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Detection and Removal of Rain in Videos Using Modern Approach

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Abstract

Rain removal from an image/video is a challenging problem and has beeninvestigated extensively. The single-image-basedrain streak removal framework via properly formulating it asan image decomposition problem based on morphologicalcomponent analysis (MCA) solved by performing dictionarylearning and sparse coding. However, thedictionary learning process cannot be fully automatic, where thetwo dictionaries used for rain removal were selectedby human intervention. The extended work proposed an automatic self-learning-basedrain streak removal framework for single image. We propose toautomatically self-learn the two dictionaries used for rain removal without additional information or any assumption. Wethen extend our single-image-based method to video-based rainremoval in a static scene by exploiting the temporal information of successive frames and reusing the dictionaries learned by theformer frame(s) in a video while maintaining the temporalconsistency of the video. 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.

Introduction:

Bad weather degrades not only the perceptual image quality but also the performance of various computer vision algorithms which use feature information such as object detection, tracking, segmentation and recognition. Thus, it is very difficult to implement these computer vision algorithms robust to weather changes.

There are different types of bad weather conditions, e.g., fog, rain, snow, haze, mist, etc. Based on the type of the visual effects, bad weather conditions are classified into two categories: steady (viz., fog, mist and haze) and dynamic (viz., rain, snow and hail) [1]. In steady bad weather, constituent droplets are very small (1–10μm) and steadily float in the air. In dynamic bad weather, constituent droplets are 1000 times larger than thoseof the steady weather. For the purpose of restoration, the dynamic bad weather model is investigated. Rain is the major component of the dynamic bad weather. Raindrops are randomly distributed in 3D space. Due to the high velocity of the raindrops, their perspectiveprojection forms the rain streaks. The major contribution of this paper is that the learning of the dictionaries used for removing rain steaks from an image/video is fully automatic and self contained without any prior knowledge, where no extra training samples are required in the dictionary learning stage.

2. RAIN ANALYSIS

Analysis of the original rain video shows that there is no correlation between the rain streaks in any two frames. If in a rain video, video frames are shuffled, then the resulting video looks as natural as the original. This shows the temporal independence property [8] of therain. One more interesting property of rain is that it gives positive fluctuations in the intensity valuesand chrominance values remain unaffected. Thesefluctuations are very small in nature. Thus, it is not easyto recognize rain by just looking into a single video frame.Rain effect is visible by looking at a certain number ofconsecutive frames in sequel. This shows the dynamicnature of the rain.

Temporal Pixel Intensity Waveform:

Evolution of intensity values of a pixel at a particular position present in the rain region for consecutive frames is quite different from the evolution for the pixel present in moving object region. Temporal pixel intensity waveforms for the rain and moving object pixels are shown in Figure 1. For the rain pixel, intensity values below and above mean are more rhythmic than those
for the moving object pixel.
Extent of symmetry of the waveforms above and below mean can be quantitatively measured by the skewness. As the symmetryof the data decreases, value of skewness increases.

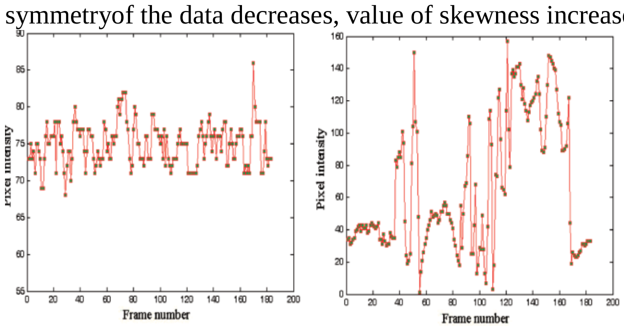

Figure 1: First column shows the temporal intensity waveform for pixels in rain region. Second column shows the samewaveform for pixels in non-rain moving object region.

Rain Removal Algorithm

Probabilistic Approach
For the discrimination between the rain pixels and the non-rain pixels for each video frame, the difference in thenature of intensity waveformshave been exploited. To make this discrimination process automatic and unbiased,a probabilistic model based discrimination is used.

