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Single Image De-raining

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of the requirements for the degree of
MSc. (Computer Science)

Declaration

I hereby declare that this dissertation is entirely my own work and that it has not been submitted as an exercise for a degree at this or any other university.

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Abstract

In this dissertation, the problem of rain streaks removal from single images is addressed. Extensive research is done on the single image de-raining methods as well as the video de-raining methods. A brief summary of all the de-raining methods studied is provided along with the categorization of the single image de-raining methods for better understanding. A single image de-raining framework is also proposed which is not build on a deep convolutional neural network with the aim to propose a model which can be executed on all systems and with little time and computation. Multiple approaches were tested for rain streak detection, false positive negation and rain streak removal processes. The best approach was selected for the comparison of de-raining capabilities with state-of-the-art methods. The proposed method uses row mean in a small image frame, which is a subset of the original rainy image, to identify the pixels with intensity higher than the average intensity of the row pixels and marks them as the rain streak pixels. A transparency channel of the input rainy image is used to create a background mask aiming to improve the de-raining quality of the output images. The transparency channel defines the transparency or the opaqueness of the details in any image. The objects which are in focus, as well as the objects that are in the background, can be separated using the transparency channel. Lastly, an average pooling function is used to change the rain streak pixel value in a way that matches the neighbouring pixels or background details. Finally, it was found that the proposed model has some flaws since it produces blurry and smooth edges de-rained images, which is due to the fact that the rain streak pixels are replaced by the average value of the neighbouring pixels. Moreover, since a background mask is used to negate false positives, therefore, the de-rained image is distorted around the edges of the objects in focus.

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Nomenclature

SE	Squeeze-and-Excitation
SP	Super Pixels
BRN	Bilateral Recurrent Network
CNN	Convolutional Neural Network
DOF	Depth Of Field
GAN	Generative Adversarial Network
GMM	Gaussian Mixture Model
HOG	Histogram of Oriented Gradients
HOS	Histogram Of Orientation
MCA	Morphological Component Analysis
PCA	Pricipal Component Analysis
PRN	Progressive Residual Network
MRF	Markov Random Fields
REU	Recurrent Enhancement Unit
RGB	Red Green Blue
RNN	Recurrent Neural Network
SRN	Single Recurrent Network
SVM	Support Vector Machine
ADMM	Alternating Direction Method of Multipliers
CGAN	Conditional Generative Adversarial Network
LSTM	Long Short Term Memory
ReLU	Rectified Linear Units
SALSA	Split Augmented Lagrangian Shrinkage Algorithm
PRNet	Progressive Recurrent Network
ResNet	Residual Network
ResBlocks	Residual Blocks

1 Introduction

The presence of unpredictable impairments such as rain, haze, snow, and fog degrade the image or video quality significantly and also hampers the performance of many computer vision systems. The diverse and unpredictable nature of these phenomenon makes it difficult for the image enhancement algorithms [86] to alleviate their presence. The visibility of rain streaks, fog, haze, rain droplets and snow severely hinders the capabilities of computer vision tasks such as object detection [87], target detection [83], event detection [89], object tracking [84], image recognition [85], action recognition [90, 91], and scene analysis [92, 93].

In autonomous driving detection of objects is imperative. The software embedded in autonomous cars needs high clarity video (collection of images) for the detection of objects. However, when it's raining, the detection of objects can become difficult depending upon the intensity of the rain. So removing rain droplets or rain streaks to increase visibility is a necessary step towards fully autonomous cars. An application that can remove rain droplets to increase the visibility of the objects in videos/images is imperative.

The aim of this study is to do extensive research on the single image de-raining methods. Since the first single image de-raining framework [23] was published ten years after the first video de-raining [1] framework, therefore to get the proper understanding of how the de-raining methods works, exhaustive research on the video de-raining methods will also be done. Finally, a novel rain removal from single images method will be developed which uses the transparency channel of the input rainy image to separate the background from the foreground, from which rain streaks will be removed to produce the de-rained output.

This study is divided into five sections. Related research on de-raining images is given in section 2, the Methodology of the new de-raining proposed is provided in section 3, section 4 presents the evaluation of the de-raining results of the proposed model and finally, the conclusion is presented in section 5.

2 Related Work

De-raining problems have gained a lot of attention due to the need for increased visibility in applications like video surveillance or autonomous driving etc. These de-raining methods can be broadly classified as Video de-raining methods and Single Image De-raining methods. The topic of the study is single image de-raining however, video based de-training methods are also studied and added in the related work section.

2.1 Video De-raining

The first de-raining method that was published was rain streak removal from videos. Video based de-raining methods utilizes the redundant temporal information between multiple frames to efficiently detect rain streak pixels and also recover the high quality backgrounds details. These methods fail to produce good quality de-raining results when the temporal information is unreliable or unavailable which happens in the case of unstabilized videos.

Since inter-frame information is used for the rain removal process in videos, therefore, these methods can not be applied for single-frame de-raining of images. In (63), a comprehensive study of the early video de-raining methods is provided.

A Brief summary of video de-raining methods

1. Detection and Removal of Rain from Videos

   (1) is the first paper ever which tackled the rain streak removal problem. The aim of the research paper is to remove rain streaks from videos using the temporal as well as photometric properties of the rain. In this paper, the authors developed a correlation model which captures the dynamics of the rain along with a physics based motion blur model which characterizes the photometry of the rain. They detect and remove rain by comparing the intensity of each pixel with the pixel's intensity of the consecutive frames.

   Rain streak pixels detection method– The authors assumed that the pixel containing a rain streak is brighter and thus has higher intensity as compared to the intensity of the same pixel in a different frame which does not contain the rain streak.

Negating false positive – They remove the false positive, i.e. the pixels which do not contain rain streaks but are evaluated as rain pixels, by applying a photometric constraint based on the assumption that the change in intensity along the streak is linearly dependent on the background intensity.

Rain pixels removal method – Finally, they remove the rain pixels in a frame by taking the average value of the pixel in the next and the previous frame.

Disadvantages – Since it was the first paper to be published aiming to de-rain videos, therefore, it did not focus on or solve all of the problems that arise in de-raining videos. So, there are a few disadvantages to using this method at present. Firstly, it is observed that the detection of raindrops through local information is not reliable. Many non-rain pixels are classified as rain pixels because they had high intensity change as compared to their neighboring frames. Their false positive removal system is not strong enough. Moreover, since the objects in the videos are often moving, therefore, the objects with bright pixels are often classified as rain pixels. Secondly, the method proposed is only applicable to static scenes; it does not incorporate the difficulties of rain removal in moving camera scenes. Finally, to optimally remove rain streaks, this method needs a video with at least 30 frames, which makes this method ineffective for de-raining short videos. [4]

2. Rain Removal in Video by Combining Temporal and Chromatic Properties

   The method proposed in paper (2) is an improved version of rain removal from videos as compared to the method in [1] since it not only incorporates the temporal properties but also incorporates the chromatic properties of the rain. The authors use the temporal properties of the rain to detect rain pixels and then uses the chromatic properties of the rain to negate false positive. Their method also de-rain videos pixel-wise.

   Rain pixels detection method – Using the temporal properties of the rain, the authors say that no pixel in the entire video sequence can always be covered by rain. So for each pixel in a frame, the pixel intensity over the entire video is evaluated to compute its intensity histogram. Then, K-means clustering with K = 2 is used to classify the pixels as rain pixels for which there is a peak in the histogram.

   Negating false positives – Then to detect and negate false positives, the authors use the chromatic properties of the rain, which says that the change in intensity for pixels covered by rain is approximately the same across the pixels' RGB (Red, Green, & Blue) channels.

   Rain pixels removal method – The final rain pixels are replaced by their corresponding background pixels obtained from the pixels with a low value in the intensity histogram. Gaussian blurring is used to improve the final rain removal results.

Disadvantages – There are a few disadvantages of the method proposed in this paper if it were to be used at present. Firstly, this method may fail to detect and thus remove rain pixels in grey colour regions/images as their false positive negation method relies on the chromatic properties of the rain. Secondly, to perform optimally, this method is applied to the entire video sequence [4]. This could prove to be ineffective for short videos and slow for long videos. Finally, the authors do propose that their method is applicable for scenes taken by moving camera, however, it is ineffective in terms of efficiency as an additional step of video stabilization is implemented before the rain removal and another step of destabilizing video is implemented after the rain removal, restoring the original camera motion, to give an effect of de-raining videos in moving camera scenes.

3. Spatio-Temporal Frequency Analysis for Removing Rain and Snow from Videos

   In (3), the authors proposed a blurred Gaussian model as a model for bright rain and snow streaks. This model can be used to remove rain and snow streaks from videos using a global appearance model of raindrops and snowflakes in the frequency domain. This model was created by combining the statistical properties of rain and snow steaks along with the the assumption that the rain streaks and snow streaks have similar shapes, brightness and orientation throughout the entire video.

   Rain pixels detection method – Rain and snow streaks are detected by selecting repeatedly occurring frequency components between different frames of the entire video under the assumption that rain and snow streaks have similar appearances.

   Rain pixel removal method – Once rain pixels with high and repeated frequency components are detected, the frequencies can be suppressed to produce the effect of de-raining the video or increased to produce to effect of increasing the rain intensity in the video.

   Advantages/ Disadvantages – Although the method does incorporate the removal of snow streaks from videos, however, as snowflakes are prone to wind, the Gaussian model does not produce satisfactory snowflakes removal effect. Moreover, this method too uses significant number of frames to produce optimal results. It requires 2N 1 frames, where N is the number of desired removal cycles [4]. So this method is not effective for short video de-raining problems. Having said that, one advantage of the proposed method over previous methods is that this method uses a video short by a moving camera.

4. Using the Shape Characteristics of Rain to Identify and Remove Rain from Video

In (4), the authors proposes a method which only uses the local frame neighborhood to identify and remove rain streaks from video sequence. In this method, only three frames are used to identify and remove rain streak from videos. This method is based on both the optical and physical properties of a rain streak along with the assumption that the velocity of the raindrop is high enough for the raindrop to be in the same pixel in more than one frame. The authors also assume that no two different raindrops can exist in the same pixel in consecutive frames.

Rain pixels detection method – To detect rain pixels, the authors uses Garg and Nayar's [1] photometric model which states that rain streaks pixels have higher intensity as compared to the intensity of the same pixel in consecutive frames. The authors in this paper identify pixels which undergo a short, positive intensity spike as rain pixels. However, unlike Garg and Nayer's method, the authors only use three frames in total, the current, the previous and the following frame, to identify their candidate rain pixels. Once they have identified their candidate rain pixels, the authors uses the physical properties of the rain streak to reduce misclassified rain pixels. The aspect ratio for all the candidate pixels is calculated to add a constraint on the diameter of the rain streak.

Negating false positives – The direction of the rainfall is used to detect and negate false positives; however, this step is only implemented if there is heavy rain in the video sequence. A histogram of stream orientation is constructed for the pixels selected as rain pixels in the rain detection method. This histogram is used to determine the direction of the rain streak and this eliminate all the selected rain pixels which do not adhere to the direction of the rain.

Rain pixel removal method – The rain removal method proposed in this paper is the same as the rain removal method in Garg and Nayer's paper [1] with the only difference here being that the rain pixel is substituted by the average of the pixel value of the previous and the following frame only.

Advantages/ Disadvantages – One advantage of the method proposed in this method is that this method is able to de-rain videos using fewer frames as compared to the techniques proposed in the past. It also makes this method effective for de-raining short duration videos.

5. Rain or Snow Detection in Image Sequences Through Use of a Histogram of Orientation of Streaks

   The aim of the research paper (5) is only to detect the presence and intensity of the rain and snow in videos. Even though this paper does not aim to remove rain streaks from the videos, it is still added in this related research section because it provides a novel method for the detection of rain streaks in videos. The method proposed in this paper uses background subtraction [68], photometric properties of the rain, Histograms of Orientation (HOS) of rain streaks, and a Gaussian Mixture Model to detect rain streaks. This method is based on the assumption that the Histogram of Orientation (HOS) of rain or snow streaks follows a Gaussian-uniform mixture model. The Gaussian distribution represents the orientation of the rain and snow streak, while the uniform distribution represents the orientation of noise.

Rain pixels detection method – The first step of rain and snow detection of the method proposed in this paper is to separate the background from the foreground using the background subtraction method [68]. Then, from the foreground, rain pixels are selected based on the photometry properties and the size information of the rain streaks. The photometric properties of the rain streak assume a raindrop is a moving object brighter than its background.

Negating false positives – Once potential rain streak pixels are selected from the foreground using the photometric properties and the size information of the rain or snow streaks, a Histogram of Orientation (HOS) of rain streaks is calculated using geometric moments. Using this Histogram of Orientation, which follows a Gaussian-uniform mixture model, the Gaussian distribution can be separated, representing the orientation of rain streaks, from the Uniform distribution, representing the orientation of noise, to give more accurate rain streak pixel detection further.

Rain pixel removal method – This paper does not aim to remove rain pixels, so clearly, no rain pixel removal method is expected.

6. A Generalized Low-Rank Appearance Model for Spatio-temporally Correlated Rain Streaks

   In (6), the authors aim to de-raining images as well as videos using a generalized low-rank appearance model. The method proposed is novel and is based on the two assumptions. First, Rain streaks usually have similar directions and occur in repeated patterns which indicates the similarity between rain streaks at different pixel locations, and Second, Raindrops fall at a nearly constant speed which implies the repeatability of rain streaks along the time axis. Based on these two assumptions, it can be said that there is a high correlation between the rain streaks in an image or a video. So the authors proposed a low-rank model from matrix to tensor structure to find and remove these Spatio-temporal correlated rain streaks.

   Rain layer removal method – the authors decomposed the input image into two layers – background layer and rain streak layer. Then they proposed the de-raining problem as an objective function to remove the rain streak layer from the input layer. The cost function of this objective function has three terms – a likelihood, a smoothed background layer, and a rain streak layer which is assumed to be low-ranked.

Advantage/Disadvantages – One advantage of the proposed model is that this model is not limited to any particular source input; it can remove rain streaks from single images as well as from videos in a unified way. Another advantage of the proposed method is that it is less time-consuming as it does not include a rain detection stage. Nonetheless, due to its ill-posed rain removal problem, the method fails to remove the rain streaks effectively, more so in the case, when the method is used for de-raining videos. Their rain removal approach is patch-based which fails to use the global structure of the background image. As a result, there are rain streak components in the background layer and background components in the rain streak layer, making it more challenging to separate them, another reason for the model's unsatisfactory results.

7. A Rain Pixel Recovery Algorithm for Videos with Highly Dynamic Scenes

   The aim of the research paper (7) is to propose a method that can effectively de-rain highly dynamic videos even with heavy rainfall, something that the previously proposed methods have failed to do. The rain pixel detection method used here is the combination of what has been used in the previous research; however, their model is different in how they propose to recover the background pixel value for the detected rain streak pixel. Their method can be categorized as a pixel-based de-raining method. Their results produce satisfactory results in de-raining highly dynamic videos even with high-density rain.

   Rain pixels detection method – The rain pixels detection method proposed in this paper combines the rain pixels detection used in [1] and [2]. They use the photometric properties [1] incorporated with the chromatic properties [2] of the rain streak to detect rain streaks infected pixels.

   Rain pixel removal method – In previous research, the value of the detected rain streak pixel was substituted by the average value of the pixels in its consecutive frames.

   This method produces undesired ghost effects or irregular pixel formation in highly dynamic videos as the value of a pixel can change drastically between consecutive frames. The proposed rain removal method considers both the dynamic properties and the motion clues of the rain streaks. It then exploits the spatial and temporal information of the rain streak to recover the rain pixel.

8. Utilizing Local Phase Information to Remove Rain from Video

   The aim of the research paper (8) is to propose a novel framework for detecting and removing rain from videos to produce better results than that time's state-of-the-art de-raining methods. To de-rain videos, the authors fully utilize the temporal and spatial information of the neighbouring frames in the video.

Rain pixels detection method – The authors use phase congruency features to estimate the candidate rain streaks pixels in the proposed framework.

Negating false positives – The authors propose using phase correlation between frames and the chromatic properties of the rain to reduce the false positives from the candidate rain streaks pixels.

Rain pixel removal method – Once rain streaks pixels are detected, the intensities and the spatial neighbours and temporal neighbours of those pixels are used to determining the new intensity value of the selected rain streak pixel. Minimization of registration of error between frames is used to estimate this new intensity value.

Advantage/ Disadvantages – The proposed framework performs well even in heavy rain scenes; however, to do so, the framework utilizes a significant number of frames which makes it unfit for removing rain from videos of short duration.

9. Stereo video de-raining and de-snowing based on spatio-temporal frame warping

   Kim et at. in (9) proposed a novel rain and snow streak removal algorithm for stereo video sequences. They observed that the rain and snow streaks can be found at different locations in Spatio-temporal neighbouring frames. To de-rain the left-view frame, they wrapped the spatially adjacent right-view frame and the next and the previous temporal neighbouring frames and then subtracted each wrapped frame from the original frame. Then they applied the median filter to the three different images to get the detected rain or snow streak pixels. Finally, they replaced these detected rain or snow streaks pixel values with the weighted average of the non-local neighbouring pixel values.

   One advantage of the method proposed in this paper is that this paper provides a de-raining framework for stereo video sequences that had not been implemented in the previous research.

10. Video de-raining and de-snowing Using Temporal Correlation and Low-Rank Matrix Completion

    Kim, Sim et at. proposed a novel method in (10) to remove rain and snow streaks from videos using the temporal correlation and low-rank matrix completion. Their method is based on the observation that the rain and snow streaks are too small and move at a high velocity such that they do not affect the optical flow estimation between consecutive frames. They get their candidate rain or snow streak pixels by subtracting temporally wrapped frame from a current frame. Then they decompose their selected rain pixels into basis vectors on the sparse representation. Support Vector Machine classifier is then used to classify these vectors into rain pixels or outliers; the outliers are removed to refine candidate rain pixels. Finally, considering the low-rank nature of clean videos, they use a low-rank matrix decomposition to remove the detected rain pixels.

The method proposed in this paper can not only work on normal video sequences but can also on stereo video sequences. Moreover, the proposed method only needs three consecutive frames to function optimally, which can also perform well in short video sequences. Finally, the proposed model is also successfully able to differentiate rain from other moving objects.

11. Adherent Raindrop Modeling, Detection and Removal in Video

    The aim of the paper (11) in not to remove rain streak but is to automatically detect and remove adherent rain drop from videos. This is a good paper for related research for rain streak removal. It extensively explains how rain drops affect light, knowledge which could lead to developing a novel algorithm for rain streak removal.

