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Rain Streaks Removal using Total Variation and Sparse Coding Based on Case Based Reasoning Approach

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Abstract: The impact of rain streaks on single images can make it difficult to recognize the surrounding environment using an outdoor camera. Furthermore, a single image is important to use in numerous areas such as in object recognition and scientific research. Therefore, outdoor images and videos in rainy weather conditions will reduce visibility and damage the performance of computer vision algorithms used for extracting features and information from images. This study proposes a new algorithm as a suggestion for the detection and removal of rain streaks in a single image using total variation and sparse coding to restore images. This proposed algorithm will use a retrieval method from a case-based reasoning approach. The experiments and statistical measurements, namely Mean Square Error (MSE), Peak-Signal Noise Ratio (PSNR), Structural Similarity Index (SSIM), Visual Information Fidelity (VIF) and Blind or Referenceless Image Spatial Quality Evaluator (BRISQUE) are used to distinguish which method has better accuracy. The results demonstrated an advantage for our proposed algorithm for the removal of rain streaks.

Key words: Rain streaks, single image, outdoor images, total variation, sparse coding, extracting

INTRODUCTION

There are many negative impacts of noise on images, Therefore, the requirements to find a technique to detect noise in the outdoor and indoor images have an important role in image analysis systems. Total Variation (TV) is very efficient to maintain edges. The researcher by Aujol *et al*. (2006) the most appropriate method for a strange texture pattern is the TV Model as mentioned by Sheikh and Bovik (2006). TV regularization denoising is an approach which supplies a pretty mathematical basis for various essential operations for image restoration such as deblurring, denoising and inpainting. Moreover, it is partaking in applications to noise removal. It smoothes noisy images and produces good signal-to-noise ratios (Zeng and Li, 2013). According to this principle, TV reduces the noisy image signals trying to reach main signal image and removes undesirable detail with maintain details edges which are important in images (Rudin and Osher, 1994). The main contributions in this study are the execution of execute 50 iterative performances for obtaining the dictionary learning DR (nonrain, rain) while MCA by Kang *et al*. (2012) and Chen *et al*. (2014) implemented 100 iterative performances. This means that our algorithm saves 50% of running time. The second contribution is related to using total variation method and matching between sparse coding and TV. The third issue is advantages in statistical results as expressed in study.

MATERIALS AND METHODS

Framework method: A great deal of analysis was conducted to investigate the weaknesses in the state of art. We found these weaknesses points to be divided into two types. The first is how to perceive the edges during rain streaks removal which is solved in this research by using total variation which has advantages over other methods to perceive the edges during the denoising processes. The second is removal of all rain streaks from images without using a lot of time. This issue was solved in this research by using spare coding with 50% of the latest best reseach in this area as well as the total variation method which is a good method to remove these kinds of noises.

The data in Fig. 1 shows the framework new technique for denoising rainy image, divided into three main phases. The first phase represents the implementation of three steps, namely guided filter, sparse coding with fifty iterations and HOG based on K-mean as

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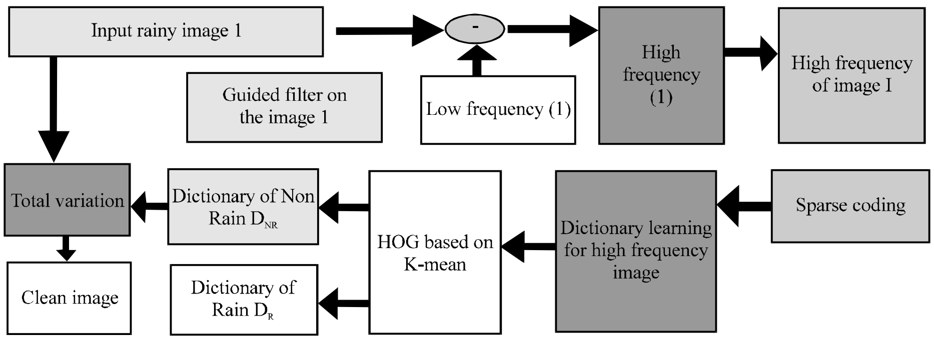

Fig. 1: Framework of proposed method for rain streaks removal

Fig. 2: a) Chen Duan; b) Proposed method; c) Chen Duan and d) Proposed method

explained in the next section. The second phase is related to processing the image in terms of the total variation of methods and the eventual process which combines the results to produce a final outcome.

