EFFICIENT DETECTION AND REMOVING OF RAIN OR SNOW IN A SINGLE COLOR IMAGE USING MULTI-GUIDED FILTER

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Abstract— *In this paper, we propose an efficient algorithm to remove rain or snow from a single colour image. Our algorithm takes advantage of two popular techniques employed in image processing, namely, image decomposition and dictionary learning. At first, a combination of rain/snow detection and a guided filter is used to decompose the input image into a complementary pair: (1) the low-frequency part that is free of rain or snow almost completely and (2) the high-frequency part that contains not only the rain/snow component but also some or even many details of the image. Then, we focus on the extraction of image's details from the high-frequency part. To this end, we design a 3-layer hierarchical scheme. In the first layer, an over-complete dictionary is trained and three classifications are carried out to classify the high-frequency part into rain/snow and non- rain/snow components in which some common characteristics of rain/snow have been utilized. In the second layer, another combination of rain/snow detection and guided filtering is performed on the rain/snow component obtained in the first layer. In the third layer, the sensitivity of variance across color channels (SVCC) is computed to enhance the visual quality of rain/snow-removed image. The effectiveness of our algorithm is verified through both subjective (the visual quality) and objective (through rendering rain/snow on some ground-truth images) approaches, which shows a superiority over several state-of-the-art works.*

Keywords— Rain and Snow Removal, Image Decomposition, Dictionary Learning, Guided Filtering, Sparse Representation

1. INTRODUCTION

It is well-known that a bad weather, e.g., haze, rain, or snow, affects severely the quality of the captured images or videos, which consequently degrades the performance of many image processing and computer vision algorithms such as object detection, tracking, recognition, and surveillance. A study by Garg et al. reveals that rain and snow belong to the dynamic weather - they contain constituent particles of relatively large sizes so that they can be captured easily by cameras. On the other hand, haze belongs to the steady weather - the particles are much smaller in size and can hardly be filmed. As a result, rain or snow leads to complex pixel variations and obscures the information that is conveyed in the image or video. Especially, the degradation on the involved algorithm's performance would be severe if the algorithm is Manuscript received xxx, revised yyy, accepted zzz. This work has been supported by National Natural Science Foundation of China (No. 61370148 and No. 61505079) and the "111" Projects (No. B17008). The authors are with Institute of Image Processing, University of Electronic Science and Technology of China, Chengdu, Sichuan 611731, China. C. Chen is also with Department of Electronic and Computer Engineering, The Hong Kong University of Science and Technology, Clearwater Bay, Kowloon, Hong Kong, China. All

We have outlined several common characteristics of rain and snow, from which two metrics are defined, namely, the sensitivity of variance across color channels (SVCC) and the principal direction of an image patch (PDIP). • A lowfrequency part that is free of rain or snow al- most completely has been generated, thanks to the use of a combination of rain/snow detection and a guidedPersonal use is permitted, but republication/redistribution requires IEEE permission.

See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.filter while the corresponding highfrequency part is made complementary to the low- frequency part. • A 3-layer hierarchy of extracting image's details from the high-frequency part has been designed. Specifically, the first layer is a 3-times classification that is based on a trained dictionary (overcomplete), the second layer applies another combination of rain/snow detection and a guided filter, and the third layer utilizes the SVCC to enhance the visual quality of the rain/snow-removed image. The rest of our paper is organized as follows. Section II presents some related works. In particular, several very recent works will be discussed on their pros and cons, which there- fore motivates us to develop our new hierarchical approach. Section III discusses some common characteristics of rain and snow, based on which the SVCC and PDIP will be defined. The details of our proposed rain/snow removal algorithm are presented in Sections IV and V. In Section VI, we show some experimental results and present comparisons between our algorithm and several state-of-the-art works. Finally, Section VII summarizes our work and concludes the paper.

