Restoration of the video by removing rain streaks

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Abstract - *Rain removal is a technique to detect rain streak pixels and then remove them and restore the background of the removed area. The goal of this paper is to remove the rain from videos with dynamic backgrounds and also to remove the hazy effect. In this paper we propose a hybrid model which combines the idea of SPAC-CNN and J4R-NET methods, to enhance the removal of rain streaks from the video. The SPAC-CNN method can be divided into two parts i.e., Optimal temporal matching and Sorted spatial temporal matching. These two tensors will be prepared as input features to J4R-NET. J4R-NET algorithm involves CNN-extractor, Degradation classification network, Fusion network, Rain removal network, Reconstruction network and finally JRC-network. The result of using this method is measured using PSNR and has achieved better results. Visual inspection shows that much cleaner rain removal is achieved especially for highly dynamic scenes with dense and opaque precipitation from a fast-moving camera.*

Key Words: Rain Removal, CNN, RNN, J4R-NET, SPAC-CNN, PSNR.

1. INTRODUCTION

The purpose of this project is to remove rain from videos without blurring the object. The algorithm helps design a system that removes rain from videos to facilitate video surveillance and improve various vision-based algorithms. The application should be able to capture the real time video which can have certain features such as object detection, tracking, segmentation and recognition. It should be able to capture the video in both steady and dynamic weather conditions. The final outcome of the application is to provide a dynamic video by removing the rain streaks where the video quality should not be reduced.

This product can be used in daily life and also can be used in military and for investigative purposes. In daily life, this product can be used by a mobile user for recording better videos while there is rain and can be used for drones, gopros etc., for recording and shooting movies or videos for personal use. It can be used for traffic surveillance, where it can read vehicle numbers and people's faces in traffic, while there is rain. It can also be used in homes for CCTV and could record clear video every time.

In video restoration by removing rain streaks, we mainly capture the video with rain which is dynamic, where both the background and foreground objects are moving. And we prepare a model which can remove the rain streaks from the video and maintain the details of the objects at the rain regions.

2. RELATED WORKS

Rain Removal algorithms can be classified into single image rain removal and video-based rain removal. Single image rain removal can be done by various algorithms like CNN, deep detail network, joint rain detection etc. But single image rain removal has less real-world application. They are easy to implement with known algorithms. Whereas, removing rain streaks from dynamically moving video is the field of interest which includes additional parameters to be considered.

The paper "Should we encode rain streaks in video as deterministic or stochastic?" by School of Mathematics and Statistics, Xi'an Jiaotong University, 2017 [4], uses the P-MoG model to encode rain streaks as stochastic knowledge and to their formulation uses a mixture of patch-based Gaussians. Later, it uses the EM algorithm to optimize the parameters and solve the P-MoG model. Finally, post-processing is performed to enforce continuity on the moving object layer. But this paper considers only static backgrounds with moving objects. It does not take into account the problem of removing rain with a moving camera.

In the paper, “A Novel Tensor-based Video Rain Streaks Removal Approach via Utilising Discriminatively Intrinsic Priors”, 2017 [5], the summary of prior and regularizations are used for formulation. Later, the ADMM algorithm is used to optimize the five auxiliary tensors. But the limitation of this method is, if the rainy direction is far away from the y-axis, we can handle it with video/image rotation, but for the digital data, the rotation causes distortion. Another problem is, how to handle remaining rain artifacts.

Kshitiz Garg and Shree K. Nayar proposed a method in which a photometric model is assumed [3]. Photometric models assumed that raindrops have almost the same size and velocity. Pixels that lie on the same rainband are also assumed to have the same irradiance because the droplet brightness is weakly affected by the background. This provides a large number of error detections. The algorithm failed to identify out-of-focus streaks of rain and streaks on a lighter background. Thus, all rainbands do not obey the photometric constraints.

The authors (J.Ramya, S.Dhanalakshmi, Dr. S.karthick) [6] used new approach for rain detection and removal of video-based rain removal framework via properly formulating rain removal as in video decomposition problem based on Analysis and Synthesis algorithm (A&S).Later use analysis and synthesis filters are often implemented with hierarchical subsampling, resulting in a pyramid. Then they use a conventional image decomposition technique, before that we first decompose an image into the high-frequency parts using a bilateral filter. The high-frequency part is then divided into rainy and non-rainy.

This article was published by KYU-HO LEE, EUNJI RYU AND JONG-OK KIM, (Member, IEEE), School of Electrical Engineering, Korea University, Seoul 02841, South Korea [7]. In this article, a new deep learning method for video rain removal based on recurrent neural network (RNN) architecture was proposed. Instead of focusing on different rainband shapes similar to conventional methods, this paper focuses on the changing behaviour of rainbands. To achieve this, progressive rain streak images have been generated from real rain videos and fed to the network sequentially in descending rain order.

