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Rain Streaks Removal from Single Image: A Survey

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Abstract: ***Method of removing rain streaks mainly works on video. There are very few methods which address the problem of rain removal from single image. Existing methods removes rain streaks from video not from single image. These methods capture non-rain data from successive images. This data is then utilized to replace rain-part in current images. Proposed method is one of the first methods which removes rain streaks from single image. Rain removal in an image also falls into the category of Image noise removal or Image restoration. In this paper we briefly study the methods which removes rain streaks from video i.e. vision-based (video-based) rain removal approaches.***

Keywords: Dictionary learning, image decomposition, morphological component analysis (MCA), rain removal, sparse representation, HOG descriptors.

1. Introduction

For detecting and removing rain streaks in video a correlation model is developed capturing the dynamics of the rain and physics based motion blur model characterizing photometry of rain. By adjusting camera parameters such as exposure time and depth of the field, effect of the rain streaks can be mitigated. To remove rain streaks improves the performance of the image detection. For example to identify pedestrians from rainy image. In rainy image, not all the target objects will be detected. But performance accuracy of the rain removed version is better.

To remove noise from image, spatial adaptive filters, stochastic analysis, partial differential equations, transform-domain methods, splines, approximation theory methods, and order statistics are utilized. Use of sparse and redundant representation over learned dictionary has become one of the specific approaches for image denoising.

Till now the work done on rain streak removal has been mainly done on video based approaches that considers temporal correlation among multiple successive frames. However when only single image is available which is captures from camera or downloaded from internet such single image based rain streak removal method is needed. To add with, some video rain removal approaches based on adjusting camera parameters are not suitable for video camcorders.

Image based applications such as mobile visual search, object detection/recognition, image registration, image stitching, and salient region detection rely on the extraction of gradient based features that are rotation and scale invariant. To calculate image gradients, descriptors such as scale-invariant feature transform (SIFT) [3], speeded up robust features (SURFs) [4] and histogram of oriented gradients (HOGs) [5 - 7] are used. Input image is rainy image and output is rain removed version of the input image [1]

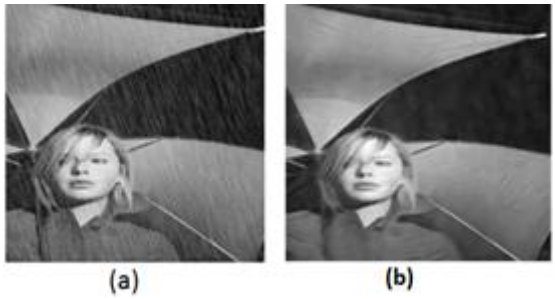

Figure 1: Input & Output

2. Previous Work

Proposed method is first method to remove rain streaks from video. All previous methods are based on removing rain streaks from video. But when only a single image is available captured from camera or downloaded from internet then single image rain removal method is needed.

a) Spatial Adaptive Filters

Post filtering process for improving appearance of video image includes motion compensated temporal filtering and spatial adaptive filtering. For each target pixel being filtered, the temporal filtering uses multiple motion vectors and one or more pixel values for prior frame to determine one of more reference values for target filter. The pixel value is reference value for target pixel value and is combined with target pixel value in a filter operation. Multiple motion vectors for blocks for blocks near or containing target pixel value point to pixel values in prior frame.

This pixel value is reference value for target pixel value. The weighting for average is selected according to the position of target pixel value. Spatial filtering determines dynamic range of pixel values in a smaller block containing target pixel value and dynamic range of pixel values in a larger block containing target pixel value.

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The two dynamic range suggest the image context of target pixel, and an appropriate spatial filter for the target pixel is selected according to the selected context. Spatial filtering can smooth discontinuity at block boundaries and reduce prominence of noise. Such spatial filtering operates on array of 3 pixel values representing a frame in a video image and modifies at least some pixel values based on neighboring pixel values.

However Spatial filtering can undesirably make edges and textures of objects in the image look fuzzy or indistinct and selective spatial filtering can cause ashing where clarity of edges of an object changes as object moves through area filtered differently.

b) Splines

Splines are curves, which are usually required to be continuous and smooth. Splines are usually defined as piecewise polynomials of degree n with function values and first n-1 derivatives that agree at the points where they join.

The abscissa values of the join points are called knots. The term "spline" is also used for polynomials (splines with no knots) and piecewise polynomials with more than one discontinuous derivative. As such, splines with no knots are generally smoother than splines with knots, which are generally smoother than splines with multiple discontinuous derivatives. Splines with few knots are generally smoother than splines with many knots. Knots give the curve freedom to bend to more closely follow the data.

For a spline of degree n, each segment is a polynomial of degree n, which would suggest that we need n+1 coefficients to describe each piece. However, there is an additional smoothness constraint that imposes the continuity of the spline and its derivatives up to order (n-1) at the knots, so that, effectively, there is only one degree of freedom per segment.