2. RELATED WORKS

The earliest work on the dynamic weather such as rain and snow can date back to the study of their statistical characteristics in the atmospheric science in 1948. Then, Nayar et al. studied the visual manifestations of different weather conditions, including rain and snow .A pioneering

In general, the recent methods for rain/snow removal from a single image can be classified into three categories. The first category is simply filtering-based where a nonlocal mean filter or guided filter is often used. Due to the use of a filter simply, its implementation is very fast. However, it can hardly produce a satisfactory performance consistently - either the output image is left over with some rain streaks (snowflakes) or quite a few image's details are lost so that the output image becomes blurred. The second category builds models for rain streaks or snowflakes. These models can discriminate rain streaks or snowflakes from the background. However, it often happens that some details of the image will be mistreated as rain streaks or snowflakes. The third category, which seems more reasonable, is to form a 2- step processing. Specifically, a well-designed filtering is first used to decompose a rain/snow image into the low-frequency part and high-frequency part. While the low- frequency part can be made free of rain or snow as much as possible, the model-based processing can be applied on the high-frequency part to further extract the image's details to be added back into the lowfrequency part. We follow this 2-step approach in our work. As compared to the existing 2-step methods [the novelty of our proposed approach is two-fold. In the first step, instead of applying a low-pass filtering simply, we combine a rain/snow detection together with a guided filter. By doing this, we can achieve a much improved balance between removing rain/snow components and preserving image's details - the resulted low-frequency part becomes free of rain or snow almost completely and at the same time contains the image's details to a reasonable extent. 3-layer hierarchy of extracting the image's details will prove to be more effective than the extraction method proposed in, though the method in also consists of 3 layers.

3. COMMON CHARACTERISTICS OF RAIN AND SNOW

. In this section, however, we try to find some common characteristics of these dynamic components. First of all, because of strong reflections by rain/snow, high intensity values tend to be resulted at pixels that are affected by rain/snow. Therefore, the values of rain/snow pixels in an image are usually larger than their neighboring non-rain/snow pixels. Secondly, edge jumps usually exist in natural images be- tween rain streaks or snowflakes and their horizontal neigh- bors. Therefore, an image patch that includes rain/snow will usually produce larger average absolute horizontal gradients. Fig. 1 shows a rain image and a snow image, respectively, where the above two characteristics can be observed clearly. Thirdly, let us decompose a rain or snow image into the lowfrequency and high-frequency parts and use {RL(i,j), GL(i,j), BL(i,j)} and {RH(i,j), GH(i,j), BH(i,j)} to denote three color values of a pixel I(i,j) in these two parts. Fig. 2 shows the decomposed results for the images presented in Fig. 1, where the detailed decomposition will be described in the next section. It can be seen that rain/snow pixels in the high-frequency part are gray or shallow white. Moreover, three color channels of a rain/snow pixel in the high-frequency

A. Sensitivity of variance of color channels (SVCC)

Based on the third characteristic of rain/snow described above, the variance of the color vector corresponding to a rain/snow pixel in the high-frequency part tends to be very small, while the variance of the color vector corresponding to a non-rain/snow pixel is usually big. This implies that the variance of a pixel's color channels can be used to discriminate the rain/snow part from the non-rain/snow part. Here, we define the sensitivity of variance of color channels (SVCC) as the differences between the dynamic component and other contents of an image. For a pixel at location (i,j) in a given image I, the color vector is formed as: I(i,j) = [R(i,j),G(i,j),B(i,j)]T . (1)

Distribution of variances for the selected 500 rain pixels. (b) Distribution of variances for the selected 500 non-rain pixels. (c) Distribution of variances for the selected 500 snow pixels. (d) Distribution of variances for the selected 500 non-snow pixels.

V (i,j) = e V (i,j) ˜ Vmax!γwhere ˜ Vmax stands for the maximum color channel variance and γ is a power function parameter to expand or compress the contrast of the SVCC map. Fig. 4 shows the SVCC maps visually for the rain and snow images of Fig. 1, where γ = 1.1. It could be observed that rain or snow areas possess low values (deep blue stands for low value according to the energy bar) in the SVCC map, while the non-rain/snow objects whose color variances are relatively large lead to high values (red areas and bright blue areas) in the SVCC map. How to make use of the SVCC map for our task of rain/snow removal will be described in Section V, together with some discussions on how to choose γ.

