May – June 2020
ISSN: 0193-4120 Page No. 1366 - 1371

Video De-Fogging based on Improved Color Attenuation Prior

Isha Kansal, Renu Popli and Geetanjali Kapoor
Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab, INDIA-140401
Email: isha.kansal@chitkara.edu.in, renu.popli@chitkara.edu.in, geetanjali@chitkara.edu.in

Article Info
Volume 83
Page Number: 1366 - 1371
Publication Issue:
May - June 2020

Article History
Article Received*: 11August 2019*
Revised*: 18November 2019*
Accepted*: 23January 2020*
Publication*:10 May2020*

Abstract:

This papercomes up with a fog removal technique for fog degraded videos based upon improved Color Attenuation Prior called as CAP. CAP uses a machine learning techniqueforfinding the depth or transmission map of a fog degraded image. Thismap is further utilized for finding the unknown parameters of physical foggy image degradation model. Window based local minimum operation is applied in an efficient way so as to speed up the process and a fast Gradient Domain Guided Filter called as GDGF is used with CAP based transmission map for making the de-fogging process more faster and visually appealing. The edge preservation property of GDGF produces better quality de-fogged images. Since the image de-fogging techniques can even be applied on foggy videos but the task involves some extra internal steps due to temporal nature of videos. In videos,large number of frames are captured per second, it is more likely to have number of frames adjacent to each other are similar or correlated. By utilizing this property, in this work the de-fogging speed is further enhanced in the proposed work.

Keywords: *Dehazing, contrast, enhancement, fog, CAP*

1. Introduction

Image/video fog removal is a challenging process. Initially when the research on image de-fogging started, many researchers applied traditional image processing techniques for de-fogging [11]. Many fog removalmethods based upon multiple images have beenintroduced] ([16] [17], [18],). A decent progress has been occurred in the area of physical fog image degradation model (1) based de-fogging ([3], [5], [10], [15], [25], [26]). Zhu *et al.* [32] put up a powerful de-fogging prior which is based upon color attenuation property of a fog degraded image called as Color Attenuation Prior. In recent years many video de-fogging techniques have been proposed mainly include three different categories. The first category includes the frame-based video defogging which applies single image de-fogging on each video frame ([1], [2], [4]), [12], [13], [31]). The second category contains fusion based video de-fogging techniques based upon fusion of enhanced background and foreground images of each frame ([8], [20], [29]). The third category is based on estimation of a universal component that can be used in all video frames ([28], [30]). In this work, a video de-fogging technique has been proposed belonging to third category which applies scene change detection algorithm to find out the key frame and then finds de-fogging parameters using improved CAP technique based on key frame and reusing those parameters to de-fog number of frames identical to key frame.

2. *CAP* based De-fogging

During a clear non foggy day, every scene point expels the energyout ofmultiple lighting sources.This energy comes from light reflected by the ground, sunlight or skylight. Immediately upon this energy comes to the imaging system, someportion of it is gone astray. Two different mechanisms take place to the images taken during foggy weather which include direct attenuation and airlight according to the fog degradation model (1). This is based upon the suspicion that the troposphere is uniform and the fog/hazemolecules are uniformly distributed in the troposphere. The model can also be represented as:

$$I(x) = L_0(x) \times e^{-b\times d(x)} + L_A \times \left(1 - e^{-b\times d(x)}\right) \qquad (1)$$

x denotes the image spatial coordinate. $L_0$is the image which is to be recovered using foggy image whereas*I*is the fog degraded image. *b*represents the scattering coefficient corresponding toa particular medium. *d*denotes the gap of an image point at *x*with respect to the camera. L_A is the atmospheric light which is considered as constant throughout the image, $t=e^{-b\times d(x)}$ represents the transmission map which is inversely related to *d*.

TEST Engineering & Management

May – June 2020
ISSN: 0193-4120 Page No. 1366 - 1371

The first term in (1) is called as direct attenuation which happens due to decline in reflected energy by the scene point and weakens the image brightness. Second additive term in (1) is airlight. It boosts the brightness but reduces the saturation of the foggy image. These two parts i.e. transmission and airlight simultaneously reflects the foggy image. Zhu *et al.* [32] discovered that foggy image's saturation and brightness change strongly with changing fog concentration and proposed a linear model to find out parameters of above image degradation model (1):

