Rain Pixel Recovery with Gaussian Noise Removal for Rainy Videos

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***Abstract* — the effects of rain on videos are very multifaceted. Therefore to rain recovery is very vital task. Rain recovery is important task for surveillance security as well as movie editing. There were different techniques are available for rain recovery. Video affected by rain means there are intensity fluctuations of pixels. Intensity changes due to rain drops. Recovery of rainy videos means we have to recalculate actual intensity of pixels and assign that intensity to respective pixel. In our framework initially motion objects are identified for separate recovery. Gaussian Noise is remove from video using Gaussian Noise Filter. System is based on motion segmentation. Static and moving objects are differentiates and recovery is done on separately. Rain affected pixels identified and that are recovered. Performance of this system is more as compared to existing once. Quality is improved; it is worked on highly dynamic scenes.**

***Key Words*- Gaussian Noise, Motion segmentation, Motion buffering, Motion exclusion, Rain removal, Quality improvement.**

I. INTRODUCTION

Different weather conditions like rain, snow or fog will cause complex visual effects of spatial or temporal domains in images or videos [3]. Removal of rain from videos is more composite task; rain drops changes the intensity of pixels and our task is to recover that intensity. There were different techniques available for rain recovery. Basic task behind these techniques is to detection of rain from videos and work on those pixels only. Rain destroy the original value of pixels either frequency changes or RGB value changes [11]. Security purposes this application is more useful. Frequency or RGB values changes due not only rain but also global lighting change, camera be in motion, or object motion. Fluctuations caused by rain are to removed, and caused by object motion is to retain [1].

Removal of rain streaks in video is a demanding problem due to the random distribution and fast motion of rain. Weather conditions differ widely in their physical properties. Based on their differences, weather conditions can be broadly classified as steady (mist, haze) or dynamic (hail, snow and frozen rain) [4]. Attention on the problem of rain which affects videos and change pixel intensity. Rain consists of a allocation of a large number of rain drops of different sizes, falling at unlike velocities. Each drop behaves like a clear globe, reflecting and refracting light from the environment towards the camera. A group of such drops falling at high velocities results in time unreliable intensity fluctuations in images and videos.

In our framework initially moving part in image is hiding and rain is highlighted. Then Gaussian Filter is used to remove Gaussian Noise. After that Motion segmentation concept is used to differentiate moving objects with respect to Static object. Moving objects are considered to be part of the foreground, whereas static objects are consider as part of the background. Using Gaussian noise filer some amount of noise is removed then rain removal algorithm applied on it.

This algorithm is base on Motion segmentation. Motion segmentation is used to detect motion objects in frames. Rain affected pixels detected and then using reconstruction method that affected pixels will be filling with its tangible color; both spatial and temporal information are then adaptively browbeaten during rain pixel recovery. To fill that color we are going used temporal information which is collected by comparing next and previous frames. To further improvement of quality we will improve quality regarding brightness and sharpness ad maintain the high resolution. Rain affected pixels are highlighted then region created after that work on that region for rain recovery. Proposed system gives better output as compare to existing techniques.