B. Principal direction of an image patch (PDIP)

gradient (HOG) proposed by Dalal et al. can be used to separate rain streaks from the image . However, snowflakes in an image do not always have con- sistent falling directions. Snowflakes with high falling speed may follow nearly consistent falling directions, but point-like snowflakes are often perceived when snow is falling down slowly, such as the example . Obviously, HOG will fail when encountering point-like snow. If an image patch contains rain streaks or snowflakes with a consistent falling direction, its HOG often forms an impulse at the angle corresponding to the rain or snow direction. By the K-means method, we can classify rain or snow from an image. Therefore, we register the angle corresponding to the HOG bin that has the maximum value as the principal direction of an image patch (PDIP) to identify rain/snow in our work.

4. OUR PROPOSED ALGORITHM

The pipeline of our proposed rain/snow removal is shown in Fig. 6. Specifically, our algorithm consists of two steps. In the first step, the input image is decomposed into the low- frequency part IL and high-frequency part IH. Note that IL1057-7149 (c) 2016 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIP.2017.2708502, IEEE Transactions on Image ProcessingIM is the Hadamard product of I and MI; IL and IH are, respectively, the low-frequency and high-frequency parts obtained after the decomposition.is free of rain or snow almost completely but usually blurred, while IH contains rain/snow components and some or even many details of the image. In the second step, we design a 3-layer hierarchy of extracting non-dynamic components (i.e., the image's details) from IH, which are denoted as IND1 H , IND2 H , and IND3 H , respectively. The final rain/snow-removed image is obtained as:

ˆ I = IL + IND1 H + IND2 H + IND3 H (5)

In this section, we pay attention to the first step and the details of the second step are described in the next section. Fig. 7 shows the details of the first step. First, a rain/snow detection is performed to produce a binary location map MI and the

A. Detection of Dynamic Components

In general, some low-pass filter (e.g. the guided filter) can be used to decompose a rain or snow image into the low-frequency part and high-frequency part. However, such a low- pass filtering can hardly filter out all dynamic components (i.e., rain or snow). To solve this problem, we propose to first perform a rain/snow detection to obtain the coarse locations of these dynamic components and then apply a guided filter to obtain the low-frequency part that would become free of rain or snow almost completely.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIP.2017.2708502, IEEE Transactions on Image Processing respectively. Through this process, it is found that we have obtained a better low-frequency part than that by directly applying the guided filter in the sense that it preserves more details of the image and retain nearly no trace of rain or snow. Finally, the high frequency part IH is obtained as IH = I − IL, i.e., IL and IH are completely complementary to each other. The low/high-frequency parts that have been shown earlier in Fig. 2 are obtained by exactly following this comple- mentary decomposition. Note that the guided filter [26] and the bilateral filter [30] are both very good smoothing filters while preserving edges. In our work, we choose the guided filter for the image decomposition.

5. A 3-LAYER HIERARCHY OF EXTRACTING IMAGE DETAILS IN IH

After the first step, almost all rain/snow components remain in the high-frequency part, but some or even many details of the image are also included in this part. Our second step is to recover these image details as much as possible so that they can be added back to the low-frequency part to obtain the final rain/snowremoved image. This job is further split into three layers, as shown in Fig. 9: • a dictionary learning and dictionary atoms classification are used to classify dynamic components (i.e., rain or snow) from non

A. Dictionary Learning for IH

Because the location of rain/snow in the image is random, it is difficult to accurately separate rain/snow with other non- rain/snow components by normal detection methods. Dictionary learning is an excellent image decomposition method, which can decompose an image into many components. Some are rain/snow components and the other are non-rain/snow components. In this subsection, we try to represent IH by a sparse coding that is based on learning an overcomplete.The trained dictionaries for the highfrequency part of (a) the rain image and (b) the snow image shown earlier . The flow chart of classifications of dictionary atoms and sparse reconstruction.dictionary iteratively:

