EFFECTIVE IMPLEMENTATION OF RAIN STREAK REMOVAL BY USING SEQUENTIAL DUAL ATTTENTION NETWORK

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Abstract— Various weather conditions, such as rain, haze, or snow, can degrade visual quality in images/videos, which may significantly degrade the performance of related applications. In this paper, a novel framework based on sequential dual attention deep network is proposed for removing rain streaks (detraining) in a single image, called by SSDRNet (Sequential dual attentionbased Single image DeRaining deep Network).Aiming at this meaningful task, in this study we present a comprehensive review for current rain removal methods for video and a single image. Sequential attention network provide better performance .

Keywords — Single image rain streaks removal, deraining, dual attention network, dilated convolution, deep learning.

I. INTRODUCTION

Restoring rain images is important for many computer vision applications in outdoor scenes. Rain degrades visibility significantly and causes many computer vision systems to likely fail. Generally, rain introduces a few types of visibility degradation. Raindrops obstruct, deform and/or blur the background scenes. Distant rain streaks accumulate and generate atmospheric veiling effects similar to mist or fog , which severely reduce the visibility by scattering light out and into the line of sight. Nearby rain streaks exhibit strong specular highlights that occlude background scenes. These rain streaks can have various shapes and directions, particularly in heavy rain , causing severe visibility degradation. In the past decades , many researchers have devoted their attention to solving the problem of restoring rain images. Some focus on rain image recovery from video sequencesOthers focus on rain removal from the single image, by regarding the rain streak removal problem as a signal separation problem or by relying on nonlocal mean smoothing while there are varying degrees of success, majority of existing methods suffer from several limitationDue to the intrinsic overlapping between rain streaks and background texture patterns, most methods tend to remove texture details in non-rain regions, leading to over-smoothing the regions.

Sequential attention based CNN is of the well-regarded machine learning method sin the literature. One of the reasons of its popularity is due to the automatic hierarchical feature representation in recognizing objects and patters in images CNNs reduce the parameters of a given problem using spatial relationships between them. This makes them a more practical classifier specially in image processing where we deal with a large number of parameters (pixels) , rotation , translation , and scale of images.

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IMAGE PROCESSING

An image processor does the functions of image acquisition, storage, pre processing, segmentation, representation, recognition and interpretation and finally displays or records the resulting image. The following block diagram gives the fundamental sequence involved in an image processing system.

II. LITERATURE SURVEY

A. Deep layer prior optimization for single image rain streaks removal:

Approaches propose to build complex prior models to formulate the appearance of rain streaks. Unfortunately, these human- designed priors tend to over-smooth the background visible distortions caused by rain streaks have significant negative effects on and leave too many rain streaks since the distribution of rain streaks is complex and disordered.

Figure 1 : Rain Streak Removal

B. Clearing the skies: a deep network architecture for single-image rain removal Authors: Xueyang Fu, Jiabin Huang.

The deep convolution neural network (CNN) we directly learn the mapping relationship between rainy and clean image detail layers from data. Because we do not possess the ground truth corresponding to real-world rainy images.

C. Residual-guide network for single image deraining– 2020:

Residual-guide feature fusion network, called ResGuideNet, for single image deraining that progressively predicts high-quality reconstruction. Speci cally, we propose a cascaded network and adopt residuals generated from shallower blocks to guide deeper blocks.

III.EXISTING SYSTEM

The Existing system SSDRNet is mainly inspired by vision-based attention mechanism. Therefore, related work on deep learningbased visual attention models, building upon a non-linear generative model of a rainy image. Imposing priors for both the background and rain streak layers of a single image based on Gaussian mixture models was proposed for removal of rain streaks in ,and a hierarchical approach for rain or snow removal from a single color image, which relied on image decomposition and dictionary learning Compared with the video based deraining problem, the single image based problem is more ill-posed, due to the lack of temporal information. Some single-image based rain removal methods regard the problem as a layer separation problem.