II. LITERATURE SURVEY

Existing algorithm depend on Physical and photometric properties of the rain. But it was used observed data to detect and recover rain. There some limitations regarding this consideration of same size rain drop falls with same velocities [2]. By using motion segmentation rain affected pixels are detected. Rain pixel detection was done. Then these pixels will be stored in three buffers Frame, Rain and Motion buffers. Recovery was done separately for static and dynamic region [1]. Rain removal in single color image is composite task because no temporal information among consecutive images can be obtained. In this structure image decomposed into a low frequency part and high frequency part. By using lexicon learning and sparse coding image has been decomposed into rain part and non rain component. Visual quality is also better [3]. A new vectorial underwater image quality metric is consider for quality evaluation for under water videos, it gives similar sharpness and correlates better with enhancement results as compare to other method. It has more potential as a guide to under water image enhancement [2]. Rain removal in single color image is complex task because no temporal information among successive images can be obtained. In this framework image decomposed into a low frequency part and high frequency part. By using dictionary learning and sparse coding image has been decomposed into rain component and non rain component. Visual quality also improved [3]. Spatial coherency and temporal coherency maps are combined to obtain the final spatiotemporal map identifying prominent regions. This method is used to segment prominent objects in videos [4]. For the background containment based moving object detection Gaussian Mixture Model (GMM) is used. This method is targeted towards civilizing GMM [5]. Rain consists of spatially spread drops falling at high velocities; every drop refracts and reflects the surroundings, produce pointed intensity differences in an image. Different methods for removal of rain belongings from the dynamic videos were define in [6]. High frequency part is detached in rain image then decaying into a “k mean algorithm”. Rain component can be without difficulty and fruitfully removed in rain image when preserving most original image details [7]. Poisson-Gaussian unbiased risk estimator is appropriate to a mixed Poisson-Gaussian noise model. A Stochastic methodology is used to assess estimator [8]. To evaluate the perceptual excellence of output images in many application like image rotten Gradient Magnitude Similarity Deviation model id used. It is sensitive to image bend, while different local structures in a distorted image undergo alternative degrees of degradations [9]. For the application of image denoising method is able to routinely decide the undesired patterns like rain streaks or Gaussian noise. It is able to identify image mechanism which corresponds to undesired noise patterns [10]. A low latency technique for analyzing surveillance video by using compressive sensing in which background and foreground is segmented by Low rank and sparse decomposition, low latency makes it possible to examine video in real time [11]. A correct evaluation of the camera motion in a dynamic environment is by RGB-D videos. Image segmentation is used; opaque pixel matching between the current and a reference color image is performed. It is used to build the 3D point cloud for dense motion inference [12]. Study of dissimilar noise like salt & pepper noise, Gaussian noise, Poisson noise and a comparative analysis of noise removal techniques as well as study of different filters like median filter, mean filter, adaptive filter in [13]. A segmentation and graph-based video sequence matching method can notice video copies successfully. It can automatically find optimal sequence matching results from the disordered matching results based on spatial features [14]. The critical thresholds to notice noise and contrast measure are browbeaten in this technique [15]. Tone-mapped operators (TMOs) are converts high dynamic range to low dynamic range images. It creates multi-scale quality maps that reflect the structural loyalty variations crosswise scale and space [16].An image retargeting database is built through the subjective rating of the human viewers, the database is analyzed from the perspective of retargeting scale, retargeting method and source image content [17]. Reduced-reference image quality assessment (RR-IQA) provides a practical solution for automatic image quality calculations in various applications where only fractional information about the original reference image is available [18]. Visual Quality Matrix (VQM) that will be able to better evaluate the quality of an image degraded by a combined blur degradation, it is a vectorial development of structure similarity using quaternion image processing (QIP) [19]. A procedure for simultaneous object segmentation and global motion estimation (GME) is from a roughly sampled motion vector field. A single image based rain removal framework via properly formulating rain removal as an image decay problem based on morphological component analysis. Rain component can be successfully detached from the image while preserving most innovative image details [20]. A flexible image-difference framework is that models, these mechanism using an experiential data mining policy. It is used to create image difference measures (IDM) based on image difference texture. A framework for color image quality metric by extending the adaptive basis concept and define that this framework is effective at discounting distortions. RRIQA algorithm is base on a discordant normalization images. This algorithm is cross-validated using two publicly easy to get to subject rated image database and gives good performance for a wide range of image distortions [21]. LU factorization is used for representation of the structural information of an image. Image quality metric is computed from the 2D distortion map. To avoid the error pooling step of many factors like in frequential and spatial domain commonly applied to obtain a last excellence score. A fast video structure analysis method based on image segmentation in each frame. Region matching between frames also measured, it supports user connections to improve the results [22]. A rain streak look model that accounts for the rapid shape distortion that a raindrop undergoes as it falls. A performance evaluation is study of diverse image quality appraisal algorithms. Database was diverse in terms of image content and distortion types. Data was publicly available. Study of different methods is for joint multi region 3D motion segmentation and 3D explanation of chronological sequences of monocular images. Their implementations are verified on synthetic and real image sequences [23]. The relation between image information and visual quality and obtainable a visual information loyalty criterion for full references image quality assessment. VIF performance well in single distortion as well as in cross bend scenarios. A new approach to motion segmentation is based on a global model. A method for motion-based segmentation of images with multiple moving objects and is based on an active contour formulation and solved with the level set methodology. It is solution of a system of joined incomplete differential equations [24]. It is fully based on psychophysics experiments and modified to image quality assessments. It gives image quality evaluation tool with full orientation providing good performance, concerning to metrics defined by VQEG [25].

