Improved Preprocessing Strategy under Different Obscure Weather Conditions for Augmenting Automatic License Plate Recognition

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Abstract

Automatic license plate recognition (ALPR) systems are widely used for various applications, including traffic control, law enforcement, and toll collection. However, the performance of ALPR systems is often compromised in challenging weather and lighting conditions. This research aims to improve the effectiveness of ALPR systems in foggy, low-light, and rainy weather conditions using a hybrid preprocessing methodology. The research proposes the combination of dark channel prior (DCP), non-local means denoising (NMD) technique, and adaptive histogram equalization (AHE) algorithms in CIELAB color space. And used the Python programming language comparisons for SSIM and PSNR performance. The results showed that this hybrid approach is not merely robust to a variety of challenging conditions, including challenging weather and lighting conditions but significantly more accurate for existing ALPR systems.

Keywords: hybrid preprocess, weather-based preprocess, non-local means denoising, dark channel prior, adaptive histogram equalization

1. Introduction

In modern society, a vehicle's automatic license plate recognition (ALPR) is a prime necessity [1-5]. When a real-time vehicle image is captured, the license plate is detected and recognized to identify the numbers, letters, and other symbols within it. Preprocessing algorithm of captured vehicle's image is a vital step for improving the precision of later stages- detection of the license plate, segmentation, and recognition of characters written over the plate. The image's quality has been enhanced at the preprocessing stage, which allows the vehicle's license plate to be easily recognized. Also, due to the improvement of clarity, the identification of characters has been promoted at the preprocessing stage. In an unclear environment, e.g., fog, rain, low light, or smog, the acquired image of the vehicle is not easily recognized. Under the conditions mentioned above, conventional preprocessing techniques, such as adaptive histogram equalization (AHE) [6], median filter [7], and bilateral filter [8], do not satisfactorily lower the effect of weather on an image.

Hence, various license plate extraction techniques are proposed in many works of literature, such as extraction based on edges, global image features, character features, textures, and colors [9-14]. The edge-based method is sensitive to undesired edges under complex conditions. The global image-based method fails to work in the exact dimensions (aspect ratio) under the presence of similar objects. The character-based scheme is sensitive to noise components within the plate. There is computational complexity for the texture-based detection method under the presence of many edges and the complex scenario. The color-based technique depends on the illumination level and noise over the license plate.

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Thus, in this work, a weather-based hybrid preprocessing method is proposed for the first time in the context of the ALPR process to enhance image quality, including its license plate. In this method, dark channel prior (DCP) [15-16], AHE, and non-local means denoising (NMD) [17] algorithms are combined at the preprocessing stage. L*A*B* (also known as CIELAB) color space and AHE are used to achieve a superior color image. This approach improves recognition activity. The proposed preprocessing method solves the ALPR problem under rainy conditions. The NMD technique has been valuable for erasing noisy raindrops and streaks [18] on regions of license plate images to a greater extent. The suggested preprocessing method is not compute-intensive and does not involve extensive prior data. Hence, it does not require a powerful computational platform.

Besides, the proposed front-end processing method provides excellent and robust performance for helping identify license plates even under complex backgrounds and/or obscure weather conditions. It improves the cons of different detection techniques mentioned before, meanwhile, augments ALPR activity. The notable advantages of the proposed method are as follows:

(1) A hybrid preprocessing method is framed to promote ALPR techniques under different critical and unfavorable weather conditions.

(2) The combination of DCP and AHE algorithms facilitates the achievement of haze-free and highly contrasting vehicle images in obscure environments instead of their usage as a processing tool.

(3) Integration of AHE and CIELAB space can significantly retain the original image's color as a device-independent color representation.

(4) Simple computational steps of preprocessing technique require a moderate capacity computational platform. Thus, the computational platform is cost-effective.

(5) NMD filter can significantly reduce noisy effects over license plates in the presence of raindrops or water streaks.

(6) Improved preprocessing performance using structural similarity index measure (SSIM) and peak signal-to-noise ratio (PSNR) is obtained more than the well-known preprocessing method.

The organization of the study is as follows. Section 2 describes the proposed preprocessing technique. Section 3 gives recognition steps. Section 4 presents results and observations to validate the superiority of the proposed preprocessing concept. Conclusions are provided in Section 5.