Applications:
1. Zooming and visualization
2. Geometric Image Transformations
3. Filter Design and fast continues wavelet transform
4. Image Compression
5. Multiscale Processing and Image Registration
6. Contour Detection
7. Analog to Digital Conversion

c) Interest Point Detection

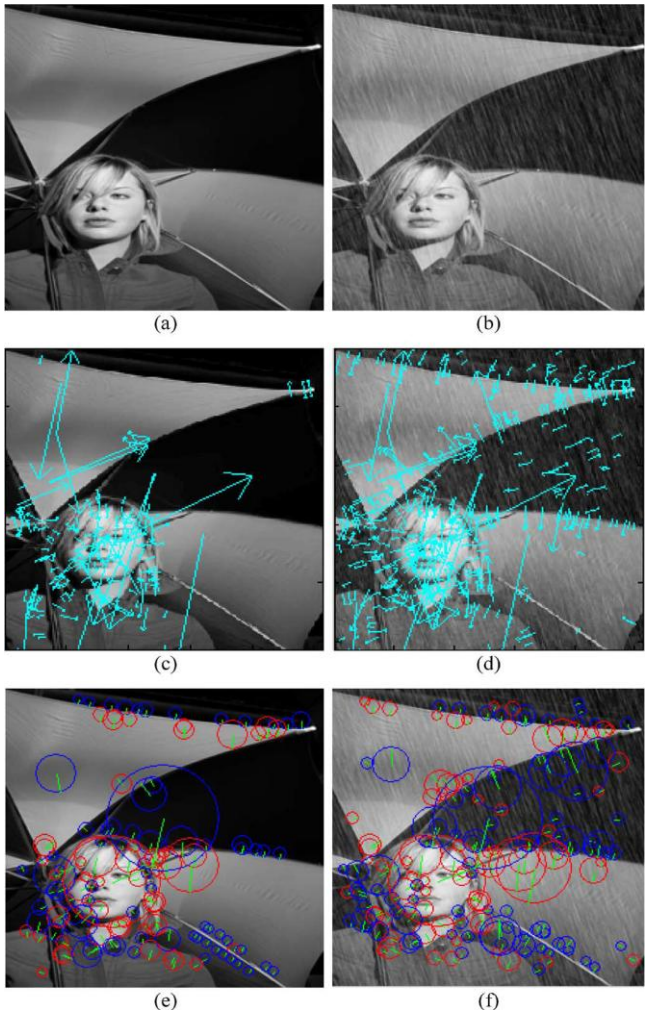

Figure 2: Example of Interest Point Detection [1]

Figure shows unreliable additional (rain points) interest points in image which degrades performance of image.
(a) original nonrain image
(b) rain image of (a)
(c) SIFT interesting point detection for nonrain image
(d) SIFT interesting point detection for rain image
(e) SURF interesting point detection for nonrain image and
(f) SURF interesting point detection for rain image

Removing those additional unwanted points from Rain image improves quality of image by removing rain points from image. Many image based applications such as Image detection, Image registration, Image stitching are all based on detecting gradient-based features from image. Some majorly used feature (descriptors) are Scale scale-invariant feature transform (SIFT) [3], speeded up robust features (SURFs) [4], and histogram of oriented gradients (HOGs) [5].

3. Image Descriptors

A. SIFT (Scale scale-invariant feature transform)

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect and describe local features in

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images. The algorithm was published by David Lowe in 1999.

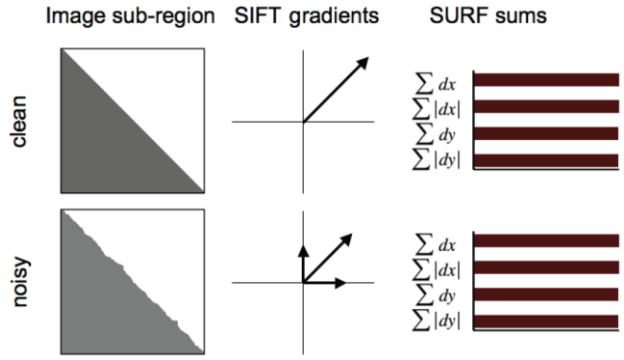

Figure 3: SIFT Descriptor

SIFT Overview -

Detector

1. Find Scale-Space Extrema
2. Keypoint Localization & Filtering
- Improve keypoints and throw out bad ones

Descriptor

3. Orientation Assignment
- Remove effects of rotation and scale

4. Create descriptor
- Using histograms of orientations

It consists of –

1. Interest Point Detection

The SIFT descriptor was computed from image intensities These interest points are obtained from scale space extrema. The Gaussian pyramid is constructed from input image by repeated smoothing & sampling. Then, interest points are obtained from the points at which the difference-of-Gaussians values assume extrema with respect to both the spatial coordinates in the image domain and the scale level in the pyramid.

It can be shown that this method for detecting interest points leads to scale-invariance in the sense that the interest points are preserved under scaling transformations and (ii) the selected scale levels are transformed in accordance with the amount of scaling. Hence, the scale values obtained from these interest points can be used for normalizing local neighborhoods with respect to scaling variations which is essential for the scale-invariant properties of the SIFT descriptor.

2. Image Descriptor

In the SIFT descriptor, the size estimate of an area around the interest point is determined as a constant times the detection scale *s* of the interest point, which can be motivated by the property of the scale selection mechanism in the interest point detector of returning a characteristic size estimate associated with each interest point.