$$d(x) = q_0 + q_1 \times v(x) + q_2 \times s(x) + \epsilon p(x) \qquad (2)$$

v is the brightness of scene and s represents the saturation, q_0,q_1 and q_2 are the linear coefficients, $ep(x)$ is the model's (2) random error. Depth mapobtained from (2) may not work for a fewconditions like white bodies and it will recognizethose as the distant objects. So, the above depth (2) is altered by employing local minimum operation (3):

$$d_r(x) = min_{y \epsilon O_r(x)} d(y) \qquad (3)$$

Here $O_r(x)$is the square window having radius $r$and x as its center. y is the pixel having the minimum intensity value in the window $O_{r\,(x)}$centered at x, d_r is the final depth map. This depth map generates halo artifacts due to applying window based operations. So, in order to deal with the halo artifacts, Zhu *et al.*used guided image filtering (*GF*) [6].

Once d, L_A and t are found, the recovered pixel value $L_0(x)$ is obtained from (1). The values for the transmission are taken between 0.1 and 0.9 to avoid false results.

Although, the technique of Zhu *et al.*produces acceptable quality de-fogged results but there are still some shortcomings as it applies window based operationsfor consideringthe impact of neighborhood of each pixel. Overall 225 × X × Y (X ×Y image) operations are performedand makes de-fogging process slow. Furthermore, for refining the depth map, guided filteringbased smoothening is performedfor preservingtexture and details in the recovered image. Despite, this filter is efficient for recovering texture details, but its performance is not good in case of recoveringminute edge details [14]. In improved *CAP*technique, these limitations have been dealt.

3. Improved *CAP* De-fogging

This section explains the improved *CAP* technique and the limitations of *CAP* technique.

3.1 Calculating Depth Map of Foggy Image

The initial depth map of a foggy image is obtained from (2) of *CAP* technique in this work. This depth $d$is alteredwith the effect of neighborhood pixels with the new down sampling approach. Down sampling is used in a manner that utmost local minimums in the foggy image are preserved. The procedure to estimate window based depth d_r is explained as following:

Depth map$d(M \times N)$, is divided into non superimposing 5 × 5 sized$n$ blocks.

Later, d^{ds} is obtained from d in a manner that its each pixel is estimated from the corresponding Bl_i by picking up smallest value in that block. Here d^{ds} is the down sampled image corresponding to d.

$$d^{ds}(xn) = \min(Bl_i), \quad i = 1,2,3 \ldots n \qquad (4)$$

After finding d^{ds}, its dark channel image d_r^{ds}, which is a square window based image is obtained as:

$$d_r^{ds}(xn) = min_{yn\, \epsilon O(x)} \left(d^{ds}(yn)\right) \qquad (5)$$

After performing the upsampling of d_r^{ds}, window based depth map d_r is obtained.

3.2 Refining Depth Map using GDGF

Guided filter *(GF)*is an edge preserving filter for smoothing digital images.The main advantage of this filter over other smoothing filters is its low computational time and cost. But aguided filter is also prone to halo artifacts and may not preserve fine texture details cleanly, therefore, Kou *et al.* [14] proposed an alteration in guided image filterby applying first order edge awareness constraints and the new filter is called asGradient Domain Guided Filter (*GDGF*). After applying a local linear model on the filtering and reference images, *GF* obtains a smooth image q which can be seen in (6). The image to be filteredisrepresented by$p$whereas G is the reference image. $O_r(k)$ denotes a square window having center $k$and radius r.

$$q_i = a_k \times G_i + b_k, \quad \forall\, i \in O_r(k) \qquad (6)$$

In window $O_r(k)$,a_k and b_k. are the constants and can be found by minimizing the function:

$$E(a_k, b_k) = \sum_{i \epsilon O_r(k)} [(a_k \times G_i + b_k - p_i)^2 + L \times a_k^2] \qquad (7)$$

$k$is a regulation parameter castigating a large a_k.Ideal a_k and $b_k$values are found by applying linear regression technique. *GDGF*, provides improved performance near by the edges with the help of applying edge attentive parameters. Apart from recovering clean edges,*GDGF* performs filtering in O(N) time which adds on to its performance. The better edge preservation of GDGF is also shown in Figure 1.

