www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 4 Issue 6 June 2015, Page No. 12781-12787

Rain Streaks Removal from Single Image

Shalaka Mhetre[1], Prof.P.M.Patil[2], Prof.Sameer Borgohain[3]

[1]Shalaka Mhetre,
Vidya Pratishthan College of Engineering,
Department Of Computer Engineering,
Baramati-41333, Pune,Maharashtra,
Mhetre.shalaka@gmail.com

[2]Prof.P.M.Patil,
Vidya Pratishthan College of Engineering,
Department Of Computer Engineering,
Baramati-41333, Pune, Maharashtra,
Patil_pradeep1061@gmail.com

[3]Prof.Sameer Bogohain,
Department of Information Technology,
NIT, Silchar Assam India,
samborg *@email.com*

Abstract: ***Rain Removal from Video is a challenging problem and has been recently investigated extensively. In this paper, we propose a single-image-based rain removal framework via properly formulating rain removal as an image decomposition problem based on morphological component analysis (MCA). Instead of directly applying conventional image decomposition technique, we first decompose an image into the low-frequency and high-frequency parts using a bilateral filter. The high-frequency part is then decomposed into "rain component" and "non-rain component" by performing dictionary learning and sparse coding. As a result, the rain component can be successfully removed from the image while preserving most original image details. Experimental results demonstrate the efficacy of the proposed algorithm. Rain introduces sharp intensity variations in images, which degrade the quality or performance of outdoor vision systems. These intensity variations depend on various factors, such as the brightness of the scene, the properties of rain, and the camera parameters. The detection and removal of rain streaks in an image is done by image decomposition which depends on Morphological Component Analysis (MCA) by performing dictionary learning and sparse coding.***

Keywords: Image Low frequency and High Frequency ,Image Patches, Image Denoising, Morphological Component Analysis (MCA), sparse representation , K-Means, Dictionary Learning Algoritham (KSVD), Image Decomposition,Image Deblur.

1. INTRODUCTION

In this project, we propose a single-image-based rain streak removal framework from literature [9]-[15] by formulating rain streak removal as an image decomposition problem based on MCA proposed in literature [13]. In our method, an image is first decomposed into the low-frequency and high-frequency parts using a bilateral filter. The high-frequency part is then decomposed into "rain component" and "non-rain component" by performing dictionary learning and sparse coding based on MCA. The major contribution of this paper is three-fold: (i) to the best of our knowledge, our method is among the first to achieve rain streak removal while preserving geometrical details in a single frame, where no temporal or motion information among successive images is required; (ii) we propose the first automatic MCA-based image decomposition framework for rain steak removal; and (iii) the learning of the dictionary for decomposing rain steaks from an image is fully automatic and self-contained, where no extra training samples are required in the dictionary learning stage. But it is hard to detect rain only using the property of intensity changes. Because there exist so many objects which have similar linear edges with rain streaks. However, in some cases, there is important application value to remove the rain from only one outdoor image is used to get more information. Computer vision is a part of everyday life. One of the most important goals of computer vision is to achieve visual recognition. Bad weather degrades the perceptual image quality as well as the performance of various computer algorithms which use feature information such as object detection, tracking, segmentation and recognition. Processing and decreases the performance of k-means algorithms. Both rains bring complex intensity changes. A region covered by a falling down raindrop seems brighter than its original background. But it is hard to detect rain only using the property of intensity changes. Because there exist so many objects which have similar linear edges with rain streaks. However, in some cases, there is important application value to remove the rain from only one outdoor image is used to get more information. All the current approaches are based on removing rain streaks from video. This is among the _rst approach which removes rain streaks from single image. In those approaches non-rain part from successive images is captured which is used to reform the current image. But when only single image is available which is downloaded from internet or captured from digital camera then single image based rain streaks removal is desired. This problem also falls into the category of image noise removal or image restoration. This method proposes single image based rain streaks removal as image decomposition problem based on morphological component analysis.