IV.PROPOSED SYSTEM

The proposed system dual attention network based rain streak removal is implemented here for removal of noise present in the image and video the rain streaks in a rainy image have various sizes and directions; the streak structure is usually still relatively simpler than the complex background of the image. Thus, it would be easier to learn the rain streaks from a rainy image than learning the background component of the image. To model such rain streaks with different intensities and directions, we propose the SDAB (sequential dual attention block) module, which refines the input feature maps from the previous block (an RDB or a SDAB) in the proposed deep network used in the test phase. It is used as a better method for model evaluation.

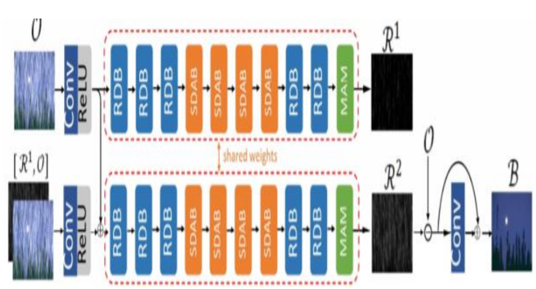

Figure 2 : The Proposed Rain Streak Removal Deep Learning Model

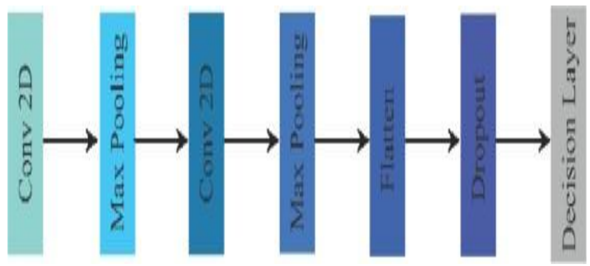

Figure 3 : Layers Function

This section first formulates the problem to be solved in this paper and briefly introduces the overall framework of the proposed SSDRNet. More specifically, the architecture is primarily comprised of three modules. The first is the residual dense block that acts as a basis for feature extraction from a rainy image. The second is the dual attention block, which is mainly designed for rain streak formation to model the rain streaks. The third is the multi-scale feature aggregation module that transforms the input feature map into the output image. The three modules are also detailed in this section, followed by a description of the presented loss function for model learning.

A. CONVOLUTION LAYERS

With regard to deep learning-based single image rain streak removal, it has been shown that it is more effective to learn the mapping from a rainy image to its rain streaks than to directly learn the mapping from input to output [17], based on the fact that the rain streak component is sparser than the background in a rainy image.

B. POOLING LAYERS

A pooling layer provides a typical down sampling operation which reduces the in-plane dimensionality of the feature maps in order to introduce translation invariance to small shifts and distortions, and decrease the number of subsequent learnable parameters. It is of note that there is no learnable parameter in any of the pooling layers, whereas filter size, stride, and padding are hyper parameters in pooling operations, similar to convolution operations.

C. MAX POOLING

The most popular form of pooling operation is max pooling, which extracts patches from the input feature maps, outputs the maximum value in each patch, and discards all the other values A max pooling with a filter of size 2x2 with astride of 2 is commonly used in practice. This down samples the in-plane dimension of feature maps by a factor of 2. Unlike height and width, the depth dimension of feature maps remain sun changed.

D. FULLY CONNECTED LAYERS

Fully Connected Layer is simply, feed forward neural networks. Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer. It connects every neuron in one layer to every neuron in another layer. It is the same as a traditional multi-layer perceptron neural network (MLP). The flattened matrix goes through a fully connected layer to classify the images.

AlexNet was primarily designed by Alex Krizhevsky. It was published with Ilya Sutskever and Krizhevsky's doctoral advisor Geoffrey Hinton, and is a Convolutional Neural Network or CNN. After competing in ImageNet Large Scale Visual Recognition Challenge, AlexNet shot to fame. It achieved a top-5 error of 15.3%. This was 10.8% lower than that of runner up. The primary result of the original paper was that the depth of the model was absolutely required for its high performance. This was quite expensive computationally but was made feasible due to GPUs or Graphical Processing Units, during training.

