [18],

$\rho x\kappa \propto \text{hist}(I * f\kappa * dx)$ -------(1)

$\rho y\kappa \propto \text{hist}(I * f\kappa * dy)$ --------(2)

where $dx = [1-1]$ and $dy = [1-1]^T$ -----(3)

For each pixel(i,j) of I we find the kullback-Leibler(KL)-divergence between the distributions ρ_{xk} and ρ_{yk},and the original distributions ρ_{x1} and ρ_{y1} for a window W_{ij} centered on the pixel (i,j),by,

$\rho y1)(n,m)$ --------(4)

Where p and q are two probability density functions. The KL-divergence is only defined when p_{ij} and q_{ij} values are greater than zero. The quantity 0log 0 is considered as zero. Based on [30],the DoF value of the image I can be calculated based on the KL-divergence value for each pixel(I,j) with each predefined kernel f_k,which is different from[30],instead of only calculating a DoF value for an image. We calculate a DoF saliency map of DoF(i,j) for the image as

$$\text{DoF}(i, j) = \Sigma_k D\kappa(i, j) \quad \text{------- (5)}$$

$D\kappa$ value tends to zero when the distributions $\rho x\kappa$ and $\rho y\kappa$ are close to $\rho x1$ and $\rho y1$, respectively. In our case, the input image is not sensitive to blur indicating that the image is already blurred, and the DoF value is low. When the value $D\kappa$ increases, it suggests that the areas under analysis are rather sharp (with high contrast) and DoF is high. The DoF saliency maps calculated based on (5) for rain image is demonstrated in Fig. 1, where the rain streaks from top to down are of different degrees of saliency ranging from high to low. But, the focused subjects are still with higher degree of DoF values than those of the rain streaks. This helps to rain removal of an image and also protecting focused subjects from blurring.

Figure.1 Input image

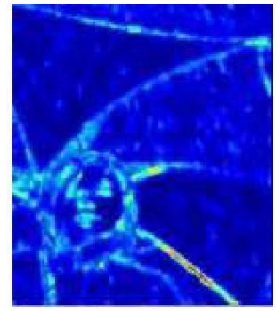

Figure.2 Saliency map of DOF

III. HYBRID FEATURE SET

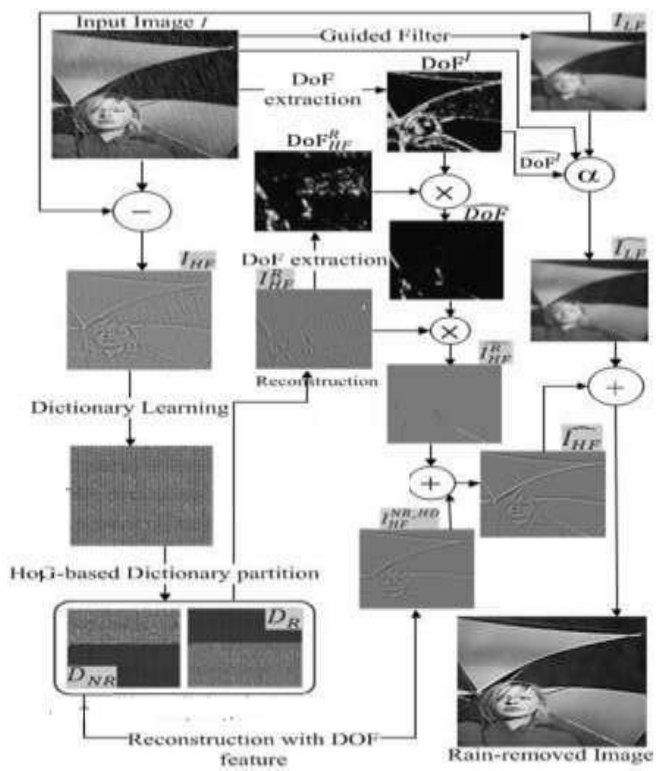

Figure. 3 Block diagram of Rain removal framework

This block diagram(fig 3) shows the framework proposed for visual depth guided removal of rain streaks is formulated as an image decomposition through sparse algorithm. In our proposed method, an input rain image I is first decomposed into low frequency part I_{LF} and the high frequency part I_{HF} using

the guided filter. The HF part can be roughly divided into rain component I_{HF}^{R} and the non-rain component $I_{HF}^{NR\_HD}$ through image decomposition further the learned dictionary D_{HF} for the HF part is separated into two sub dictionaries ,D_{NR} and D_R where D_{HF} =[D_{NR} | D_R]via the Histogram of Gradient feature based dictionary atom clustering .From the I_{HF}^{R} the misclassified region of non rain is extracted to refine I_{HF}^{R} .The DoF saliency map of I_{HF}^{R} is multiplied by DoF saliency map of the input image I to obtain DoF saliency map of the non rain region extracted from I_{HF}^{R} . I_{HF}^{R} (High frequency rain component)

