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Video Deraining Mechanism by Preserving the Temporal Consistency and Intrinsic Properties of Rain Streaks

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Abstract: The problem of video deraining is one of the most focused research areas where several techniques are introduced to achieve higher visual quality in the results. The process of video deraining tries to eliminate the presence of rain streaks in the videos so that the overall quality of the video can be enhanced. The existing frameworks tried to accurately eliminate the rain streaks in videos, but there is still room for improvement to preserve the temporal consistencies and intrinsic properties of rain streaks. This work does the job with the combination of handcrafted and deep priors that deeply extract and identify the nature of rain streaks in different dimensions. The proposed work included three main steps: Prior extraction, Derain modelling and optimization. Four major priors are extracted from the frames where the gradient prior (GP) and sparse prior (SP) are extracted from the rain streaks, and the smooth temporal prior (STP) and deep prior (DP) are extracted from the clean video. The unidirectional total variation (UTV) is applied to extract the GP, and the L1 normalization method is followed to extract the SP and STP. The DP is then extracted from the clean frames using the residual gated recurrent deraining network (Res-GRRN) model based on deep learning. Derain modelling is carried out based on the extracted priors, and the stochastic alternating direction multiplier method (SADMM) algorithm is utilized to solve the optimization problem. The proposed approach is then implemented in python and evaluated using the real-world dataset. The overall PSNR achieved by the proposed approach is 39.193dB, which is more optimal than the existing methods.

Keywords: Video deraining, temporal inconsistency, deep learning, handcrafted priors, deep priors, prior extraction, and optimization.

I. INTRODUCTION

Due to bad weather conditions, outdoor vision systems are seriously affected; rain is the most popular among these conditions. As a consequence, the visibility of any image is impaired by the unnecessary introduction of interferences [1]. This hinders and causes problems in follow-up processing, such as tracking, recognition, object detection, etc. [2]. During rainy days, the images and videos captured using outdoor vision systems consist of large rain streaks, diminishing the overall quality of images/videos. The major problems and interferences include occlusions in captured scenes and reduced contrast in background scenes [3, 4]. These images and videos provide much important information for several applications. Therefore, the problem of rain streak removal becomes crucial in computer vision research [5].

Generally, there are two classes of rain streak removal methods: single image-based rain streak removal methods and video-based rain streak removal methods [6]. Among these classes, most of the research works are done only for single image-based removal, as single images are more convenient than videos. The complexities lie in video rain streak removal methodologies since multiple frames must be processed to detect and remove the rain streaks [7, 8]. The single image-based method uses a single rainy image as input and recovers a clear image through removal methodologies. While in the case of videos, the information collected from multiple neighbouring frames is utilized to recover a clear image from the current rainy frame [9, 10]. The neighbouring frames considered in a video are capable of providing more information along with the maintenance of temporal consistency. Thus, the video-based methods have more potential to offer satisfactory derained results than the image-based methods [11]. The rain streaks in any video are distributed randomly and exhibit fast movement, hindering the same scene of neighbouring frames from being always occluded by rain streaks [12]. Usually, this intensity fluctuation among consecutive video frames is utilized in detecting rain streaks from videos. It is later observed that the movement of objects and cameras also results in such fluctuations that are difficult to be discriminated. These issues restrict the video-based methods to preserve the structure and texture of the original image background while removing the rain streaks [13-15].

Several methodologies and techniques are followed in the existing works to differentiate the rain streaks from videos. Some works incorporated the different properties of rain streaks, such as phase, geometric, dynamic, and chromatic properties [16, 17]. These cases consider only the manually extracted features, and these methodologies are not very effective as they may sometimes fail where more details features are needed [18]. To cope up with the challenges, learning-based methodologies are introduced, including the Gaussian mixture model (GMM), sparse coding and Markov random fields (MRFs) [19]. But these methods are found to be time-consuming, which presented the use of convolutional neural networks (CNNs) for faster extraction and better predictions [20]. Therefore, this work combines deep and handcrafted features to get the desired performance.

A) Motivation

Rain streak removal is a concept that has been under investigation for the past few years as it benefits a wide range of automated applications. Most research works consider only a single image where the problem can be modelled as a decomposition task. Working with a single image is more convenient as most information can be captured to train any network model to predict the rain streaks from the image. Recently, rain streak removal methodologies from videos are becoming popular due to their adverse benefits. Compared to a single image, videos are harder to process as it is necessary to consider multiple frames from a single video and capture more useful information from all these frames. Another major factor is preserving the temporal consistency across the video frames, as each frame might depend on the previous and future frames. Traditionally, this problem is addressed with the help of convolutional and recurrent models, as these are well-known to capture useful information and preserve temporal consistency. Though the models resulted in noticeable outcomes, several insightful characteristics of rain streaks in a video must be deeply explored. This remained a major motivation of this work, and the proposed work aims to develop an effective architecture that prioritizes model training over model complexity to attain beneficial outcomes.

B) Contribution

The specific contributions of this work are described as follows:

- Proposing a novel and effective rain streak removal mechanism from videos with the consideration of intrinsic features of rain streaks and temporal consistencies between the frames using deep learning.
- The proposed work combines handcrafted and deep features to provide more information about the videos. This enables the approach to accurately predict and remove the rain streaks present in any complex videos.
- The handcrafted features deeply identify the intrinsic features of rain streaks based on two major priors: gradient prior (GP) and sparse prior (SP). The clean video extracts the deep priors (DP) and the smooth temporal prior (STP).
- The GP, SP and STP priors are obtained from the clean and rain streak videos using the L1 normalization and unidirectional total variation (UTV) approaches.
- To extract the crucial and most informative deep features, the proposed work introduces the residual-gated recurrent deraining network (Res-GRRN) model that captures the priors from rain-free videos in a supervised manner.
- The resultant optimization problem is finally solved using the stochastic alternating direction multiplier method (SADMM) to remove the rain streaks effectively.
- Extensive simulations are carried out, and the methodology is evaluated using the rainy videos collected from the public dataset to prove the model's efficacy compared to other existing models.