2. Proposed Preprocessing Methodologies for Augmenting Identification

Different types of weather produce different types of obscuration. This poses a problem for automatic license plate recognition. To counter these constraints, a hybrid preprocessing technique is proposed. The suggested hybrid technique is described as follows:

2.1. Weather-based proposed preprocessing method

As shown in Fig. 1, the proposed preprocessing method of weather-based consists of DCP, NMD, and AHE in CIELAB color space. In this research, the hybridization of different algorithms is determined based on the weather type [19-20] of obscureness in the local environment. The DCP algorithm is used to remove the hazy effect in the image. However, there is a drawback that using the DCP method can lower the contrast level of the image. Therefore, the AHE technique is adopted later in the proposed hybrid method to enhance the contrast of processed images by the DCP algorithm. In this study, AHE in CIELAB color space retains colors in the image instead of using AHE alone. NMD algorithm removes noise in the presence of raindrops/streaks by replacing pixel value with the average value of all similar pixels via vast scanning of the entire image. The steps of the DCP, AHE, image inversion, and NMD algorithms are presented as follows:

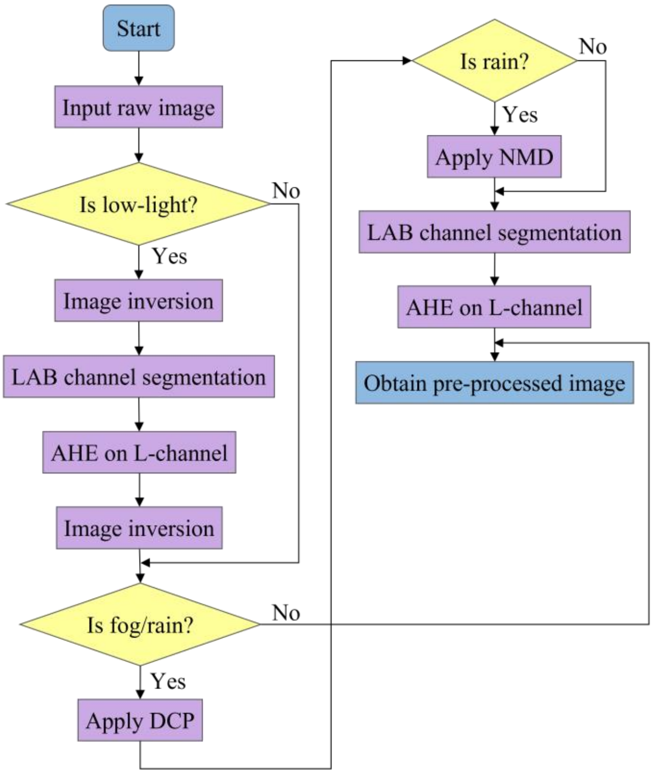


Fig. 1 Proposed weather-based pre-processing methodology

(1) DCP: The main steps of the algorithm are sequentially mentioned as separation of RGB components, computation of DCP, estimation of transmission map, recovery of scene radiance, and obtainment of haze-free image.

(2) AHE: This method facilitates spreading pixel histogram values to improve the image's contrast. The main steps are the decomposition of the entire image into blocks, histogram equalization for each block, and avoidance of noise amplification via contrast limit.

(3) Image inversion: Black and white image inversion refer to an image processing technique where light areas are mapped to dark, and dark areas are mapped to lighter areas. In other words, after image inversion, black becomes white, and white becomes black. An inverted black-and-white image can be thought of as a digitally inverted version of the original image.

In this work, the inversion algorithm is applied to the red (R), green (G), and blue (B) components of an image, which are generally captured from a USB camera. A color digital negative effect happens due to inversion logic. The image's R, G, and B components are represented as "uint8" values. Thus, any color component can take a range of values from 0 to 255. Assuming that the intensity value at position (x, y) of the image is I(x, y), the inversion mapping is defined by Inverted (x, y) = 255 - I(x, y).

(4) NMD: These steps are the selection of a pixel "i" and similarity window. Determination of similarity index "S(i, j)" between the neighborhood of pixel "i" and neighborhood of non-local pixel "j" for a set (i, j), calculation of weight "W(i, j)," and computation of output of non-local means filter for any pixel "NL(i)" by taking weighted average value.

Then, preprocessing steps for individual (fog/low-light/rain) and mixed (low-light fog, low-light rain, and fog and rain) weather conditions are described below.

2.2. *Preprocessing method under smoke/fog/smog*

As shown in Fig. 1, different algorithms for preprocessing methods under smoke/fog/smog. In sequence order, these are DCP, segmentation on LAB axes, and AHE on the L channel. In this work, the DCP algorithm plays a vital role in removing the fog/smog effect over the image.

2.3. Preprocessing method under low-light conditions

The suggested preprocessing strategy on captured car images under low-light conditions is also presented in Fig. 1. Low-light pixel values are converted into high-valued pixels that result in a highly bright image (it can depict a case of extreme superficial fogginess). Then, histogram equalization is done for the inverted image. Finally, image inversion is adopted to achieve a brighter image at output.