- $DOF^{\wedge}=DOF(I_{HF}^{R})*DOF(\text{input image})$ --- (6)
- $I_{HF}^{R\wedge} = DOF^{\wedge} * I_{HF}^{R}$ ------- (7)

To refine further the low frequency part $DOF^{\wedge}I$ derived from DOF^{i} is used to combine I and low frequency part to obtain the low frequency enhanced version. To remove non rain region from the rain component I_{HF}^{R} the integration of $I_{HF}^{R\wedge}$, $I_{HF}^{NR\_HD}$ is done. Finally the low frequency enhanced version and non rain high frequency part are integrated to obtain the final output rain-removed image.

$$\text{High frequency}^{\wedge} = \int I_{HF}^{R\wedge}, I_{HF}^{NR\_HD} \text{-----(8)}$$

The key characteristics compared to [12] are 1)The low frequency enhancement using saliency map .2)The misclassified non rain component recovery obtained from the rain component.3)Enhancement of the non rain region from HF part.

A.LF Part

The guided filter is used as a preprocessing step to decompose I into the LF part and HF part ($I=I_{LF}+I_{HF}$).This guided filter is an fastest edge preserving operator like bilateral filter [19].It shows better behavior near edges. To enhance the low frequency part of the input image I, DoF saliency map is calculated denoted by DOF^{I} .The low DoF value region would be the area in which rain streaks appear.

$$I_{LF}^{\wedge} = \alpha I + (1-\alpha) I_{LF} \text{-------(9)}$$

$I_{LF}^{\wedge}$ is the non rain low frequency part

B.Rain Removal using Sparse Coding

To further decompose the HF part of the image into non rain component and rain component, the sparse representation [13] is done. The each component of I is decomposed iteratively by two steps: 1) the sparse coefficients is updated and 2)update the components. Sparse coding is the representation of a signal with a small nonzero number or coefficients corresponding to each atoms in the online dictionary. Here the texture of training patches are extracted and sparsely represented.

To reduce the computational complexity dictionary partition is done. The dictionary is automatically sub identified into rain and non rain sub dictionaries. The mini batch parameter size is used in the online dictionary learning algorithm. It is used to determine the computational complexity of dictionary learning process. To speed up the process of dictionary learning and to obtain better sub dictionary for non rain after Histogram of Gradient based dictionary partitioning, the mini batch parameter is decreased in dictionary learning. $R^{\wedge}$ Theis subobtainedictionariesbymultiplyiforraingand non rain is obtained by HoG based K-means clustering algorithm.

$$\min_{D_{HF}^{K} \in R^{m}} \| b^{k}_{HF} - D_{HF}\, \Theta_{HF}^{K} \|_{2}^{2}$$

subject to $\| \Theta_{HF}^{K} \|_{0} <= L$ --------- (10)

is K sparsity or maximum of nonzero coefficients of Θ_{HF} .The problem of rain removal by sparse coding,

$$\Theta_{HF}^{K\wedge} \|_{1}) \text{----------} (11)$$

λ is the regularization parameter. This equation is the efficient implementation for sparse coding.

IV. EXPERIMENTAL RESULTS

To estimate the performance of proposed image rain streaks removal framework, this method was implemented in MATLAB on a computer .The implementation of gray scale image and filtered image is given below,

Figure.4 Input image

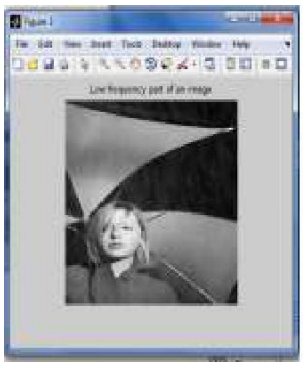

Figure.5 LF part of an image

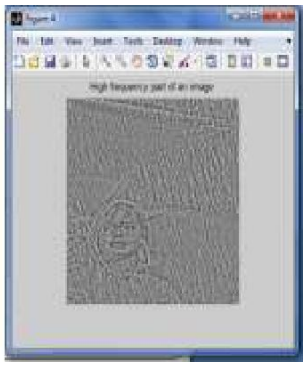

Figure.6 HF part of an image

A. Results for Rain Streaks Removal

Figure.8 Input image

Figure.9 Output image

V.CONCLUSION

In our paper, we proposed a rain streaks removal of an image framework via image decomposition which is based on sparse representation. In our method, by using the guided filter the input image is decomposed into LF & HF part. The HF part of an image is further decomposed into rain and non rain component by applying online dictionary learning and sparse coding. In HF part, the rain streaks can be removed by using hybrid feature set which consists of Histogram of Gradient and Depth of Field. Using this Hybrid feature set, most of the rain streaks can be removed and simultaneously the non rain component can also be enhanced.

In future, the proposed method can be extended to video based rain streaks removal, where the dictionary learning process is applied once for the first frame in a video clip. The learned dictionary can be used for removing rain streaks, which is useful to reduce computational complexity and to maintain the temporal complexity of that video. The proposed method can be combined with any kind of sparse representation to achieve super resolution frame in videos.

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