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An Approach for Reduction of Rain Streaks from a Single Image

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Abstract: ***Various weather conditions such as rain, snow, haze, or fog will cause complex visual effects of spatial or temporal domains in images or videos. Such effects may significantly degrade the quality of outdoor vision systems. Rain removal from a video is a challenging problem and has been recently investigated extensively. Nevertheless, the problem of rain removal from a single image was rarely studied in the literature, where no temporal information among successive images can be exploited, making the problem very challenging. In this paper, we propose a single-image-based rain removal framework. We first decompose an image into the low-frequency and high-frequency parts using a smoothing (bilateral) filter. Bilateral filter is edge preserving, noise reducing, smoothing filter for images. Bilateral filter extends the concept of Gaussian smoothing by weighting the filter coefficients with their corresponding relative pixel intensities. This weight is based on Gaussian distribution. Pixels that are very different in intensity from the central pixel are weighted less even though they may be in close proximity to the central pixel. After 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. The refined guidance image can be used to get a better removal result. Reduction or removal of rain streaks fall into the category of image noise reduction.***

Keywords*:* Rain removal, sparse coding, dictionary learning, image decomposition, morphological component analysis (MCA)

1. Introduction

We propose a single-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 a bilateral filter. Bilateral filter is edge preserving, noise reducing, smoothing filter for images. The high-frequency part is then decomposed into "rain component" and "non-rain component" by performing dictionary learning and sparse coding based on MCA.

Instead of directly applying a conventional image decomposition technique, the proposed method first decomposes an image into the low- and high-frequency (HF) parts using a bilateral filter. The HF part is then decomposed into a "rain component" and a "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.

Removal of rain streaks has recently received much attention to the best of our knowledge; current approaches are all based on detecting and removing rain streaks in a video. This paper is among the first to specifically address the problem of removing rain streaks in a single image. Rain removal in an image may also fall into the category of the problem about image noise removal or image restoration.

Different weather conditions such as rain, snow, haze, or fog will cause complex visual effects of spatial or temporal domains in images or videos. Such effects may significantly degrade the performances of outdoor vision systems relying on image/video feature extraction or visual attention modelling, such as image registration, event detection objects detection, tracking, and recognition, scene analysis and classification, image indexing and retrieval, and image copy/near-duplicate detection. A comprehensive survey of detection approaches for outdoor environmental factors such as rain and snow to enhance the accuracy of video-based automatic incident detection systems can be found in.

a) Vision-Based Rain Detection and Removal

A pioneering work on detecting and removing rain streaks in a video was proposed, where the authors developed a correlation model capturing the dynamics of rain and a physics-based Motion blur 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.

Furthermore, a model of the shape and appearance of a single rain or snow streak in the image space was developed to detect rain or snow streaks. Then, the amount of rain or snow in the video can be reduced or increased. Moreover, an improved video rain streak removal algorithm incorporating both temporal and chromatic properties was proposed. These temporal and chromatic properties utilize the shape characteristics of rain.

b) Image Noise Removal

Image noise removal or de noising 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 acquired in the presence of an additive noise. Numerous contributions the past 50 years addressed this problem from many and diverse points of view. For example, spatial adaptive filters, stochastic analysis, partial differential equations, transform-domain methods, splines, approximation theory methods, and order statistics are some of the directions explored to address this problem. Recently, the use of sparse and redundant representations over learned dictionaries has become one specific approach toward image de noising, which has been proven to be effective and promising. Based on the assumption that image signals admit a sparse decomposition over a redundant dictionary, by using the K-SVD (single value decomposition) dictionary training algorithm.

c) Motivations of Single-Image-Based Rain Streak Removal

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. 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, this was rarely investigated before. In addition, some video rain removal approaches based on adjusting camera parameters may not be suitable to consumer Camcorders and cannot be applied to existing acquired image/video data. Furthermore, for removing rain streaks from videos acquired from a moving camera, the performances of existing Video-based approaches may be significantly degraded.

The reason is that, since these video-based approaches usually perform rain streak detection, followed by interpolating the detected pixels affected by rain streaks in each frame, the non stationary background due to camera motions and inaccurate motion estimation caused by the interference of rain streaks would degrade the accuracy of video-based rain streak detection and pixel interpolation. Although some camera motion estimation techniques can be applied first to compensate for the camera motions, its performance may be also degraded by rain streaks or large moving activity.

Figure.1.Shows Examples of interesting point detection: (a) original non rain image; (b) rain image of (a); (c) SIFT interesting point detection for (a) (169 points); (d) SIFT interesting point detection for (b) (421 points); (e) SURF interesting point detection for (a) (131 points); and (f) SURF interesting point detection for(b) (173 points). And scale invariant. Some widely used features (descriptors) such as scale-invariant feature transform (SIFT) , speeded up robust features (SURFs) , and histogram of oriented gradients (HOGs) 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.