2.4. Preprocessing method under rainy conditions

The NMD algorithm plays a pivotal role in rainy weather in the proposed study. The NMD filter is applied after the DCP algorithm. This filtering action significantly reduces the noisy effect of raindrops /streaks in captured car images, keeping the image's finer details intact. The NMD algorithm is advantageous as it is a patch-based method for denoising. The idea behind this denoising method is to average any given patch based upon similar patches from all over the image, regardless of their locations (also known as neighborhood filtering).

2.5. Preprocessing method under mixed weather conditions

(1) The logical steps are followed in three kinds of mixed conditions (mixed weather conditions, low-light cum fog, low-light cum rain, and fog cum rain) as proposed study: Low-light fog condition: image inversion, segmentation on LAB axes, AHE on L channel, image inversion, DCP, segmentation on LAB axes, and AHE on L channel. The preprocessing steps for low-light are initially used, and then, preprocessing steps for fog conditions are applied.

(2) Low-light rain condition: image inversion, segmentation on LAB axes, AHE on L channel, image inversion, DCP, NMD, segmentation on LAB axes, and AHE on L channel. The preprocessing steps for low light are initially used, then preprocessing steps for rain conditions are applied.

(3) Fog and rain condition: DCP, NMD, segmentation on LAB axes, AHE on L channel.

3. Recognition of Vehicle Plate

After obtaining a preprocessed image, the license plate is recognized via the following steps:

(1) Detection of edges: Canny edge detection method is used in this work.

(2) Look for contours in the image: Contours can be explained simply as a curve joining all continuous points with the same color or intensity. Once the contours have been detected, sorting these from large to small for the area is done. Only the first ten prominent contours are considered, and others are ignored. In the vehicle's image, the contour could be anything that has a closed surface. The license plate number will be present in the resultant sorted contours due to the prominent size and closed surface. A rectangle shape contour with four sides having a suitable aspect ratio is searched to filter out the license plate contour among the obtained sorted contours. A license plate should be rectangular, a four-sided object. After saving the detected correct contour in a variable named 'screenCnt', a rectangle box is drawn around it to identify the license plate correctly.

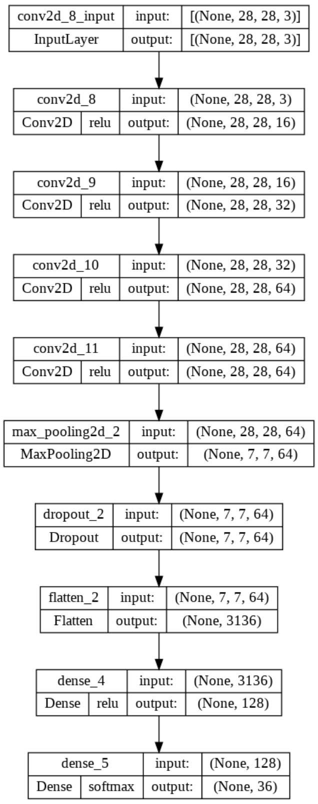
(3) Character Segmentation: To segment characters in the cropped image.

(4) Character Recognition: Identifying numbers or/and letters from the segmented image. The Pytesseract package, CNN, and SVM classifiers (Fig. 2) are used to recognize characters in different studies.

```
text = pytesseract.image_to_string(cropped, config = '--psm 11
# psm -> Tesseract Page Segmentation Modes (PSMs)
# psm 11 -> Sparse text. Find as much text as possible in no particular order.
```

(a) Pytesseract package

Fig. 2 Different classifiers



(b) CNN classifier

```
# Splitting the data into test and training set for our SVM testing
from sklearn.model_selection import train_test_split
train_x, test_x, train_y, test_y = train_test_split(X,y, test_size = 0.20.
Random_state = 42, stratify =y)

# Creating our linear SVM Model
From sklearn.svm import SVC
clf = SVC(C=1, kernel = 'linear)

# Fitting the training data in the SVM object declaring before
clf.fit(train_x, train_y)
Y_predict = clf.predict(test_x

"""
Parameters used in SVC Model
C: float, default=1.0 Regularization parameter. The strength of the
regularization is inversely proportional to C. Must be strictly positive.

kernel: {'linear', 'poly', 'rbf', 'sigmoid', 'precomputed'} or callable,
default='rbf'. Specifies the kernel type to be used in the algorithm. If none
is given, 'rbf' will be used.
"""
```

(c) SVM classifier

Fig. 2 Different classifiers (continued)

4. Results and Experiments

Various studies using Python programming language (using OpenCV library) are conducted under diversified weather conditions to validate the working and usefulness of the proposed preprocessing method. The library functions and parameters used for different algorithms are mentioned in Table 1. Table 2 shows the system specifications of our computational platform.