III. METHODOLOGY

There were different techniques and methods already introduced in previous work. In our framework we initially convert video into frames. Fig. 1 shows the methodology of our system. Further details explain as below,

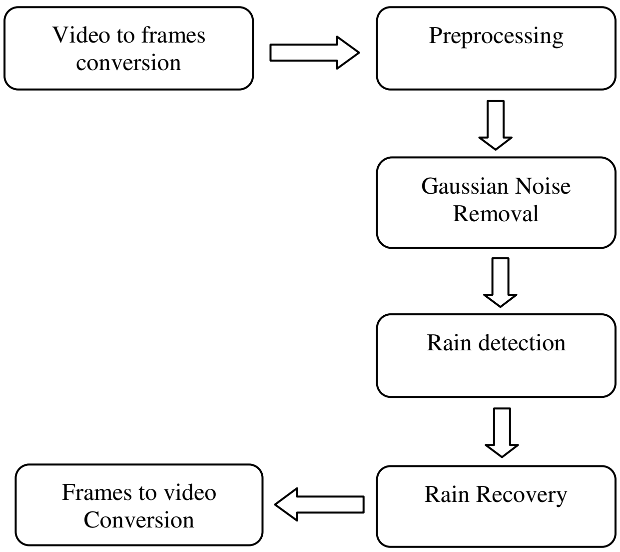


Fig. 1 Rain Recovery System

A. *Video to frames conversion and pre processing*

Rainy video provided as input to our framework. We have to work on each and every frame therefore input video divided into number of frames. All frame stored with .jpeg extension and sequentially. Frames are buffered so less memory required.
Pre processing involves removing low-frequency background noise, normalized the intensity of the individual particles images, removing reflections and masking portion of frames. All frames converted into gray scale for detection of rain affected pixels.

B. *Gaussian Noise Removal*

The effects imposed by Gaussian noise and by rain drops on videos are nearly same there all frames passes for noise removal to improve some quality. Gaussian noise is removed by using Gaussian noise removal filter. Therefore we have to take away noise before Rain pixel recovery. Noise removed constraint help us to get better quality of videos.

C. *Rain Detection*

Basic task is to detect rain from frames. Fundamental part of this algorithm is Motion segmentation. Motion segmentation includes Motion cues and local cues. Motion cues used to detect moving objects in frames. To detect moving object from frame we used Gaussian mixture model (GMM). In this technique k component are presumed to exist in optical flow field. Optical flow field gives the correct estimating the comparative displacement between two adjacent frames for most objects. Local cues include the local properties of pixels like pixel location and chromatic values [1]. Gray scale intensity differences between two successive frames are intended and threshold. This threshold value is set that all the intensity variations caused by rain can be detected, typically value is 3. Binary difference map is designed for evaluating rain affected pixels. Then photometric and chromatic constraints are applied on the binary difference map. If pixels in this map which fail the constraints are excluded from the final rain mask.

D. *Rain Recovery*

Rain pixels on motion object and the background require to be treated separately. Therefore final rain mask is separated into one is rain pixels in the motion target area and second is rain applicant pixels in the background. We created three different buffer for rain removal that is to say video frame buffer, rain buffer and motion buffer with size *(len, wid, stk),* here *len X wid* is the video frame size, *stk* is depth of the buffer, and it is set as *stk = 9* in test for a better recover performance [1].
The scene recovery algorithm works on the current frames compare with previous and next four sequential frames. For evaluate information in video, rain and motion buffer could be retrieved for a better scene recover performance. Reconstruction is done for recovering rain affected pixels by filling RGB values as per boundary pixels color values. Here we use RGB fill method to color the rain affected pixels. Comparing adjacent pixels RGB value we are going to assign RGB value to respective pixel. As per this filling of color is to pixel improves the quality of frames.

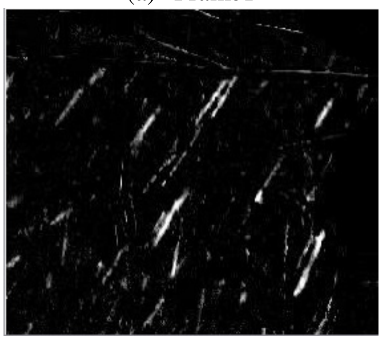
A. *Frames to Video Conversion*

Finally all recovered frames are converted into output video. Quality of this output video is more as compare to input video. Performance of this framework is stated in next section.

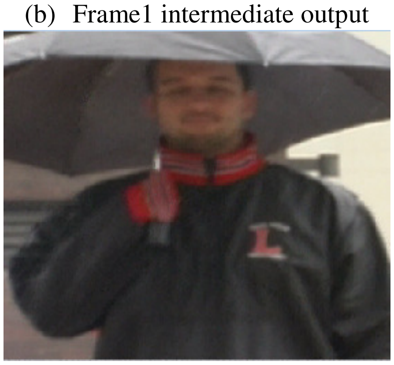
IV PERFORMANCE ANALYSIS

Performance is major on rainy videos. As per previous work this method is used to remove rain from highly dynamic scenes. The moving objects are not blurred by the rain removal algorithm in spite of its large motion, and no leave-taking trails (ghost effect) [1] are observable. When we use rain removal algorithm then this algorithm is effective for scenes with compound motions and at the same time is insensitive to time-varying textures that have temporal frequencies similar to those due to rain [2]. Existing algorithms for sleet removal performs poorly in highly dynamic scene. Performance major i.e. Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) are consider for performance evolutions. Gaussian noise is statistical noise having a probability density function equal to that of the normal distribution. Sources of Gaussian noise in digital images occur during gaining e.g. sensor noise caused by poor lighting or high temperature, or broadcast e.g. electronic circuit noise. This noise will be removed using Gaussian Filter through smoothing of image [14].