C) Paper planning

The paper planning is as follows: Section 2 elaborates on the literature survey of the presented research work, Section 3 covers the proposed work with explanations and formulations, Section 4 presents the proposed work's results and discussion, and Section 5 concludes the paper with future scopes.

II. RELATED WORK

Some most effective and recent methodologies related to rain streak removal from videos are discussed below:

Wang et al. [21] introduced a video rain streak removal model based on tensor optimization. The model considered the intrinsic characteristics of rain streaks and raw videos to remove the rain streaks specifically. The rain streaks in the videos were smooth and group sparse along the direction of rain streaks. The raw video was smooth along the temporal and perpendicular directions of the rain streaks. The unidirectional total variation (UTV) and group sparsity were characterized by the rain streaks using $\ell_{2,1}$ normalization. Similarly, the smoothness of raw

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videos was enhanced using two UTV regularizers. Further, the proposed problems were solved using the alternating direction method of multipliers (ADMM) algorithm. The experimental verification of the method over synthetic and real datasets proved the model's efficacy.

Zhuang et al. [22] presented a new video rain streak removal method that reconciles handcrafted and self-supervised deep priors. The sparse prior, learned gradient prior, and temporal local smooth prior were considered in handcrafted priors. Without training data, the deep convolutional neural network (CNN) model captured the self-supervised deep priors from the raw videos. Those two priors were organically integrated to achieve higher representation and generalization abilities. The ADMM algorithm was followed to address the model, and the methodology thus resulted in the removal of directional rain streaks from clean videos. The superiority of a method was proved against the existing state-of-the-art.

Sharma et al. [23] introduced a new methodology for rain streak removal from videos based on deep learning. The frame-recurrent multi-contextual adversarial network model was constructed upon the conditional generative adversarial network (CGAN) model. Using the multi-contextual adversary, the generator directly predicted the de-rained frame from the previous predicted frame. The perceptual loss function and Euclidean distance were utilized to optimize the model. Several experiments were conducted using 11 test sets to 14 image-quality metrics to prove the effectiveness in both computationally and visually.

Islam and Paul [24] presented an effective methodology for removing rain streaks from videos using feature-based and data-driven models. Extracting appropriate and meaningful features was considered highly challenging, and finding datasets with more variations was also considered complex. The method focused on addressing the above two issues using a hybrid technique. The rain removal strategy was constructed with the extraction and effective combination of physical and data-driven features. The evaluation of the method with several benchmark datasets proved the method's efficacy in comparison with existing rain streak removal methods.

Kulkarni et al. [25] proposed a method for video deraining by embedding deep learning methodology. The authors framed a lightweight methodology since the video deraining process was just a pre-processing step in most automated applications. The progressive subtractive lightweight network was thus introduced to enable the deraining of videos. The rain streaks of different sizes were learnt initially using the multi-kernel feature sharing residual block (MKSRB) followed by progressive subtraction operations to remove the rain streaks from videos completely. Mocking MKSRB features with the previous frame output maintained temporal consistency. A multi-scale multi-receptive difference block (MMRDB) was introduced to perform multi-receptive subtraction of features to enable high-frequency information extraction and avoid losses. Finally, the outputs from both blocks were merged to acquire the rain-free frame. The experimental validations proved the efficiency of the method compared to previous works.

D) Problem statement

After reviewing the existing techniques, it can be concluded that most existing frameworks relied on deep learning methods to enhance performance. Identifying the intrinsic nature of rain streaks while working with a deraining problem is also important. Moreover, video-based applications involve a temporal inconsistency across frames that must be analyzed well. The lack of such research led to the development of this work, where a combination of handcrafted and deep priors are utilized to explore temporal inconsistencies of videos across the frames.

III. PROPOSED METHODOLOGY

A new and effective video deraining mechanism is formulated in this work based on handcrafted and deep priors. The proposed framework includes three main stages: prior extraction, Derain modelling and optimization. The deep priors used in this framework are highly significant to provide deep knowledge regarding the clean video so that the rain streaks present in the video can be effectively discarded. Moreover, temporal consistency is maintained across the frames to enhance the overall performance. The architecture of the proposed video deraining mechanism is displayed in Figure 1.

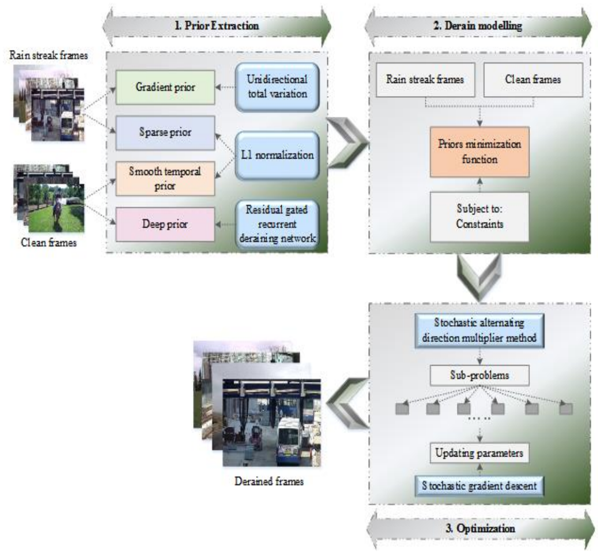

Figure 1: Proposed video deraining mechanism

The rain streak and clean videos are provided as input to the proposed framework from which the priors are extracted. The

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framework extracts four major priors: GP, SP, STP and DP. The GP and SP are extracted from the rain streak frames, and STP and DP are extracted from the clean frames. For prior extraction, the approach utilizes the UTV and L1 normalization methods. After extracting priors, the derain modelling is carried out, where a minimization problem is formulated based on the priors. Finally, the minimization problem is solved using the SADMM algorithm, where the problem is partitioned into several sub-problems. The traditional ADMM algorithm is improved by adding an SGD algorithm that tunes the parameters of the ADMM algorithm in successive iterations. Finally, the algorithm estimates a clean video that is clearer and matches the ground truth.