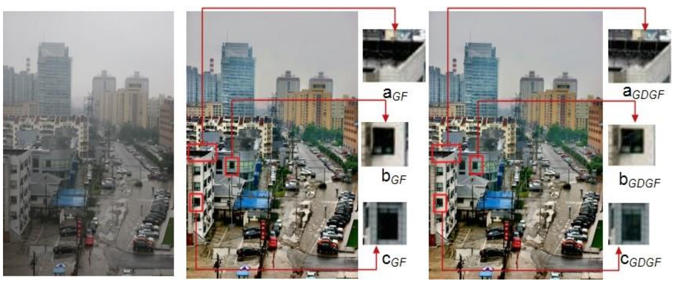


Figure 1: (a) Foggy Image. Recovered images retrieved by applying (b) *GF* [6] (c) *GDGF* [14]

The pursuance of *GDGF* is further enhanced by doing the above procedure on down sampled images with scaling factor 4. According to [7], if guided filtering is applied on down sampled images, it causes increase in processing speed almostten times and no significant visible degradation is observed.

3.3 Atmospheric Light

Global atmospheric light L_A is one of the valuable parameter in model based foggy image recovery. If the value of L_A is too high, it will lead to produce darker images whereas if vice versa then it produces brighter de-fogged images respectively. According to He*et al.* [5], brightest portion of the dark channel image represents the maximum fog covered regions of a degraded image. This region is considered as the best to estimate L_A. According to (1), a foggy image pixel is very close to L_A in regions of infinite depth. From (1):

$$I(x) = L_0(x) \times e^{-b\times d(x)} + L_A \times \left(1 - e^{-b\times d(x)}\right)$$

When ($d(x) \rightarrow \infty$), then $e^{-b\times d(x)} \rightarrow 0$, hence, $L_A \cong I$

Immense depth areas usually lie at image's upper section. So in order to reduce the computational time, L_A is obtained from the depth map of top 25% image rows in this work. The *R, G, B* color channel values with respect to top 0.1% brightest pixels in this depth image are selected as L_A.

4. Proposed Video De-fogging

In this work, improved *CAP* based image de-fogging technique is applied to foggy videos. Flickering may occur in videos when there is a scene change. However, if two neighboring frames reflect same scene, a gentle changeover is observed. But, if the image de-fogging process is applied frame by frame directly to videos, accidental flickers may arise even in the same scene frames. It can be observed from physical fog image degradation model (1) that foggy image itself *I*, transmission, *t* and global atmospheric lightL_A are the factors which may cause this problem of flickering. Whenavideo is captured with a good quality camera, it is usually smooth without flickers.Therefore, these accidental flickers may not be definitely due to video frame itself. Moreover, every de-fogged frame pixel is independently found during de-fogging process, hence this is even not altered with the effect of neighboring pixels. From these facts it can be concluded that *I*representing a foggy video frame is a steady factor and henceL_A and *t*can be the factors generating flickering effects among foggy video frames. In this work, rather than applying de-fogging process frame by frame, a scene transition detection method is used to find out the representative frame called as key frame as explained in further sections.

4.1 Frame based Scene Change Detection in Foggy Videos

Estimating the de-fogging parameters independently for each frame is computational expensive. It may also cause some unexpected flickers. For utilizing the parameters from previous frames, there is a need to find out relation between current and earlier frames by using scene detection algorithms. In this work, detection of change in scene is found by finding the correlation between Histograms of video frames [19]. Here correlation narrates the strength of relationship between two frames. Different foggy frames might be comprised of gentle transitions, motions and sudden transitions. For gentle transition, neighboring frames differ not considerably in intensity but havingidentical texture and edge details. This reflects a stronger correlation in spatial domain. The other case is motion transition in which the neighboring frames differ in intensity and texture details moderately. In sudden transitions, a complete scene transition between the contiguous frames is observed.So they are treated as uncorrelated frames. For n^{th} video frame, histogram Hst_n is computed as:

$$Hst_n(r_j = num_j) \qquad (8)$$

Here num_j is the number of pixels, *n*is the n^{th}frame, r_j is the j^{th} intensity level. The coefficient of correlation (*cor*) between Hst_n and Hst_{n-1} is computed as explained in [19]. Since there is not any threshold available which can categorize the type of correlation between the neighboring video frames. The fundamental rationale forcorrelating two coefficients is that, if the frames *i-1* and *k* are immensely correlated, and frames*i* and *k* are also immensely correlated, then there are higherchances that theircoefficient of correlation's $cor_{i,k}$and $cor_{i-1,k}$disparity is very less. Therefore, in this work, for detecting change in scene, two adjacent correlation values $cor_{n,k}$ and $cor_{n-1,k}$ are compared.

4.2 Algorithm

The proposed *CAP* based video de-fogging Algorithm is explained in this section

I. Pick the first frame Fr_1 and obtainthe histogram Hst_1[19]. AcknowledgeFr_1as the background image Bg_kinitially. Address k = 1 initially.