1. Detection of Rain:

Due to heavy rain, the same pixel may be corrupted in consecutive frames. Due to the presence of the moving objects, this detection process contains some false rain pixel candidates. Thus, this detection process requires some

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refinement. In this stage, the moving and static edge pixels are removed from the rain candidate pixels.

2.Navie Bayes Classifier:

A naive Bayes classifier is a simple probabilisticclassifier based on applying Bayes' theorem withstrong independence assumptions, or more specifically,independence feature model. Naive Bayes classifiercombines naive Bayes probability model with a decisionrule, such as the maximum a posteriori or MAP decision. Sum of the prior probability for the rain and non rainpixels is unity. If there is heavy rain then prior probability of the rain pixels is more than the prior probability of the non-rain pixels. Posteriori probability distributions obtained from aparticular frame are considered same for all other video frames.

3. Inpainting of Rain Pixels:

Intensity variations produced by the raindrops aresomewhat symmetric about the mean of the intensitiesof consecutive frames at particular pixel position. Hence,inpainting of detected rain pixels can be achieved byreplacing it with the corresponding temporal mean ofthe intensity waveform.

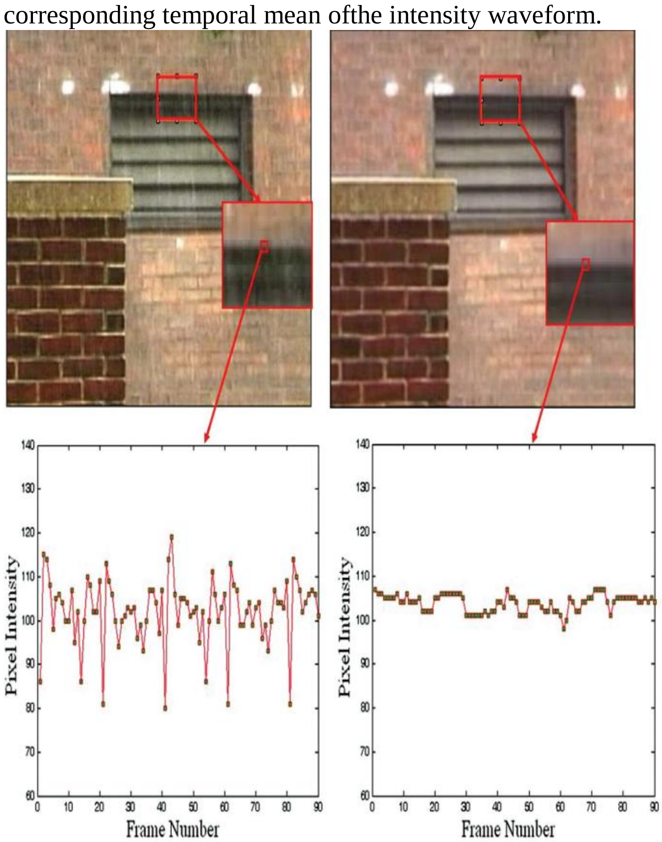

Figure: (Left) Frame from the "test" rain video and temporal intensity waveform at a pixel position. (Right) Frame from the same rain video with rain removed by temporal-mean and -intensity waveform at the same pixel position.

MCA (Morphological Component Analysis)Approach:

MCA-BASED IMAGE DECOMPOSITION, SPARSE CODING, AND DICTIONARY LEARNING

A. MCA-based Image Decomposition:

Suppose that an image I of N pixels is a superposition of layers (called morphological components), denoted byI = Σ Is, where Is denotes the s-th component, such as thegeometric or textural component of I.MCA based decomposition algorithm is

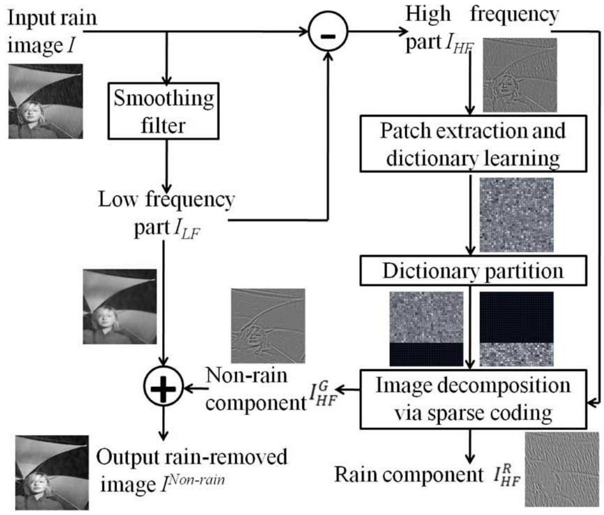

Fig . (a) Block diagram of the proposed rain streak removal method.