E) Prior extraction

This is the foremost step of the proposed approach, which extracts the major priors to enhance the deraining process. Four major priors are extracted in this step: GP, SP, STP and DP, where the DP is highly consistent and provides deep knowledge about the video. In this step, the GP and SP are extracted from the rain streaks, and the STP and DP are extracted from a clean video.

1) Prior extraction using rain streaks

The rain streaks extract two priors such as GP and SP. The UTV method is applied to extract the GP, and the L1 normalization method is applied to extract the SP. An example of the rain streak frames utilized in the proposed work is shown in Figure 2.

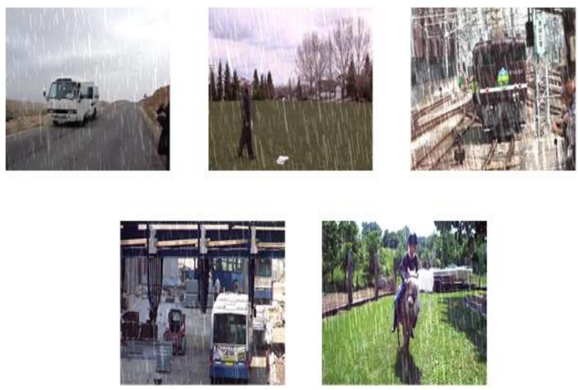

Figure 2: Example of rain streak frames from the dataset

2) Gradient prior extraction

The GP is one of the significant prior extracts to identify the rain streaks falling in different directions. Generally, rain streaks fall in different directions, which are identified as piecewise and smooth in the falling directions. The UTV methodology is applied to extract the GP, a popular regularization technique in identifying horizontal and vertical stripes in the frame. Compared to the general isotropic total variation, this method is highly significant because it can deal with the directional characteristics of the frames. This work considers the rain streaks present in horizontal and vertical directions. The stripes or the streaks present in the frames vary in the gradient across the streaks. Therefore, it is decided to preserve the gradient along the streaks, and the gradient across the streaks is constrained. The formulation for UTV can be given as follows:

$$R_{TV}(u)=\gamma_1\left\|\nabla_x \Re\right\|_1+\gamma_2\left\|\nabla_y(\Re-O)\right\|_1 \tag{1}$$

Where, O indicates the rainy image, $\Re$ indicates the rain streaks, ∇_x, ∇_y indicates the horizontal and vertical derivative operators and γ_1, γ_2 specify the regularization parameters.

3) Sparse prior extraction

Another major characteristic of rain streaks is that they are sparse. When the rain is not extremely heavy, these streaks are sparser than the clean video. These streaks are identified to exhibit structural line patterns instead of random distribution apart from being sparse. Therefore, the L1 normalization method extracts the sparse priors from the rain streaks.

4) Prior extraction using clean video

The clean video extracts two main priors, such as STP and DP. The STP is extracted using the L1 normalization method, and the DP is extracted using a new deep-learning model called Res-GRRN. An example of the clean video frames present in the dataset is shown in Figure 3.

Figure 3: Example of clean video frames from the dataset

5) Smooth temporal prior extraction

Temporal consistency is one of the major aspects to consider while dealing with video-based tasks. This is because the dependencies between the frames provide valuable information that can be captured and utilized to enhance performance. Generally, at least 25 frames per second in a video would exhibit strong smoothness along the temporal direction. In the

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temporal direction, the rain streak derivatives are not sparse, whereas the clean video derivatives are sparse. Thus, the L1 normalization technique is applied to enhance the smoothness of clean video in the temporal direction.

6) Deep prior extraction

This is the most significant and informative prior obtained with the help of a deep learning approach called Res-GRRN. This model is mainly employed to capture clear rain-free video self-supervised. Based on the characteristics of a clean video, the crucial image details are preserved, and the clean video is obtained.

The introduced deep learning model combines residual neural network (ResNet) and gated recurrent unit (GRU). The original ResNet model is highly extractive and can effectively learn the image details. With the accommodation of different convolutional and pooling layers, the ResNet model can be effectively trained with any number of inputs. The major drawback of this model is that it results in network degradation due to the gradient descent. The GRU model is identified to be an excellent model for solving gradient exploration issues. However, using the GRU separately may result in network degradation when increasing the size of an input. Therefore, this work combined these two models to improve performance and reduce network degradation.

The GRU model consists of gated units such as the update and reset gates as well as these gates are responsible for preserving the memory so that it can be utilized in future predictions. The model of GRU is displayed in Figure 4.