As shown in Fig. 1, in the proposed framework rain removal is formulated as an image decomposition problem. It can be observed from Figure applying HOG based Pedestrian that directly applying the MCA based image decomposition algorithm by treating rain streaks as the textured component in an image will seriously blur the image even if the rain streaks can be removed.

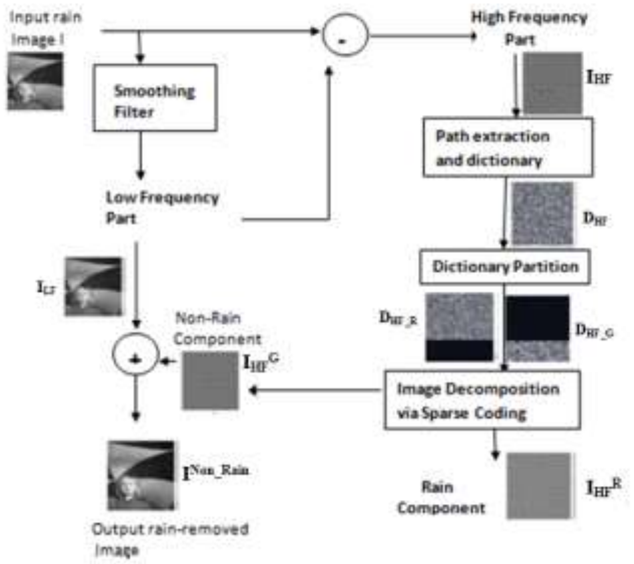


Fig. 1. Proposed rain removal framework

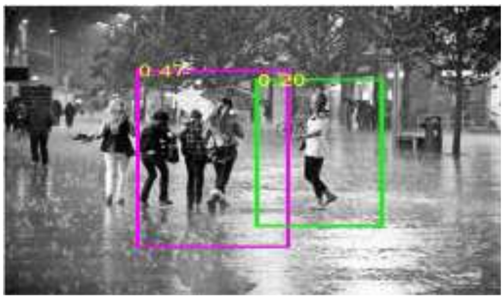
2. LITRETURE REVIEW

Proposed a method in which detection of rain is done using histogram of orientation of streaks. In this the orientations of the different connected components are obtained by the method of geometric moments. The data of this histogram are then modeled as a Gaussian-uniform mixture. A decision criterion on the smoothed histogram then allows detecting the presence or absence of rain. When rain is detected, the rain pixels can be detected accurately. The disadvantage is that rain with small intensity is difficult to be seen for human eyes, and thus to be detected with the proposed method. In the presence of light rain, the Mixture of Gaussian is no longer relevant. However, in the absence of rain, this method may also detect rain presence. In our proposed method it is able to remove rain without blurring the background. This works in any rain conditions such as light rain, heavy rain, rain in reflection, rain with wind etc. The method does not assume the size, shape and orientation of rain. This requires only 15 or less consecutive frames for detection and removal process.

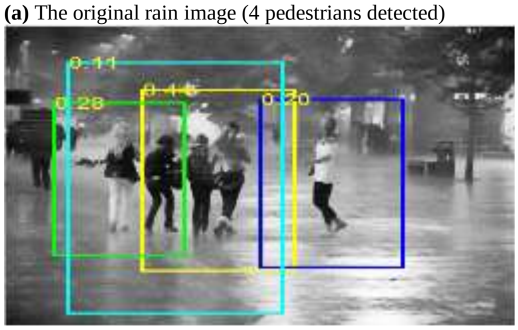
So far, the research works on rain streak removal found in the literature have been mainly focused on video-based approaches that exploit temporal correlation in multiple successive frames includes in literature [6]-[8]-[9]. Nevertheless, when only a single image is available, such as an image captured from a digital camera/camera-phone or downloaded from the Internet, a single-image based rain streak removal approach is required, which was rarely investigated before? Moreover, many image-based applications such as mobile visual search, object detection/recognition, image registration, image stitching, and salient region detection heavily rely on extraction of gradient-based features that are rotation- and scale-invariant. Some widely-used features (descriptors) such as SIFT (scale-invariant feature transform) [7], SURF (speeded up robust features) [8], and HOG (histogram of oriented gradients) [9] are mainly based on computation of image gradients. The performances of these gradient-based feature extraction schemes, however, can be significantly degraded by rain streaks appearing in an image since the rain streaks introduce additional time-varying gradients in similar directions,