Table 1 Library functions and parameters of different algorithms

AHE on LAB channel: bgr = cv2.imread(image_path), lab = cv2.cvtColor(bgr, cv2.COLOR_BGR2LAB), lab_planes = cv2.split(lab), clahe= cv2.createCLAHE(clipLimit=2.0,tileGridSize=(gridsize,gridsize)), lab_planes[0] = clahe.apply(lab_planes[0]) lab = cv2.merge(lab_planes), bgr = cv2.cvtColor(lab, cv2.COLOR_LAB2BGR)

Dark channel prior:
 	
def boxfilter(I, r),
def guided_filter(I, p, r=40, eps=1e-3),
R, G, B = 0, 1, 2 # index for convenience
L = 256 # color depth,
def get_dark_channel(I, w),
def get_atmosphere(I, darkch, p),
def get_transmission(I, A, darkch, omega, w), def get_radiance(I, A, t),
def dehaze(im, tmin=0.2, Amax=220, w=15, p=0.0001, omega=0.95, guided=True, r=40, eps=1e-3)

Image inversion: def inverte(imagem, name): imagem = (255-imagem) cv2.imwrite(name, imagem)

Table 1 Library functions and parameters of different algorithms (continued)

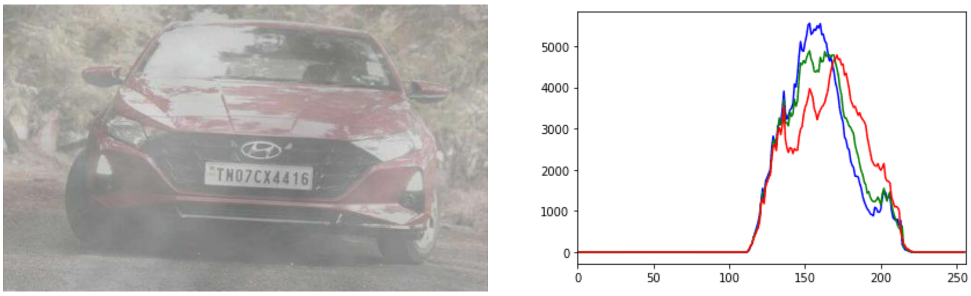
Non-local means denoising: cv.fastNlMeansDenoising(src, dst, h, templateWindowSize, searchWindowSize]) “”” src = Input 8-bit 1-channel, 2-channel, 3-channel or 4-channel image. DST = Output image with the same size and type as src. templateWindowSize = size in pixels of the template patch used to compute weights. It should be odd. Recommended value 7 pixels searchWindowSize = size in pixels of the window used to compute the weighted average for a given pixel. It should be odd. h = Parameter regulating filter strength. An increased 'h' value perfectly removes noise but also removes image details, while decreased h value preserves details but also preserves some noise. “””

Table 2 Test platform and software

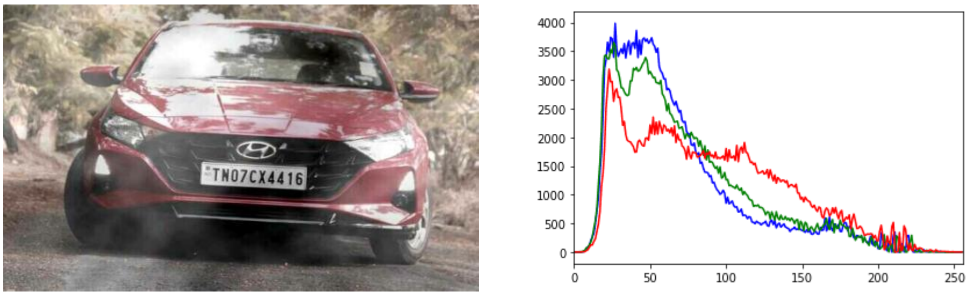
Devices	Specifications
Central processing unit	Intel i5-7200, 2.71 GHz (x64)
Memory	8 GB
Python	Version 3.7.2
GPU	NIL
IDE	Jupyter Notebook

4.1. Performance of the proposed preprocessing scheme under fog/smog/smoke conditions

As shown in Fig. 3, the captured images of vehicles under fog/smog/smoke conditions and processed images after implementing the proposed method. The comparative histogram plots are also shown in Fig. 3 for the raw image, preprocessed image via DCP alone, preprocessed image via AHE alone, and preprocessed image via the proposed one (hybrid), respectively. From the case study, the quality of the vehicle’s image has improved due to the proposed DCP-based preprocessing method under a foggy/smoggy environment. Besides, Fig. 3 shows the usage of the proposed approach so that a clearer vehicle image with a distinct license plate is obtained.