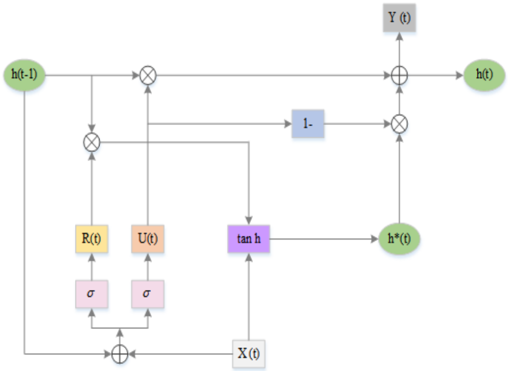

Figure 4: Model of GRU used in the proposed work

The reset gate determines the combination of new input and previous memory, and the update gate defines the count of previous memories attained at the current time step. The reset and update gates are computed based on the current iteration's input and the previous iteration's hidden state information. The next step is to identify the count of new information stored in the hidden layer. Finally, an output of the hidden layer at a current iteration is computed using the update gate. The computations that take place in the GRU are provided below:

$$U_t = \sigma(\omega_U x_t + \nu_U h_{t-1} + b_U) \tag{2}$$

$$R_t = \sigma(\omega_R x_t + \nu_R h_{t-1} + b_R) \tag{3}$$

$$\hat{h}_t = \tanh(\omega_h x_t + \nu_h (R_t \otimes h_{t-1}) + b_h) \tag{4}$$

$$h_t = (1 - U_t) \otimes h_{t-1} + U_t \otimes \hat{h}_t \tag{5}$$

where, U_t specifies update gate, R_t indicates reset gate, $\omega_U, \omega_R, \omega_h, \nu_U, \nu_R, \nu_h$ are weight matrices of the layers, b_U, b_R, b_h are the bias values, h_t is the hidden layer output at current iteration t, $\otimes$ specifies the Hadamard product and $\hat{h}_t$ indicates the sum of input state x_t and previous state output h_{t-1}. A larger value of the update gate indicates that more information from the previous iteration can be retained in the current iteration. Also, a smaller value of the reset gate indicates that more state information will be forgotten from the previous iteration.

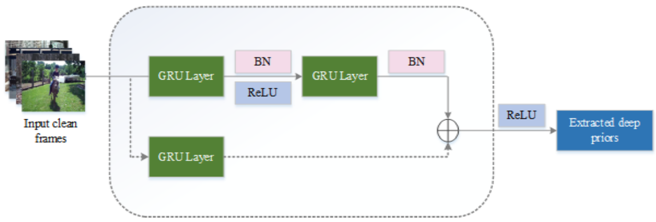

Figure 5: Architecture of ResGRRN for deep prior extraction

For better and more effective prior extraction, the GRU module is included in the residual block of the ResNet model. The ResGRRN model utilized in the proposed work is displayed in Figure 5.

Based on this arrangement, the output of a residual block can be computed as the sum of the input and output of the final layer of GRU. Thus, the overall output of a residual block can be mathematically expressed as follows:

$$Y_R = \mathrm{Re}\,LU(N_{\lambda,\beta}(Y) + G(x_t)) \tag{6}$$

Where, $\mathrm{Re}\,LU(\,)$ indicates the activation function, N is the batch normalization function, λ *and* β are the learned parameters, $G(\,)$ specifies the adjustment function to make x_t and h_t in the same dimension. Including the GRU model

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preserves the temporal consistency across the frames and results in effective extraction.

F) Derain modelling

The deraining model can be formulated for the proposed work using the priors extracted in the previous steps. The mathematical formulation for deraining is provided as follows:

$$\min_{C,S,\theta_i} \frac{1}{2}\|O-C-S\|_F^2+\alpha_1\|\nabla_\theta S\|_{L1}+\alpha_2\|S\|_{L1}+\alpha_3\|\nabla_t C\|_{L_1} \quad (7)$$

Subject to,

$$C=f_w(O),\ 0\le f_w(O)\le O,\ 0\le S\le O \quad (8)$$

Where, O indicates the original video, C indicates clean video, S indicates rain streak video and $\|O-C-S\|_F^2$ is the fidelity term.

G) Optimization

The deraining model is an optimization problem solved with the SADMM algorithm. Equation (7) can be re-written using three auxiliary variables as follows:

$$\min_{w,S,\theta_i,Z_k} \frac{1}{2}\|O-f_w(O)-S\|_F^2+\alpha_1\|Z_1\|_{L1}+\alpha_2\|Z_2\|_{L1}+\alpha_3\|Z_3\|_{L1} \quad (9)$$

Subject to,

$$\begin{aligned} &Z_1=\nabla_\theta S,\ Z_2=S,\ Z_3=\nabla_t f_w(O)\\ &0\le f_w(O)\le O,\ 0\le S\le O \end{aligned} \quad (10)$$

The augmented lagrangian function of equation (9) can be written as follows:

$$\begin{aligned} L(w,S,\theta_i,Z_k,M_k)=&\frac{1}{2}\|O-f_w(O)-S\|_F^2+\alpha_1\|Z_1\|_{L1}+\alpha_2\|Z_2\|_{L1}+\\ &\alpha_3\|Z_3\|_{L1}+\frac{\rho}{2}\|\nabla_\theta S-Z_1\|_F^2+\frac{\rho}{2}\|S-Z_2\|_F^2+\frac{\rho}{2}\|\nabla_t f_w(O)-Z_3\|_F^2+\\ &\langle M_1,\nabla_\theta S-Z_1\rangle+\langle M_2,S-Z_2\rangle+\langle M_3,\nabla_t f_w(O)-Z_3\rangle \end{aligned} \quad (11)$$

Where, ρ indicates the penalty parameter and $M_k(k=1,2,3)$ specify multipliers.