As

Applying the HOG-based pedestrian detector:



(a) The original rain image (4 pedestrians detected)



(b) The rain-removed version (obtained by the proposed method) of (a) (5 pedestrians detected).

Fig. 2 Detection of Rain in image

My analyzed the literature [2] which specify the method for rain removal in sequential images. They have used spatial temporal property and the chromatic property. As per the spatial-temporal property, rain is detected by using improved k-means. Then a new chromatic constraint is advanced to mend detection results. They have considered the image in which rain is close to the camera. Rain in image is removed, but new image means non-rain image is a little blurry.

Further Explained in literature [3] which specify the method in which detection of rain is done using histogram of orientation of streaks. In this the orientations of the different connected components are obtained by the method of geometric moments. The data of this histogram are then modeled as a Gaussian-uniform mixture. A decision criterion on the smoothed histogram then allows detecting the presence or absence of rain. When rain is detected, the rain pixels can be detected accurately and easily in the images and rain intensity can be estimated as well. The disadvantage is that rain with small intensity is difficult to be seen for human eyes, and thus to be detected with the proposed method.

The literature's [8]-[7][9]-[11] which specified the rain image which use for further process i.e. High frequency image HF2, need to decomposed , rain part and non-rain part of image stored in image object thereafter sparse reprentaion of decomposed image use to detect the rain dictionary and non-rain components of image.

3. RELATED WORK

The main objectives of removal of rain streaks in an image are that it completely removes the rain streaks from the image while it preserves the original (non-rain) image as it is. Firstly in the removal of rain streaks in an image there is use of MCA as image decomposition. Morphological Component Analysis (MCA) will use to separate the texture from the natural part in images**.** The important idea of MCA is to decompose the different features contained in the data or in the image. Removal of rain streaks is done by MCA based image decomposition [8] by performing dictionary learning and sparse coding.

3.1 MCA-Based Image Decomposition

MCA can be used for separating the texture from the piecewise smooth component, for inpainting applications or more generally for separating several components which have different morphologies. The main idea for using MCA is to use the morphological diversity of the different features contained in the data to be separated and to associate each morphology to a dictionary of atoms for which a fast transform is available.

Applications that can benefit from the sparsity and over completeness concepts (together or separately) include compression, regularization in inverse problems, feature extraction, and more. Indeed, the success of the JPEG2000 coding standard can be attributed to the sparsity of the wavelet coefficients of natural images [13]. In denoising, wavelet methods and shift-invariant variations that exploit over complete representation are among the most effective known algorithms for this task [2]–[5]. Sparsity and over completeness have been successfully used for dynamic range compression in images [6], separation of texture and cartoon content in images [7], [8], inpainting [9], and more.

Extraction of the sparsest representation is a hard problem that has been extensively investigated in the past few years. We review some of the most popular methods in Section II. In all those methods, there is a preliminary assumption that the dictionary is known and fixed. In this paper, we address the issue of designing the proper dictionary in order to better fit the sparsity model imposed.

The Fig.1 shows the steps for removal of rain streaks.

Step 1:Pre-processing

For the input rain image in the pre-processing step we have to apply edge preserving smoothing filter called bilateral filter [4].Smoothing filter is edge preserving and noise-reducing filter. After applying smoothing filter the input rain image is decomposed into LF(Low-frequency) and HF(High-frequency) part, where the basic information is in the LF part while the rain drops or rain streaks and the other edge or texture information will be in the HF part of the image.