    This paper uses the spatial and temporal information of raindrops to detect adherent raindrops in the input video. Then, these raindrop infected pixels are removed based on how much they are occluding the scenes. For partially occluding rain droplet pixels, a blending function is solved using the selected rain pixels' temporal intensity derivatives to produce a de-raining effect. Whereas, for removal of completely occluding rain pixels, video completion technique, i.e. getting pixel information from consecutive frames, is used.

12. Video de-snowing and de-raining Based on Matrix Decomposition

    The authors of (12) categorized rain and snow streaks as sparse ones and dense ones for de-raining and de-snowing of video problems. They observed that the previous research method failed to effectively remove the rain and snow streaks from videos with heavy rain/snow and dynamic scenes. They believe this failure is because the authors of previous research have assumed that all snowflakes and rain streaks are sparse in snowy and rainy videos and also, did not differentiate moving objects with snowflakes and rain streaks.

    To solve these problems, the authors of this paper propose that snowflakes and rain streaks be categorized into – sparse ones and dense ones. They used background fluctuations and optical flow to detect moving objects and snowflakes/ rain streaks. The moving objects and sparse snowflakes/ rain streaks are modelled using multi-label Markov Random Fields (MRF) and the dense snowflakes/ rain streaks are modelled using Gaussian distribution. Matrix decomposition is then used to remove the sparse as well as the dense snowflakes/ rain streaks from videos.

13. A Novel Tensor-based Video Rain Streaks Removal Approach via Utilizing Discriminatively Intrinsic Priors

    In (13), a novel tensor based video de-raining approach is proposed using the directional and inherent properties of rain streaks and clean videos. The authors made two observations, first, the rain streaks are sparse and smooth in the direction of rain, and second, clean videos possess smoothness along the rain-perpendicular direction and the global and local correlation along time direction. Using these, the authors developed a model utilizing the discriminately intrinsic characteristics of rain streaks and clean videos. One advantage of the proposed method does not require a rain detection stage nor does it require a time consuming dictionary learning stage.

14. Should We Encode Rain Streaks in Video as Deterministic or Stochastic?

    The aim of the research paper (14) is also to remove rain streaks from videos, however, in this research rain streaks are not formulated as deterministic as they were in the previous research, instead, the authors of this paper formulate rain streaks as stochastic. The authors argue that there are limitations in the video de-raining methods proposed in the previous research because, firstly, the researchers assume the rain streaks to be deterministic, i.e. with specific features and structures, whereas the authors believe that rain streaks vary based on diverse scenes and circumstances in which the video is made and so generalizing rain streaks by specific prior structures will produce satisfactory results only in those circumstances, making their methods non-robust. Secondly, the authors believe that the proposed methods in the previous research do not fully exploit the useful information of spatio-temporal smoothness of a moving object and low-rank property of the background scene.

    To solve these problems, the authors propose a method to stochastically formulate the rain streaks as mixtures of Gaussians. They decompose the input video frames into three layers – rain streak layer, moving object layer and background layer. They use a likelihood term for separation of the rain streak layer and a regularization term for moving object layer and the background layer each. They remove the rain streak and recover the rain free video simultaneously. Robustness is the biggest advantage of the proposed method.

15. Video Rain Streak Removal By Multiscale Convolutional Sparse Coding

    In (15), the convolutional sparse coding (CSC), which performs very well in image cartoon-texture decomposition [44] is adapted here to remove rain streaks from videos. The authors of this paper observed that the rain streaks in a video are spatially correlated to each other, that is, they appear in repetitive patterns scattered over different locations in the video.

Also, the rain streaks in the videos are with multi-scale configurations due to being present in locations with different distances from the camera. They use these intrinsic properties of rain streaks to create their multiscale convolutional sparse coding model for de-raining videos. The proposed method is robust to videos with dynamic scenes.

16. FastDeRain: A Novel Video Rain Streak Removal Method Using Directional Gradient Priors

    (16) is an extension of [13] where the authors now completely utilize the discriminative properties of rain streaks and clean videos in the gradient domain with the aim to de-rain videos. The authors extend their observation made in [13] as - "The rain streaks are sparse and smooth in the direction of rain and clean videos exhibit smoothness along the rain-perpendicular direction and the continuity along temporal direction".

    The smoothness continuity of the clean video results in the sparse distribution of rain streaks in the gradient domain which they use to remove rain streaks from videos. They use l1 norm and split augmented lagrangian shrinkage algorithm (SALSA) to model their de-raining method. The proposed method has a fast running time and can de-rain videos very quickly.

17. Erase or Fill? Deep Joint Recurrent Rain Removal and Reconstruction in Videos

    In (17), a deep recurrent convolutional network is constructed for the purpose of de-raining videos. The hybrid model is developed not just to remove conventional rain streak but also to reconstruct the regions which are completely occluded by rain streaks. Completely occluded rainy regions refers to the regions in the video frame where the light transmitted through the rain is very low, leaving little to no details of the background features.

    The proposed model uses the abundant temporal information to built a Joint Recurrent Rain Removal and Reconstruction Network (J4R-Net) which incorporates rain degradation classification with rain removal using spatial texture appearances and background reconstruction/ refinement using temporal coherence. The rain degradation classification output provides a binary map with value 1 representing the location of rain streak or rain occluded region.

    The recurrent network uses this information to find a perfect balance between removal of rain streaks and reconstruction of background features. The advantage of the proposed method is that this is the first method in the video de-raining problem which considers the reconstruction of occluded rainy regions.

18. Robust Video Content Alignment and Compensation for Rain Removal in a CNN Framework

    The aim of the research paper (18) is to propose a novel deep video de-raining algorithm which uses superpixel (SP) segmentation method to decompose the input scene into depth consistent units. In this method, two alignment output tensors are used, one is an optimal temporal match tensor and another is a sorted spatial-temporal match tensor. These two tensors provide information regarding the location of the rain streaks and the occluded background areas to generate an intermediate de-rained output.

    A convolutional neural network, with the two tensors as input, restore the high frequency details of the intermediate de-rained output to produce a much cleaner de-rained output and also compensate for mis-alignment blur.

19. D3R-Net: Dynamic Routing Residue Recurrent Network for Video Rain Removal

    The aim of the research paper (19) is to propose a deep recurrent network for de-raining videos. The method proposed in this paper is different from the methods proposed previously as this method aims not only to remove conventional rain streaks but also to remove rain occlusion regions in the videos. Rain occlusion regions, as explained in the brief summary of [17], are the regions in video frames where the light being transmitted through the rain streak is very low making it extremely difficult to extract the background feature information.

    The proposed model is a hybrid model which depicts both the rain streaks and rain occluded regions. Their hybrid model integrated with motion segmentation information creates their Dynamic Routing Residue Recurrent Network (D3R-Net) which is their final de-raining model.

20. Frame-Consistent Recurrent Video de-raining With Dual-Level Flow

    In research paper (20), a two-stage recurrent network is used to solve the video de-raining problem. The proposed method is a deep learning method which considers additional degradation factors in the real world, something that was not considered in previous research. This is an interesting paper as the final de-rained output is obtained through a two-stage de-raining process.

    In the first stage a de-rained output is estimated by the recurrent network using the original video as input. This estimated de-rained output is then used as input to the recurrent network to generate the final and more accurate de-rained output in the second stage. The two-stage recurrent network is able to capture reliable information from the estimated de-rained output at the first stage and maintain motion consistency between different frames at the second stage. The network achieves motion consistency between frames at the second stage using a dual-level flow based regularization at both coarse and fine pixel level.

21. Rain removal system for dynamic scene in diminished reality

    The authors of (21) are a little ambitious. Their aim extends to three objectives – first is to solve the video de-raining problem in the scenes shot by a moving camera, second is to not only remove rain streaks and rain drops from videos but also to remove drizzle and defocused rain. Their third objective is that they want their system to have high scalability and extensibility. They want high scalability so that their system can adapt to the increase of resolution with time.

    The authors design an optimized intuitive alignment system to solve the problem of moving cameras in dynamic scenes. They explore dark tail and chromatic pair removal along with spatial chromatic priors and apply the extended chromatic properties to remove rain streaks and rain drops from the input video. They use anti-flicker to completely remove defocused rain and drizzle, their method achieves best performance for removing drizzle and defocused rain from videos.

    They achieve the high scalability and extensibility for their system by using parallel and scalable pixel-based chromatic priors.

22. Progressive Rain Removal via a Recurrent Convolutional Network for Real Rain Videos

    The proposed video de-raining method in (22) is a deep recurrent convolutional neural network which differs from the previously proposed de-raining recurrent network in the dataset on which the model is trained. Since the ground truth image (clear image) of a rainy scene is impossible to create, previously proposed deep de-raining recurrent networks use synthetic rain datasets consisting of a pair of clean and artificially induced rainy images. Then these pair of images were then fed to a recurrent neural network that learns to map clean images from their counterpart rainy images.

    Although the synthetic dataset incorporates rain streak of different shapes, sizes, and orientations, the networks still perform poorly in case of de-raining real rainy videos. To solve this problem, the authors of this paper used a pseudo-ground-truth of the real rainy video sequence, constructed by using temporal filtering, to feed it to their recurrent network for supervised learning. Instead of incorporating different shapes, sizes or orientations in their pseudo-ground-truth videos, the authors mainly focused on the changing nature of the rain in a video. They fed images of progressive rain streaks, with decreasing rain intensity, to their network. The final model was efficiently able to detect and remove rain streaks from real rainy videos.

2.2 Image De-raining

The first paper on single image de-raining problem was published in 2011 [23], since then the single image de-raining problem as gained a lot of popularity among researchers with more than 42 papers being published after 2011 [23 - 66]. The popularity of the de-raining methods only rose after the first paper to use convolutional neural networks for the de-raining single images is published [37] in 2017. After 2017, more than 20 papers have been published in just four years.

These single image de-raining methods can be categorized on the basis of - the rain model or the rain accumulation model or no model they use, the methods they implement for the de-raining process or whether these methods follow a patch-based method or pixel based approach. In the first subsection, the major single image de-raining papers are categorized on the basis of the topic mentioned above. Then, in the second section, a brief summary of all the single image de-raining studies [23 - 66] is provided.

2.2.1 Single image de-raining method categorization

The single image de-raining studies can be classified on the basis of the rain model they use, or the rain accumulation model they use, or they do not use a rain model, or the framework on which they are implemented or lastly, their approach being patch-based or pixel-based. The classification of the single image de-raining methods [23 - 66] are as follows -

Rain models

There are plenty of rain models that are proposed in the single image de-raining studies, these models are explained in brief below -

1. Input image decomposition

   The most common rain model that is used is an image decomposition de-raining where the input rainy image is assumed to be a combination of a background layer superimposed by a rain streak layer. This model is used in [23, 24, 27, 28, 30, 31, 33, 35, 37, 39, 40, 43, 44, 52]. The mathematical equation of this type of rain decomposition model is as follows -

   $$I = B + R \tag{1}$$

   Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

   The de-rained output of the methods built upon this model is the predicted background layer B recovered from the input layer I. The rain streak layer is separated from the background layer by either using dictionary learning [23, 24, 28, 31, 33, 43] or by using the sparse representation of the rain streaks [23, 24, 28, 31, 40, 44], or by using low rank filtering [27, 30, 43, 44] or by using some newly developed priors [35, 39] or by utilizing a deep convolutional neural network [52].

2. Image decomposition using Rain Residual

   In the previous model, the background layer is predicted to produce the final de-rained output. In this model, however, the rain streak layer is predicted, which is then subtracted from the input rainy image to produce the final de-rained output. This model is also an image decomposition model; however, the output image is decomposed into the input and rain streak layers. This model is used in [38, 45, 47, 56, 59, 64]. The mathematical equation of the model is as follows -

$$O = I - R \tag{2}$$

   Here, O represents the output de-rained image or the background layer, I represents the input rainy image, and R represents the rain streak residual.

   In this rain model, the negative rain streak residual is determined which is then subtracted from the input rainy image to obtain the output de-rained image. Another representation of this model is -

$$-R = B - I$$

   Here, -R represents the negative rain residual, B refers to the background layer and I represents the input rainy image.

   The negative rain residual is obtained from subtracting the input rainy image from the background layer. All of the methods which are built upon this model [38, 45, 47, 56, 59, 64] are based on deep convolutional networks.

3. Image Decomposition on frequency components

   This model is built on the observation that most of the background details exist in the low frequency component of the input rainy image and the rain streaks along with the high textured and edges details exist in the high frequency component of the input rainy image. This model is an extension of the first rain model (1). This model is used in [23, 24, 27, 28, 31, 33, 37, 38, 43]. The mathematical equation of the model is as follows -

$$I = I_{LF} + I_{HF} \tag{3}$$

   Here, I represents the input rainy image, I_{LF} represents the low frequency component of the input image and I_{HF} represents the high frequency component of the input image.

The de-raining methods which are implemented on this model extract the low frequency and high frequency component from the input rainy image, usually through the use of a guided filter, then remove rain streaks from the high frequency components and add back the non-rain high frequency component back to the low frequency component to produce the final de-rained output.

In papers [37, 38, 43] the low frequency component and the high frequency component are referred to as the base layer and the detail layer respectively. The rain streaks are separated from the high frequency component by either using dictionary learning [23, 24, 28, 31, 33, 43] or by using the sparse representation of the rain streaks [23, 24, 28, 31], or by using low rank filtering [27] or by utilizing a deep convolutional neural network [37, 38].

4. Image decomposition based on pixel intensity and time average irradiance

   This model based upon the observation that the rain streak pixel are brighter than their surrounding pixels. This model is used in [25, 26]. The mathematical equation of the model is as follows -

$$I_r = \alpha I_E + (1 - \alpha) I_b \tag{4}$$

   Here, $\mathrm{I_r}$ represents the intensity of the rain streak pixel, $\mathrm{I_E}$ represents the intensity of a stationary rain streak, $\mathrm{I_b}$ represents the intensity of the background and finally, α is a function of time that a rain streak takes to pass a pixel.

   All of the methods which are built upon this model use low rank filtering to produce de-rained images.

5. Rain streaks modelled using the visibility and saturation

   In this model the rain streaks are modelled as the visibility layer multiplied by the inverse of the saturation layer. This model is used in [32]. The mathematical equation of the model is as follows -

$$R = V * (1 - S) \tag{5}$$

   Here, R represents the rain streak layer, V represents the visibility and S represents the saturation in the HSV color model.

   The methods proposed using the model uses low rank filtering for the de-raining process.

6. Non-linear image decomposition model

   This model is an extension of (1), where the input rainy image is decomposed into a background layer and a rain streak layer. However, in this model, another term is introduced which is a product of the background layer and the rain streak layer. This model is used in [34]. The mathematical equation of the model is as follows -

$$I = B + R - B * R \tag{6}$$

Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

The input image is decomposed into a background layer, a rain streak layer and the negative product of the background layer and the rain streak layer. The method built upon this model [34] uses dictionary learning and sparse coding for the de-raining process.

7. Scalar decomposition model

   This model is also an extension of (1) where the input rainy image is decomposed into a background layer and a rain streak layer. However, in this model, a new scalar term is introduced to maintain the balance between the background layer details and the rain streak details. This model is used in [36]. The mathematical equation of the model is as follows -

$$I = (1 - \alpha)B + \alpha R \tag{7}$$

   Here, I represents the input rainy image, B represents the background layer, R represents the rain streak layer and α is a scalar constant which quantifies the presence of rain streak density in the input image.

   α equal to 0 means the input image is rain free and α equal to 1 means there are no background details that can be extracted from the input rainy image. The method built on this model uses low rank filtering for the rain removal from single images problem.

8. Region dependent rain model

   With the aim to give more attention to the regions with rain streak pixels, a new model is proposed which is also an extension of (1), in which a rain streak map is used along with a rain streak layer to model the rain pixels in the input image. In this This model is used in [41]. The mathematical equation of the model is as follows -

$$I = B + RM \tag{8}$$

   Here, I represents the input rainy image, B represents the background layer, R represents the rain streak layer and M is the binary rain streak mask.

   In M, '1' represents the presence of the rain streak and '0' represents the absence. The method which uses this rain model is a convolutional neural network [41].

9. Image decomposition with multiple rain streak layers

   This model as well, is an extension of (1) where the input rainy image is decomposed into a background layer and a rain streak layer. However, in this model, multiple rain streaks layers are assumed to be superimposing on the background layer. This was done based on the observation that the rain streaks in a rainy image, especially in heavy rain scenes, are diverse in nature with different sizes, shapes and orientations and that one rain layer is not enough to represent all of these diverse rain streaks. Moreover, the light scattering properties of the rain streaks are also incorporated in this model. [42, 50] used this rain model. The mathematical equation of the model is as follows -

$$I = \alpha * (B + \sum_{i=1}^{n} R_i) + (1 - \alpha) * A \tag{9}$$

   Here, I represents the input rainy image, B represents the background layer and R_i represents the i^{th} rain streak layer, n is the total number of different rain streak layers added to the model, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively and finally '*' represents the element multiplication. A and α are further described in haze removal papers such as [79]. The methods which are built upon this network are convolutional neural networks [42, 50].

10. Image decomposition with multiple rain streak layers and their corresponding intensity transparency.

   This model is an extension of (9), in which not only the multiple rain streak layers are assumed to be superimposing on the background layer but different α values are also assigned to each rain streak layer. This model is used in [48] and The mathematical equation of the model is as follows -

$$I = (1 - \sum_{i=0}^{n} \alpha_i)B + \alpha_0 A + \sum_{i=1}^{n} \alpha_i R_i \tag{10}$$

   subject to

$$\alpha_i \geq 0$$

   and

$$\sum_{i=0}^{n} \alpha_i \leq 1$$

   Here, I represents the input rainy image, B represents the background layer and R_i represents the i^{th} rain streak layer, n is the total number of different rain streak layers added to the model, A $\in$ [0,1] and $\alpha_0 \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively, and finally, α_i is the brightness of the i^{th} rain streak layer.

A and α are further described in haze removal papers such as [79]. The methods which are built upon this model are deep convolutional neural networks [48].

11. Rain modelled using Gaussian Mixture Model

    In this rain model the rain streaks are modelled using different coefficients of the Gaussian mixture model. Then these modelled rain streaks are detected and removed from the input rainy image to produce the final de-raining result. The model assumes to have multiple layers of rain streaks in the input rainy image. The mathematical equation of the rain model is as follows -

$$R \sim \sum_{i=0}^{n} \pi_n N(R|\mu_n, \Sigma_\mathrm{n}) \tag{11}$$

    Here, R represents the rain streak layer and π_n, μ_n and Σ_n are the coefficients of the Gaussian Mixture Model. This model is used in [53] and the method implemented to solve this model is a deep convolutional neural network.