7) SADMM for optimization

Generally, the existing works preferred using the ADMM algorithm to solve the optimization process as it is simple and effective. In the ADMM framework, the problem is partitioned into sub-problems that are further solved. The proposed work follows the procedures of the ADMM algorithm to solve the optimization problem. But this algorithm is influenced by certain algorithmic parameters that often diverge the results obtained. Since the proposed work focuses on obtaining a more accurate estimate of the clean video, it utilizes the SGD algorithm to tune the influential parameters of an ADMM algorithm. The above problem in equation (11) can be formulated into sub-problems as follows:

a) Z Sub-problems: The sub-problems formulated for $Z_k(k=1,2,3)$ include the following:

$$\begin{cases} Z_1^{t+1}=\arg\min_{Z_1}\frac{\rho}{2}\left\|\nabla_\theta S^t+\frac{M_1^t}{\rho}-Z_1\right\|_F^2+\alpha_1\|Z_1\|_{L1}\\ Z_2^{t+1}=\arg\min_{Z_2}\frac{\rho}{2}\left\|S^t+\frac{M_2^t}{\rho}-Z_2\right\|_F^2+\alpha_2\|Z_2\|_{L1}\\ Z_3^{t+1}=\arg\min_{Z_3}\frac{\rho}{2}\left\|\nabla_t f_w(O)+\frac{M_3^t}{\rho}-Z_3\right\|_F^2+\alpha_3\|Z_3\|_{L1} \end{cases} \quad (12)$$

The above formulation can be exactly solved using a thresholding operator as follows:

$$\begin{cases} Z_1^{t+1}=Soft_{\frac{\alpha_1}{\rho}}\left(\nabla_\theta S^t+\frac{M_1^t}{\rho}\right)\\ Z_2^{t+1}=Soft_{\frac{\alpha_2}{\rho}}\left(S^t+\frac{M_2^t}{\rho}\right)\\ Z_3^{t+1}=Soft_{\frac{\alpha_3}{\rho}}\left(\nabla_t f_w(O)+\frac{M_3^t}{\rho}\right) \end{cases} \quad (13)$$

Where, $Soft_\beta(\cdot)$ indicates the soft-thresholding operator with a threshold value β .

b) w and θ_i sub-problems: The sub-problem for parameters w and θ_i can be written as follows:

$$\begin{aligned} w,\theta_i\in\arg\min_{w,\theta_i}&\frac{1}{2}\|O-f_w(O)-S^t\|_F^2+\\ &\frac{\rho}{2}\left\|\nabla_t f_w(O)-Z_3^t+\frac{M_3^t}{\rho}\right\|_F^2+\frac{\rho}{2}\left\|\nabla_\theta S^t-Z_1^t+\frac{M_1^t}{\rho}\right\|_F^2 \end{aligned} \quad (14)$$

The problem defined in equation (14) is non-convex, and the efficient SGD algorithm is followed in this work to solve this problem. Thus, the SGD algorithm [] runs along with the ADMM algorithm in each iteration to tune these two parameters.

c) Sub-problem for S: The sub-problem for S can be given as follows:

$$\begin{aligned} S^{t+1}=\arg\min_S&\frac{1}{2}\|O-f_w(O)-S\|_F^2+\\ &\frac{\rho}{2}\left\|\nabla_\theta S-Z_1^t+\frac{M_1^t}{\rho}\right\|_F^2+\frac{\rho}{2}\left\|S-Z_2^t+\frac{M_2^t}{\rho}\right\|_F^2 \end{aligned} \quad (15)$$

The above formulation can be exactly solved using the following:

$$\begin{aligned} (S^{t+1})^{(i)}=&\mathfrak{I}^{-1}\left(\mathfrak{I}\left(O^{(i)}-(f_w(O))^{(i)}+\rho\left(Z_2^t-\frac{M_2^t}{\rho}\right)^{(i)}\right)+\rho\bar{\mathfrak{I}}(\Theta_i)\mathfrak{I}\left(\left(Z_1+\frac{M_1^t}{\rho}\right)^{(i)}\right)\right)\\ &\left((1+\rho+\rho\bar{\mathfrak{I}}(\Theta_i)\mathfrak{I}(\Theta_i))^{-1}\right) \end{aligned} \quad (16)$$

Where, $\mathfrak{I}^{-1}$ indicates the inverse transform of $\mathfrak{I}$.

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d) Updating multipliers $\mathrm{M}_k \; k=(1,2,3)$: The update for the multipliers used in the problem can be written as follows:

$$\begin{cases} \mathrm{M}_1^{t+1} = \mathrm{M}_1^t + \rho\left(\nabla_\theta S^t - \mathrm{Z}_1^t\right) \\ \mathrm{M}_2^{t+1} = \mathrm{M}_2^t + \rho\left(S^t - \mathrm{Z}_2^t\right) \\ \mathrm{M}_3^{t+1} = \mathrm{M}_3^t + \rho\left(\nabla_t f_w(O) - \mathrm{Z}_3^t\right) \end{cases} \tag{17}$$

At the end of each iteration of the SADMM algorithm, the intensities of $S \text{ and } f_w(O)$ are contracted to meet the constraints $0 \le f_w(O) \le O \text{ and } 0 \le S \le O$. The pseudocode of the SADMM algorithm is provided in Algorithm 1.

Algorithm 1: SADMM for rain streaks removal

Input: Frames of rainy video

Initialize the random variables $w,\ S=0,\ \mathrm{M}=0$

While stopping criteria is not met **do**

Update $Z_k\left(k=1,2,3\right)$ using equation (13)

Update the values of $w \text{ and } \theta_i \left(i=1,2,3.....t\right)$ using equation (14)

Update $w \text{ and } \theta_i \left(i=1,2,3....t\right)$ in further iterations using SGD

Update the value of using equation (16)

Update the values of using equation (17)

End while

Output: Provide the rain-free clean video estimate

$C = f_w(O)$

IV. RESULTS AND DISCUSSION

Several experiments are conducted, and the resultant outcomes are discussed in this section to prove the effectiveness of proposed approach. The experiments are conducted with a real-world dataset of different rainy videos from various locations. The evaluation dataset can be downloaded using the following link: https://drive.google.com/drive/folders/1ds-SGL___2GXiSN8HKJvlGJ60Q10QeW7. This dataset includes the rainy video frames and respective ground truths. The dataset included a count of 17 videos, including heavy rain streaks. The frames of these videos provided varying streaks in different directions, and the temporal consistencies can be well exploited using this dataset. The parameter values of $\alpha_1, \alpha_2 \text{ and } \alpha_3$ are set to 0.1, 0.3 and 0.6 and the total number of iterations included is 10. For each video in the dataset, the total count of frames included is 20, and the pixel size of each frame lies in the range 640×480. The entire implementations of the proposed work are carried out in the Python platform, and the system configuration is as follows: the system is provided with an Intel(R) Core(TM) i5-3570 processor @ 3.40 GHz with an installed RAM of 8 GB running on a 64-bit Windows 10 operating system.