In this method, an imageis first decomposed into the low-frequency (LF) and high-frequency
(HF) parts using a bilateral filter. The HF part is thendecomposed into "rain component" and "nonrain component"by performing dictionary learning and sparse coding based onMCA. The major contribution of this paper is threefold: 1)to the best of our knowledge, our method is among the firstto achieve rain streak removal while preserving geometricaldetails in a single frame, where no temporal or motion informationamong successive images is required; 2) we propose thefirst automatic MCA-based image decomposition frameworkfor rain steak removal; and 3) the learning of the dictionary fordecomposing rain steaks from an image is fully automatic andself-contained, where no extra training samples are required inthe dictionary learning stage. In addition, the proposed methodalso offers another option in dictionary learning by collectingexemplar patches from a set of nonrain training images to learnan extended dictionary to enrich the dictionary.

B. Sparse Coding and Dictionary Learning

Sparse coding is a technique of finding a sparserepresentation for a signal with a small number of nonzero orsignificant coefficients corresponding to the atoms in a dictionary. The pioneering work in sparse coding proposedby Olshausen states that the receptive fields ofsimple cells in mammalian primary visual cortex can be characterizedas being spatially localized, oriented, and bandpass. It was shown that 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 bandpass receptive fields. The proposed rain removal framework described uses two local dictionaries learned from the training patches extracted from the rain image itself to respectively decompose a rain

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image into its rain component and geometric (nonrain) component without using any global dictionary. Themain reasons include: 1) we do not assume or empirically decide any type of global dictionary for representing either of the rain and geometrical components in the rain image; 2) because the geometric component is usually highly mixed with rain streaks in some regions of the rain image, segmenting the image into local patches would be easier to extract rain patches that mainly contain rain streaks to facilitate self-learning of rain atoms; and 3) since rain streaks in different local regions of an image often exhibit different characteristics, local-patch-based dictionary learning would usually learn rain atoms that better represent rain streaks than a global dictionary does.

Automatic Rain Streak Removal Frame work:

Fig3shows the proposed single-image-based rain streak removalframework, in which rain streak removal is formulatedas an image decomposition problem. In our method, the inputrain image is first roughly decomposed into the LF and HFparts using the bilateral filter where the most basicinformation will be retained in the LF part whereas the rainstreaks and the other edge/texture information will be includedin the HF part of the image .Then, we perform the proposed MCA-based image decompositionto the HF part that can be further decomposed into the raincomponent and the geometric (nonrain) component. In the image decomposition step, a dictionarylearned from the training exemplars extracted from the HFpart of the image itself can be divided into two subdictionariesby performing HOG feature-based dictionary atom clustering.Then, we perform sparse coding based on the twosubdictionaries to achieve MCA-based image decomposition,where the geometric component in the HF part can be obtained,followed by integrating with the LF part of the image to obtainthe rain-removed version of this image.

Major Differences Between the Automatic Method andTraditional MCA-Based Approaches:

As mentioned in Section II, traditional MCA algorithms usuallyuse a fixed global dictionary based on wavelets/curveletsto represent the geometric component of an image. To represent
the textural component of an image, either a fixed global(global DCT) or a local (local DCT) dictionary is used. In addition,a learned dictionary may be also used to represent the texturalcomponent. Based on our experience,it is not easy to select a proper fixed dictionary to represent rainstreaks due to its variety.Moreover, learning a dictionary for representing texturalcomponent usually assumes that a set of exemplar patches forthe texture to be represented can be either known in advance orextracted from an image to be decomposed itself. Nevertheless, in practice, it is usually not easy to select correct rain patches ina single rain image automatically. It is also not easy to directlyextract pure rain patches for dictionary learning from a rainimage because rain streaks usually cover most regions in arain image. That is, the geometric and rain components areusually largely mixed. Moreover, although a traditional fixedglobal dictionary based on wavelets/curvelets can well sparselyrepresent the geometric component of an image, using a learneddictionary based on the exemplar patches extracted from thecomponent itself would be much better [38].Therefore, rather than using a fixed dictionary, assuming priortraining exemplar patches available, or resorting to tuning parametersfor the used dictionary, our method extracts a set ofselected patches from the HF part of a rain image itself to learna dictionary. Then, based on the features extracted from individualatoms, we classify the atoms constituting the dictionaryinto two clusters to form two subdictionaries for representingthe geometric and rain components of the image .Traditional MCA algorithms are all directly performed on animage in the pixel domain. However, it is typically not easy todirectly decompose an image into its geometric and rain componentsin the pixel domain because the geometric and raincomponents are usually largely mixed in a rain image. Thismakes the dictionary learning process difficult to clearly identifythe “geometric (nonrain) atoms” and “rain atoms” fromthe pixel-domain training patches with mixed components. Thismay lead to removing too many image contents that belong tothe geometric component but are erroneously classified to therain component. Therefore, we propose to first roughly decompose a rain image into the LF and HF parts. Obviously, the most basic information of the image is retained in the LF part, whereas the rain component and the other edge/texture information are mainly included in the HF part. The decomposition problem can be therefore converted to decomposing the HF part into therain and other textural components. Such decomposition aidsin the dictionary learning process as it is easier to classify in the HF part “rain atoms” and “nonrain atoms” into two clustersbased on some specific characteristics of rain streaks.

Furthermore, traditional MCA-based image decomposition approaches are all achieved by iteratively performing the MCA algorithm and the dictionary learning algorithm until convergence. In contrast, the proposed method is noniterative except for that the utilized dictionary learning, clustering, and sparse coding tools are essentially iterative, as will be explained below.

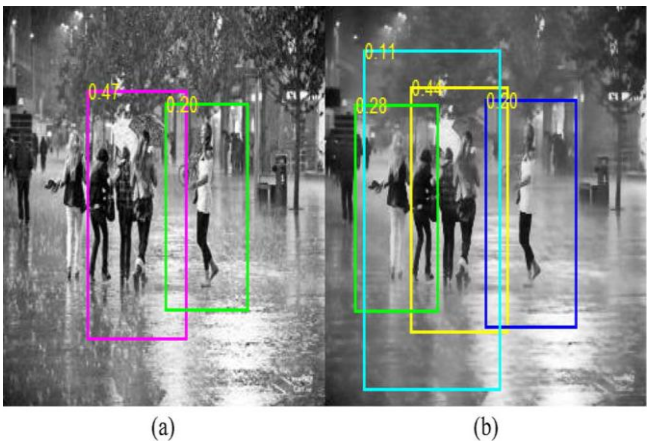

Fig: Applying the HOG-based pedestrian detector to: (a)original rain image (four pedestrians detected) and (b) rain-removed version(obtained by the proposed method) of (a) (five pedestrians detected).

CONCLUSION:

Probabilistic method for videos:

A novel, efficient and probabilistic modelbased rain removal algorithm is proposed for videos. The advantage of this proposed approach is that it automates the algorithm and reduces the user intervention. Here, it is assumed that the video capturing camera is static. There is a significant difference in time evolution between the rain and non-rain pixels in videos. This difference is analyzed with the help of the skewness and Pitman testfor 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 intensity of rain, which makes it robust to different rain conditions. As the proposed algorithm works only on the intensity plane, it helps to reduce the complexity and execution time ofthe algorithm. In summary, the proposed algorithm hasoutperformed all the existing algorithms in all respect.

Single image Rain streaks Removal:

We have proposed a single-image-based rain streak removal framework by formulating rain removal as anMCA-based image decomposition problem solved by performing sparsecoding 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 nonrain atoms learned from nonrain training images. Our 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 forrain streak detection and filtering among successive frames.

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