12. Rain modelled using gamma expansion

    This rain model is a combination of the rain model expressed in (7) and (9). This model is used in [54] and the mathematical representation of the model is as follows -

$$R = \alpha * B^{\gamma} + (1 - \alpha) * A \tag{12}$$

    Here, R is the rain streak layer, B is the background layer, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively, $\gamma > 1$ is a decoding gamma, '*' represents element wise multiplication, and finally, B^{γ} is the gamma expansion of the background layer.

    A and α are further described in haze removal papers such as [79]. The methods which is built upon this network is deep convolutional neural network [54] and uses wavelet transformation for rain removal from single images.

13. Rain modelled on the basis of rain streak layers with similar direction

    This rain model is an extension of the rain accumulation model (16) used in [41]. This rain model takes the rain accumulation model and incorporates the rain streaks in the model as well. The rain streak layers are divided on the basis of the diversity of the rain steaks as well as their direction. This rain model is used in [55] and the mathematical representation of the model is as follows -

$$I = \alpha(B + \sum_{i=1}^{n} S_i M) + (1 - \alpha)A \tag{13}$$

Here, I represents the Input image, B represents the background layer, S_i represents the i^{th} rain streak layer of the same direction, M is the binary map of the individual rain streaks, n represents the maximum number different rain streak layers in the model, and finally, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively.

A and α are further described in haze removal papers such as [79]. In M, '1' indicates the presence of the rain streak at a pixel and '0' indicates the absence of the rain streak at a pixel. This binary map of rain streaks provides additional information as well as a constraint in the network training process. This model is used in [55] and the method implemented to solve this model is a deep convolutional neural network.

14. Depth based rain model

Based on the observation that the rain streaks varies in depth and the rain streaks that are far away from the camera that shot the rainy image takes the appearance of fog, a new rain model was proposed in which not only the rain streaks are incorporated but the presence of fog, light scattering properties of the rain streak and a depth parameter are also incorporated. This model is used in [58] and the mathematical representation of the model is as follows -

$$I = B(1 - R - F) + R + AF \tag{14}$$

Here, I represents the input rainy image, B represents the background layer, R $\in$ [0,1] represents the rain layer, F $\in$ [0,1] represents the fog layer and A $\in$ [0, 1] is the atmospheric light. High values of R or F indicate high intensity of rain streaks or fog in the rainy image, respectively, while '0' mean that there is no rain or fog in the input rainy image.

The rain layer is further modelled as a combination of rain streak intensity and the rain streak intensity map. The mathematical equation of the rain streak layer model is as follows –

$$R = Int * M$$

Here, R $\in$ [0,1] represents the rain streak layer, as shown above. Int $\in$ [0,1] is rain streak intensity image in the image space, M represents rain streak intensity map which is modelled as a function of depth of the rain streaks in the rainy image and finally, '*' represents pixel-wise multiplication.

In the rain streak mask M, '1' indicates the presence of the rain streak at a pixel and '0' indicates the absence of the rain streak at a pixel. This binary map of rain streaks provides additional information as well as a constraint in the network training process.

The fog layer is modelled as an exponential function of the depth of the rain streaks, the mathematical equation of which is as follows –

$$F = 1 - e^{-\beta d}$$

Here, F $\in$ [0,1] is the fog layer, β is the attenuation coefficient, and d is the scene depth. The value of β represents the thickness of the fog, greater the value of β, thicker the fog and as the value of β decreases the thickness of the fog decreases as well. $\beta = 0$ mean there is no fog in the rainy image.

This model is used in [58] and the method implemented to solve this model is a deep convolutional neural network.

15. Motion blur based rain model

    In this model the motion blur of the rain streaks, a mechanism which leads to the line pattern appearances of the rain streaks, is incorporated in the rain model. This model is used in [60] and the mathematical representation of the model is as follows -

$$I = B + K(\theta, l) * M \tag{15}$$

    Here, I represents the input rainy image, B represents the background layer, $K(\theta, l)$ is motion blur kernel – a function of the angle θ and the length of the motion blur l, '*' is the spatial convolutional operator, and finally, M is a binary mask of the rain streak pixels.

    This model is used in [60] and the method implemented to solve this model is a deep convolutional neural network.

Rain accumulation models

Rain accumulation refers to the overlapping of rain streaks in an image. Rain accumulation is a phenomenon which is usually observed in heavy rain scenes images. Rain accumulation regions are harder to remove than rain streaks as there is lesser background information that is available. The first rain accumulation model was proposed in [41] which modelled the rain streaks (8) and the rain accumulation (16) separately. Studies published after [41] usually proposed a single model for rain streaks as well as for rain accumulation [50, 54, 55, 58]. Below are the four different rain accumulation models explained in brief.

1. Rain accumulation model based on rain streaks layers with similar direction

   [41] extended its region dependent rain streak model (8) into a rain accumulation model by introducing the light scattering properties of the rain streak as well as the multiple rain streak layers divided by the direction of the rain streak. The same model

was used in [55]. However, unlike [41], [51] used this model to represent rain streak as well as rain accumulation, whereas, [41] defined two different models for rain streaks and rain accumulation.

This rain accumulation model also incorporates the light transmission properties of the rain streaks. The mathematical representation of the model is as follows -

$$I = \alpha * (B + \sum_{i=1}^{n} S_i M) + (1 - \alpha) * A \tag{16}$$

Here, I represents the Input image, B represents the background layer, S_i represents the i^{th} rain streak layer of the same direction, M is the binary map of the individual rain streaks, n represents the maximum number different rain streak layers in the model, and finally, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively.

A and α are further described in haze removal papers such as [79]. In M, '1' indicates the presence of the rain streak at a pixel and '0' indicates the absence of the rain streak at a pixel. This binary map of rain streaks provides additional information as well as a constraint in the network training process. This model is used in [41, 55] and the method implemented to solve this model is a deep convolutional neural network.

2. Rain accumulation using dark channels

Like [41], [50] also uses two different models for rain streak (9) and rain accumulation. In [50] however, instead of (16), the dark channel of the input rainy image is utilized for the removal of rain accumulated regions from the rainy images.
The dark channel in the input image can be mathematically represented as follows -

$$dark\_channel(R, G, B) = min(R, G, B) \tag{17}$$

Here, RGB are the Red, Green and Blue channels of the colored image. This model is used in [50] and the method implemented to solve this model is a deep convolutional neural network.

3. Rain accumulation using gamma expansion

The rain accumulation model here is the same as the rain model expressed by (12) this is because in [54] as a single model is used for rain streak as well as rain accumulation. The mathematical equation of the model is as follows -

$$R = \alpha * I^{\gamma} + (1 - \alpha) * A \tag{18}$$

This model is used in [54] and the method implemented to solve this model is a deep convolutional neural network.

4. Depth based rain accumulation model

   The rain accumulation model here is the same as the rain model expressed by (14) because in [58] a single model is used to incorporate the rain streak as well as the rain accumulation. Based on the observation that the rain streaks varies in depth and the rain streaks that are far away from the camera that shot the rainy image takes the appearance of fog, a new rain accumulation model was proposed in which not only the rain streaks are incorporated but the presence of fog, light scattering properties of the rain streak, a depth parameter and rain accumulation are also incorporated.

   This model is used in [58] and the mathematical representation of the model is as follows -

$$I = B(1 - R - F) + R + AF \tag{19}$$

   Here, I represents the input rainy image, B represents the background layer, R $\in$ [0,1] represents the rain layer, F $\in$ [0,1] represents the fog layer and A $\in$ [0, 1] is the atmospheric light.

   High values of R or F indicate high intensity of rain streaks or fog in the rainy image, respectively, while '0' means that there is no rain or fog in the input rainy image. Here, a fog layer indirectly represents the rain accumulation as rain accumulated regions are most often perceived as fog or mist.

   The rain layer is further modelled as a combination of rain streak intensity and the rain streak intensity map. The mathematical equation of the rain streak layer model is as follows –

$$R = Int * M$$

   Here, R $\in$ [0,1] represents the rain streak layer, as shown above. Int $\in$ [0,1] is rain streak intensity image in the image space, M represents rain streak intensity map which is modelled as a function of depth of the rain streaks in the rainy image and finally, '*' represents pixel-wise multiplication.

   The fog layer is modelled as an exponential function of the depth of the rain streaks, the mathematical equation of which is as follows –

$$F = 1 - e^{-\beta d}$$

   Here, F $\in$ [0,1] is the fog layer, β is the attenuation coefficient, and d is the scene depth. The value of β represents the thickness of the fog, greater the value of β, thicker the fog and as the value of β decreases the thickness of the fog decreases as well. $\beta = 0$ mean there is no fog in the rainy image.

Here, a fog layer indirectly represents the rain accumulation as rain accumulated regions are most often perceived as fog or mist. This model is used in [58] and the method implemented to solve this model is a deep convolutional neural network.

No rain model

Removal of the rain streak from single images is easier to implement when the method is built upon a rain streak or input image decomposition model. However, the utilization of a rain model is not necessary for the single image de-raining process and so there are a few studies that have been published that do not use any rain streak or input image decomposition models [29, 46, 49, 51, 61 - 63, 65, 66].

De-raining methods

There are several de-raining methods that are implemented for the removal of rain streaks from rainy images. The most proficient and popular methods are ones which are built upon the deep convolutional neural networks. Nonetheless, the single image de-raining research can also be classified based on the methodology on which they are built upon.

1. Sparse Coding or sparse representation of rain streaks

   Due to the thin and sparse nature of the rain streaks, initial studies [23, 24, 28, 31, 34, 40, 44] have used sparse coding for rain streaks representation. In [40], centralized sparse coding and in [44], convolution sparse coding is used for the detection of rain streaks in the input rainy image.

2. Dictionary Learning

   [23, 24, 28, 31, 33, 34, 43] are all the papers which employ a dictionary learning stage in their de-raining process. Dictionary learning is a representation learning method which uses sparse representation [23, 24, 28, 31, 34] of the rain streaks for the de-raining problems.
   In [43] dictionary learning is used but only to classify the high frequency component details as non-rain, rain or snow. Employing a dictionary learning stage in a de-raining method is not optimal since it is time consuming and requires significant computation.

3. Low Rank Filtering

   Low rank filtering or guided filtering is implemented in [25 – 27, 29, 30, 32, 36, 43, 44] for the de-raining of single images problem. Low rank filtering de-raining approach is based on the observation that the background layer has a low rank nature and so by using a low rank filter most of the background details can be extracted from the input rainy image. However, in doing so the output de-rained image often has smooth edges and blurred background.

4. Gaussian Mixture Model priors

   [35, 39] are the only papers to use Gaussian Mixture Model priors for the rain streak removal from input rainy images. In [35, 39] two Gaussian Mixture models are trained, one to represent the clean background layer and another to represent the rain layer. This method is built upon the image decomposition rain model (1) in which a rain streak layer is assumed to be superimposing on a background layer.

5. Wavelet transformation

   Wavelet transformation is used to separate the low frequency or the base layer from the high frequency or the detail layer (3) of input rainy images. In wavelet transformation, Haar wavelet transformation is used to separate the rain streaks layer and the background layer, but only to some extent, using the prior knowledge that most of the background details can be found in the low frequency component of the input rainy image and the rain streaks as well as high detail background information can be found in the high frequency component of the background image.

   Now, using the Haar basis function for discrete wavelet transformation produces four-sub images. These four-sub images are – diagonal detail HH, vertical detail HL, horizontal subband LH, and finally, approximation subband LL. The LL subband consists of the rainy image's low frequency or the primary content information. In contrast, the HH, HL and LH subband consists of high frequency and detailed information of the rainy image. More specifically, the LL subband contains most of the details of the background layer, LH subband contains high textured and edges information of the background layer. Finally, the HL subband contains the rain streaks as the raindrops fall from the top.

   Wavelet transformation is implemented in [50, 54].

6. Deep Convolutional Neural Network

   The de-raining methods implemented on deep convolutional neural networks [37, 38, 41, 42, 45 - 65] produce the best de-rained images as compared to any other method explained before. The de-raining methods gained tremendous popularity after the first method to use convolutional neural networks was published back in 2017 [37]. Since then more than 25 papers on de-raining single images using convolutional networks have been published in just four years. The current state-of-the-art performance is held by the methods implemented on convolutional neural network architecture.

Pixel-based and patch-based categorization

1. Patch-based de-raining methods

   Patch-based de-raining approach refers to the process in which rain streaks are detected and removed from the patches of the input rainy images. In this type of approach, only the neighbouring pixels information is utilized to reconstruct the background details or the construction of the de-rained output.

   This type of approach fails to use the background image's global structure. As a result, there are either rain streak components in the background layer or background components in the rain streak layer or both, making it more difficult to separate them. This type of approach is implemented in [23, 24, 28, 30, 31, 33 – 35, 39, 43, 47].

2. Pixel-based de-raining methods

   The pixel-based de-raining approach refers to how the pixel information, such as its intensity, is used for the de-raining of single images problem. Deep convolutional network approaches usually follow a pixel-based approach, predominantly end-to-end mapping from the input rainy image to the output de-rained image.

   Unlike the patch-based approach, the pixel-based approach does not fail to use the global structure of the image as it is not confined in limited patch space. So, pixel-based approaches usually produce better de-raining results than patch-based approaches. This type of approach is implemented in [25 – 27, 29, 32, 36 - 38, 40 - 46, 48 - 65].

2.2.2 A Brief summary of single image de-raining methods

1. Single Frame Based Rain Removal Via Image Decomposition

   [23] is the first paper published to extend the de-raining problem to single images. The authors model the image de-raining problem as image decomposition problem based on morphological component analysis (MCA). In this paper, the authors took the input image and decomposed it into low frequency and high frequency components using a bilateral filter. More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

   $$I = I_{LF} + I_{HF}$$

   Here, I represents the input rainy image, I_{LF} represents the low frequency component of the input image and I_{HF} represents the high frequency component of the input image.

   Most of the background details can be extracted using the low frequency component of the rainy image. The authors then decompose the high frequency part into rain components and non-rain components using sparse coding and dictionary learning. The non-rain component of the image is added back to the low frequency part of the image to enhance the background details and produce a de-raining effect in single images. The proposed method is a 2-step process which removes rain in single images using morphological component analysis (MCA).

The disadvantages of the proposed method is that the method is extremely time consuming due to a dictionary learning process being implemented and the de-rained results of the method are also not satisfactory as the resultant de-rained images are grayscale, losing all of the colour information in the image. Moreover, the proposed method is patch-based which fails to use the global structure of the background image. As a result, there are rain streak components in the background layer and background components in the rain streak layer, another reason for poor quality de-raining results.

2. Automatic Single-Image-Based Rain Streaks Removal via Image Decomposition

   In [24] as well, the authors modelled the de-raining of images problem as a decomposition problem. Their rain removal model is based on morphological component analysis (MCA). Like that in [23], in the proposed model, the input images are decomposed into low frequency and high frequency components using a bilateral filter. More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

$$I = I_{LF} + I_{HF}$$

   Here, I represents the input rainy image, I_{LF} represents the low frequency component of the input image and I_{HF} represents the high frequency component of the input image. The low frequency part of the rainy image contains most of the background structure details whereas the high frequency part contains the rain streaks as well as the edges of the background features. The high-frequency component is decomposed into the rain component and non-rain component.

   Unlike that in [23], the rain component is extracted from the high frequency component using two sparse-represented based dictionaries – one for the rain component and another for the non-rain component. Based on the assumption that rain streaks have similar edges orientation and gradients, Histogram of Orientated Gradients (HOG) is used to model the two dictionaries. The dictionaries are separated using a K-means clustering (K=2) algorithm and the obtained non-rain component from the high frequency component is added back to the low frequency component to enhance the background in the de-rained image.

An advantage of the proposed method is that there is no rain detection stage; the input rainy image is de-rained and is decomposed into high and low frequency components which is further de-rained using morphological component analysis. However, there are several disadvantages of the proposed method. Firstly, the proposed method is time consuming and requires significant computation due the the presence of a dictionary learning state.

Although the proposed method performs well in de-raining images with simple structure it performs poorly in de-raining images with complex structures with over-smooth results and blurry edges. If compared with the current state of the art methods, which even adds a feature enhancement step in the de-raining model, the proposed method performs poorly even for images with simple structures. Secondly, using histogram of oriented gradients is not able to completely separate the rain streak layer and the background layer, especially when the non-rain components have similar structure and orientation as that of the rain streaks, in which case these non-rain components are also removed from the image. Furthermore, all the color-information is lost as the resultant image is in grayscale.

Finally, the proposed method is patch-based which fails to use the global structure of the background image. As a result, there are rain streak components in the background layer and background components in the rain streak layer, making it more difficult to separate them.

3. Removing Rain and Snow in a Single Image using Guided Filter

In [25], the authors proposed a novel method to remove rain streaks and snowflakes from single images based on a newly developed rain model. This rain model uses pixel intensity and time average irradiance to model the rain streaks. More information on the rain model can be obtained at (4). The mathematical representation of the used rain model is as follows -

$$I_r = \alpha I_E + (1 - \alpha) I_b$$

Here, $\mathrm{I_r}$ represents the intensity of the rain streak pixel, $\mathrm{I_E}$ represents the intensity of a stationary rain streak, $\mathrm{I_b}$ represents the intensity of the background and finally, α is a function of time that is taken by a rain streaks to pass a pixel.

The proposed method uses a guided filter to de-rain single images. The colour channel difference is used as guidance to model the non-rain prior to the guided filtering. Due to the low pass filtering nature of a guided filter, a lot of information is lost during the de-raining process, and the end de-rained result is of poor quality and unrealistic. The non-rain prior can only roughly capture most of the background details, and in the de-raining process of large raindrops, over-smooth edges and textures are achieved.

However, one advantage is that the proposed model's de-raining output is a coloured image, unlike in [23, 24], so this approach has no loss of coloured information. Finally, since the guided filter is used directly on the input rainy image, no pixel-based statistical details was required to de-rain the input, resulting in very fast implementation of the proposed model.