H) Performance metrics

The performance of the proposed approach is analyzed using different measures such as peak signal-to-noise ratio (PSNR), structure similarity (SSIM) and root mean square error (RMSE). The mathematical formulations for the metrics are as follows:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \tag{18}$$

$$SSIM(x,y) = f\left(c(x,y), l(x,y), s(x,y)\right) \tag{19}$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(\hat{y}_i - y_i)^2}{N}} \tag{20}$$

where, $R = 255$, MSE is the mean square error, $c(x,y)$ indicates the contrast comparison, $l(x,y)$ indicates the luminance comparison, $s(x,y)$ indicates the structure comparison, y_i is the actual output, $\hat{y}_i$ is the predicted output and N indicates the total sample size.

I) Performance analysis

The performance of the proposed approach is compared with other video-deraining mechanisms, and the effectiveness of the approach is analyzed. The proposed method is highly advanced as it explores both the handcrafted and deep priors in the video deraining process. The handcrafted priors help to deal with the rain streaks in different directions and provide a better perspective of the video. The deep priors provide more informative features to the model to accurately discriminate the clean video from the rain streak video. Also, the deraining model is solved using the improved algorithm, where the influential parameters are tuned using the SGD algorithm. This process of fine-tuning helped the proposed model to provide an accurate estimate of clean video. The deraining process followed in the proposed work effectively reduces hard rain streaks in the frames. The methodology can exploit the rain streaks present in all possible directions. The deep priors are extracted using an improved deep learning model, hybridizing two units to enable effective extraction. The main achievement of the proposed model is that the temporal consistencies across the frames are preserved, and the intrinsic properties of rain streaks are explored well for deraining. Since the rain streaks are analyzed in different dimensions, the proposed model accurately provided an estimate of clean video through prior

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minimization. The derained results of the proposed approach are compared with the ground truth frames, and the results are displayed in Figure 6.

Figure 6: Comparison of input, derained and ground truth frames of the proposed approach

Figure 6 shows that the proposed approach is highly accurate and effective in deraining the video and resulting in accurate estimates. In the figure, the first column presents the input rainy image, the second column shows the deraining output of the proposed work, and the third column presents the ground truth images. It is clear from the images that the input images are affected by hard rain streaks in different directions. When the rain streaks in the videos are hard, it needs proper and effective deraining tools to remove them completely. Compared with ground truth, the proposed method's results are highly optimal and accurate. The rain streaks are analyzed in vertical, horizontal and temporal directions, and all the priors are minimized to provide a clean video without rain streaks accurately. The methodologies and techniques utilized in the proposed framework helped to achieve the desired results. The combination of handcrafted and deep priors enhanced the effectiveness of the proposed model in identifying the clean video estimate for the input. This can be justified through the visual representation where the visual quality of the derained frame and ground truth frame shows maximum correlation.

TABLE 1: Quantitative analysis of the proposed approach

Video	PSNR	SSIM	RMSE	Time
Video 1	27.941	0.609	1.725	108.17
Video 2	27.123	0.448	1.586	214.43
Video 3	28.037	0.157	1.549	117.008
Video 4	27.884	0.324	1.236	191.26
Video 5	27.713	0.364	1.086	145.97
Video 6	27.954	0.186	1.3001	207.87

The quantitative results of the proposed approach are presented in Table 1. The values obtained show that the proposed method is highly optimal. The analysis has been done on 6 videos, and the proposed model resulted in highly effective results for each video. The PSNR values of the proposed approach seem optimal and stable on different videos. This proves the proposed model can provide better outcomes even on heavily rainy images with more rain streaks. In the case of SSIM outcomes, there are some deviations in results for different videos. These deviations occur due to the problem of gradients and continuity issues in rain streaks. The RMSE values of the proposed approach are identified to be very low for all the considered videos. This proves the proposed approach resulted in an accurate, clean rain-free video estimate. Moreover, the time taken to process each video is analyzed, and it is identified that the time varies based on the length of a video and the complexities in rain streaks. When the complexities in rain streaks are low, and the video length is minimal, then the time taken by the model to complete the deraining process is also low. The quantitative analysis proves that the proposed approach is highly authentic and effective in deraining complex videos.

TABLE 2: Ablation experiments of the proposed approach

Proposed method	PSNR	SSIM	RMSE	Time
With deep prior	39.193	0.998	1.3	300.25
W/o deep prior	37.941	0.4853	2.9	236.53

The outcomes of the ablation experiments conducted for the proposed work are presented in Table 2. This experiment analyses the proposed method's importance and the contribution of different units. The values for the proposed approach with and without deep prior are included in the table. The deep priors are one of the most crucial features of the proposed work, where a deep learning-based model is utilized

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to extract these features. Compared to the model without deep prior, the model with deep prior resulted in better outcomes. This proves that the deep priors are significant in achieving the desired results in the proposed approach. Using only handcrafted priors resulted in insignificant results as the model cannot completely diminish the streaks, and the temporal consistencies are not well preserved. This resulted in the degradation of the model to completely analyze the streaks in different directions in the videos.