E. CNN ARCHITECTURES

Before exploring AlexNet it is essential to understand what is a convolutional neural network. Convolutional neural networks are one of the variants of neural networks where hidden layers consist of convolutional layers, pooling layers, fully connected layers, and normalization layers. Convolution is the process of applying a filter over an image or signal to modify it. Now what is pooling? It is a sample-based discretization process. The main reason is to reduce the dimensionality of the input. Thus, allowing assumptions to be made about the features contained in the sub-regions binned.

A detailed explanation of this can be found at Understanding Neural Networks. A stack of distinct layers that transform input volume into output volume with the help of a differentiable function is known as **CNN Architecture.** (e.g. holding the class scores)In other words, one can understand a CNN architecture to be a specific arrangement of the above-mentioned layers. Numerous variations of such arrangements have developed over the years resulting in several CNN architectures.

F. *ADVANTAGE*

- High accuracy
- High sensitivity
- High specificity

G. *SOFTWARE USED*

MATLAB 2017a

V. SIMULATION RESULTS

We trained the number of video sample and using denoising algorithm implemented based on rainy videos we are cleared video and recover the original videos of image and then video.

A. *TRAINED SAMPLES*

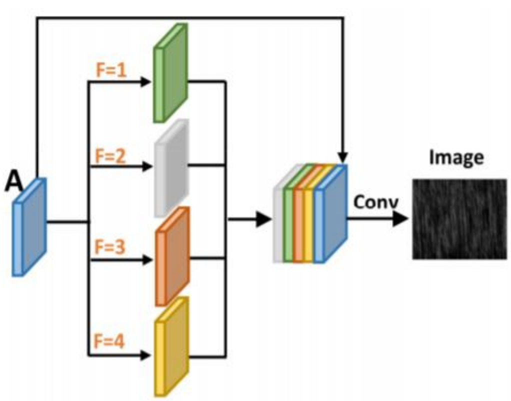

Figure 4 : The structure of the proposed multi-scale feature aggregation module, where F represents the used dilated factors.

B. *TESTING REPORT*

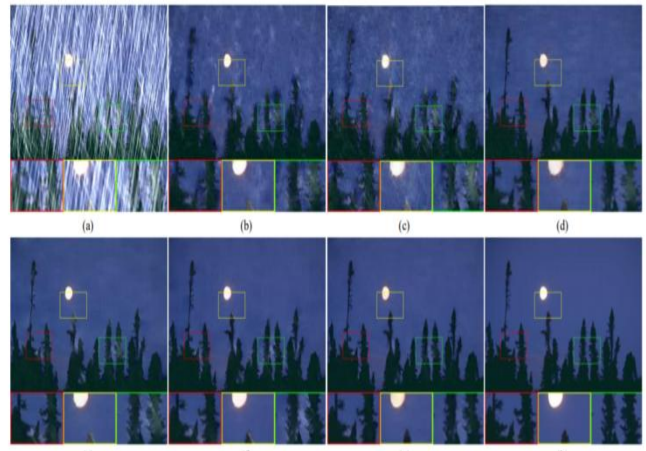

Figure 5 : Detraining of image

The resting result we give the testing image as given as input for tested input for provide the result of testing samples of images.

VI.RESULT

Figure 6 : Detrain denoising image and video

VII. CONCLUSION

The proposed SDAB consists of the component attention (ca) module and the subsidiary attention (sa) module, which are used to find “what” is significant and “where” is informative for the input image. Based on the inherent correlation among the rain steaks within an image, which should be stronger than that between the rain streaks and the background (non-rain) pixels, the rain streak components of the input image can be extracted well through our two-stage deep network. The final derained image can be reconstructed accordingly. Extensive experimental results have shown that the proposed deep framework achieves state-of-the-art results qualitatively and quantitatively.

Comprehensive ablation studies have further verified the feasibility of the proposed rain streak removal method.

FUTURE WORK

In future work deep convolution network is implemented for fast detraining of system.

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