4. An Improved Guidance Image Based Method to Remove Rain and Snow in a Single Image (same author as above; jing xu)

   In [26], the authors improved the performance of their model which was proposed in [25] by refining the guidance image. Their aim, again, was to remove both the rain streaks and snowflakes from single images. The same rain model which was used in [25] is used in [26] for modelling the rain streaks. More information on the rain model can be obtained at (4). The mathematical representation of the used rain model is as follows -

$$I_r = \alpha I_E + (1 - \alpha) I_b$$

   Here, I_r represents the intensity of the rain streak pixel, I_E represents the intensity of a stationary rain streak, I_b represents the intensity of the background and finally, α is a function of time that a rain streak takes to pass a pixel.

   Although the performance of their proposed model increased as compared to that of [25], still the model produced unsatisfactory de-rained images with either the resultant de-rained image consisting of rain streaks or snowflakes or some important image information being lost which produced a blurry effect. Regardless, as their approach does not include a rain detection stage, the implementation of their method is very fast.

5. Single-Image-Based Rain and Snow Removal Using Multi-guided Filter

   In [27], the authors proposed the de-raining and de-snowing problem as an image decomposition problem, unlike that in [25, 26], where the input rainy image is decomposed on the basis of pixel intensity and time average irradiance. The proposed model is developed to remove rain streaks as well as snowflakes from a single image.

   Based on the assumption that the low frequency component of an image can differentiate between the clear background edges and rain streaks or snowflakes, the authors of this paper decomposed the input rainy image into low frequency and high frequency components. More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

$$I = I_{LF} + I_{HF}$$

Here, I represents the input rainy image, I_{LF} represents the low frequency component of the input image and I_{HF} represents the high frequency component of the input image.

The authors also believed that the high frequency component is composed of the rain streak or snowflakes layer along with the high frequency component of the background layer. So, after dividing the input rainy image into low frequency and high frequency components, they extract the non-rain component from the high frequency component using a guided filter. This non-rain component is added back to the low frequency component of the input image to produce a de-raining effect.

The proposed method is not different from previously proposed methods in [25, 26] as it too produces colored de-rained images so there is no loss of color information in the de-raining process. Moreover, it too is a fast process since it does not involve long dictionary learning or rain detection process unlike that in [23, 24]. The resultant de-rained image is a smooth image, just like that in [25, 26]. However, the rain removal model which is used in [27] is different from the one used on [25, 26].

6. Context-Aware Single Image Rain Removal

   The objective of the research paper [28] is to propose a learning based rain removal framework for single images. The proposed method presents the rain removal from single images problem as an integration of image decomposition and self-learning process.

   The input image is decomposed into a background layer and a rain streak layer which can be obtained from the low frequency and high frequency components of the image. More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

$$I = I_{LF} + I_{HF}$$

   Here, I represents the input rainy image, I_{LF} represents the low frequency component of the input image and I_{HF} represents the high frequency component of the input image. The rain streak layer is extracted and removed from the high frequency component using self-learning and classification process and the rest of the high frequency component is added back to the background layer to produce a de-raining effect.

   The proposed method is similar to the method proposed in [23, 24] however, unlike those methods, the proposed method presents context-dependent rain removal from images. Moreover, the proposed method is trained on a single image and not on a training image dataset, saving time in the learning process.

   In this method, the low frequency component of the input rainy image is obtained using a bilateral filter. Then context-constrained image segmentation is applied to the input image to get the high frequency component of the rainy image. Then, in the high frequency component, dictionaries are learned based on different context categories using sparse coding. Finally these dictionaries are classified into rain and non-rain components using Principal Component Analysis (PCA) and Support Vector Machine (SVM) classifiers. The extracted non-rain details of the high frequency component are added back to the low frequency component. This way the proposed method is automatically able to identify and remove rain streaks from a rainy image.

7. Single-Image De-raining Using An Adaptive Non-local Means Filter

   The authors of [29] propose a two-stage approach to de-raining the single image problem – rain detection and removal stages. In [29] as well, the image de-raining problem is presented as an image decomposition problem where the input rainy image is assumed to be the integration of a rain streak layer and a background layer. The method proposed in this paper is a pixel-based de-raining approach.

   Based on the observation that the rain streaks are elliptical in shape and have a vertical orientation, the paper's authors decided to detect the rain streaks by analyzing the angle of rotation and the aspect ratio of the elliptical kernel. This method is called rain detection using kernel regression and is the first stage of the proposed approach.

   In the second stage, the selected rain pixels are removed using a non-local means filter which uses the non-local similarity of image patches to reconstruct the rainy patches. The resultant de-rained images are of poor quality as the method detects individual rain streaks based on their orientation and shape. In contrast, rain streaks can have different orientations, shapes and densities in a rainy image. Moreover, seeing rain streaks using kernel regression is not optimal as it fails to detect a significant number of rain streaks in the rain streak detection stage.

8. A Generalized Low-Rank Appearance Model for Spatio-Temporally Correlated Rain Streaks

   In [30], the authors aim to de-raining images as well as videos using a generalized low-rank appearance model. The method proposed is novel and is based on the two assumptions, First, Rain streaks usually have similar directions and occur in repeated patterns which indicates the similarity between rain streaks at different pixel locations, and second, raindrops fall at a nearly constant speed which implies the repeatability of rain streaks along time axis.

   Based on these two assumptions, it can be said that there is a high correlation between the rain streaks in an image or a video. So the authors proposed a low rank model from matrix to tensor structure to find and remove these spatio-temporal correlated rain streaks. The authors decomposed the input image into two layers – a background layer and a rain streak layer. More information on the rain model can be obtained at (1). The mathematical representation of the used rain model is as follows -

$$I = B + R$$

Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

The authors proposed the de-raining problem using an objective function, the cost function of which has three terms – a likelihood, a smoothed background layer and a rain streak layer which is assumed to be low-ranked. One advantage of the proposed model is that this model is not limited to any particular source input; it can remove rain streaks from single images as well as from videos in a unified way. Another advantage of the proposed method is that it is less time consuming as it does not include a rain detection or long dictionary learning stage.

Nonetheless, due to its ill-posed rain removal problem, the method fails to remove the rain streaks effectively. Their rain removal approach is patch-based which fails to use the global structure of the background image. As a result, there are rain streak components in the background layer and background components in the rain streak layer, making it more difficult to separate them, another reason for the model's unsatisfactory results.

9. Visual Depth Guided Color Image Rain Streaks Removal Using Sparse Coding

   Like that in [23, 24, 27, 28], in [31] as well, the image de-raining problem is modelled as image decomposition problem where the input image is assumed to be the collection of a background layer and a rain streak layer which are further decomposed into low frequency and high frequency component. More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

$$I = I_{LF} + I_{HF}$$

   Here, I represents the input rainy image, I_{LF} represents the low frequency component of the input image and I_{HF} represents the high frequency component of the input image. The clean background details are assumed to be stored in the low frequency component of the rainy image and the rain streaks as well as background textures and edges are assumed to be stores in the high frequency component of the rainy image.

   Similar to the approaches proposed in [23, 24, 27, 28], de-rained output is obtained by adding the extracted non-rain component from the high frequency component using dictionary learning and sparse coding to the low frequency component of the input image. A bilateral filter is used to decompose the input rainy image into high frequency and low frequency components.

The high frequency component is further decomposed into rain component and non-rain component by implementing dictionary learning and sparse coding on a set of hybrid features including Histograms of Oriented Gradients (HOGs), Depth Of Field (DOF) and Eigen colors.

The proposed method is similar to those proposed in [23, 24, 27, 28], however, in this approach a hybrid feature set is used which removes most of the rain streaks and enhances the non-rain component in the high frequency component of the rainy image – the background textures and edges. The enhanced non-rain component is added back to the low frequency component of the rainy image to produce a de-raining effect.

Since this approach involves a dictionary learning process therefore it is time consuming and requires significant computation. Although the usage of hybrid dataset can help in removing most of the rain streaks it also ends up removing some of the background details which have structure and orientation similar to that of rain streaks.

10. REMOVING RAIN AND SNOW IN A SINGLE IMAGE USING SATURATION AND VISIBILITY FEATURES

In [32], two different approaches are proposed, one for removing rain streaks and another for removing snowflakes from rainy images. Only the de-raining of single images approach will be discussed in this section to be consistent with the topic of the dissertation.

The authors of this paper proposed a novel rain streaks model which is a combination of the visibility layer and the inverse of the saturation layer. More information on the rain model used can be found at (5). The mathematical equation of the model is as follows -

$$R = V * (1 - S)$$

Here, R represents the rain streak layer, V represents the visibility and S represents the saturation in the HSV color model.

The proposed de-raining approach is a two-step process involving rain streak detection and rain removal process. There are four steps implemented in the rain detection process of the proposed model. Based on the assumption that rain streaks have high visibility and low saturation, pixel-wise multiplication of the visibility layer and the inverse of the saturation layer is performed to determine the candidate rain pixels, this is the first step in the rain detection process.

As shown in the previous research [23, 24, 27, 28, 31], rain streaks exist in the high frequency component of the input image, using this observation, the authors use a high pass filter to further refine the candidate rain pixels which is the second step of the rain detection process. In the third step, an orientation filter is used on the remaining selected rain pixels. An Orientation filter is used based on the observation that the rain streaks have similar orientation.

In the final step of the rain detection process, an intensity threshold is added to the model to select only the top 13% of the most intensified remaining rain pixels. After the rain detection process is completed, the selected rain pixels are removed using the Inpainting algorithm [69] and the final de-rained image is produced.

Even after an exhaustive rain pixel detection process, the model does not perform well in detecting all of the rain streaks pixels. Furthermore, due to the instability and averaging property of the Inpainting algorithm, the final de-rained image is of poor quality.

11. Exploiting Image Structural Similarity For Single Image Rain Removal

In [33], like that in [23, 24, 27, 28, 31], the authors propose the de-raining of single images problem as image decomposition problem. They decompose the input rainy image into the background layer and rain streak layer. Their proposed model is based on the assumption that most of the background layer details can be extracted from the low frequency component of the rainy image and the rain streak layer can be removed with the textured and edges details of the background extracted from the high frequency component of the image.

More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

$$I = I_{LF} + I_{HF}$$

Here, I represents the input rainy image, I_{LF} represents the low frequency component of the input image and I_{HF} represents the high frequency component of the input image.

The high frequency and low frequency components of the images are obtained using a bilateral filter. Unlike that in the previously proposed models, instead of using a single dictionary learning stage on some feature model to remove the rain streaks from the high frequency component, the proposed model uses an incremental dictionary learning process based on the structural similarity of the rain streaks in the high-frequency component of a rainy image. However, like that in the previously proposed models, the extracted non-rain component is added back to the low frequency component to get the final de-raining result.

The incremental dictionary learning stage was implemented in the hope to not lose additional background details in the de-raining stage of the high-frequency component, however, it not only made the framework complex but the final de-raining results of the model are also not optimal; the final de-rained image tend to have blurred background. Furthermore, the proposed model is patch-based and therefore it fails to utilize the global structure of the background details, as a result, there are rain streak components in the background layer and background components in the rain streak layer.

12. Removing rain from a single image via discriminative sparse coding

    The authors of [34] also propose the single image de-raining problem as an image decomposition problem where the input rainy image is decomposed into de-rained image or background layer and rain streak layer, like that in [23, 24, 27, 28, 30, 31, 33]. However, unlike that in the previously proposed models, the background layer and rain streak layer is separated and modelled using a non-linear composite model and not by using the low frequency and high frequency component of the rainy image, as it was done in [23, 24, 27, 28, 31, 33].

    The used model is called screen blend model which is an in-build feature of Photoshop. More information on the rain model used can be found at (6). The mathematical equation of the model is as follows -

    $$I = B + R - B * R$$

    Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

    The input image is decomposed into a background layer, a rain streak layer, and the background layer's negative product and the rain streak layer. Patches of the rain and background layers are estimated using discriminative sparse coding and are separated using two set of learned dictionaries that are mutually exclusive. The proposed model uses a greedy pursuit algorithm and simultaneously detects and removes rain streaks from the input rainy image. This is done through an iterative numerical scheme.

    Since the proposed model is patch-based therefore it fails to utilize the global structure of the background details, as a result, there are rain streak components in the background layer and background components in the rain streak layer. The proposed model is ineffective as some thin residual structures can be observed at the location of the removed rain streaks. Moreover, the proposed model requires significant computation as it implements a dictionary learning phase to separate the rain streak and background layers.

13. Rain Streak Removal Using Layer Priors

    The authors of [35] as well proposed the rain streak removal from single images as an image decomposition problem where the rain streak layer is assumed to be superimposed on the clean background layer. More information on the rain model can be obtained at (1). The mathematical representation of the used rain model is as follows -

$$I = B + R$$

    Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

    Unlike the previously proposed methods [23 – 34], the proposed method in [35] does not use any dictionary learning [23, 24, 28, 31, 33] or any low rank filtering methods [25 – 27, 29, 30, 32], instead it uses patch-based priors based on Gaussian Mixture Models (GMM). The authors noticed that by using dictionary learning or low rank filtering methods, the previously proposed model produced poor quality de-rained images; with either the resultant image being blurry because of the over-smoothed background details or the de-rained image still having some rain streaks in the background.

    In the proposed method, two Gaussian Mixture Models priors are trained on pre-collected clean and rainy image patches. The prior model trained on clean and natural image patches is used for modeling the background layer and the prior model trained on rainy patches - incorporating multiple rain streaks orientation and scales, is used for modeling the rain streak layers. The rain patches on which the GMM model is trained, incorporates diverse rain streaks which allows the authors to account for the dynamic nature of the rain streaks.

    The proposed model achieved the state-of-the-art performance of its time however the de-rained images still have a slightly smooth background. Since the model uses a patch-based de-raining approach, its discriminative power is hindered as it fails to utilize the global structure of the background details, a possible reason for not being able to produce perfectly de-rained images.

14. Single image rain and snow removal via guided L0 smoothing filter

    The aim of the research paper [36] is to remove rain streaks or snowflakes from single images. In [36], a new rain model is developed which is a scalar decomposition of the input rainy image. More information on the rain model used can be found at (7). The mathematical equation of the model is as follows -

$$I = (1 - \alpha)B + \alpha R$$

Here, I represents the input rainy image, B represents the background layer, R represents the rain streak layer and α is a scalar constant which quantifies the presence of rain streak density in the input image. α equal to 0 means the input image is rain free and α equal to 1 means there are no background details that can be extracted from the input rainy image.

The proposed model uses a guided L0 smoothing filter to de-rain or de-snow rainy or snowy images. The proposed method is similar to the methods presented in [25, 26, 32], where rain streaks are removed from input rainy images using a filtering process, and the de-raining method is pixel-based. The proposed method is pixel-based; however, the filtering method used here to produce the de-raining or de-snowing result is different from the ones used in the previous research.

Here, a guided L0 smoothing filter is used based on the L0 gradient minimization [70]. Since the proposed method does not involve any long dictionary learning process, its implementation is fast. Moreover, the model is able to produce not the perfect but satisfactory de-raining effects in single images. The proposed model outperforms previously proposed similar models [25, 26, 32] in its de-raining effects.

15. Clearing the Skies: A deep network architecture for single-image rain removal

    [37] is the first paper to address the single image de-raining problem using a deep convolutional neural network (CNN) [71]. Their proposed model is a shallow deep neural network and is called DerainNet. Seeing the recent success of CNNs in several low level computer vision tasks, such as image Inpainting [76], image denoising [72], image deconvolution [75], image filtering [77] and super-resolution [73, 74], the authors of this research paper felt motivated to use the CNN for the de-raining of single images problem.

    The authors of this paper too, like those of [23, 24, 27 – 31, 33 – 35], formulated the single image de-raining problem as the image decomposition problem, where the input rainy image is considered to be a background layer superimposed by the rain streak layer. Similar to the consideration in [23, 24, 27, 28, 31, 33], it is considered that most of the background information is stored and can be extracted from the the low frequency component of the input rainy image and the rain streaks as well as background textures and edges information is stored in the high-frequency component of the rainy image.

    In this paper the low frequency component is referred to as the base layer and the high frequency component is referred to as the detail layer. More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

$$I = I_{Base\_Layer} + I_{Detail\_Layer}$$

Here, I represents the input rainy image, I_{Base_Layer} represents the low frequency component of the input image and I_{Detail_Layer} represents the high frequency component of the input image.

Similar to the approach in [23, 24, 27, 28, 31, 33], in the proposed method too, a low pass filter is used to get the base layer and the detail layer from the input rainy images.

Previous proposed approaches [23-36] either use dictionary learning [23, 24, 28, 31, 33, 34] or low pass filtering [25 – 27, 29, 30, 32, 36] or pre-learned Gaussian Mixture Model priors [35], to detect and remove rain streak layer from the high frequency component and add the remaining high frequency background features to the low frequency features to produce a final de-rained image. However, in the proposed framework, a deep trained convolutional neural network (CNN) is used to extract the rich background details from the high frequency component of the rainy image and is added back to the low frequency component to get the final de-rained results. Moreover, a feature enhancement step is also added in the framework to produce better de-raining results.

The proposed framework works as follows – first, the input rainy image is divided into the base layer and the detailed layer using a low-pass filter. Next, a trained deep convolutional neural network, with hidden 3-layers, is used to detect and remove rain streaks from the detail layer leaving only the background textures and edges details. Now, feature enhancement is used on the CNN processed detail layer and on the base layer. The results of both are added together to produce a final de-rained output.

Training of the deep Convolutional model – To train a CNN on the set of real rain images, ground truth images for those real rain images in the same setting would be required, which is impossible due to the dynamic nature of the rain. The authors of this paper realized this and so they used a synthetic rain images dataset which was created by adding artificial rain streaks of diverse intensity, orientation and shape to non rainy scenes. These synthetic rain images were fed to the CNN for it to learn the non-linear mapping function between the high frequency component of clean images and the high-frequency component of their counterpart synthetic rainy images. The authors trained their CNN model on the detail layer because they observed that it is difficult to directly map clean images from rainy images.

Once the CNN model was trained, the proposed de-raining method produces state-of-the art de-rained results and is also faster than the previously proposed methods. Moreover, the proposed model also shows good performance in keeping the texture details, however, in the case of heavy rain with dense rain streaks, the de-rained output is not optimal.

16. Removing rain from single images via a deep detail network

    [38] is an improved version of [37], proposed by the same authors. In [38], however, the de-raining problem is addressed by using a deeper convolutional neural network based on the structure of deep Residual Network (ResNet) [78]. In [38], like that in [23, 24, 27, 28, 30, 31, 33 – 35, 37], the de-raining of single images problem is considered to be an image decomposition problem where the rain streaks are considered to be present in a layer separate from the background layer. However, instead of using a conventional de-raining rain decomposition model (1) or (3), the authors use the image decomposition using a rain residual model. More information on the rain model can be obtained at (2). The mathematical representation of the used rain model is as follows -

    $$-R = B - I$$

    Here, B represents the background layer, I represents the input rainy image, and -R represents the negative rain streak residual.