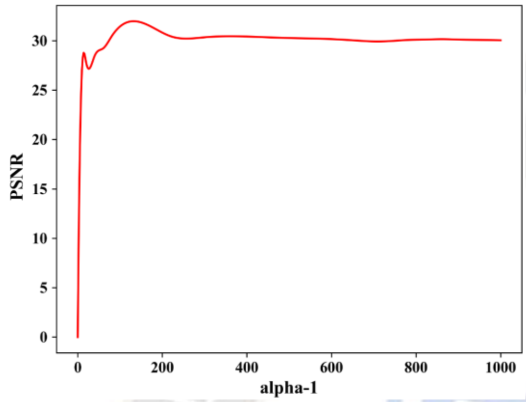

Figure 7: PSNR performance for alpha-1

The PSNR values of the proposed method are analyzed in terms of alpha-1, and the result is graphically presented in Figure 7. From the figure, it is identified that the parameter has a greater impact on the overall PSNR performance of the model. The value of PSNR rises when the alpha-1 value is initially increased and maintains a constant PSNR for the remaining values of alpha-1. There are still some minor deviations in the values when the parameter value is abruptly changed. For the first 200 values, the PSNR is slightly increased and maintained at a constant PSNR to some extent. This proves that the performance of the proposed approach lies in the parameter settings of alpha-1.

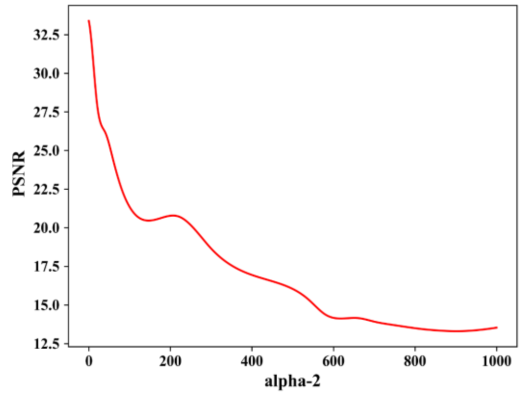

Figure 8: PSNR performance for alpha-2

The proposed model's PSNR values are determined in terms of alpha-2, and the result is graphically presented in Figure 8. From the figure, it is clear that the alpha-2 parameter also has a larger influence on the overall performance of the proposed approach. It can be well identified from the graph that the PSNR value of the proposed approach is higher at the initial values of alpha-2 and gradually decreases with increasing values. When the alpha-2 value reached 1000, the overall PSNR value of the proposed approach was reduced to about 13.124 dB. This indicates that the alpha-2 parameter must be properly tuned to obtain effective outcomes.

The proposed approach's PSNR values are analyzed in terms of alpha-3, and the results are graphically presented in Figure 9. From the figure, it can be justified that the alpha-3 parameter has the largest influence on the overall performance of the proposed approach. This value must be maintained within a particular value to attain better performance outcomes. When the values of alpha-3 are small, the PSNR is small, and the PSNR value slowly increases with higher alpha-3 values. Again, the PSNR decreases when the alpha-3 is increased beyond 400. Thus, it can be identified that the alpha-3 parameter has the greatest influence on the overall results obtained.

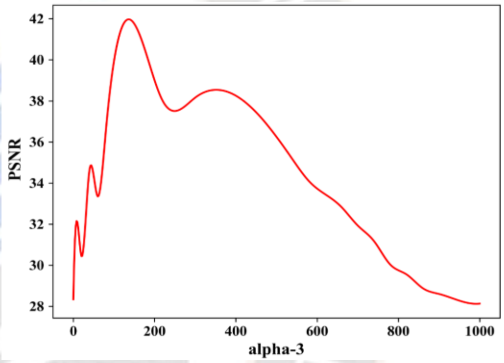

Figure 9: PSNR performance to alpha-3

TABLE 3: Comparative analysis of the proposed and existing methods

Methods	PSNR	SSIM	Time
Rainy	28.151	0.751	-
LRMC	30.496	0.848	2230.193
DIP	35.196	0.955	190.997
Tensor model [21]	38.486	0.971	230.311
Proposed	39.193	0.998	300.25

The comparative analysis of the proposed and existing works is presented in Table 3. From the obtained values, it is clear that the proposed approach performs better than the other compared techniques in terms of all the metrics. The proposed method resulted in a higher PSNR compared to other techniques. The tensor model improved PSNR and SSIM values among the compared techniques. The time taken by the proposed model is somewhat high as it considers deep priors, which require a neural network to complete the task. Overall, the proposed approach's performance is more optimal than the other works.

V. CONCLUSION

In this work, a new and effective video-deraining mechanism is modelled based on different techniques. The proposed work introduces the combination of handcrafted and deep priors to promote accurate estimation of clean video from the rainy video. The major priors, such as GP, SP, STP and DP, are initially extracted from the rain streaks and clean videos. The UTV approach is utilized to extract GP, and the L1 normalization is followed by extracting SP and STP. Further, a new deep learning-based Res-GRRN network model is built to analyze the clean videos and extract the DP effectively. The deraining model is then provided, and the SADMM framework is introduced to solve the deraining optimization problem. The SADMM model is boosted by integrating the SGD algorithm that updated the influential parameters in the ADMM framework. The proposed approach is implemented in the python platform and evaluated using real-world dataset videos. The result outcomes are discussed further for different rainy videos, and the contribution of components present in the model is analyzed. The overall simulation outcomes proved that the proposed model is highly optimal and effective in video deraining and provided effective results. The average PSNR value attained by the proposed model is 39.193, and the average SSIM value of the approach is 0.998, which is higher than the compared models.

Though the results offered by the projected work are impressive, these results can be further improved. In this work, general videos are considered in the evaluations, whereas more videos with large and irregular motions can be considered in the future to perform depth evaluations. Moreover, adversarial learning models can be adopted in the future to preserve the normal textures of frames by modelling the natural background layers.