II. With the help of Bg_k, find initial and refined transmission values t_k and t'_k respectively. Also obtain atmospheric light L_A^k by using this video frame.

III. For n = 2 to <u>N</u>, repeat the below steps:

a. Pick n^{th} frame of the foggy video and find its histogram Hst_n.

b. Find $cor_{n,k}$ between histograms of the current Hst_n and the background frames Hst_k.

c. $cor_{n,k}$ is then rounded off to three decimal places. If the value of $cor_{n,k}$ = 1, set its value to $cor_{n,k}$ = 0.999.

d. Obtain current frame *n* parameters t_n, L_A^n as:

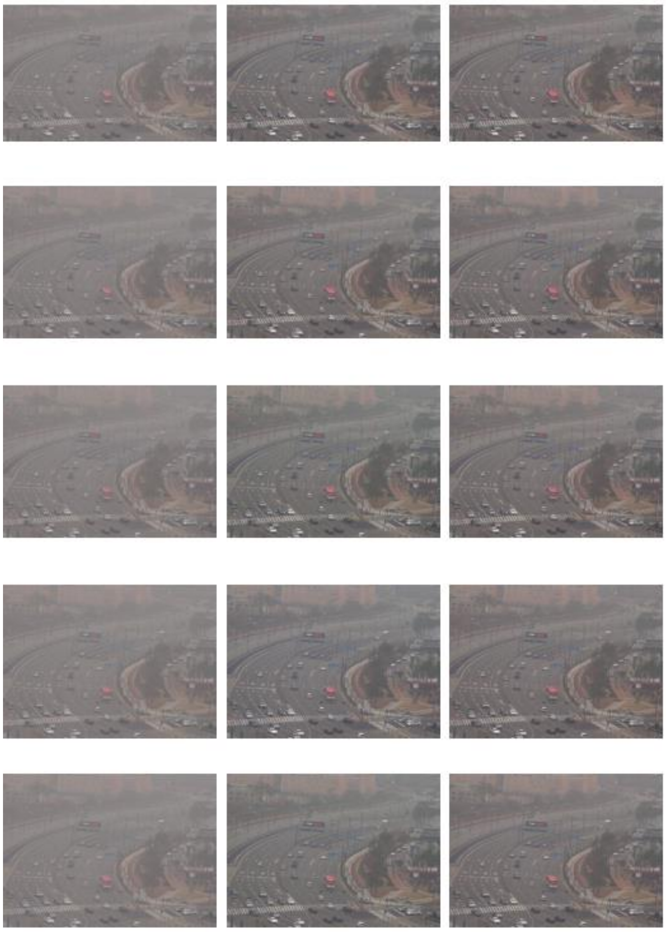
i. Compare $cor_{n,k}$ and $cor_{n-1,k}$ values.

ii. When coefficient values are same at

1stdenary place, directly move to next step. If not, then n and k frames are uncorrelated. For this case, find initial, refined transmission and global atmospheric light usingpresent frame n. Revise the background image frame by $Bg_k = Fr_n$. Set $k = n$, $t_k = t_n$, $t'_k = t'_n$ and $L_A^k = L_A^n$. Obtain de-fogged frame F_{dn} from (1). Go to step 3.1.

iii. Comparing correlation at second denary place,in case they are also same, move to next step. If not, then both frames are acknowledged as weakly correlated frames. For this, the previous transmission map is considered as such*i.e.*$t_n = t_k$ and t'_n isobtained by applying guided filter on t_n having present frame image Fr_n as the reference image. For this case, perform $L_A^n = L_A^k$. Obtain F_{dn} from (1). Go back to step 3.1.

iv. Whether the third denary place of correlation coefficients are same or not, as these are the least significant digits, both the frames are treated as correlated. For this case, (1) parameters are required not to be estimated for n^{th} frame. Directly perform, $t_n = t_k$, $t'_n = t'_k$ and $L_A^n = L_A^k$. Obtain F_{dn} from (1).