    The proposed model is constructed on the assumption that most of the background information is stored and can be extracted from the the low frequency component of the input rainy image and the rain streaks as well as background textures and edges information is stored in the high-frequency component of the rainy image, the authors train their rain residual model on the high frequency component of the input rainy image to learn the negative rain residual mapping. In this paper, the low frequency component is called the base layer and the high frequency component is called the detail layer.

    In the proposed model, the input rainy image is first decomposed into the base layer and the detail layer using a guided filer. Next, the detail layer is fed to their deep detail network, which has ResNet [78] architecture, to get a negative residual map of the rain streaks in the detail layer of the input rainy image. This negative residual is added back to the base layer to produce the final de-rained image. The results achieved in [38] create a new state-of-the-art performance and even surpasses the results achieved in [37].

    The proposed model is based in the idea used in [24] where the high frequency component is fed to the proposed model in [24] which uses dictionary learning to produce a negative residual map of the rain streaks in the high frequency component of the rainy image, which is then added back to the low frequency component to produce de-rained images. In [38] however, instead of using a dictionary learning process to learn the negative residual map of the rain streaks, the authors use a deep convolutional neural network.

The authors adopted a ResNet [78] structure for their deep detail network because they observed that in using a ResNet [78] structure the learning process of the non-linear mapping function from the input image to the output image is significantly easier and faster, as the mapping range has been reduced. They also used their deep detail network on the detail layer of the input rainy image to learn the negative residual mapping of the rain streaks based on their priori knowledge that rain streaks as well as high textured background details are stored only in the high frequency component or the detail layer of the input image, an assumption that is also made in [23, 24, 27, 28, 31, 33, 37].

The proposed deep detail model is trained on a synthetic rain dataset of 14,000 rainy/clean image pairs, which the authors created. They increased their number of images in training data compared to the numbers used in network training in [37] to produce better de-raining results, which their model does. They conclude that a deeper structure improves de-raining performance by avoiding gradient vanishing.

The proposed model is a pixel-based de-raining model. Although it produces state-of-the-art de-raining results, there is still room for improvement, as it was shown a year after that, the proposed method tends to remove some critical information from the background layer [45]. One possible reason for this could be the absence of diverse rain streak orientation in the training dataset [40], or, the reason could be that a single network may not be sufficient enough to be able to lean all types of rain streaks variations in the training dataset [45], or the reasons can be both.

17. Single Image Rain Streak Decomposition Using Layer Priors

[39] is an extension of [35] in which a structure residue recovery step is added to the framework proposed in [35] to produce better de-raining results. In [39], like that in [35], the rain streaks removal from single images problem is formulated as an image decomposition problem where the rain streak layer is assumed to be superimposed on the clean background layer. More information on the rain model can be obtained at (1). The mathematical representation of the used rain model is as follows -

$$I = B + R$$

Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

The proposed model does not use any dictionary learning [23, 24, 28, 31, 33, 34] or any low rank filtering methods [25 – 27, 29, 30, 32, 36] or deep learning approaches

[37, 38], instead it uses patch-based priors based on Gaussian Mixture Models (GMM). The authors noticed that by using dictionary learning or low rank filtering methods, the previously proposed model produced poor quality de-rained images; with either the resultant image being blurry because of the over-smoothed background details or the de-rained image still having some rain streaks in the background.

Similar to the proposed model in [35], in the proposed model of [39] as well, two Gaussian Mixture Models priors are trained on pre-collected clean and rainy image patches. The prior model trained on clean and natural image patches is used for modeling the background layer and the prior model trained on rainy patches - incorporating multiple rain streaks orientation and scales, is used for modeling the rain streak layers. The rain patches on which the GMM model is trained, incorporates diverse rain streaks which allows the authors to account for the dynamic nature of the rain streaks.

However, unlike the proposed framework in [35], an additional structural residue recovery step is added to enhance the structure of the de-rained image and produce a final de-rained output. The proposed model achieved better de-raining results than the results achieved in [35], however, the de-rained images still have a slightly smooth background. Since the model uses a patch-based de-raining approach, its discriminative power is also hindered as it fails to utilize the global structure of the background details.

18. Joint Bi-layer Optimization for Single-image Rain Streak Removal

In [40], the authors proposed a novel single image de-raining framework by decomposing the input rainy image into background layer and rain streak layer. More information on the rain model can be obtained at (1). The mathematical representation of the used rain model is as follows -

$$I = B + R$$

Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

Unlike previously proposed de-raining methods used for decomposed rainy images [23, 24, 27, 28, 30, 31, 33, 35, 37, 39], in [40], the authors aim to jointly remove rain streaks from the background layer and the non-rain component from the rain streak layers. The process is not simultaneous as the proposed model alternates between removing the rain streaks from the background layer and the background details from the rain streak layer.

The proposed model smoothes the background layer to push the rain streaks into the rain streak layer and smoothes the rain streak layer to push the non-rain details into the background layer. The proposed framework uses 3 newly proposed image priors - for preserving the background details and removing rain streaks from the background layer a Centralized Sparse Representation prior is used.

For rain streaks detection, a novel rain detection prior is used which is built on the observation that rain streaks span across narrow directions in even heavy rainy scenes. A rain direction prior is previously used but only in a video de-raining setting [8]. The proposed framework in [40] is the first framework in which rain directional prior is used in single images de-raining problems.

Finally, the third prior is used for removing the non-rain component in the rain streak layer by exploiting the self-similarity between rainy patches. These priors model the objective function of the rain removal problem and are solved using the Alternating Direction Method of Multipliers (ADMM). The proposed method produces better de-raining results as compared to its previously proposed non-deep de-raining methods.

19. Deep Joint Rain Detection and Removal from a Single Image

In [41], a novel generalized rain model is proposed, different from the previously proposed rain models [23-40], in which the input rainy image is decomposed into a background layer and a rain streak layer multiplied by the binary map of rain streak pixels. More information on the rain model used can be found at (8). The mathematical equation of the model is as follows -

$$I = B + RM$$

Here, I represents the input rainy image, B represents the background layer, R represents the rain streak layer and M is the binary rain streak mask. In M, '1' indicates the presence of the rain streak at a pixel and '0' indicates the absence of the rain streak at a pixel.

The authors incorporated the light scattering and attenuation properties of the rain drops and proposed another model for rain accumulation. More information on the rain model used can be found at (16). The mathematical equation of the proposed model is given as –

$$I = \alpha * (B + \sum_{i=1}^{n} S_i M) + (1 - \alpha) * A$$

Here, I represents the Input image, B represents the background layer, S_i represents the i^{th} rain streak layer of the same direction, M is again the binary map of the individual rain streaks, n represents the maximum number different rain streak layers in the model, and finally, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively. A and α are further described in haze removal papers such as [79].

The binary map of rain streaks provides additional information as well as a constraint in the network training process. This model was used in [41, 55] and the method implemented to solve this model is a deep convolutional neural network. Although it is very easy to estimate M, the binary map of rain streak pixels, once S, the rain streak layer, is obtained, however, the authors believe that it is beneficial to model R separately as it will not only provide additional information to the network being trained to detect rain streaks, but it will also provide a new rain removal system which first detects rain regions and then operate on the rainy areas and the non-rainy areas differently. The binary map rain streak has ‘1’ to signify the presence of rain streak in the input image pixel and ‘0’ to signify the absence.

The proposed model consists of two components; one is to represent the accumulation of rain streaks in which the rain streaks are so dense that it is not possible to see an individual streak, and another is to represent different orientations and shapes of the overlapping rain streaks which usually happens in heavy rain scenes.

Based on the proposed rain streak and rain accumulation model, the authors proposed a multi-task deep learning architecture to de-rain single images problem. This multi-task network performs JOint Rain DEtection and Removal (JORDER), which simultaneously detects and removes rain streaks from the input rainy image. It uses a contextualized dilated network based on a recurrent structure which can detect and remove rain streaks iteratively and progressively.

The proposed network performs exceptionally well in the de-raining of single images with heavy rainfall as well as de-raining rain streak accumulated areas.

The proposed method is a pixel-based rain removal method that learns R, the binary mapping of rain streak pixels, the different appearance of rain streaks, and a clean de-rained output. In the proposed method, a binary rain streak map is learned from the rain detected region, which is fed to the recurrent network to learn the intensity and orientation of the rain streaks, which is subtracted from the input rainy image to produce the final de-raining output.

The proposed model is trained on a synthetic rain image dataset and although the model produces good quality results still, being trained on a synthetic dataset is considered to be a disadvantage when de-raining real rainy images [45] as the model trained by a synthetic rain dataset is bounded by its rain streak exhaustiveness. Since the proposed method is not patch-based, it is able to utilize a larger size of receptive field for the de-raining process.

20. Single Image Deraining using Scale-Aware Multi-Stage Recurrent Network

    In [42], the authors addressed the single image de-raining problem as a decomposition problem, however, unlike the previously proposed rain image decomposition models [23, 24, 27, 28, 30, 31, 33, 35, 37, 39, 40] which assumes the input rainy image to be a combination of a background layer superimposed by a rain streak layer, the authors of this paper took the rain decomposition model a step further by modeling the input rainy image as a combination of the background layer superimposed by multiple rain streaks layers.

    The authors also incorporated the light scattering and attenuation properties of the rain drops into their model just like the authors of [41] did. However, unlike the rain model proposed in [41], the authors in [42] did not use a rain streak mask in their proposed rain model. More information on the rain model used can be found at (9). The mathematical equation of the model is as follows -

    $$I = \alpha * (B + \sum_{i=1}^{n} R_i) + (1 - \alpha) * A$$

    Here, I represents the input rainy image, B represents the background layer and R_i represents the i^{th} rain streak layer, n is the total number of different rain streak layers added to the model, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively and finally '*' represents the element multiplication. A and α are further described in haze removal papers such as [79].

    The motivation of the authors for using multiple rain streak layers in the image de-raining model was the observation that in the real world, the rain streaks in the single rainy image have different sizes and densities and a single rain streak layer model is ineffective to detect all of these different rain streaks. This is especially the case in heavy rainfall settings where rain streaks can overlap on each other to produce rain streak appearance of different sizes and orientations.

    The authors observed that the further the rain streak is from the camera which shot the rainy image, the more dense but smaller it is, and vice versa. Realizing the need to be able to detect rain streaks of diverse nature, the authors propose a novel scale-aware multi-stage convolutional neural network which consists of several parallel sub-networks each trained on a different scale of the rain streak. Although the authors are correct in their observation that rain streaks in any rainy image are diverse in nature in terms of their sizes and densities, still the trained convolutional neural network model is susceptible to the synthetic dataset on which it is trained.

21. A hierarchical approach for rain or snow removing in a single color image

In [43], the authors propose the single image de-raining and de-snowing problem as an image decomposition problem, like that in [23, 24, 27, 28, 30, 31, 33, 35, 37, 39, 40], where the input rainy image is decomposed into a background layer and a rain streak layer. It is further postulated that most of the background details can be extracted from the low frequency component of the input rainy or snowy image and the rain streaks or snowflakes can be removed from the high frequency component leaving the remaining non-rain/non-snow high frequency component to be added back to the low frequency to produce a de-rained or de-snowed result of the input rainy/snowy image.

In this paper the low frequency component is referred to as the base layer and the high frequency component is referred to as the detail layer. More information on the rain model can be obtained at (3). The mathematical representation of the used rain model is as follows -

$$I = I_{Base\_Layer} + I_{Detail\_Layer}$$

Here, I represents the input rainy image, $\mathrm{I}_{\mathrm{Base\_Layer}}$ represents the low frequency component of the input image and $\mathrm{I}_{\mathrm{Detail\_Layer}}$ represents the high frequency component of the input image.

The proposed model of [43] utilizes rain/snow detection, mean and guided filter, dictionary learning, and variance sensitivity across colour channels to produce their final de-raining results.

In the proposed model, the input rainy/snowy image is first decomposed into low frequency and high frequency component in a two step process. In the first step, the input rainy image is passed through a rain/snow detector which provides the location map of the rain/snow streaks in the input image. This location map is multiplied with the input rainy image using Hadamard multiplication and fed to a mean and guided filter which is the second step of the decomposition process. The output of this second step is the decomposition of input rainy image into low frequency and high frequency components.

The advantage of using rain/snow detection before the low pass filtering process is that now the low frequency component is almost entirely free of the rain streaks and contains only the background details.

Now that the high frequency component of the input image has been obtained, the rain removal process begins, which follows as 3-layer hierarchical scheme. In the first layer, a dictionary learning process is implemented which classifies the high frequency component details into three classes – non-rain, rain and snow. The classification process utilizes common properties of rain and snow.

In the second layer, the high frequency component is first passed through a rain/snow detector, the result of which is multiplied with the result of the first layer using Hadamard multiplication and is then passed through the mean and guided filter. This makes the result of the second layer. In the third layer, the sensitivity of variance across the RGB channels is computed to enhance the quality of the de-rained results.

The output of all the three layers added back to the low frequency component of the input image creates the final de-rained output of the proposed method. The de-raining results of the proposed method is better than the de-raining results of similar studies done in the past [23, 24, 27 – 31, 33 – 35, 37 – 40], however, the results are still not better than the de-raining results produced by deep convolutional neural networks [37].

22. Convolutional Sparse and Low-Rank Coding-Based Rain Streak Removal

The authors of [44], like that of [23, 24, 27, 28, 30, 31, 33, 35, 37, 39, 40, 43], proposed the single image de-raining model as an image decomposition model in which the input rainy image is considered to be the combination of a background layer superimposed by a rain streak layer. More information on the rain model can be obtained at (1). The mathematical representation of the used rain model is as follows -

$$I = B + R$$

Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

The authors propose a novel Convolutional Coding-based Rain Removal (CCRR) method for the de-raining of single images problem. This CCRR method is based on Convolutional Sparse Coding (CSC) and Convolutional Low-rank Coding (CLC). In the proposed method, two convolutional filters are learned and used to effectively represent the background layer and the rain streak layer. The learned CSC filter is used to represent the background layer and the learned CLC filter is used to represent the rain streak layer.

Using these two convolutional filters, an optimization problem is formulated for the separation of background layer from the rain streak layer which is solved using Alternating Direction Method of Multipliers (ADMM). In the proposed method the image is not decomposed into low frequency or high frequency components, instead, the model uses the entire input rainy image for the de-raining process which makes the de-raining processing faster as compared to the decomposition models proposed in the past [23, 24, 27, 28, 30, 31, 33, 35, 37, 39, 40, 43]. Nonetheless, the quality of the final de-raining results do not match the quality of the de-raining results in [37, 38], which uses deep CNN for the de-raining process of single images.

23. Density-aware Single Image De-raining using a Multi-stream Dense Network

In [45], like that in [38], the single image de-raining problem is modelled as an image decomposition problem where the input rainy image is considered to be the combination of a background layer superimposed by a rain streak layer. More information on the rain model can be obtained at (2). The mathematical representation of the used rain model is as follows -

$$-R = B - I$$

Here, B represents the background layer, I represents the input rainy image, and -R represents the negative rain streak residual.

Similar to that in [38], the model proposed here learns the rain streak residual from the input rainy image using a Convolutional Neural Network and then subtracts it from the input rainy image to produce the final de-rained image; however, unlike the framework in [38], the proposed model de-rains the input image by taking the rain density into consideration. The proposed model is a Density-aware Image De-raining method using a Multi-stream Dense Network (DID-MDN) which is a densely connected Convolutional Neural Network developed for jointly detecting rain density and removing rain streaks from input rainy images.

The proposed method automatically identifies and classifies the rain density label in the input rainy image as – heavy, or medium, or light. This rain density label is then used as a guide by the convolutional neural network to learn the residual rain streak information which is then subtracted from the input image to produce the de-rained results. There are two main components in the architecture of the proposed CNN – one is the novel residual-aware rain-density classifier which determines and classifies the rain density in the input rainy image. Another is a multi-stream densely connected de-raining convolutional network which uses the rain density label to remove rain streaks from input rainy images.

In the proposed framework, the input rainy image is fed to the residual-aware rain density CNN classifier which is trained on different scales and shapes of rain streaks to be able to classify the rain density in the input rainy image as heavy, medium or light. The input image is also fed to the multi-stream densely connected de-raining CNN which receives the rain density label from the residual-aware density classifier and uses it to create a rain streak residual map of the input image. This residual rain streak information is subtracted from the input rainy image after which then 2 additional convolutional layers are used to refine the de-rained output and produce the final de-raining results.

The de-raining results of the proposed framework create a new standard of the state-of-the-art de-raining capabilities by surpassing the quality of de-raining results of [38]. The proposed framework proved that using a multi-scale network is beneficial for single image de-raining problem, a tread that can be seen in the work published after this paper [56, 57, 63 – 65]. It was pointed out in a future work that although the proposed framework gives sate-of-the-art results but since it estimates image level priors which does not consider the location information of the rain streaks, the propose framework tends to introduce some artifacts in the final de-rained results [56].

24. Non-locally Enhanced Encoder-Decoder Network for Single Image De-raining

    According to the authors of [46], the previously proposed deep learning based de-raining methods either focuses only on the end-to-end learning where the CNN is trained to learn the non-linear mapping function from the detail layer of a clean image to the detail layer of its counterpart rainy image to solve the image decomposition problem of dividing the image into high frequency and low frequency component [37], or focuses only on utilizing residual learning to decrease the mapping range to solve the image decomposition model [38] or focuses only on the implementing cascade learning in multi-stage rain removal process [45].

    The authors of the paper [46] argue that even though the existing deep CNN frameworks [37, 38, 41, 42, 45] perform substantially well in the de-raining of single images problem however, these frameworks fail to fully utilize the rationality and superiority of convolutional neural network design. To solve this, the authors propose Non-locally Enhanced Encoder-Decoder Network (NLEDN) which is a fully-convoluted encode-decoder network capable of learning pixel-wise mapping from rainy images to clean images using the self-similarities between the real rain-free background scenes and the structural similarities of the rain streaks.

    The main component of the proposed framework (NLEDN) is a series of Non-locally Enhanced Dense Blocks (NEDBs) that are capable of utilizing not only the hierarchical features from all convolutional layers but also capture the dependencies and structural information of the rain streaks as well as the background details. The proposed framework is shown to produce better de-raining results of the real world rainy images as compared to the results obtained in [37, 38, 45].