(a) Frame1



(b) Frame1 intermediate output



(c) Frame1 output

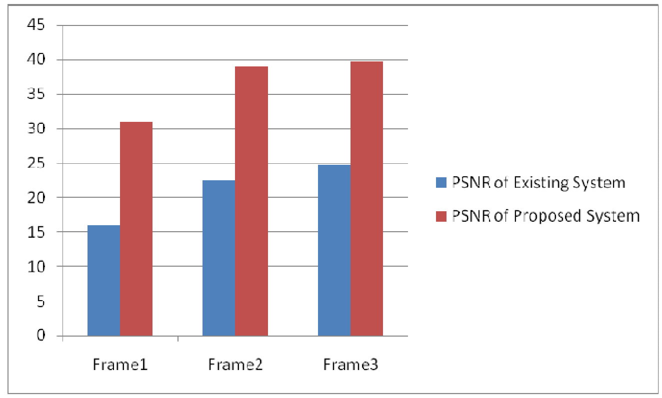
Fig. 2 Frames in rain recovery algorithm

Fig. 2 show the intermediate output and rain recovery frame. Fig. 2 (b) shows the rain detection output, here white strips shows the rain. Pixels on these white strips consider as rain pixels. We have to work on these pixels. After applying our technique output shows like Fig. 2(c).

Table I PSNR value of existing and proposed System

Frame name	PSNR of Existing System	PSNR of Proposed System
Frame1	15.94	30.94
Frame2	22.39	38.99
Frame3	24.68	39.68

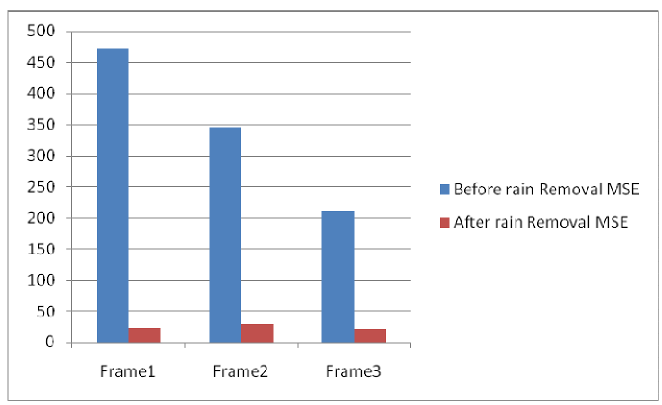
Above Table I show the PSNR values of existing system and proposed system. PSNR value of Frame 1 of existing system is 15.94 db and proposed system it is 30.94 db and it increment for frame 2 and 3. Hence we can say that PSNR Value is more for proposed system as compared to existing system. PSNR value is major in db. Graph I shows the graphical representation of PSNR values of frame 1, 2, and 3 respectively for existing and proposed system.



Graph I PSNR value of existing and proposed System

Table II MSE Values before and after rain removal

Frame name	MSE before rain removal	MSE after rain removal
Frame1	472.1	22.08
Frame2	345.67	29.33
Frame3	210	20.44



Graph II MSE values before and after rain removal

Table II shows the Mean Square Error values before and after rain removal. Table I shows MSE is 472.1 before rain removal and 22.08 after rain removal. As per input video output video define better output. Graph II shows the histogram of MSE. MSE values decreases as per quality is improved.

As per above Performance analysis we can say that our Framework shows better output.

CONCLUSION

This paper presents a Rain Pixel Removal algorithm to recover the rain affected pixels by using motion segmentation. Existing algorithms for rain removal gives poor performance for highly dynamic scene. Motion segmentation includes motion cues and local cues for moving objects and considers RGB values. Rain pixel recovery with Gaussian noise removal gave better performance as compare to existing ones. Here Noise filter is used to remove unwanted noise from rainy video. After noise removal PSNR values increases and after rain recovery PSNR increases.

Many research issues have been highlighted and give direction for prospect work. Quality of output image will be improved as well as we can remove noise.

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