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REFERENCES

[1] H. Wang, Y. Wu, M. Li, Q. Zhao, D. Meng, "A survey on rain removal from video and single image," arXiv preprint arXiv: 1909.08326, 2019.

[2] P. Hettiarachchi, R. Nawaratne, D. Alahakoon, D. D. Silva, N. Chilamkurti, "Rain streak removal for single images using conditional generative adversarial networks," Applied Sciences vol. 11, no. 5, pp. 2214, 2021.

[3] S. Wang, L. Zhu, H. Fu, J. Qin, C.B. Schönlieb, W. Feng, S, Wang, "Rethinking Video Rain Streak Removal: A New Synthesis Model and a Deraining Network with Video Rain Prior," In Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XIX, Cham: Springer Nature Switzerland pp. 565-582, 2022.

[4] L. Zhu, Z. Deng, X. Hu, H. Xie, X. Xu, J. Qin, P.A. Heng, "Learning gated non-local residual for single-image rain streak removal," IEEE Transactions on Circuits and Systems for Video Technology vol. 31, no. 6, pp. 2147-2159, 2020.

[5] K. H. Lee, E. Ryu, J. K. Kim, "Progressive rain removal via a recurrent convolutional network for real rain videos," IEEE Access vol. 8, pp. 203134-203145, 2020.

[6] M. R. Islam, M. Paul, "Video Deraining Using the Visual Properties of Rain Streaks," IEEE Access vol. 10, pp. 202-212, 2021.

[7] P. E. Darney, I. J. Jacob, "Rain Streaks Removal in digital images by Dictionary based sparsity process with MCA Estimation," Journal of Innovative Image Processing vol. 3, no. 3, pp. 174-189, 2021,

[8] V. Frants, S. Agaian, K. Panetta, "QSAM-Net: Rain streak removal by quaternion neural network with self-attention module," arXiv preprint arXiv: 2208.04346 2022.

[9] Y. Ding, M. Li, T. Yan, F. Zhang, Y. Liu, R.W. H. Lau, "Rain streak removal from light field images," IEEE Transactions on Circuits and Systems for Video Technology vol. 32, no. 2, pp. 467-482, 2021.

[10] Y. Wang, T.Z. Huang, "A tensor-based low-rank model for single-image rain streaks removal," IEEE Access vol. 7, pp. 83437-83448, 2019.

[11] R. Quan, X. Yu, Y. Liang, Y. Yang, "Removing raindrops and rain streaks in one go," In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 9147-9156, 2021.

[12] M. R. Islam, M, Paul, "Rain streak removal in a video to improve visibility by TAWL algorithm," arXiv preprint arXiv: 2007.05167 2020.

[13] T. Wang, X. Yang, K. Xu, S. Chen, Q. Zhang, R. W. H. Lau, "Spatial attentive single-image deraining with a high quality real rain dataset," In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 12270-12279, 2019.

[14] M. Li, X. Cao, Q. Zhao, L. Zhang, D. Meng, "Online rain/snow removal from surveillance videos," IEEE Transactions on Image Processing vol. 30, pp. 2029-2044, 2021.

[15] E. Khatab, A. Onsy, M. Varley, A. Abouelfarag, "A Lightweight Network for Real-Time Rain Streaks and Rain Accumulation Removal from Single Images Captured by AVs," Applied Sciences vol. 13, no. 1, pp. 219, 2023.

[16] H. Wang, Q. Xie, Q. Zhao, D. Meng, "A model-driven deep neural network for single image rain removal," In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition pp. 3103-3112, 2020.

[17] Z. Sun, S. Xiong, R. W. Liu, "Directional regularized tensor modeling for video rain streaks removal," arXiv preprint arXiv: 1902.07090, 2019.

[18] W. Yan, R. T. Tan, W. Yang, D. Dai, "Self-aligned video deraining with transmission-depth consistency," In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 11966-11976, 2021.

[19] Ahmed Abdelaziz, Machine Learning Approaches for Predicting Stock Market Volatility , Machine Learning Applications Conference Proceedings, Vol 3 2023.

[20] L. Yi, Q. Zhao, W. Wei, Z. Xu, "Robust online rain removal for surveillance videos with dynamic rains." Knowledge-Based Systems vol. 222, pp. 107006, 2021.

[21] ARECHE, F. O. ., & Palsetty , K. . (2021). Ubiquitous Counter Propagation Network in Analysis of Diabetic Data Using Extended Self-Organizing Map. Research Journal of Computer Systems and Engineering, 2(2), 51:57. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/33

[22] H. Wang, Y. Wu, M. Li, Q. Zhao, D. Meng, "Survey on rain removal from videos or a single image," Science China Information Sciences vol. 65, no. 1, pp. 111101, 2022.

[23] Y.T. Wang, X.L. Zhao, T.X. Jiang, L.J. Deng, T.H. Ma, Y.T. Zhang, T.Z. Huang, "A total variation and group sparsity based tensor optimization model for video rain streak removal," Signal Processing: Image Communication vol. 73, pp. 96-108, 2019.

[24] J.H. Zhuang, Y.S. Luo, X.L. Zhao, T.X. Jiang, "Reconciling handcrafted and self-supervised deep priors for video directional rain streaks removal," IEEE Signal Processing Letters vol. 28, pp. 2147-2151, 2021.

[25] P. K. Sharma, S. Ghosh, A. Sur, "High-quality frame recurrent video de-raining with multi-contextual adversarial network," ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) vol. 17, no. 2, pp. 1-24, 2021.

[26] M. R. Islam, M. Paul, "Video rain-streaks removal by combining data-driven and feature-based models," Sensors vol. 21, no. 20, pp. 6856, 2021.

[27] A. Kulkarni, P. W. Patil, S. Murala, "Progressive subtractive recurrent lightweight network for video deraining," IEEE Signal Processing Letters vol. 29, pp. 229-233, 2021.