25. Residual-Guide Network for Single Image Deraining

    In [47], the authors propose a novel framework based on a recursive convolution neural network called Residual-Guide feature fusion network (ResGuideNet) to address the single image de-raining problem. They built their network on the rain residual image decomposition model. More information on the rain model can be obtained at (2).

The mathematical representation of the used rain model is as follows -

$$-R = B - I$$

Here, B represents the background layer, I represents the input rainy image, and -R represents the negative rain streak residual.

The proposed network is a cascaded network in which the deeper blocks are guided by the residuals of the shallower blocks. Using this framework, the proposed model is able to progressively produce finer de-rained results while using fewer learning parameters than the previously proposed deep convolutional neural networks [37, 38, 41, 42, 45, 46]. The network is based on recursive convolution and the final de-rained output is the merged image of all of the different blocks in the network.

The network performs at reasonable standard in the case of de-raining single images with light rain but its performance is poor in case of de-raining images with heavy or even medium rainfall. The only advantage of the proposed method over previously proposed deep convolutional neural networks is that in this method the number of network parameters that needs to be trained to produce the final de-raining output are considerably very few. For instance, the proposed model only needs 19,000 parameters to be trained while JORDER [41] needs 370,000 trained parameters.

26. Recurrent Squeeze-and-Excitation Context Aggregation Net for Single Image De-raining

    In [48], the authors address the single image rain removal problem by using an image decomposition model which is an extension of the one used in [41]. Similar to the rain removal model used in [41], the authors propose to have multiple rain streaks layers superimposed on the background layer. These rain streak layers are different from each other in respect to the different sizes and densities of the rain streaks that are observed to be present in single rainy images, especially in the case of heavy rainfall.

    Moreover, similar to the model proposed in [41], the authors of this paper also incorporate the global atmospheric light and atmospheric transmission into their model, however, in the proposed model the authors assign alpha-values to the rain streak layers based on the rain streak intensity transparency and they also do not include a rain streak mask in their model.

    The authors observed that in real world settings the rain streak's brightness is hugely affected by the light scattering property of rain droplets in single images, especially in the heavy rainfall scenes, so the authors believed that it is essential to incorporate the global atmospheric light into their model but since their model had multiple rain streak layers, therefore they had to assign different α values to different rain streaks layers. More information on the rain model used can be found at (10). The mathematical equation of the model is as follows -

$$I = (1 - \sum_{i=0}^{n} \alpha_i)B + \alpha_0 A + \sum_{i=1}^{n} \alpha_i R_i$$

subject to

$$\alpha_i \geq 0$$

and

$$\sum_{i=0}^{n} \alpha_i \leq 1$$

Here, I represents the input rainy image, B represents the background layer and R_i represents the i^{th} rain streak layer, n is the total number of different rain streak layers added to the model, A $\in$ [0,1] and $\alpha_0 \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively, and finally, α_i is the brightness of the i^{th} rain streak layer. A and α are further described in haze removal papers such as [79].

Based on this model, the authors propose a novel deep convolutional and recurrent neural network called REcurrent Squeeze-and-Excitation Context Aggregation Network (RESCAN). The proposed framework uses a multi-stage context aggregation network constructed using multiple fully convoluted layers to remove rain streaks from the input image stage by stage. The network is constructed using multiple channels where each channel corresponds to each type of rain streak layer.

The Squeeze-and-Excitation (SE) block uses the correlation information between neighboring stages to assign alpha values to various channels. The framework is built upon Recurrent Neural Network (RNN) structure to be able to utilize useful information from previous stages and produce better de-raining results. The proposed method, by recurrently utilizing dilated CNN and SE blocks, is able to produce good quality de-raining results even in heavy rainfall and rain streak accumulation scenes.

27. Lightweight Pyramid Networks for Image Deraining

    In [49], no rain model is used to address the rain removal from single images problem just like that in [29, 46]. The authors acknowledges the recent success of using deep convolutional neural networks in the single image de-raining problem [37, 38, 41, 42, 45 – 48] but also point out the drawback of using those methods – requirement of significant computation to learn the network parameters which in themselves are in enormous numbers. Realizing the need to develop a faster deep CNN, the authors propose Lightweight Pyramid of Networks (LPNet) for the single image de-raining problem.

The proposed model framework is based on residual and Recurrent Neural networks (RNN) which used the Gaussian-Laplacian image pyramid decomposition algorithm to simplify the model learning process. The resultant model can produce state-of-the-art de-raining results and only need around 8,000 parameters to be trained, less than half of the parameters required in the previously proposed fastest model [47].

28. Deep joint rain and haze removal from a single image

    Based on the observation that the rain streaks which are near to the lens capturing a scene looks like image noise and the rain streaks which are far away from the lens looks like haze veil, the authors of [50] propose a rain model to address this phenomena in the de-raining of single images problem. More information on the rain model used can be found at (9) and (17). The mathematical equation of the model is as follows -

    $$I = \alpha * (B + \sum_{i=1}^{n} R_i) + (1 - \alpha) * A$$

    Here, I represents the input rainy image, B represents the background layer and R_i represents the i^{th} rain streak layer, n is the total number of different rain streak layers added to the model, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively and finally '*' represents the element multiplication. A and α are further described in haze removal papers such as [79]. The proposed rain model is the same model used in [42].

    For the removal of rain accumulation appearing haze, the authors propose that the dark channel of the input rainy image is utilized for the removal of rain accumulated regions from the rainy images. The dark channel in the input image can be represented mathematically as follows -

    $$dark\_channel(R, G, B) = min(R, G, B)$$

    Here, RGB are the Red, Green and Blue channels of the colored image.

    Based on the proposed rain model and rain accumulation model, the authors built a novel convolutional neural network for removing rain streaks and haze from single rainy images using wavelets and dark channels. In this network Haar wavelet transformation is used to separate the rain streaks layer and the background layer, but only to some extent, using the prior knowledge that most of the background details can be found in the low frequency component of the input rainy image and the rain streaks as well as high detail background information can be found in the high frequency component of the background image.

    Now, using the Haar basis function for discrete wavelet transformation produces four-sub images. These four-sub images are – diagonal detail HH, vertical detail HL, horizontal subband LH, and finally, approximation subband LL. The LL subband consists of the low frequency or the main content information of the rainy image, while the HH, HL and LH subband consist of high frequency and detailed information of the rainy image. More specifically, LL subband contains most of the details of the background layer, LH subband contains high textured and edges information of the background layer and finally, the HL subband contains the rain streaks as the raindrops are falling from the top.

Using this specific decomposition of the rainy image obtained from Haar wavelet transformation can not only benefit in removing rain streaks but can also benefit in preserving the high frequency textures and edges background details. Now, to remove haze or long distance accumulated rain streaks, the dark channel of the input rainy image is used as a feature map in the network. The network increases the dark channel mapping between the input rainy image and the output de-rained image to give an effect of de-hazing.

The proposed de-raining and de-hazing deep convolutional neural network is called Simple Rain Removal Network (SRR-Net) which uses a trained Deep Joint Rain and Haze Removal Network (DJRHR-Net). Due to (DJRHR-Net), the proposed framework is able to jointly remove rain streaks and haze from the input rainy images and surpasses the previously proposed de-raining method in its de-raining performance and creates a new state-of-the-art de-raining network.

29. Progressive Image Deraining Networks: A Better and Simpler Baseline

    The de-raining of single images using deep convolutional neural network approaches had gained immense popularity after the first study to use deep CNN was published in 2017 [37]. After that, more than fifteen new studies were published for the single image de-raining using deep convolutional neural networks in just two years [37, 38, 41, 42, 45 – 50]. Although the performance of these deep convolutional neural networks increased considerably, the models also got more complex and diverse, making it increasingly difficult for researchers to analyse these methods while developing new de-raining methods. Realising this, the authors of the paper [51] decided to propose a better and simpler baseline de-raining network for the single image de-raining problem. The performance of their proposed de-raining network was comparable to the previously submitted state-of-the-art more profound, and more complex de-raining network.

    The authors propose a Progressive Recurrent Network (PReNet) de-raining model, the architecture of which consists of a shallow Residual network (ResNet) [78], a Progressive ResNet (PRN) and finally a recurrent layer.

The presence of the recurrent layer is the only difference between progressive recurrent network (PReNet) and progressive recurrent network (PRN). The shallow residual network consists of five residual blocks (ResBlocks), Progressive ResNet (PRN) is implemented by recursively unfolding the residual network (ResNet) [78] into multiple stages without the model parameters being increased. Furthermore, the recurrent layer which exploits the deep feature dependencies across the recursive state of the proposed model is added to the architecture using Convolutional Long Short-Term Memory (LSTM) [80]. Their 6-stages progressive recurrent network removes most of the rain streaks from the input image in the first stage and the rest of the streaks are removed by the following five stages, producing their final de-rained results.

30. Single Image Deraining via Recurrent Hierarchy Enhancement Network

The authors of [52], like that of [23, 24, 27, 28, 30, 31, 33, 35, 37, 39, 40, 43, 44], proposed the single image de-raining model as an image decomposition model in which the input rainy image is considered to be the combination of a background layer superimposed by a rain streak layer. More information on the rain model can be obtained at (1). The mathematical representation of the used rain model is as follows -

$$I = B + R$$

Here, I represents the input rainy image, B represents the background layer and R represents the rain streak layer.

The authors propose a novel deep convolutional neural network for stage by stage de-raining of single images called Recurrent Hierarchy Enhancement Network (ReHEN). The proposed network is composed of two main units – a Hierarchy Enhancement Unit (HEU) and a Recurrent Enhancement Unit (REU).

The HEU is used to generate effective features from the fully extracted local hierarchical features and the REU is used to keep the useful information received from the HEU and assist in the rain removal process in the later stages. In the proposed network different shapes, sizes, orientation and densities of the rain streaks is accounted for by the Squeeze-and-Excitations (SE) block which is added in Hierarchy Enhancement Unit as well as Recurrent Enhancement Unit.

31. Semi-supervised Transfer Learning for Image Rain Removal

In [53], the authors model the rain using a Gaussian Mixture Model (GMM). The proposed rain model is not like the one proposed in [35, 39] as in [35, 39], the rain is modelled as an image decomposition model (1) where GMM priors were used to separate the rain streak layer from the background layer. In [53] however, a new rain model was proposed in which the rain streaks in the single rainy image are approximately represented by the coefficients of the Gaussian Mixture Model.

More information on the rain model used can be found at (1). The mathematical equation of the model is as follows -

$$R \sim \sum_{i=0}^{n} \pi_n N(R|\mu_n, \Sigma_n)$$

Here, R represents the rain streak layer and π_n, μ_n and Σ_n are the coefficients of the Gaussian Mixture Model.

In [53], the authors propose a deep convolutional neural network, which can be trained using supervised as well as unsupervised learning, to remove rain streaks from single rainy images. The authors observed the weakness of the previously proposed deep convolutional de-raining networks as being prone and biased to the nature and exhaustiveness of the rain streaks in the synthetic rain dataset on which they are trained. They also realized that getting a clean view of a real world rainy image is almost impossible; however, it is also pertinent for the deep convolutional networks to be trained on real world rainy images for them to be competent de-raining networks. So they propose a network which is capable of learning non-linear mapping functions from the supervised learning on synthetic rainy images as well as from the unsupervised learning on the real world rainy images.

The proposed network is able to utilize transfer learning from the supervised learning part to learn to de-rain the images in unsupervised learning. This is done by formulating the residual network between the input and the output of the de-raining network as a parameterized rain streak distribution. The de-raining results of the proposed network are better than the de-raining results of network used in [41].

32. Scale-Free Single Image Deraining Via Visibility-Enhanced Recurrent Wavelet Learning

In [54], the authors propose a recurrent neural network for the single image de-raining problem, especially for the case of heavy rain scenes with large rain streaks along with the rain streak accumulation problem in which the rain streaks overlap with each other and create a mist or fog-like appearance. The proposed network is built upon a new rain model which incorporates rain streaks as well as rain accumulation in a single model. More information on the rain model used can be found at (12) and at (18). The mathematical equation of the model is as follows -

$$R = \alpha * B^{\gamma} + (1 - \alpha) * A$$

Here, R is the rain streak layer, B is the background layer, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively, $\gamma > 1$ is a decoding gamma, '*' represents element wise multiplication, and finally, B^{γ} is the gamma expansion of the background layer. A and α are further described in haze removal papers such as [79].

The proposed network is similar to that proposed in [50], as both of the networks use Haar wavelet transformation to separate the rain streaks layer and the background layer, only to some extent though, however, unlike the network in [50], the proposed network is a recurrent neural network.

In the proposed network wavelet transformation is used based on the prior knowledge that most of the background details can be found in the low frequency component of the input rainy image and the rain streaks as well as high detail background information can be found in the high frequency component of the background image. Haar basic function is used for wavelet transformation which produces four-sub images – diagonal detail HH, vertical detail HL, horizontal subband LH, and finally, approximation subband LL. The LL subband consists of the low frequency or the main content information of the rainy image, while the HH, HL and LH subband consist of high frequency and detailed information of the rainy image. More specifically, LL subband contains most of the details of the background layer, LH subband contains high textured and edges information of the background layer and finally, the HL subband contains the rain streaks as the raindrops are falling from the top. Using this specific decomposition of the rainy image obtained from Haar wavelet transformation can not only benefit in removing rain streaks but can also benefit in preserving the high frequency textures and edges background details.

The hierarchical wavelet transformation is embedded into the proposed recurrent de-raining network which removes most of the rain streaks from the low frequency component of the input image and, being a recurrent network, the recovered low frequency component is used as a guide to obtain the background details from the high frequency component. This recurrent recovery process is built upon a dilated residual dense network.

The multi-scale recurrent model built on wavelet transformation enables the proposed network being trained on one side of the rain streak to adapt to rain streaks of different sizes. A new rain model is proposed especially for the removal of rain streaks accumulation and image recovery in low light degradation which improves the visibility and enhances the background details in dark regions. The de-raining results of the proposed model surpass the quality of the de-raining results in [41].

33. Joint Rain Detection and Removal from a Single Image with Contextualized Deep Networks

The authors of [55], address the single image de-raining problem as an image decomposition problem, similar to the rain model proposed in [41], the proposed rain model incorporates different shapes, sizes and densities of rain streaks by assuming multiple rain streak layers superimposing the background layer, where each layer represents a specific type of rain streak. However, unlike [41], [51] uses a single model to represent rain streaks as well as rain accumulation; which appears like mist or fog in the rainy image.

The proposed model also addresses the overlapping of rain streaks of different directions, something that has not been addressed in the previously proposed rain models. More information on the rain model used can be found at (13) and (16). The mathematical equation of the model is as follows -

$$I = \alpha(B + \sum_{i=1}^{n} S_i M) + (1 - \alpha)A$$

Here, I represents the Input image, B represents the background layer, S_i represents the i^{th} rain streak layer of the same direction, M is the binary map of the individual rain streaks, n represents the maximum number different rain streak layers in the model, and finally, A $\in$ [0,1] and $\alpha \in$ [0,1] are the global atmospheric light and atmospheric transmission, respectively. A and α are further described in haze removal papers such as [79].

In the rain streak mask M, '1' indicates the presence of the rain streak at a pixel and '0' indicates the absence of the rain streak at a pixel. This binary map of rain streaks provides additional information as well as a constraint in the network training process. Based on the proposed rain model, the authors propose a Joint Rain Streak Detection and Removal de-raining recurrent neural network.

The proposed network jointly learns the rain streak map, removes rain streaks from the input image, and also restores the background layer details. It uses a multi-task contextualized dilated network which is able to exploit the regional contextual information for image restoration and rain streaks removal. To incorporate the ability to de-raining single images with diverse rain streaks, a recurrent rain removal process is implemented which removes rain streaks from the input rainy image progressively. The proposed de-raining network is able to produce better de-raining results than the networks proposed in [38, 41].

34. Uncertainty Guided Multi-Scale Residual Learning-using a Cycle Spinning CNN for Single Image De-Raining

In [56], the authors propose a rain model for the purpose of removing rain streaks from single rainy images as an image decomposition model. However, instead of decomposing the input rainy image as a combination of a background layer and a rain streak layer, the authors decompose the final de-rained image as a rain streak layer or a residual map of rain streaks subtracted from the input rainy image. More information on the rain model can be obtained at (2). The mathematical representation of the used rain model is as follows -

$$-R = B - I$$

Here, B represents the background layer, I represents the input rainy image, and -R represents the negative rain streak residual.

The authors also propose an uncertainty map that stores the network's confidence score for the residual value of the rain streak at each pixel. The uncertainty map is a quantitative measure of how certain the network is about the presence of a rain streak at each pixel. The uncertainty map was added in the de-raining network because the authors wanted to utilize the rain streak location information as they believed it would yield better de-raining performance, which is valuable information the previously proposed deep learning frameworks have failed to operate.
The authors also believed that the rain streaks, howsoever diverse, do not change drastically with different scales, so they did not add rain streak density detection [45] in their model.

The authors developed an Uncertainty-guided Multi-scale Residual Learning network based on the proposed rain model, which utilizes the rain streak location information to produce final de-rained images using a recurrent neural network. The rain streak location information here refers to the uncertainty map that is estimated by the recurrent network. The proposed network combines the residual and confidence information, which is used as a guide for the recurrent network's future stages to produce the final de-raining image.

35. Multi-scale Attentive Residual Network for Single Image Deraining

In [57], the authors propose a rain model which is a combination of the model used in [41] and [45]. The proposed model utilizes information regarding both the location as well as the density of the rain streak to construct a multi-scale attentive residual network for the joint detection and removal of diverse rain streaks from single rainy images.

The proposed network is a novel end-to-end recurrent network build upon two-stages. In the first stage, a multi-scale progressive network is used to locate the rain streaks and create a rain streak map which is used as a guide in the next stages of the de-raining network. This rain streak map is used as a guide in the second stage which uses it to remove diverse rain streaks from the input rainy image.

A multi-scale residual network based on dilated convolution and residual learning is also constructed for incorporating diverse rain streaks with different scales and density into the network. This network predicts the density of the rain streak in the rainy image and uses this information for the joint detection and removal of rain streaks from the input rainy images.

36. Depth-Attentional Features for Single-Image Rain Removal

Based on the observation that the rain streaks vary in depth and the rain streaks that are far away from the camera that shot the rainy image takes the appearance of fog, the authors of [58] proposed a new rain model in which they not only incorporated the rain streaks but also incorporated the presence of fog in the input rainy image. Their rain model is also an image decomposition model where the background image is assumed to be superimposed by a rain streak layer, however, they also incorporated fog, light scattering properties of the rain streak as well as a depth parameter into their model.