Step 2: Patch extraction

For learning dictionary of HF part (DHF) a set of overlapping patches are extracted from HF part. Then separate atoms in the dictionary into two sub-dictionaries [6]-[7] for representing rain component and textural component of HF part.

Step 3: Partitioning

For representing the rain and geometric component of HF part,the atoms which consists of dictionary of HF part is divided into two sub-dictionaries i.e. rain and geometric sub-dictionaries. Image gradient is used for extracting the most significant feature of rain atom. The HOG(Histogram of Oriented Gradient) feature descriptor [5] is used to describe each atom in DHF.

After extracting the each atom in DHF by using HOG feature, then applying K -means algorithm for separating all of the atoms in DHF into two sub-dictionaries D1 and D2 based on HOG feature descriptors. For identifying which cluster consists of rain atoms and which cluster consists of geometric atoms, for that we calculate the variance of gradient direction for each atom dij, j=1,2,……N, in cluster Di, as VGij, also i=1, 2. Then, calculate the mean of VGij for each cluster Di as MVGi. Based on the fact that edge directions of rain streaks in an atom are mostly consistent, means the rain atom has the small variance of gradient direction, then after this we identify the cluster with the smaller MVGi as rain sub-dictionary DHF_R and other one as geometric (or non-rain) sub-dictionary DHF_G .

Step 4: Removal of rain streaks

Sparse coding is performed on these two sub-dictionaries for finding sparse coefficients for each patch extracted from the HF part. Then we get the rain-removed version of the input rain image by combining LF and non-rain image of HF part by separating rain component. Proposed in literature [8]. They explained about image decomposition and sparse representation.

Step 5: Noise Removal

Image Denoising using median Filter: The proposed technique optimally finds the threshold level of the noisy image wavelet decomposition that minimizes the energy of the error between the restored and the noisy image. So we used median filter which propose in literature [14].

Step 6: Remove Blur

Deblur Image: we Used Smart deblur filter to remove blur of image and fix the respective pixel.

Following example images shows the result of image which has been processed i.e. High Frequency part of image we already showed in rain removal framework fig.1

An Example:-

((a) the original non-rain image (ground-truth))

(b) The rain image of (a);

(c) The HF part of (b) the rain sub-dictionary

((d) The rain-removed version of (b) via the proposed method (Bilateral filter);)

((e) The rain-removed version of (b) via the proposed method with extended dictionary (KSVD);)

(k) The rain-removed version of (b) via the K-SVD-based denoising [7] (using median Filter).

Algorithm: **Single-Image-Based Rain Streaks Removal**

Input: Single rainy image
Output: Input image with removed rain streaks

1. Apply the bilateral filter to obtain LF part I_{LF} and HF part I_{HF} of image, such that
$$I = I_{LF} + I_{HF}$$

2. Extract set of image patches y^k ($k = 1,2. . P$) from I_{HF} . Apply online dictionary learning for sparse coding algorithm to obtain dictionary D_{HF} consisting of atoms that can sparsely represent y^k ($k = 1,2$ P).

3. Extract HOG feature descriptor for each atom in $D_{HF.}$ Apply k-means algorithm to classify all of the atoms into two clusters based on their feature descriptor.

4. One of the two clusters is identified as rain sub dictionary D_{HF_R} and other as geometric sub dictionary D_{HF_G}.

5. Apply MCA for each patch $b^k{}_{HF}$ by performing OMP(Orthogonal Matching Pursuit) for each patch in I_{HF} with respect to D_{HF} .

6. Reconstruct each patch $b^k{}_{HF}$ to recover either geometric component or rain component of I_{HF} based on corresponding sparse coefficient.