Multiple images with different amounts of rain streaks were used as RNN inputs for more efficient rain streak identification and subsequent removal. Experimental results show that this method is suitable for a wide range of rainy images.

3. EXISTING METHODS

Title of the paper	Year	Method	Limitations
Detection and Removal of Rain from Videos	2013	photometric model	The algorithm could not identify defocused rain streaks and streaks on brighter backgrounds
Should We Encode Rain Streaks in Video as Deterministic or Stochastic?	2017	P-MoG model	It doesn't consider the rain removal problem with a moving camera
A Novel Tensor-based Video Rain Streaks Removal Approach via Utilizing Discriminatively Intrinsic Priors	2017	prior and regularizers, ADMM algorithm	If the rainy direction is far away from the y-axis, we can handle it with video/image rotation, but for the digital data, the rotation causes distortion. Handling remaining rain artifacts
Robust Video Content Alignment and Compensation for Rain Removal in a CNN Framework	2018	SPAC-CNN algorithm	Less focus on reconstruction of regions with rain streaks.
Erase or Fill? Deep Joint Recurrent Rain Removal and Reconstruction in Videos	2018	Joint Recurrent Rain Removal and Reconstruction Network	Less focus on fast moving cameras.
D3R-Net: Dynamic Routing Residue Recurrent Network for Video Rain Removal	2019	Dynamic Routing Residue Recurrent Network (D3R-Net)	Less focus on fast moving cameras.
Progressive Rain Removal via a Recurrent Convolutional Network for Real Rain Videos	2020	temporal filtering, RNN	Producing suitable progressive rain images would be difficult as moving regions are wider in the image. It is not suitable for hazy effects caused by rains.
Should We Encode Rain Streaks in Video as Deterministic or Stochastic?	2017	P-MoG model	It doesn't consider the rain removal problem with a moving camera

4. MATERIALS AND METHODS

4.1. SYSTEM DESIGN AND FLOW DIAGRAM

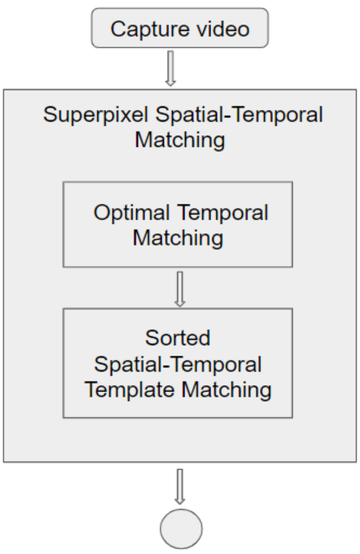
This involves collection of video datasets which have both non-rain and rain videos. After collection of datasets, they have to be processed to facilitate training. The priority of this function is high.

Collection of videos from various sources on the Internet. The videos collected may be of different formats, but it may include videos with rain, corresponding videos without rain. The collected video may be in different format, structure, size, representation etc. For the ease of training, we have to bring all the video datasets to the same format and structure.

For this project, we have considered the LasVR dataset and SPAC-CNN dataset along with RainSynLight25. This makes around 12000 frames taken from around 900 videos making it a training dataset. And around 1400 frames taken from around 100 videos making it a testing dataset.

We use two types of datasets for training the model required for removing rain streaks. One type of dataset is synthetic dataset, where we take the video with normal background and add the rain streaks to the video. The other type of dataset is real dataset, where we consider the real videos containing the rain streaks.

4.2. METHODOLOGY



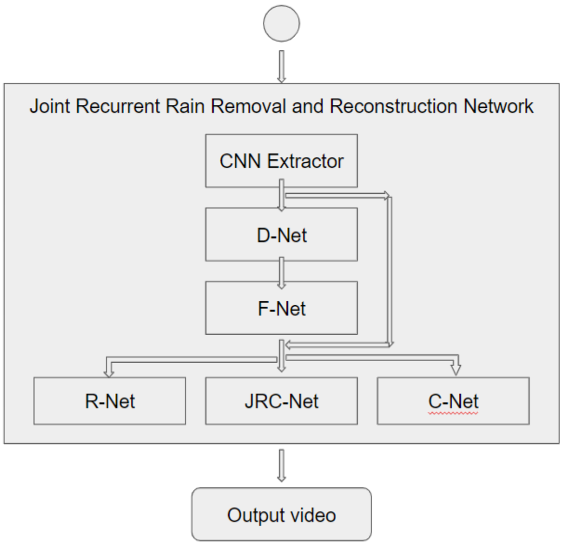


Fig-1 Flow diagram of Proposed Method

In video restoration by removing rain streaks, we mainly capture the video with rain which is dynamic, where both the background and foreground objects are moving. And we prepare a model which can remove the rain streaks from the video and maintain the details of the objects at the rain regions.