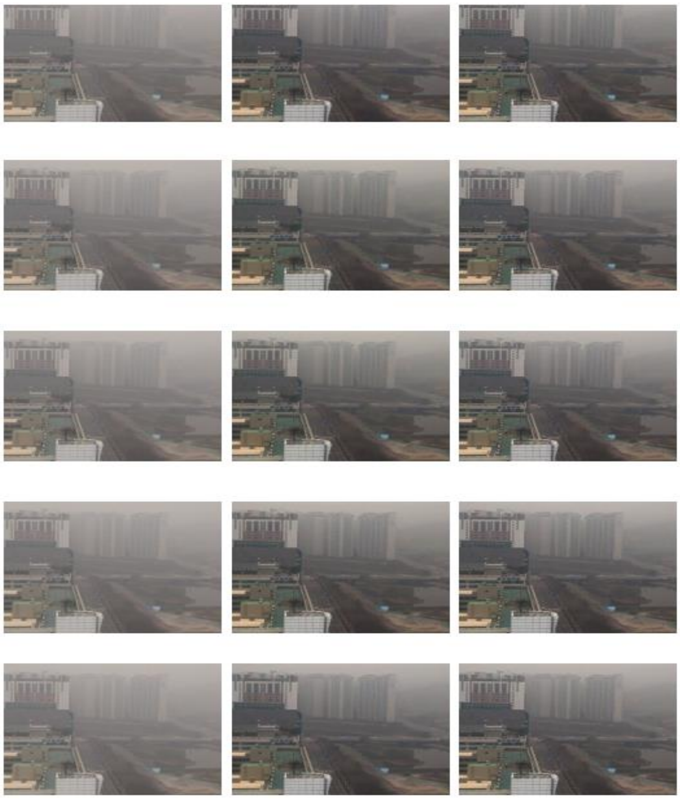


(a) (b) (c)

Figure 2: “Cross.avi” Video Frames, (a) Input foggy frames, results of (b) Proposed de-fogging (frame by frame approach) (c) Proposed video de-foggingtechnique.

(a) (b) (c)

Figure 2: “Bali.avi” Video Frames, (a) Input foggy frames, results of (b) Proposed de-fogging (frame by frame approach) (c) Proposed video de-foggingtechnique.



(a) (b) (c)

Figure 2: “Riverside.avi” Video Frames, (a) Input foggy frames, results of (b) Proposed de-fogging (frame by frame

May – June 2020
ISSN: 0193-4120 Page No. 1366 - 1371

approach) (c) Proposed video de-fogging technique.

5. Results Analysis

The above technique is applied on videos “cross.avi” (480 × 640 × 657), “bali.avi” (270 × 480 × 220) and “riverside.avi” (480 × 640 × 489). The video size is $P \times Q \times R$, where $P \times Q$ depicts the size of each video frame, R represents total frames in a video. The frames recovered with the help of proposed technique can be seen in Figures 2, 3 and 4. For comparison, the proposed work is also applied on videos with frame by frame approach. From the Figures, it can be visualized that the proposed video de-fogging when applied on videos, obtains better frames than that of simple frame by frame de-fogging approach. The mean parameters of evaluation *i.e.* Color Naturalness Index (*CNI*), Visual Contrast Measurement (*V CM*) and Color Information Entropy (*CIE*) [30] are then calculated between foggy and the corresponding de-fogged frames for the above described approaches. The values of parameters obtained by all three techniques are given in Table 1. Proposed de-fogging parameter values are slightly improved than frame by frame approach. From this, it can be concluded that quality of the video is not sufferedif previous frames are used to find parameters of de-fogging. The overall de-fogging effect is better in different aspects like spatial and temporal coherence etc. In this work, other than improving the visual quality, the frame rate is also improved as shown in Table 2. Frame rate time.

Table 1: Frame by frame approach vs.proposed technique based upon *CNI*, *VCM* and *CIE*.

	Frame by Frame Approach			ProposedVideo De-foggingTechnique		
	CNI	VCM	CIE	CNI	VCM	CIE
Bali	0.52	49.86	7.59	0.53	50.80	7.63
Cross	0.45	48.63	5.98	0.45	50.96	6.01
Riverside	0.53	49.97	6.96	0.53	50.36	6.97
Average	0.50	49.49	6.84	0.50	50.71	6.87

Table 2: Frame by frame approach vs.proposed technique based upon frame rate

	Cross	Bali	Riverside
Frame by Frame Approach	10.56	20.47	10.97
Proposed Video De-fogging Technique	36.52	30.02	30.00

6. Conclusion

In this work, improved *CAP* technique is extended for video de-fogging. This approach enhances the defogging performance in terms of spatial and temporal coherence, and also reduces the execution time. First video frame is extracted and considered as a reference frame. Parameters of physical model are calculated using reference frame with the help of improved *CAP* technique and for further frames, the histogram based correlation is checked between upcoming and the reference frames. If they are correlated, the previous parameters are used to de-fog upcoming frames, otherwise, new parameters are estimated. This improves the video’s spatial/temporal coherence and computational complexity.