More information on the rain model used can be found at (14) and (19). The mathematical expression of the proposed complex rain model is as follows –

$$I = B(1 - R - F) + R + AF$$

Here, I represents the input rainy image, B represents the background layer, R $\in$ [0,1] represents the rain layer, F $\in$ [0,1] represents the fog layer and A is the atmospheric light. High values of R or F indicate the high intensity of rain streaks or fog in the rainy image, respectively, while '0' mean that there is no rain or fog in the input rainy image. Here, a fog layer indirectly represents the rain accumulation as rain accumulated regions are most often perceived as fog or mist.

The rain layer is further modelled as a combination of rain streak intensity and the rain streak intensity map. The mathematical equation of the proposed layer streak layer model is as follows –

$$R = Int * M$$

Here, R $\in$ [0,1] represents the rain streak layer, as shown above. Int $\in$ [0,1] is rain streak intensity image in the image space, M represents rain streak intensity map which is modelled as a function of depth of the rain streaks in the rainy image and '*' represents pixel-wise multiplication. In the rain streak mask M, '1' indicates the presence of the rain streak at a pixel and '0' indicates the absence of the rain streak at a pixel. This binary map of rain streaks provides additional information as well as a constraint in the network training process.

The fog layer is modelled as an exponential function of the depth of the rain streaks, the mathematical equation of which is as follows –

$$F = 1 - e^{-\beta d}$$

Here, F $\in$ [0,1] is the fog layer, β is the attenuation coefficient, and d is the scene depth. The value of β represents the thickness of the fog, greater the value of β, thicker the fog and as the value of β decreases the thickness of the fog decreases as well. $\beta = 0$ mean there is no fog in the rainy image.

Based on the proposed rain model, the authors propose a depth guided rain removal network that learns the depth attenuation features which are used as a guide to remove the rain streaks from the input rainy image. Although the authors tries to add another parameter to improve the de-raining results, they evidently failed to understand the rainy scenes and so their proposed network is not able to produce better de-raining results than the state-of-the-art de-raining models.

37. Single Image Deraining Using Bilateral Recurrent Network

In [59], a recurrent network is built on the rain residual image decomposition model. More information on the rain model can be obtained at (2). The mathematical representation of the used rain model is as follows -

$$-R = B - I$$

Here, B represents the background layer, I represents the input rainy image, and -R represents the negative rain streak residual.

The authors observed that the previously proposed deep de-raining networks focus only on learning the rain streaks residual to remove the rain streaks from the input rainy images. The authors believe that although these methods perform very well in de-raining single rainy images, their performance can be increased if they were to also focus on the background layer restoration and so they proposed a Bilateral Recurrent Network (BRN) composed of two individual Single Recurrent Network (SRN) coupled together.

The proposed bilateral recurrent network is used to simultaneously remove the rain streaks and restore the background details of the input rainy image. Moreover, each single recurrent network uses Long Short–Term Memory (LSTM) [80] to learn not only the residual map of the rain streaks but also to learn the direct mapping from the input rainy image to the output de-rained image so that the network can exploit the composition patterns of the rain streak layer as well as the background layer to produce the final de-rained images.

38. Rain Streaks Removal for Single Image via Kernel-Guided Convolutional Neural Network

    In [60], the authors propose a rain model as an image decomposition model, however, they also incorporated the motion blur mechanism, a mechanism that leads to the line pattern appearances of the rain streaks, into their rain model. More information on the rain model used can be found at (9). The mathematical representation of the model is as follows -

$$I = B + K(\theta, l) * M$$

    Here, I represents the input rainy image, B represents the background layer, $K(\theta, l)$ is motion blur kernel – a function of the angle θ and the length of the motion blur l, '*' is the spacial convolutional operator, and finally, M is a binary mask of the rain streak pixels.

    Based on the proposed rain model, the authors propose a novel kernel-guided convolutional neural network for the de-raining of single rainy images. The proposed framework consist of three stages, in the first stage, a motion blur kernel is learned from the high frequency component or the detail layer of the input rainy image. In the second stage, this learned kernel is stretched into a degradation map, which is used in the third stage along with the high frequency component or the detail layer of the input rainy image to train the de-raining network. The proposed de-raining network has residual network (ResNet) [78] architecture and is used to remove rain streaks from the rainy image under the guidance of the motion blur kernel.

39. Image De-raining Using a Conditional Generative Adversarial Network

    In [61], the authors, instead of proposing an image decomposition rain model, proposed a framework that aims to directly learn the non-linear end-to-end mapping function from the input rainy image to the corresponding rain-free output. They constructed a Generative Adversarial Network (GAN) based de-raining network called Image De-raining Conditional Generative Adversarial Network (ID-CGAN) which is composed of 3 components – a generator, a discriminator, and a new perpetual loss-function.

    The proposed de-raining network prevents the degradation of the background details to produce better de-raining results. Same as any traditional Generative Adversarial Network (GAN), the Image De-raining Conditional Generative Adversarial Network also has two sub-networks, a generator sub-network and a discriminator sub-network.

    A generator sub-network is a densely connected symmetric deep convolutional neural network whose primary goal is to synthesize the de-rained output image from the rainy input image. Whereas, a discriminator sub-network distinguishes between the de-rained input produced by the generator from the corresponding rain-free or the ground truth of the input rainy image. The purpose of the perpetual loss function is to make sure that there are no artefacts that are introduced in the de-rained output produced by the generator to ensure the better visual quality of the final output.

40. Beyond Monocular Deraining: Stereo Image Deraining via Semantic Understanding

    The authors of [62] noticed that there had been a lot of research published for the single image rain removal problem however, no previous research had addressed the rain removal problem from stereo images. There had been few pieces of research published on the rain removal from stereo media but they were either for removing adherent rain droplets in stereo images [81] or for removing rain streaks from stereo videos [9]. So in [62], the authors propose a Paired Rain Removal Network (PRRNet) for the single image rain streak removal problem.

    The proposed network is a stereo semantic-aware de-raining network that uses the per-pixel loss function as well as the semantic information to remove rain streaks from single stereo input rainy images. The proposed Pair Rain Removal Network consists of three sub-networks – first is a Semantic-Aware De-raining Module (SADM), second is a Semantic-Fusion Network (SFNet) and finally the third is a View-Fusion Network (VFNet).

    The Semantic-Aware De-raining Module (SADM) jointly de-rains the stereo images and along with that, also understands the semantic information in the image. The Semantic-Fusion Network (SFNet) fuses the semantic information with the coarse de-raining images. The View-Fusion Network (VFNet) fuses the different views information to produce the final de-rained output.

    The proposed de-raining network simultaneously utilize the semantic information along with the cross views in the stereo images to remove rain streaks from the input rainy stereo images. The authors of [62] also propose a new stereo based rain images dataset for creating a new benchmark for the stereo de-raining networks.

    The proposed network can effectively extract and exploit the semantic information as well as the multi-view information present in the stereo images for its de-raining process.

41. Multi-Scale Progressive Fusion Network for Single Image Deraining

    The authors of [63] believed that rain streaks across different scales are highly correlated and that the previous deep learning frameworks have failed to utilize this information in their de-raining networks. So they proposed a Multi-Scale Progressive

Fusion Network (MSPFN) which successfully exploits the correlated information of the rain streaks across different scales of the input rainy image.

The proposed network consists of four components – the first is a multi-scale pyramid structure generator, the second is a multi-scale Coarse Fusion Module (CFM), the third is a multi-scale Fine Fusion Module (FFM) and finally, the fourth is a Reconstruction module (RM).

A multi-scale pyramid structure is generated in the first component which is a gaussian pyramid of the input rainy image constructed using Gaussian Kernels. The Coarse Fusion Module (CFM) is used to capture the global structure details of the multi-scale input rainy images. These global texture details are used to cooperatively represent the target rain streaks and are extracted using a recurrent convolutional Long Short-Term Memory (LSTM) [80].

The Fine Fusion Module (FFM) is used to fuse the correlated information of different scales of the input rainy images. Multiple Fine Fusion Modules are cascaded in the network to create a progressive multi-scale fusion network. Finally, the Reconstruction Module (RM) is concatenated to the network or producing the final de-rained results of the network. This is done by combining the coarse rain streak information, obtained from the Coarse Fusion Module, with the fine rain streak information obtained from the Fine Fusion Module.

42. Multi-Scale Attentive Residual Dense Network for Single Image Rain Removal

In [64], the authors propose a Multi-scale Attentive Residual Dense Network (MARD-Net) to extract the rain streak residual while preserving the original structure and colour information of the rainy image for the de-raining of single rainy images problem. The proposed network is built upon an image decomposition model where the output de-rained image is decomposed into the combination of the input rainy image along with the negative rain streak residual image.

More information on the rain model can be obtained at (2). The mathematical representation of the used rain model is as follows -

$$-R = B - I$$

Here, B represents the background layer, I represents the input rainy image, and -R represents the negative rain streak residual. The rain streak residual is subtracted from the input rainy image to produce the final de-rained output.

The proposed network uses the feature reuse and feature propagation technique for the representation o the rain streaks in the proposed model. The architecture of the dense network consists of multiple convolutional layers coupled with multiple Multi-scale Attention Residual Blocks (MARB). These blocks are used as guidance for the feature extraction and representation of the rain streaks.

The input of each layer in the network is a new feature that is obtained by concatenating the output features of the previous layers. The concatenated combination of the features of different scales and layers is done to efficiently capture the diverse rain streaks components, especially in the heavy rain image scenes.

The Multi-scale Attention Residual Blocks uses different convolutional kernels, which are fused together, to extract the multi-scale rain features and a feature attention module to detect the rain streak regions and different colour channels. The multi-scale attention residual block with the same colour representation shares the same parameters. The accelerate the convergence, multi-scale attention residual block also uses ship connections and feature aggregation at multiple levels inside the network.

43. See clearly on rainy days: Hybrid multiscale loss guided multifeature fusion network for single image rain removal

    The authors of [65] observed that the rain streaks in a rainy image are diverse in nature, with different sizes, shapes and densities and the regions with rain accumulation appears to be foggy or misty. Based on this observation, the authors propose a hybrid Multi-Scale loss Guided Multiple Feature Fusion Network (MSGMFFNet) which treats the rain streaks regions and rain accumulation regions differently for the purpose of removing them from the input rainy images.

    The proposed network is built upon four modules, the first is an attention map learning module, the second is a multi-input feature extraction module, the third is a multiple feature fusion module and finally, the fourth is a reconstruction module.

    The attention map learning module generates the rain streak location map which helps the network to focus on the regions with rain streaks along with the texture details around those regions. After this, two enhanced images are created from the original input rainy image using gamma correlation and contrast enhancement for better global visibility of the original image features.

    The contrast enhancement improves the global visibility but at the cost of the details in the bright areas, however, using a gamma correlation enhancement these details can be preserved. The two enhanced images along with the original input rainy image are fed to the multi-input feature extraction module where image features are extracted under the guidance of the rain streak or rain attention map. Then, the multiple feature fusion module computes the weight map or the confidence map of the characteristics of each input and blends the features together. Finally, the reconstruction module produces the final de-rained image after restoring the original resolution of the image.

44. Successive Graph Convolutional Network for Image De-raining

    In [66], like that in [29, 46, 49, 51, 61, 62, 63, 65], no rain model is used to represent the rain streaks or the rain accumulation in the input rainy image. The authors of [66] observed that the previously proposed deep convolutional neural networks fail to utilize the long-range contextual information by only utilizing the local spatial information in the input rainy image and so proposed a Graph Convolutional Network (GCN).

    In the proposed network two graphs are built to represent the new dimensions that are introduced by the authors. The first graph is used to represent the global spatial relationship between the pixels in the input rainy image and the second graph is used to represent the irrelationships across the rain channels. The proposed network is built upon a convolutional recurrent network framework and uses a comprehensive feature set built upon channel correlation, global spatial coherence and local spatial patterns to de-rain the input rainy images.

    The model proposed in [66] produces good quality de-raining images and is the current state-of-the-art de-raining model for single image de-raining problems.

3 Methodology

As seen in the previous research, for any type of de-raining method, single image-based or video-based, two processes are imperative – detection of the rain streak pixels in the media and the simultaneous removal and reconstruction of those pixels. The method proposed in this research is for removing rain streaks from single rainy images.

Most of the de-raining methods use deep neural networks which are complicated and requires tremendous resources for model training as well as image de-raining in both time and computational power. The proposed model aims to remove rain streaks from input rainy images without using deep neural networks; instead, it will use traditional python computation to de-rain still images.

The method proposed in this study is based on two assumptions, first, the rain streaks infested pixels in an image have intensity value greater than their neighbouring pixels and second, the background details can be obtained by utilizing the information existing in those neighbouring non-rain pixels.

In any de-raining method, single image or video, the first step is always to detect rain streaks pixels, the second step, which is not necessary to implement, is the removal of false positives detected in the first step. In the final step of the de-raining method, the rain streak pixels are augmented by the neighbouring or background matching pixels. In this study, two approaches are tested for the rain detection process, three approaches are tested for the negation of false positives and finally, four approaches are tested for the rain streak removal method.

Rain streak detection using pixel brightness as well as rain streak detection using edge detection are the two approaches that are tested for the rain streak detection process. For negating the false positives process, in the first test approach, face, body and object detection is used. In the second test approach, OpenCV background subtraction is used, and finally, the transparency channel of the coloured image is used as the third testing approach. For the removal of rain streaks, the Inpaint algorithm, patch Row-min, patch row-mean and average pooling approaches are tested. This study will use and compare all of the approaches mentioned above and finally present the result using the best approach.

3.1 Rain Streaks Detection

Rain streaks tends to be much brighter than their background [1, 3, 5, 48, 65], so by determining the pixels which are brighter than their neighboring pixels, rain streaks can be identified. Another method to detect rain streaks is by using Edge Detection. Due to the sparse and translucent nature of the rain streaks, they appear to have thin edges. OpenCV library has a powerful edge detection algorithm – Canny [82]. Using this algorithm, edges of rain streaks can be identified within an image and further processing can be done to remove them. This study will use and compare both the "detection of rain streaks using the brightness of the pixels" and "the detection of rain streaks using edge detection" and finally present the best rain streak detection method.

Detection of rain streaks is done in Gray Scale image of the colored image, to save processing time. Moreover, it is easier to detect brighter pixels in gray scale images than it is in RGB images. Plus, the location of rain streak pixels detected in gray scale image remains the same as it is in the RGB image. This makes gray scale images better for rain streak detection.

3.1.1 Using pixel brightness

Rain streaks tend to be much brighter than their background [1, 3, 5, 48, 65], so by determining the pixels which are brighter than their neighbouring pixels, rain streak pixels can be identified. There are two ways to detect pixels that are brighter than their neighbours. One is by using the "Relative luminance" formula and another is by selecting the pixels which are greater than the row mean of the frame they are in.

Relative Luminance

Luminance of each pixel can be calculated by the formula given as –

$$Luminance = (0.2126 * R + 0.7152 * G + 0.0722 * B) \quad (1)$$

Here, RGB are the RGB of the colored image. The pixels which are brighter will have greater luminance value.

Row Mean of a Frame

The second method is hypothesized by me. A frame is a subset of the image of size 80x30 (chosen by me by hit and trail). I choose the size 80x30 because the row average of 30 columns pixels is the best option for choosing the threshold value of the brightness of the row pixels. Any pixel which is greater than this threshold value is brighter than its neighbours and is considered as a rain streak pixel.

In 80x30 frames, the small number of columns considers 30 pixels as neighbouring pixels for accurate rain streak identification and the large value of the row decreases the number of times the system has to loop over, thus increasing the processing speed. Row average is used instead of column average because rain streaks are vertically inclined. Below is an example of a frame selected from the greyscale version of the original image along with the results of de-raining this frame by two different methods of rain streak detection.

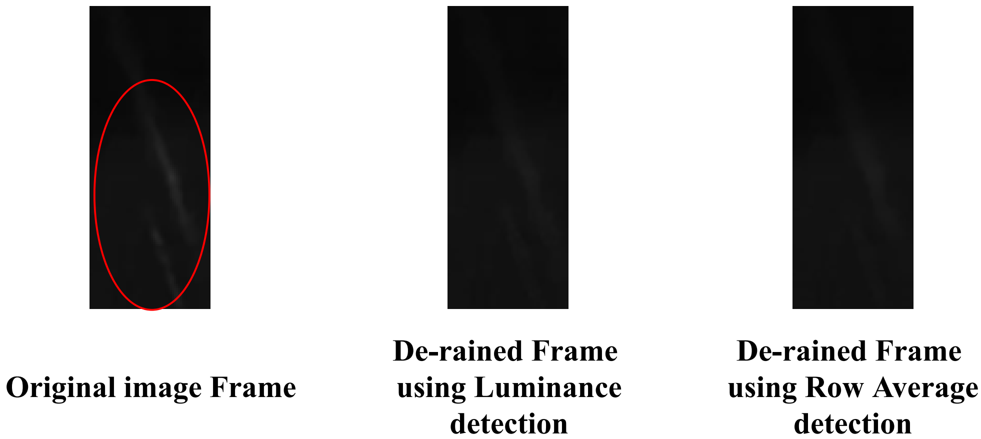


Figure 3.1: De-raining using Luminance VS De-raining using Row mean brightness

The red shape in the original frame shows a rain streak which is detected by two different methods and is then removed. The de-raining results obtained from these two methods are similar and so both of these methods can be used for rain streaks identification. The final results of the entire image will be compared in the results section.

3.1.2 Using edge detection

Another method to detect rain streaks is by using Edge Detection. OpenCV library has a powerful edge detection algorithm – Canny [82]. Using this algorithm, edges of rain streaks can be identified within an image and further processing can be done to remove them.

Three different Edge Detection models are used to detect edges in the images. These are explained below.

Sobel Edge Detection

Sobel Edge Detection works by calculating the gradient of image intensity at each pixel within an image. Since rain streaks are vertically inclined therefore I will use a Y-directional kernel to detect vertical edges. This Y-directional kernel is given as –

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Laplacian Edge Detection

Laplacian Edge detector compares the second derivative of an image, i.e. it compares the rate of change of the first derivative in a single pass [10]. It uses only one kernel and contains negative values in a cross pattern, as given below –

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Canny Edge Detection

Canny Edge Detection [82] is the most frequently used edge detection technique. Canny is based on the idea that the intensity of an edge is higher than its neighbours, however, one drawback is that Canny is prone to noise and so it detects more than just edges. The thresholds values of cranny are selected as (9, 15) by hit and trial.