7. Return rain removed version of I , $I^{NonRain} = I_{LF} + I_{HF\_G}$.

Step by Step result [1] is shown in Fig.
Where

b) Input rain image
c) LF part of rain Image is
d) HF part
e) Rain Sub dictionary
f) Non rain sub dictionary
g) Rain component
h) Non Rain component
i) Rain removed version of the image

This System consists of 5 modules:
1. Decompose image into LF and HF parts using bilateral filter
2. Patch Extraction and Dictionary Learning
3. Patch Extraction
4. Image Decomposition via Sparse Coding [8] [9].
5. Integration of Non-rain component and LF Image.

Bilateral Filter

Low Pass Filter, High Pass Filter comprises Bilateral Filter [8]-[13]- [14].Using bilateral filter image is decomposed into Low Frequency Image I_{LF} and high frequency image I_{HF} .The most basic information is retained in LF part whereas rain streaks and other texture information is included in HF part of the image. Image I is supposed to be comprised of S layers which is called as Morphological Components. In case of decomposing I into two components, main step is to select two dictionaries built by combining two sub dictionaries D_1 , D_2 which can be either global or local dictionaries and those should be mutually incoherent.

Dictionary Learning

After getting High frequency image from rainy image, patches are extracted from HF image for example 16 * 16 patches are extracted.

For each patch, dictionary is learned DHF using dictionary learning algorithm-SVD [8] algorithm is used for dictionary learning.

Fig 3 shows dictionary learned from the patches extracted from HF patch via Online Dictionary Learning algorithm.

Fig 3: Dictionary Learned from patch

Dictionary Partition

Dictionary learned in previous stage, can be further divided into two clusters which represents two components of the image rain (textural) and non-rain(geometric) component of the image. In proposed method, HOG descriptors are used to describe each atom in DHF .To extract HOG feature from the image, image can be divided into several small regions. For each region a local 1-D histogram of gradient direction or edge orientation over the pixels of cell can be collected. The combined histogram entries of all the cells form HOG representation of the image.

Two sub dictionaries representing rain D_{HF_R} and Non-rain D_{HF_G} component are obtained. Below Fig 4 shows Dictionary partition Fig (4.a) is rain sub dictionary and fig (4.b) is Non-rain sub dictionary.

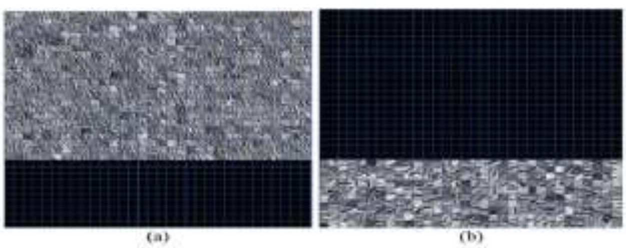


Fig 4: Rain & Non-rain Sub dictionary

Sparse Coding

Based on two sub dictionaries, Sparse Coding [14] [15] is applied using Orthogonal Matching Pursuit (OMP) for each patch of HF Image to find its sparse coefficient vector. Each constructed patch is used to recover either geometric or rain component of the image.

Non Rain Component of the HF image obtained from this step and Low frequency image obtained in the first step are combined to form Non-rain version of the original rainy image.

Extended Dictionary

In proposed method, dictionary learning step is self-explained where no extra training samples are required. Dictionary is learned from input image itself. Decomposition performance can be further improved by collecting set of patches from HF part of some non-rain training images to learn extended dictionary D_E.Then integrate D_E with Non-rain Sub dictionary D_{HF_G} of each image to form geometric sub dictionary of the image.