References

[1] Archa, S. and Abdul, A., “A novel method for video dehazing by multi-scale fusion”, International Journal Scientific Engineering and Technology Research, Vol. 3, pp. 4808-4813, 2014.

[2] Cai, B., Xu, X. and Tao, D., “Real-time video dehazing based on spatio-temporal mrf”, in Pacific Rim Conference on Multimedia, pp. 315-325, Springer, Cham, September 2016.

[3] Fattal, R., “Single image dehazing”, ACM Transactions on Graphics, Vol. 27, No. 3, pp. 1-9, 2008.

[4] Gibson, K., Vo, D. and Nguyen, T., “An investigation in dehazing compressed images and video”, in Proceedings of OCEANS 2010 MTS/IEEE SEATTLE, pp. 1-8, Seattle, WA, USA, September 2010.

[5] He, K., Sun, J. and Tang, X., “Single image haze removal using dark channel prior”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 33, No. 12, pp.2341-2353, 2011.

[6] He, K., Sun, J. and Tang, X., “Guided image filtering”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 6, pp. 1397-1409, 2013.

[7] He, K., “https : //github.com/accessify/fast − guided−filter/blob/master/fastguidedfilter.m”, Fast Guided Filter, accessed January 5, 2018.

[8] John, J. and Wilscy, M., “Enhancement of weather degraded video sequences using wavelet fusion”, in Proceedings of 7th IEEE International Conference on Cybernetic Intelligent Systems, pp. 1-6, London, UK, September 2008.

[9] Kansal, I. and Kasana, S. S., “Weighted image defogging using luminance dark prior”, Journal of Modern Optics, Vol. 64, No. 19, pp. 2023-2034, 2017.

[10] Kansal, I. and Kasana, S. S., “Minimum preserving subsampling-based fast image de-fogging”, Journal of Modern Optics, Vol. 65, No.

TEST Engineering & Management
May – June 2020
ISSN: 0193-4120 Page No. 1366 - 1371

18, pp. 2103-2123, 2018.

[11] Kim, T. K., Paik, J. K. and Kang, B. S., "Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering", IEEE Transactions on Consumer Electronics, Vol. 44, No. 1, pp. 82-87, 1998.

[12] Kim, J. H., Jang, W. D., Sim, J. Y. and Kim, C. S., "Optimized contrast enhancement for real-time image and video dehazing", Journal of Visual Communication and Image Representation, Vol. 24, No. 3, pp. 410-425, 2013.

[13] Kim, Y. M., Park, K. T., Lee, D. S., Choi, W. and Moon, Y. S., "Video dehazing without flicker artifacts using adaptive temporal average", in Proceedings of 18th IEEE International Symposium on Consumer Electronics, pp. 1-2, June 2014.

[14] Kou, F., Chen, W., Wen, C. and Li, Z., "Gradient domain guided image filtering", IEEE Transactions on Image Processing, Vol. 24, No. 11, pp. 4528-4539, 2015.

[15] Meng, G., Wang, Y., Duan, J., Xiang, S. and Pan, C., " Efficient image dehazing with boundary constraint and contextual regularization", in Proceedings of IEEE International Conference on Computer Vision, pp. 617-624, 2013.

[16] Narasimhan, S. G. and Nayar, S. K., "Chromatic framework for vision in bad weather", in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Vol. 1, pp. 598-605, 2000.

[17] Narasimhan, S. G. and Nayar, S. K., "Interactive (de) weathering of an image using physical models", in Proceedings of IEEE Workshop on Color and Photometric Methods in Computer Vision, Vol. 6, No. 6.4, France, October 2003.

[18] Nayar, S. K. and Narasimhan, S. G., "Vision in bad weather", in Proceedings of 7th IEEE International Conference on Computer Vision, Vol. 2, pp. 820-827, Kerkyra, Greece, Greece, September 1999.

[19] Radwan, N. I., Salem, N. M. and El Adawy, M. I., "Histogram correlation for video scene change detection", in Advances in Computer Science, Engineering and Applications, Springer, pp. 765-773, Berlin, Heidelberg. 2012.

[20] Ramya, C. and Rani, D. S. S., "Contrast enhancement for fog degraded video sequences using BPDFHE", International Journal of Computer Science and Information Technologies, Vol. 3, No. 2, pp. 3463-3468, 2012.