Dk = arg min D∈1 kk X(12kui − Dαik2 2)

where k = 1,2,...,K, K is the number of training samples and also the iteration number, Dk is the dictionary obtained after the kth iteration, and the dictionary DK obtained after the Kth iteration is the final dictionary D. For fear of having too large values, Dk must be subjected to the following constraint: C = {D ∈ Rm×ns.t.∀j = 1,...,n,dT j dj ≤ 1} (10) where dj is the jth column vector in dictionary D and named as the jth dictionary atom, m is the dimension of an atom, and n is the number of atoms in D. Here, the parameter αi in

the atoms back to 16 × 16 × 3 cubes. Fig. 10(a) and (b) show these atoms for the rain and snow images of Fig. 1.

B. Layer-1 Extraction

From the dictionary obtained above, dynamic components and non-dynamic components can be separated by dictionary atoms. Namely, some dictionary atoms stand for dynamic components and others for non-dynamic components. To this goal, three classifications of dictionary atoms are implemented, as shown in Fig. 11. In the end, dynamic component ID H and non-dynamic component IND1 H are achieved by a sparse reconstruction. First classification. According to the third characteristic discussed in Section II, dictionary atoms standing for dynamic components will have a smaller sum of pixel color channel variance.

classification, the dynamic component is denoted as ID C2 and the non-dynamic component as IND C2 , respectively. Third classification. For the non-dynamic details in ID C2, we further propose to find the PDIPs of dictionary atoms corresponding to ID C2. Here, we treat a dictionary atom as a patch. Majority of texture components in ID C2 is dynamic. Hence, a large number of dictionary atoms corresponding to ID C2 are dynamic atoms, while only a small part of atoms corresponds to non-dynamic components whose textures are very different from the dynamic weather. While the PDIPs of dynamic atoms are nearly

holds, atom Dj is classified as non-dynamic; otherwise it is viewed as dynamic. Here, ρ is the control parameter to get accurate results. After the third classification and reconstru tion which is similar to the first two reconstruction processes, we obtain the dynamic component ID C3 and non-dynamic component IND C3 . Eventually, after three times of classification, we obtain the non-dynamic component IND1 H and dynamic component ID H as follows: IND1 H = IND C1 + IND C2 + IND C3 ID H = ID C3 Extraction A minority of non-dynamic details still exist in ID H. In order to get more image's details, we detect dynamic components in IH again by the method described in Section III (i.e., a combination of rain/snow detection and a guided filter) and employ the newly calculated location map MH to fill the hole. Then, by applying the guided filter, we get the nondynamic part IND2 H (Layer-2) as IND2 H = Fg Fm{ID H ◦ MH} .

D. Layer-3 Extraction

The result is rain and snow, respectively. The principle for choosing γ in the computation of the SVCC map is as follows. If rain/snow is bright (i.e., with high intensity values), we should choose $\gamma > 1$ to minimize the rain/snow trace in the final result. On the other hand, for rain/snow with very low intensity, γ could be smaller than 1. In this case, a little rain/snow trace remains, which nevertheless is hard to recognize visually because rain/snow has a very low intensity. Either too big or too small γ would destroy this purpose. In our experiments, we choose $\gamma = 1$.

E. Individual Contributions

In order to show the individual contribution of each of the three layers described above, we present the resulted images in Fig. 16 for rain and Fig. 17 for snow, respectively. The results show that Layer-1 extraction provides a more significant contribution as compared to Layer-2. This is because that only very little nonrain/snow details still exist in ID H. In the meantime, however, Layer-3 extraction seems to play a very positive role. It can be seen from Fig. 16(d) and 17(d) that the contrast and color textures have been improved a lot by using the SVCC map. Notice that, for some specific images that have high-intensity rain/snow, SVCC will leave a littleRain-removed results: (a) the input image; (b) rain-removed image obtained by IL+IND1 H ; (c) rain-removed image obtained by IL+IND1 H +IND2 H ; and (d) rain-removed image obtained by IL + IND1 H + IND2 H + IND3 H . Snow removed results: (a) the input image; (b) snow removed image obtained by IL + IND1 H ; (c) snow removed image obtained by IL + IND1 H + IND2 H ; and (d) snow-removed image obtained by IL + IND1 H + IND2 H + IND3 H .