Case based reasoning: This research is based on a Case Based Reasoning (CBR) strategy which means a study and review of existing methods that have succeeded on detecting and removing rain streaks from a single image. In CBR there are four steps (Arshadi and Jurisica, 2004; Auriol *et al*., 1994) to apply. Retrieval will restore all the superior solutions for the selected problem. Second step is case adaptation which mean is retrieved and adapted the new solution for the current problem. Third phase will apply the method which adapted or suggested solving our problem. Finally, case-base updating is an assessment of a new approach to solve the case.

Total variation technique: Total variation is very effective to restore the rain streaked images which will be elaborated on later in this study. This study uses Total Variation (TV) to remove rain streaks from outdoor images. According to Aujol *et al*. (2006) and Rudin and Osher (1994), TV is able to solve a structure-texture image problem in this case an unknown structure-texture and does not demand inclusive texture information.

Sparse coding: Tsai *et al*. (2008) which define sparse coding a technique of finding a sparse coding regard to a signal to create matrix contain some of nonzero or parameters congruent to the atoms in a dictionary (Buades *et al*., 2008). The sparse coding characteristics represent spatially, orientation and bandpass. It was shown by Tsai *et al*. (2008), that sparsity coding is sufficient to compute these three features to discover sparse codes for outdoor images using a learning algorithm.

RESULTS AND DISCUSSION

To verify the effectiveness of new technique performance a data set for used from this website and others which has included the most of common images used in previous research. All images are sized 256×256, using MATLAB Software. Likewise, the four measurement metrics are Mean Square Error (MSE) (Tiwari and Gupta, 2015), Peak Signal-To-Noise Ratio (PSNR) (Yoo and Ahn, 2012), Structural Similarity Index Method (SSIM) (Wang *et al*., 2004) and Visual Information Fidelity (VIF) (Sheikh and Bovik, 2006).

Images with references: This mean that with the original image (references) and rainy images, the rainy image will undergo the restoration algorithm then compare the result with the original image. Figure 2 and 3 show the results images also Table 1 and 2 illustrate the outcome values. TV sparse coding takes advantage of all measurements expect SSIM which shows equal values in Chen Duan-Yu

Fig. 3: a) Rainy image; b) Chen method; c) L0 smoothing; d) Proposed method; e) Rainy image; f) Chen method; g) L0 smoothing; h) Proposed method

Table 1: The experiment result using images in Fig. 2a and b

Measurement/Technique	MSE	PSNR	SSIM	VIF
Chen *et al.* (2014)	0.0097	68.2862	0.9988	0.4195
L0 smoothing (Kang *et al.*, 2012)	0.0104	68.0043	0.9986	0.3206
TV sparse coding	0.0092	68.5174	0.9988	0.4436

Table 2: The experiment result using images in Fig. 2a and b

Measurement/Technique	MSEP	SNR	SSIM	VIF
Chen Duan-Yu	0.0133	66.9166	0.9982	0.4099
L0 smoothing	0.0139	66.7318	0.9981	0.3762
TV sparse coding	0.0121	67.3270	0.9983	0.4422

and TV sparse coding. MSE, PSNR and VIF together produce good results for a new method of TV sparse coding.

Image without references: The image without references that means only the rainy image is present without the original. The measurement uses the Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) (Mittal *et al.*, 2012). It is implemented in cases in which there are no image references he values close to zero are considered better for (BRISQUE). A score is zero means the image has noise.

The data in Table 3 demonstrate that TV_sparse coding is better than Chen Duan-Yu in all images. L0 smoothing based on Table 3 is better than Chen and TV sparse coding. But the results for L0 smoothing are incompatible with a human perspective (Fig. 3). A lot of edges and details are missing from the images.

Table 3: The experiment result using BRISQUE on images in Fig. 2 and 3

Variables	Rose	Ladypink
Chen Duan-Yu	7.5628	46.5009
L0 smoothing	24.0836	39.0477
TV sparse coding	5.9423	45.7434

CONCLUSION

This study has demonstrated the progress of our new method, particularly at low and high rainy streak ratios. Moreover, according to the results in the proposed method using TV Sparse coding performance is superior to Chen *et al.* (2014). And L0 smoothing. Otherwise, the new proposed method TV Sparse coding shows clear advantages in all measurement, namely MSE, PSNR, SSIM, VIF and unreferenced BRISQUE. Moreover, future research will expand this method to remove different kinds of noises for indoor and outdoor images.

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