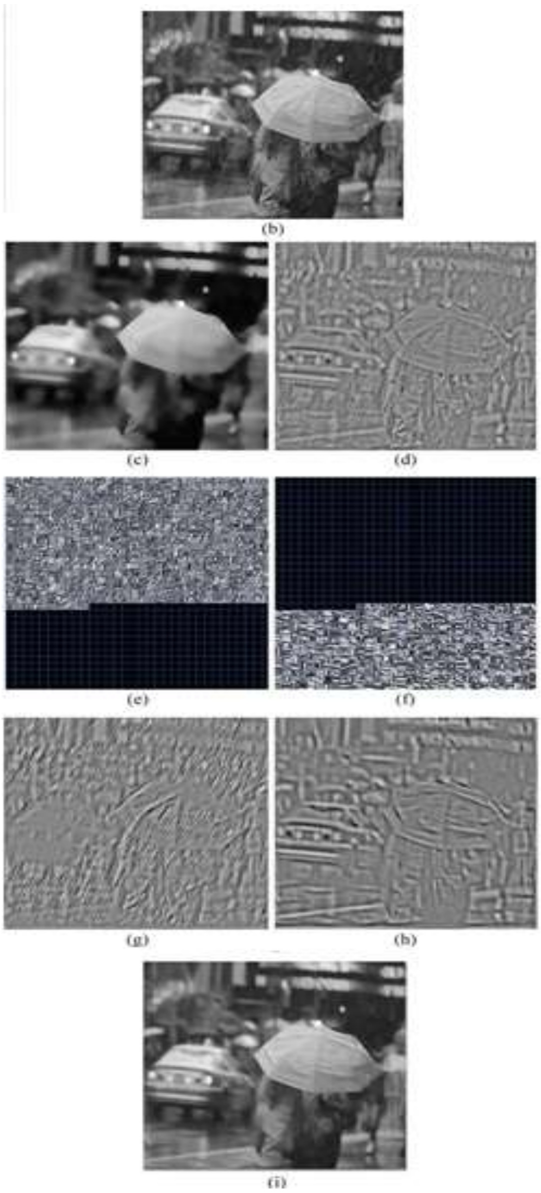
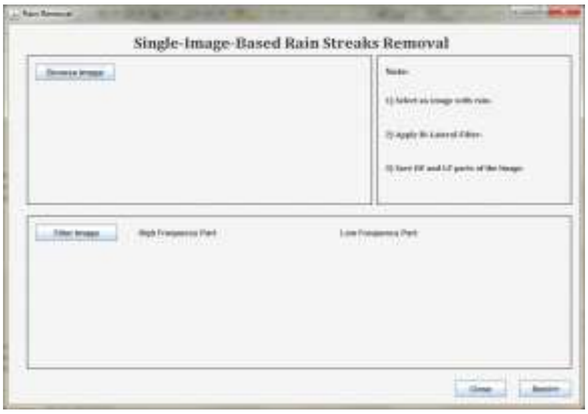