rain/snow trace in the final results. This problem can be solved partially by a fine-tuning on the parameter γ. To show their individual contributions quantitatively, we have synthesized a rain image and a snow image, i.e., a ground-truth image is known and rain or snow is rendered on the ground-truth. We list in Table II the contribution of every layer by computing the peaksignal-to-noise-ratio (PSNR) and structural similarity (SSIM). It could be observed from this table that the above-described results (i.e., the individual con- tributions from three layers) have been verified

6. EXPERIMENTAL RESULTS

In this section, we demonstrate the rain/snow-removing effectiveness of our proposed algorithm by comparisons with several state-of-the-art works. In our experiments, three pa- rameters T1, T2, and ρ used in the classification of dictionary

atoms are chosen to be {0.1, 0.02, 1.5} for rain and {0.12, 0.03, 2} for snow, respectively. We would like to point out that, for a specific rain/snow image, these parameters could be fine-tuned to achieve a better performance. Figs. 20 and 21 show, respectively, some rain-removed results and snow- removed results by different algorithms. In order to assess these results fairly, we first present the subjective evaluations in the following.

A. User Study

Lu et al., Chenet al., Li et al. and our method. Another 10 groups of snow-removed results are selected and every group involves the results by Ding et al., X et al., Chen et al. and our method. To ensure the fairness, the results in each group are arranged randomly. For each group, the viewers are asked to select only one result which they like most. The evaluation result is shown in Table III. It is clear that our rain/snow removal results are favored by a huge majority of viewers (65.50% for rain and 87.50% for snow).

B. Objective Assessment

To facilitate the objective assessment, we render rain or snow on ground-truth images1. Several examples and their corresponding rain/snow-removed results by different methods

1Here, we follow to render rain streaks and also use it for rendering snowflakes with a different setting of parameters.are sadopted as the quantitative metrics to assess the performance of different methods. In Tables IV and V, we list the PSNR and SSIM values of 11 rain images and 11 snow images, respectively. According to these results, it could be observed that our method outperforms the selected state-of-the-art works for removing rain or snow. Especially, our method produces much better results for snow images.

C. Result Analysis

The fifth column in Fig. 20 is the results by Li et al.. This work can obtain an excellent rain-removed result for a rain image which has less small details. While for an image with many small image details (the second and third ones), this work will loss some image details. The fourth column in Fig. 20 is the results by Chen et al. [18]. It is found that this

Fig. 20. Rain-removal results: (a) rain image; (b) results by Ding et al. (d) results by Chen et al. [18]; (e) results by Li et al. (f) results by our method. method has produced very good results for light rain images, such as the first, second and third images. However, when the intensity of a rain pixel is large, i.e., the relatively heavy rain (such as the fifth one) or the edge of rain streaks are blurry (e.g., the sixth one), this method falls. The third column in Fig. 20 is the results by Luo et al. The results by Ding et al. are displayed in second column in This method produces satisfactory results for the fifth and sixth images. However, this method only removes rain streaks, cannot revise the shadows produced by rain streaks (the second one). The results of our proposed algorithm are shown in the last column. By comparison, it could be observed that our method is suitable to all rain images tested in our experiments and produces a highly competing performance. For some relatively heavy rain image, a hazy effect will appear in the rain-removed results. We can further implement the de- haze algorithm to solve this problem to a certain extent.