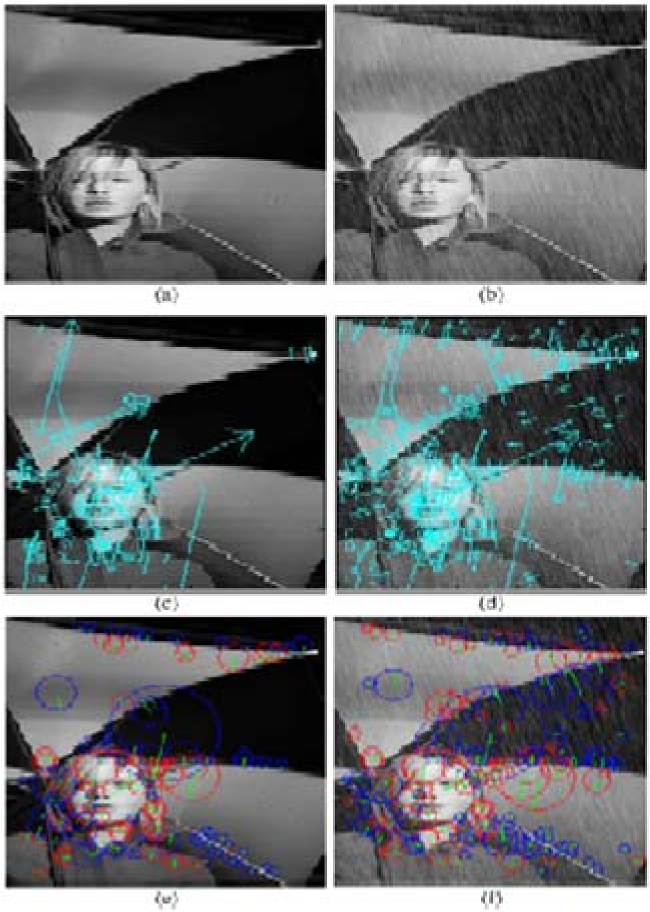

Figure 1: Examples of interesting point detection: (a) original nonrain image;(b) rain image of (a); (c) SIFT interesting point detection for (a) (169 points);(d) SIFT interesting point detection for (b) (421 points); (e) SURF interesting point detection for (a) (131 points); and (f) SURF interesting point detection for(b) (173 points).

2. MCA-Based Image Decomposition

The proposed single-image-based rain streak removal framework, in which rain streak removal is formulated as an image decomposition problem. In this method, the input rain image is first roughly decompose 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.

Suppose that an image I of N pixels is a superposition of layers (called morphological components), denoted by I = Σ Is, where Is denotes the s-th component. To decompose the image I into, $\{I_s\}_{s=1}^{s}$, the MCA algorithms iteratively minimize the following energy function:

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

Where θ denotes the sparse coefficients corresponding to with respect to dictionary Ds, and Es is the energy defined according to the type of Ds (denoted by Dgs for a global dictionary or by Dls for a local dictionary). For a global dictionary, energy function is defined as,

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

Usually to decompose 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.

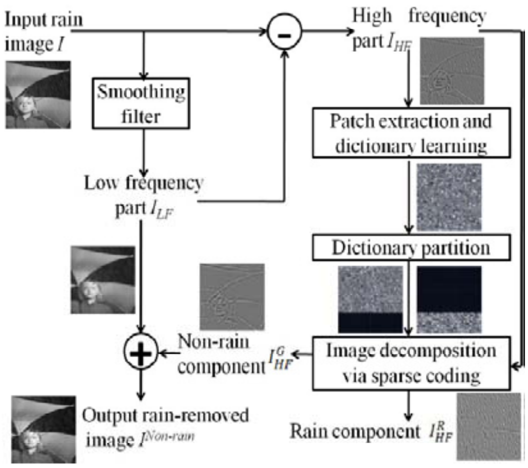

Figure 2 (a): Block diagram of the proposed rain streak removal method.

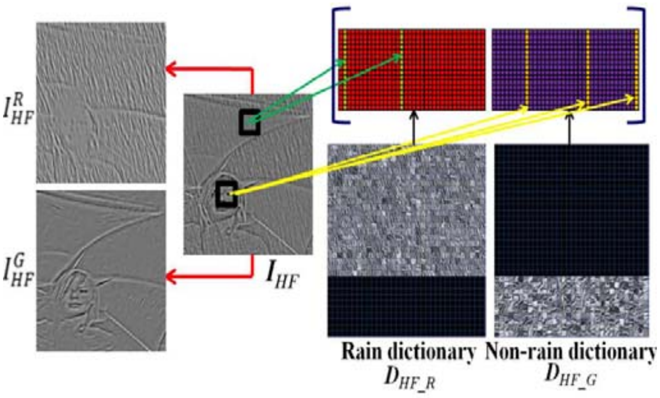

Figure 2 (b): Illustration of the proposed method based on two learned local dictionaries

3. Dictionary Learning and Partition

Atoms constitutes can be roughly divided into two clusters (sub dictionaries) for representing the geometric and rain components of image. Intuitively, the most significant feature for a rain atom can be extracted via "image gradient."

The basic idea of HOG is that local object appearance and shape can be usually well characterized by the distribution of local intensity gradients or edges, without precisely knowing the corresponding gradient or edge positions.