In Figure 3.2, the comparison of the result of all three edge detection techniques along with the original greyscale image is shown.

As it can be seen in the Figure 3.2, the Laplacian technique performs the worst and fails to detect rain streaks. Sobel Technique performs better but also fails to detect all of the rain streak edges. Canny performs best among these edge detection techniques, however being prone to noise, detects more than just edges. Changing the threshold values either result in more noise detection or fewer rain streaks edges detection. Nonetheless, since Canny was successful in detecting all of the rain streaks edges, so it will be used for rain detection and final results comparison.

Note – To use Canny for rain streaks detection, an extra step has to be added. As Canny only detects the edges, therefore, the result of canny contains only the edges of rain streaks. Since we want to remove entire rain streaks and not just their edges, therefore the canny edges need to be filled and the value in between these edges should also be tagged as rain pixels. To do this, a code was written which marks all the pixels between two edges as rain pixels, if and only if, there are less than or equal to three pixels in between any two-row edges. A snippet of the result of this code is shown in Figure 3.3.

Modified results of Canny Edge detection, that is the canny edge detection results with filled edges, will be used for comparison in results section.

3.2 Negating False Positives

When detecting the rain streaks, by either using the bright pixels method or by using edge detection, the bright pixels, as well as the edge details of the background layer, are also selected. If these pixels are augmented with the average neighbouring values then the visibility of the objects gets degraded, which is not desirable. To fix this, a mask matrix is used which stores the positions of the pixels of the objects in the image. When pixel removal/augmentation is done, these object pixels are ignored.

Three techniques were used for the creation of this mask matrix, each is explained below.

3.2.1 Using Face, Body or Object Detection

Face and body can be detected using Haar cascades which is a machine learning approach where a cascade function is trained with a set of input data. To use Haar cascades, the Face and body classifiers need to be downloaded from the OpenCV GitHub repository.
Once downloaded, these classifiers can be used to detect face/body in the image which can be excluded from the augmentation of pixels. Object detection in images is done by a similar technique. Use a pre-trained classifier to detect an object in the image. However, this method of determining the mask array is not optimal due to the following reasons –

- These classifiers fail to detect face/body unless they are clearly and fully visible in the image, which is not the case in most of the images.
- Since not every image may contain a face or a body, therefore using this method will decrease the robustness of the study to be applied in any rainy image.
- These classifiers are pre-trained on specific objects, for instance, a stop sign. However, no classifier exist that can identify any object in any image.

The results of using facial detection (identified by a rectangular area) on two different images are shown in figure 3.4.

Full-body classifiers, as well as upper-body classifiers, also were not able to detect Thor in either of the images. Moreover, with no classifier is present for detection of hammers or objects in general and these classifiers not yielding desired results, this method is not an optimal method for detecting objects/people in images.

3.2.2 Using OpenCV background subtraction

Background Subtraction is a widely used technique used for generating foreground mask. This technique is mainly used for creating foreground mask in videos, however, it can also be used in single images. Regrettably, it does not produce desirable output.

The output of Background Subtraction when applied to the gray scale of the original image is shown in Figure 3.5.

The gray mark highlighted with the red circle, in the figure 3.5, is the only part of foreground this method was able to detect. Needless to say, this method is also not feasible for the development of this study.

3.2.3 Using Transparency Channel

The transparency channel is different from RGB channels and is used to define the transparency of specific areas of the photos. Using this channel, areas which are opaque, usually, the background can be determined.

Using the transparency channel, the foreground was differentiated from the background and a background mask was obtained. The result of using the transparency channel, with threshold values selected by hit and trial, is shown in the Figure 3.6.

The black pixels, in Figure 3.6, represent the background while the white pixels represent the foreground. All the rain streaks pixels identified in the first component, which are also the foreground pixels, will be ignored for augmentation/removal. Giving the best results, this method will be used for the creation of a background mask.

3.3 Rain Streaks Removal

Removing the rain streak after detection is the final component of the development of this model. Rain streaks can be removed in four ways, three out of which are hypothesized by me. The description of these techniques is given below.

3.3.1 Using Inpaint Algorithm

the Inpaint algorithm can be used to remove undesired areas of images [72]. However, to use Inpaint, a mask is to be used which contains the location of the pixels of the unwanted area. This mask is created by the user. This is not possible to be done for de-raining of images as the user can not be expected to mark all the rain streaks in an image. This fails the main purpose of de-raining images.

Despite being fast, it is not optimal to use the Inpaint algorithm because it does not produce good visual coherence in most cases [47]. But, the logic of the Inpaint algorithm – replacing undesired pixels by the average of neighbouring pixels, can be used to remove rain streaks after rain streaks pixels have been identified.

3.3.2 Using Image Patch Row-Minimum

Even though the Inpaint algorithm can't be used for the development of this study but the idea on which it is based can be used. It takes the unwanted pixels and replaces them with the average of its neighbouring pixels. Since rain streaks are vertically inclined therefore I will use the minimum value of the neighbouring row pixels to replace the rain streak pixel. Minimum of the neighbouring pixels is used for attaining a higher de-raining effect. How many neighbouring pixels to use can be selected manually for getting optimal results.

The de-raining result using 3 neighbors is shown in Figure 3.7.

Using the Minimum value of the 3 neighboring pixels produces distorted image. So this should not be used in any case.

3.3.3 Using Image Patch Row-Mean

Using the same logic as above, the rain streak pixel can be replaced with the average value of the neighbouring row pixels. How many neighbouring pixels to use can be selected manually for getting optimal results.

Averaging of the neighbouring pixels has a less de-raining effect as compared to that of the previous method. Results were obtained using 5 neighbours and 7 neighbours and are shown in Figure 3.8.

From Figure 3.8, it is evident that using the Average value of the 5 neighbouring pixels does not produce much de-raining effect and if neighbours are increased to 7, then the resulting image is of low quality. In any case, this is also not an optimal method for rain removal.

3.3.4 Using Average Pooling

In this method, a pooling matrix is created. This matrix can be of size 3x3 or 5x5 or 7x7 and so on. The element in the middle of the matrix is the identified rain streaks and all the other elements are its neighbouring elements. This method is inspired by the Max Pooling layer of the convolutional neural networks. In this, the rain streak pixel is replaced by the average of all the neighbouring elements. If the rain pixel is a corner pixel, then the average is calculated on its neighbouring pixels. Zero is not filled in the unavailable pixel values to maintain the accuracy of the model.

Results obtained using 5x5, 7x7 and 9x9 average pooling matrix are shown in Figure 3.9.

From Figure 3.8, it is evident that de-raining using 5x5 average pooling yields a better result than all of the de-raining methods given above. De-raining using 7x7 average pooling produces better de-raining results than 5x5 but at the cost of quality degradation. 9x9 produces the maximum de-raining effect but also given the lowest image quality. Regardless, since this method gives the best results along with all the other methods therefore this will be used for de-raining in the final results.

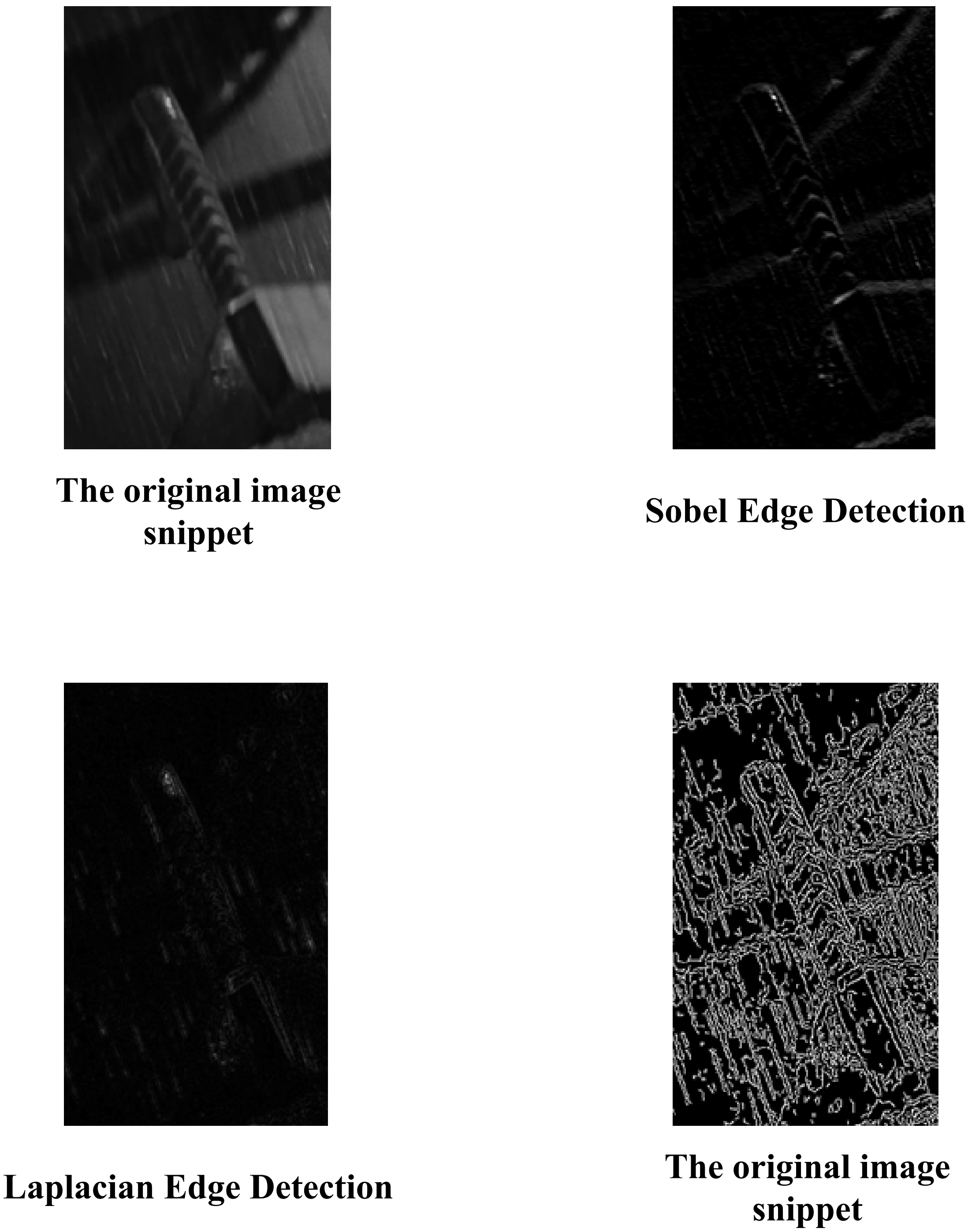
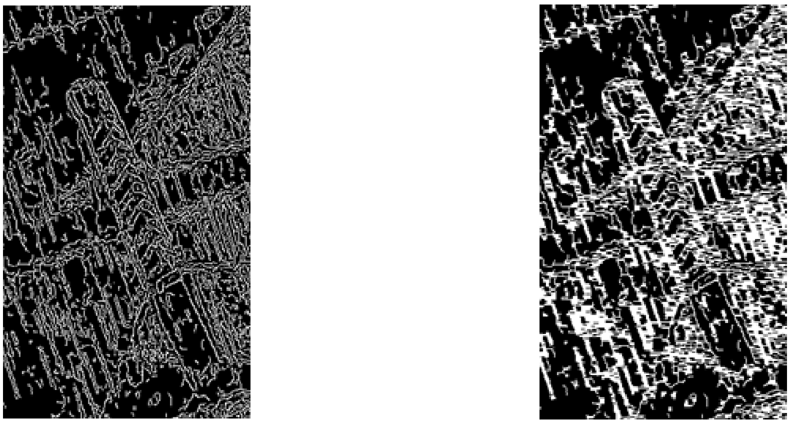


Figure 3.2: Edge detection techniques results

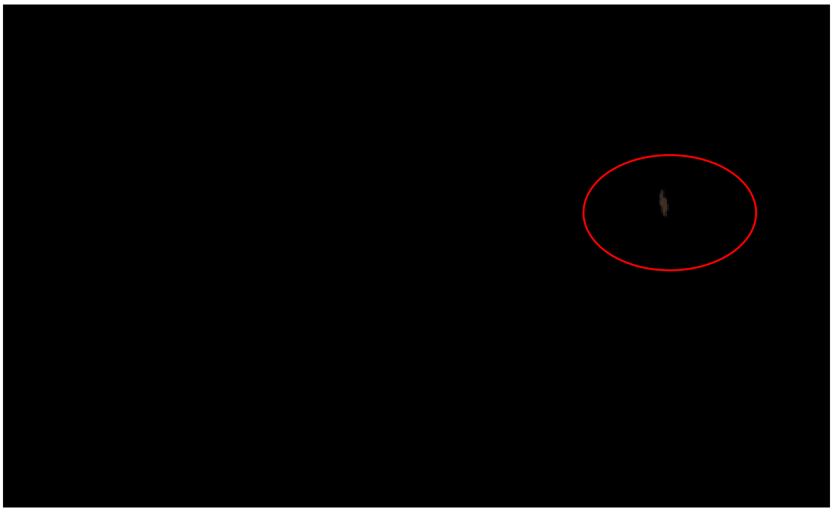


Result of Canny Edge Detection **Result of Filled-Edges**

Figure 3.3: Filled edges result for rain streak detection

Face Detection on original Image **Face Detection on another photo**

Figure 3.4: Face detection results on multiple photos



Text

Figure 3.5: Background Subtraction result of original image

Figure 3.6: Background Mask using Transparency Channel

Using Minimum of 3 neighbours

Figure 3.7: De-raining results using row minimum replacement

Using row average of 5 neighbours

Using row average of 7 neighbours

Figure 3.8: De-raining results using row average replacement

Using 5x5 average pooling

Using 7x7 average pooling

Using 5x5 average pooling

Figure 3.9: De-raining results using average pooling replacement

4 Evaluation

From the methodology section, it was decided that

- Identification of rain droplets will be done using Luminance, Row mean values and Canny edge detection, with filled edges.
- Transparency Channel will be used for generating background mask matrix.
- Finally, average pooling will be used for rain removal.

The results of de-raining the original coloured image using a 5x5 average pooling matrix for rain removal, transparency matrix for generating background mask and Luminance, Row mean and modified Canny for rain identification are shown in the Figure 4.1.

If the final outputs in Figure 4.1 are enlarged and looked closely, the de-raining results are best achieved when using the Row Mean Detection technique clubbed with background mask generation using Transparency channel and average pooling using a 5x5 matrix.

Since the transparency channel, which separates the background from the foreground based on the transparency values of the objects in the rainy image, is used in the proposed model, it can be said that the proposed model is built on the image decomposition model where the input rainy image is assumed to be a combination of the background layer and the rain streak layer. For more details on the model refer to (1). The mathematical representation of the model is as follows -

$$I = B + R$$

Here, I is the input rainy image, B is the background layer and R is the rain streak layer.

Based on the model configurations specified above, further testing was done on a subset of the rainy image dataset. The results of this testing are shown in Figure 4.2, Figure 4.3, Figure 4.4 and finally, Figure 4.5.

Furthermore, the proposed model de-raining results are compared with the de-raining results of the methods proposed in [40] and [41] in Figure 4.6 and Figure 4.7 respectively. The de-raining results of [40] as well as [41] surpasses the quality of the de-raining results of the proposed model.

From Figure 4.1 to Figure 4.7, it is clear that the proposed model is not efficient in removing rain streaks as the resultant de-rained images are blurred and have lost image details in abundance. It can be observed in Figure 4.3 that the proposed de-raining method fails to remove most of the rain streaks, especially in the case when the rain streaks are in focus. This is due to the utilization of a background mask based on the transparency channel which prevents the de-raining of objects focused in the image. Obviously, then focused rain streaks will then not be removed using this model.

On the bright side, the proposed model is a single image de-raining that does not require significant computation or system specification for the implementation of the de-raining process. The proposed model does not involve any time-consuming model training stages and is able to produce the final de-rained output within minutes.

The average time it takes to produce a de-rained image (without using GPU) –

- Using Row Min function is approximately 10 seconds.
- Using Row Average function is approximately 15 seconds.
- Using Average pooling function, with matrix size 5x5, is approximately 50 sec.

These performance results are better than most deep neural network models which usually take minutes to de-rain an image.

Original Image

De-rained image using Luminance detection

De-rained image using Row Mean detection

De-rained image using filled edges in Canny Edge detection

Figure 4.1: Final De-raining Results in the input rainy image

Original input rainy image

De-raining using the proposed method

Figure 4.2: Test 1 results of the proposed de-raining method

Original input rainy image

De-raining using the proposed method

Figure 4.3: Test 2 results of the proposed de-raining method

Original input rainy image

De-raining using the proposed method

Figure 4.4: Test 3 results of the proposed de-raining method

Original input rainy image

De-raining using the proposed method

Figure 4.5: Test 4 results of the proposed de-raining method

Original input rainy image

De-raining results using method proposed in [40]

De-raining using the proposed method

Figure 4.6: Comparison of de-raining results - Method of [40] VS method proposed in this study

Original input rainy image

De-raining results using method proposed in [41]

De-raining using the proposed method

Figure 4.7: Comparison of de-raining results - Method of [41] VS method proposed in this study

5 Conclusion

In this study, various single image de-raining as well as video de-raining methods are studies and categorized based on the method or the model they use. Furthermore, a new de-raining model was introduced in section 3 which uses the transparency channel of the input rainy image to remove rain streaks. Few approaches were tested for rain streak detection, as well as, for negating false positives and rain streak removals.

As seen in section 4, the proposed de-raining model is not optimal as it produces blurry de-rained images with plenty of background information being lost. The proposed method was able to produce some de-raining effect in the final de-rained images however, these results do not compare to the current state-of-the-art de-raining methods [66]. Nonetheless, the proposed de-raining method, which only produces some de-raining effects, is built on a system with standard specification, no GPU or graphic card and without the time consuming neural network architecture. It does not involve any model training nor does it require significant computation to produce the final results. Moreover, the final results are obtained within minutes.

Lastly, few assumptions were made during the development of the proposed model. For instance, the size of the frame that was decided as 80x30, threshold values used for Cranny Edge detection and finally, the threshold values used for Transparency Channel. These values were used without any validation. Proper research for selecting the values of these parameters should have been conducted and perhaps cross-validation should be used to determine the best parameter values for these variables.

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A1 Appendix

Additional model testing results are provided here.

A1.1 Test 5 results

Original input rainy image

De-raining using the proposed method

Figure A1.1: Test 5 results of the proposed de-raining method