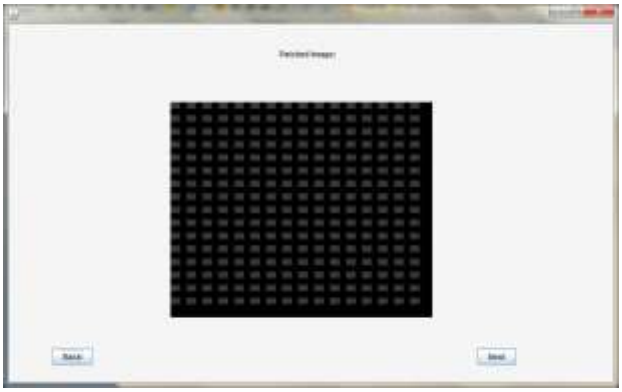
Fig . Step by step Result

Screenshots:-



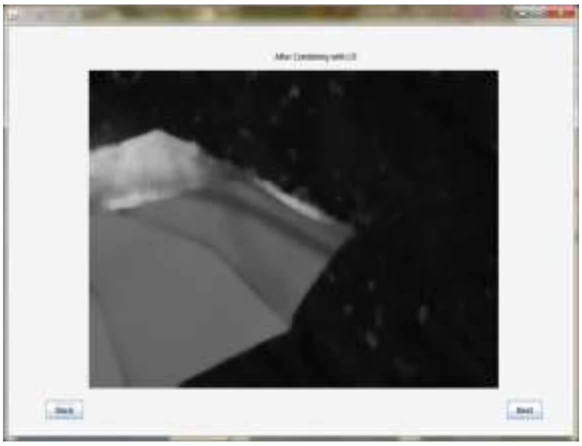
Screenshot 1: Enter Input Image

Screenshot 2 : LF & HF Images of Input Image



Screenshot 3: Patched Image of HF Image

Screenshot 4: Rain &Non Image of HF Image



Screenshot 5: Final Output

Screenshot 6: After Denoising

Screenshot7: After Deblur

4. CONCLUSION

This method is among the first to achieve rain streak removal while preserving geometrical details in a single frame, where no temporal or motion information among successive images is required. This is first automatic MCA-based image decomposition framework for rain steak removal is proposed. Learning of the dictionary [8] for decomposing rain steaks from an image is fully automatic and self-contained, where no extra training samples are required in the dictionary learning [8] stage.

REFERENCES

[1] K. Garg and S. K. Nayar, "Vision and rain," *Int. J. Comput. Vis.*, vol.75, no. 1, pp. 3–27, Oct. 2007.

[2]. Fang Rain,"Rain Detection and Removal of Sequential Iamges",IEEE Chines Control and Decision Conference (CCDC), pp. 615-618,2011.

[3] J. Bossu, N. Hautière, and J. P. Tarel,"Rain or snow detection in image sequences through use of a histogram of orientation of streaks" *Int. J. Comput. Vis.*, vol.93 no. 3, pp. 348–367, Jul. 2011

[4] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Proc. IEEE Int. Conf. Comput. Vis.*, Bombay, India, Jan. 1998,pp. 839–846.

[5] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, San Diego, CA, Jun. 2005, vol. 1, pp. 886–893.

[6]

[7] L.-W. Kang, C.-W. Lin, and Y.-H. Fu,"Automatic single-image-based rain streaks removal via image decomposition," *IEEE Trans. Image Process.*, vol. 21, no. 4, pp. 1742–1755, Apr. 2012.

[7]. Y. H. Fu, L. W. Kang, C. W. Lin, and C. T. Hsu, "Single- frame-based rain removal via image decomposition," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Prague, Czech Republic, May 2011, pp. 1453–1456.

[8] J. M. Fadili, J. L. Starck, J. Bobin, and Y. Moudden, "Image decomposition and separation using sparse representations: An overview," *Proc.IEEE*, vol. 98, no. 6, pp. 983–994, Jun. 2010.

[9]. Y. H. Fu, L. W. Kang, C. W. Lin, and C. T. Hsu, "Single-frame-based rain removal via image decomposition," in *Proc. IEEE Int. Conf. Acoustics, Speech and Signal Process.*, May 2011, Prague, Czech Republic.

[10]. S. Maji, A. C. Berg, and J. Malik, "a Classification using intersection kernel support vector machine is efficient," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Anchorage, Alaska, USA, June 2008, pp. 1-8.

[11]. J. M. Fadili, J. L. Starck, J. Bobin, and Y. Moudden, "Image decomposition and separation using sparse representations: an overview," *Proc. IEEE*, vol. 98, no. 6, pp. 983–994, June 2010.

[12]. H. Baya, A. Essa, T. Tuytelaarsb, and L. V. Gool, "Speeded-up robust features (SURF)," *Comput. Vis. Image Understanding*, vol. 110, no. 3, pp. 346–359, June 2008.

[13]. M. Elad and M. Aarons, "Image denoising via sparse and redundant representations over learned dictionaries," *IEEE Trans. Image Process.*, vol. 15, no. 12, pp. 3736–3745, Dec. 2006.

[14]. M. Elad, *Sparse and Redundant Representations: from Theory to Applications in Signal and Image Processing*, Springer, 2010.

[15]. Li-Wei Kang, Chia-Wen Lin, and Yu-Hsiang Fu, "Automatic single-frame-based rain streak removal via image decomposition," *IEEE Trans. Image Processing*. (Submitted, March 2011, revised, August 2011).