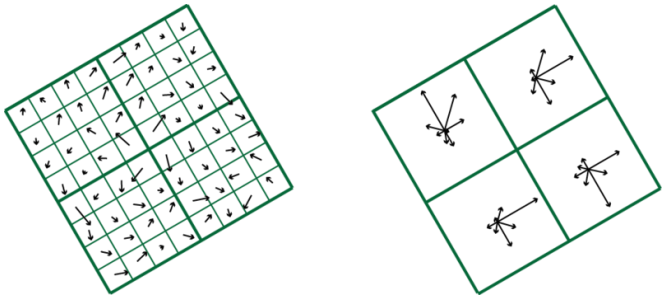

Figure 4: Scale and orientation normalization

B. Speeded Up Robust Features (SURF)

SURF (Speeded Up Robust Features) is a robust local feature detector, first presented by Herbert Bay et al. in 2006, that can be used in computer vision tasks like object recognition or 3D reconstruction. It is partly inspired by the SIFT descriptor. The standard version of SURF is several times faster than SIFT and claimed by its authors to be more robust against different image transformations than SIFT. SURF is based on sums of 2D Haar wavelet responses and makes an efficient use of integral images.

It uses an integer approximation to the determinant of Hessian blob detector, which can be computed extremely quickly with an integral image (3 integer operations). For features, it uses the sum of the Haar wavelet response around the point of interest. Again, these can be computed with the aid of the integral image.

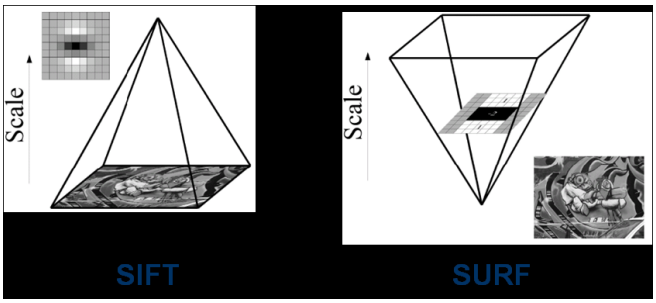

Figure 5: SIFT & SURF

The task of finding point correspondences between two images of the same scene or object is part of many computer vision applications. Image registration, camera calibration, object recognition, and image retrieval are just a few. The search for discrete image point correspondences can be divided into three main steps. First, `interest points' are selected at distinctive locations in the image, such as corners, blobs, and T-junctions. The most valuable property of an interest point detector is its repeatability. The repeatability expresses the reliability of a detector for find ing the same physical interest points under different viewing conditions. Next, the neighborhood of every interest point is represented by a feature vector. This descriptor has to be distinctive and at the same time robust to noise, detection displacements and geometric and photometric deformations. Finally, the descriptor vectors are matched between different images. The matching is based on a distance between the vectors.

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C. Histogram of oriented gradients (HOG)

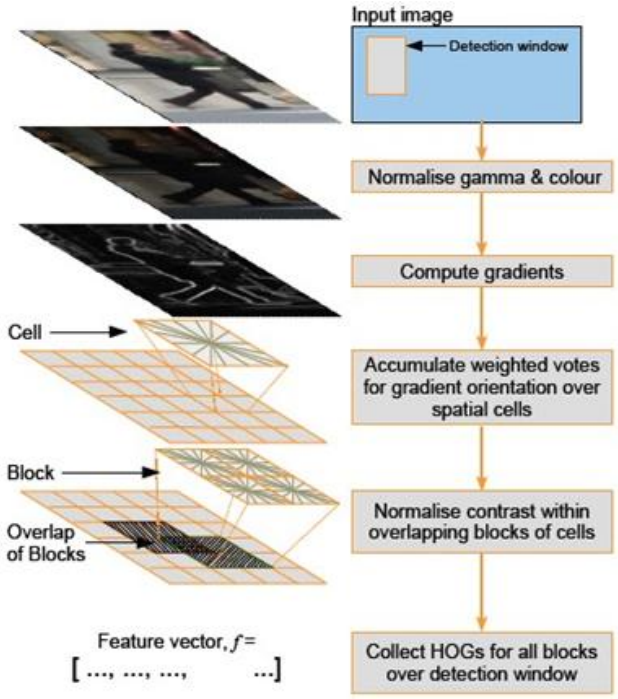

Figure 6: Overview of HOG feature extraction

HOG is a standard image feature used in object detection and deformable object detection. It decomposes the image into square cells of a given size, compute a histogram of oriented gradient in each cell, and then renormalizes the cells by looking into adjacent blocks.

Objective: object recognition
Local shape information often well described by the distribution of intensity gradients or edge directions even without precise
information about the location of the edges themselves.

Algorithm Overview

- Divide image into small sub-images: “cells”
- Cells can be rectangular (R-HOG) or circular (C-HOG)
- Accumulate a histogram of edge orientations within that Cell
- The combined histogram entries are used as the feature vector describing the object
- To provide better illumination invariance (lighting, shadows, etc.) normalize the cells across larger regions incorporating multiple cells: “blocks”

4. Conclusions

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.

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