In this method, we will combine the ideas of two methods. For the first method, video content alignment is carried out at Super Pixel level, which consists of two SP template matching operations that produce two output tensors: the optimal temporal match tensor, and the sorted spatial-temporal match tensor. An intermediate Derain output is calculated by averaging the slices of the sorted spatial-temporal match tensor.

Second, these two tensors will be prepared as input features to a Joint Recurrent Rain Removal and Reconstruction Network. The J4R-Net architecture consists of Single Frame CNN Extractor, Degradation Classification Network, Fusion Network, Rain Removal Network, Reconstruction Network, and finally combined to Joint Rain Removal and Reconstruction Network. A loss function is used to minimise the mis-alignment blur.

The hyperparameters used in the implementation of this method are, learning rate is taken as 1e-3 and then we are considering 100 epochs with mean squared error loss as loss function and Adam optimizer as optimizer, we are using 72 processors and 2 GPU for this project. The structure of the network implementation is a fusion of the structure mentioned in [1] and [2].

5. RESULTS

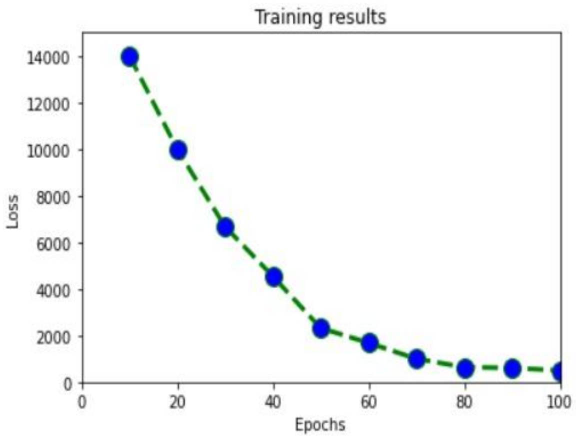


Fig-2: Loss vs Epochs

The above graph has L2 loss values on y-axis and the number of epochs calculated on x-axis, when we plot the values on the graph we have a decreasing curve, at first there is a sharp drop in the curve and then it gradually stabilizes and the loss is around 500 when the Epoch value is 100.

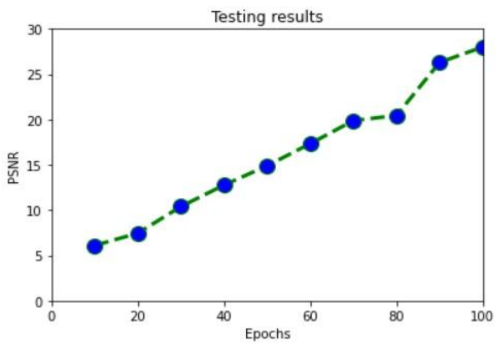


Fig-3: PSNR vs Epochs

Peak signal-to-noise ratio (PSNR) is a technical term for the ratio between the maximum possible signal strength and the strength of the interfering noise, which affects the fidelity of its representation.

In the graph above we have plotted the epochs over PSNR, on the y-axis we have the PSNR values and on the x-axis, we have the number of epochs. The curve gradually increases and reaches 28.01 when Epoch is 100.

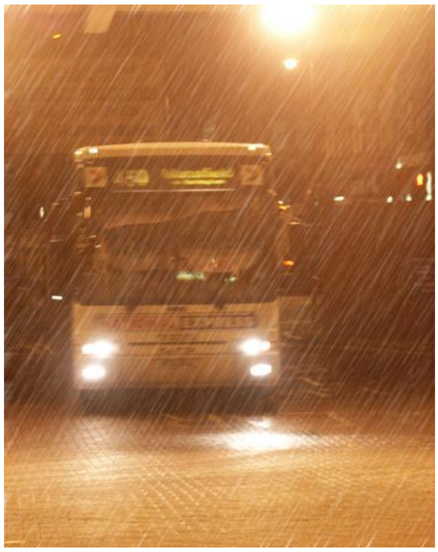


Fig-4: Input video frame

Fig-5: Output video frame

After the video is uploaded, the deep learning model will be run, and then after processing all the frames of the video, the above layout of the website will be displayed, the video on the left is the input video, and the video on the right is the output with the rain removed.

6. CONCLUSION AND FUTURE WORKS

In this paper, we proposed a hybrid rain model to depict both rain streaks and occlusions and handle torrential rain fall with opaque streak occlusions from a fast-moving camera. CNN and RNN were built to seamlessly integrate rain degradation classification, rain removal based on spatial texture appearance, and background detail reconstruction based on temporal coherence. The

CNN was designed and trained to effectively compensate for the misalignment blur caused by the water exclusion operations. The entire system demonstrates its efficiency and robustness in a series of experiments that significantly outperform state-of-the-art methods.

The proposed method network is slow for high fps videos. An enhancement using mobile net can be used in future to speed up the network.

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