The image can be divided into several small spatial regions or cells. For each cell, a local 1-D histogram of gradient directions or edge orientations over the pixels of the cell can be accumulated. The combined histogram entries of all cells form the HOG representation of the image.

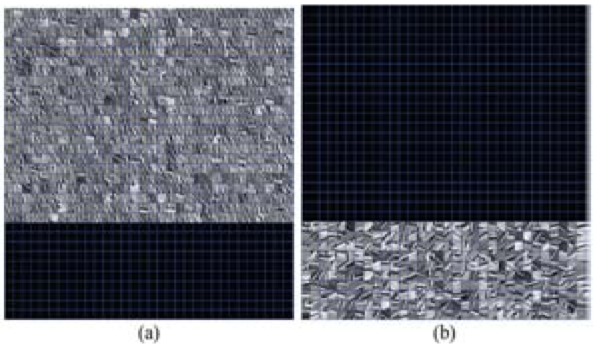

Figure 3 (a): Rain sub dictionary and geometric or nonrain sub dictionary

The size of a local image patch/dictionary atom is chosen to be 16* 16, which leads to reasonable computational cost in dictionary partition into two clusters and based on their HOG feature descriptors. The following procedure is to identify which cluster consists of rain atoms and which cluster consists of geometric or non rain atoms.

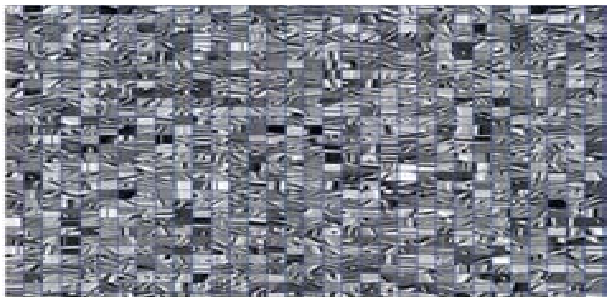

Figure 3 (b): Learned extended dictionary

Dictionary learning step is fully self-contained and we are not adding any extra samples. It is very difficult to learn a rain dictionary by collecting a set of rain patches because of following reasons:

1. It is not easy to collect pure rain patches because rain streaks are mixed with non-rain part of the image.
2. It is also not easy to learn a dictionary which is adapted to wide range of lightening conditions for rain streaks.

4. Sparse Coding

Sparse coding is a technique of finding a sparse representation for a signal with a small number of nonzero or significant coefficients corresponding to the atoms in a dictionary. A coding strategy that maximizes sparsity is sufficient to account for these three properties and that a learning algorithm attempting to find sparse linear codes for natural scenes will develop a complete family of localized, oriented, and band pass receptive fields.

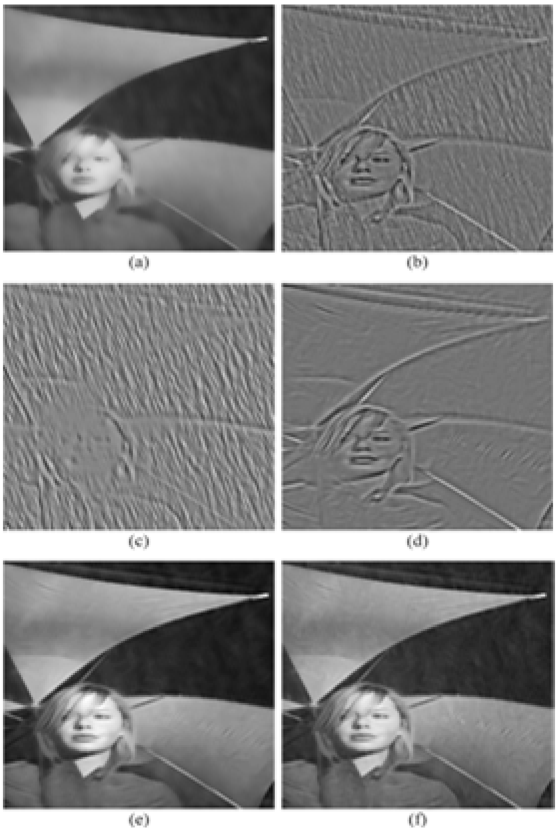

Figure 4: Step-by-step results of the proposed rain streak removal process: (a) LF part of the rain image (b) HF part; (c) rain component; and (d) geometric component. (e) rain-removed version for the rain

5. Experimental Results

Figure 5(a): Input Rainy Image

Figure 5(b): K-SVD-based denoising

Figure 5(c): Proposed method

Figure 5(d): Proposed method with extended dictionary

6. Conclusion and Future Work

In this paper, 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. Experimental results show that the proposed method achieves comparable performance with state-of-the-art video-based rain removal algorithms without the need of using temporal or motion information for rain streak detection and filtering among successive frames.

For future work, the performance may be further improved by enhancing the sparse coding, dictionary learning, and partition of dictionary steps. For example, when performing sparse coding, some locality constraint may be imposed to guarantee that similar patches should have similar sparse codes/coefficients. Moreover, the proposed method may be extended to remove rain streaks from videos or other kinds of repeated textures.

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