We analyze the performance of each method as follows. The work by [18] only uses a low-pass filter to separate the rain/snow image into the low-frequency and high-frequency parts. When the intensity of rain/snow is large, it is difficult to obtain a rain/snowfree low-frequency part. Hence, this work

Fig. 21. Snow-removal results: (a) snow image; (b) results by Ding et al. [22]; (c) results by Xu et al. [19]; (d) results by Chen et al. [18]; (e) results by our method.can not

remove rain/snow with high intensity. Besides, this work uses HOG as the descriptor to identify rain streaks.
to remove rain/snow from images. Even though the guided filtering is a good edge-preserving low-pass filter, it is inevitable that the processed image gets blurred.
D. Complexity Analysis
We implement our algorithm using MATLAB on an Intel (R) Xeon (R) CPU E5-2643 v2 @ 3.5 GHz 3.5 GHz (2 pro- cessors) with 64G RAM. We test the run
time on a 256×256 image. The total time consumed by our method is 82.60 seconds, where the detection takes 5.71 seconds and the SVCC takes 1.85 seconds. Majority of time is spent in the dictionary learning part, which is 60.82 seconds. Classifications and sparse reconstruction spend 13.81 seconds. The remaining run

(a) (b) (c) (d) (e) (f) (g)
Fig. 22. (a) Ground-truthes. (b) Original synthesized rain images. (c) results by Ding et al. [22]; (d) results by Luo et al. [23]; (e) results by Chen et al. [18]; (f) results by Li et al. [24]; (g)results by our method. The values at top left corner are PSNR/SSIM. (e) results by Chen et al. (f) results by our method. The values at top left corner are PSNR/SSIM.t is consumed by intermediate steps of our algorithms. The time consumed by the works of Chen et al., Luo et al. Ding et al.Xu et al. , Li et al. are 95.17, 68.66, 1.18, 0.27 and 1260.40 seconds, respectively.The run time changes with the size of images. Therefore, we analyze the complexity of major steps as follows. Suppose that the size of an given rain/snow image is M×N, l is the number of windows we use to identify rain/snow pixel from the given rain/snow images (which is 5 in this paper). The computational complexity of rain/snow detection is O(M × N × l). For the online dictionary learning, the number of training samples is K, the size of every training sample is L × 1, the number of dictionary atoms is Q, the size of every dictionary atoms is L × 1 (L < Q K), S is the target sparsity, and T is the iteration number. Then, the complexity of the online dictionary learning and sparse reconstruction are O(T × K(N × S2 + 2 × L × Q)) and O(Q), respectively. We use the same dictionary learning method as the work by Chen et al. [18]. Therefore, the dictionary learning and sparse reconstruction have the equal computational complexity. On the other hand, we implement 3 classifications. Every classification has its own feature descriptors to describe dictionary
E. Limitations Our proposed method uses some universal characteristics of rain and snow and develops accurate descriptors to represent rain and snow so that some very good results have been obtained. However, some shortcomings still exist in our work. First, for some relatively heavy rain images, such as the fourth images in Fig. 20, our method still produces blurring. Second, we notice that the parameters selected in our work are suitable for majority of rain and snow images except for some special images such as very blurred rain images or heavy snow images. Under this situation, we believe that the parameters need to be fine tuned for a better result. Finally, little snow trace can still be seen in some of our results when the size of snowflakes are large. Our future work will focus on solving these problems and obtaining better rain/snow- removed images.

7. CONCLUSIONS

This paper has attempted to solve the rain/snowremoving problem from a single color image by utilizing the common characteristics of rain and snow. To this end, we defined the principal direction of an image patch (PDIP) and the sensitivity of variance of color channel (SVCC) to describe the difference of rain or snow from other image components. We acquired the low and high frequency parts by implementing a rain/snow detection and applying a guided filter. For the high- frequency part, a dictionary learning and three classifications of dictionary atoms are implemented to decompose it into non- dynamic components and dynamic (rain or snow) components, where some common characteristics of rain/snow defined earlier in our work are utilized. Moreover, we have designed two additional layers of extracting image details from the high- frequency part, which are based on, respectively, the SVCC map and another combination of a rain/snow detection and a guided filtering. Finally, we have presented a large set of results to show that our method can remove rain or snow from images effectively, leading to an enhanced visual quality in the rain/snowremoved images.

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