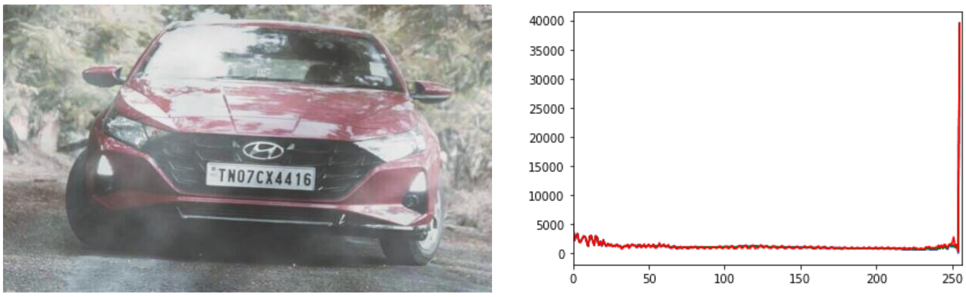


(a) The captured image

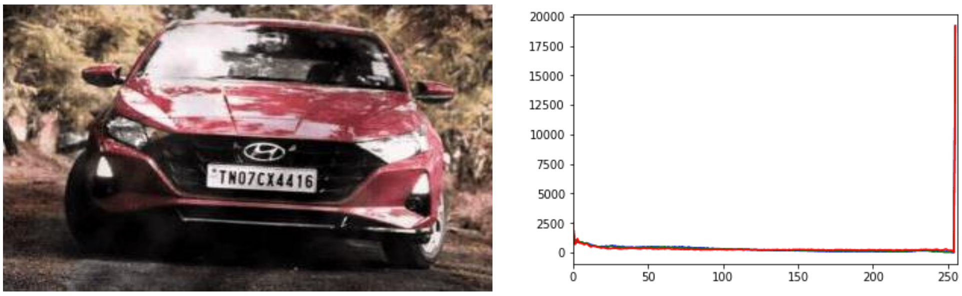


(b) Processing an image with DCP alone

Fig. 3 Performance of the proposed preprocessing method under fog/smog/smoke conditions



(c) Processing an image with AHE alone



(d) Processing an image with the proposed hybrid algorithm

Fig. 3 Performance of the proposed preprocessing method under fog/smog/smoke conditions (continued)

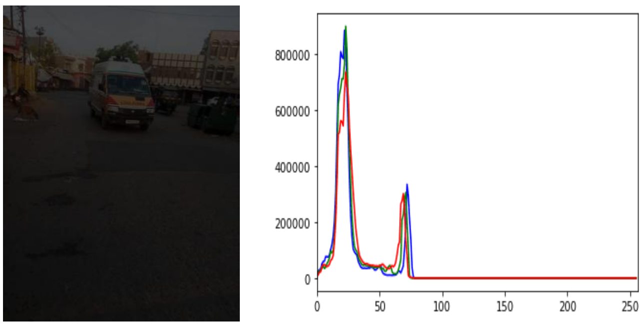
4.2. *Performance of the proposed preprocessing method under low-light conditions*

Fig. 4 shows the original sample car image under a low-light environment and the processed image after the proposed preprocessing method. Images at different processing stages and respective histograms for another sample image under low light conditions are given in Fig. 5. This figure reveals that pixel count values shift from the left side (dark phase of the input image) to the right side (bright phase of the output image). It indicates that a significantly improved bright image is obtained due to the usage of the suggested preprocessing stage. Therefore, the proposed method strengthens the convenient identification of the license plate of captured vehicle's image under dark conditions.

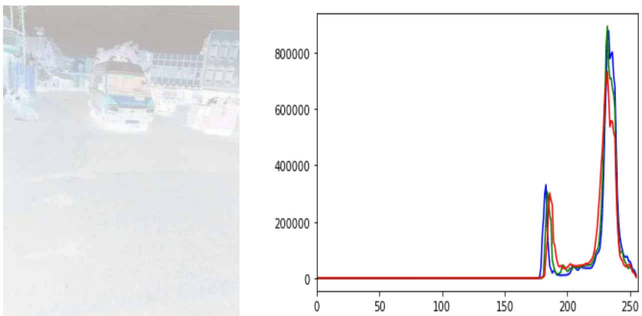
(a) The captured image

(b) Preprocessed image

Fig. 4 Performance of the proposed preprocessing method under low-light conditions

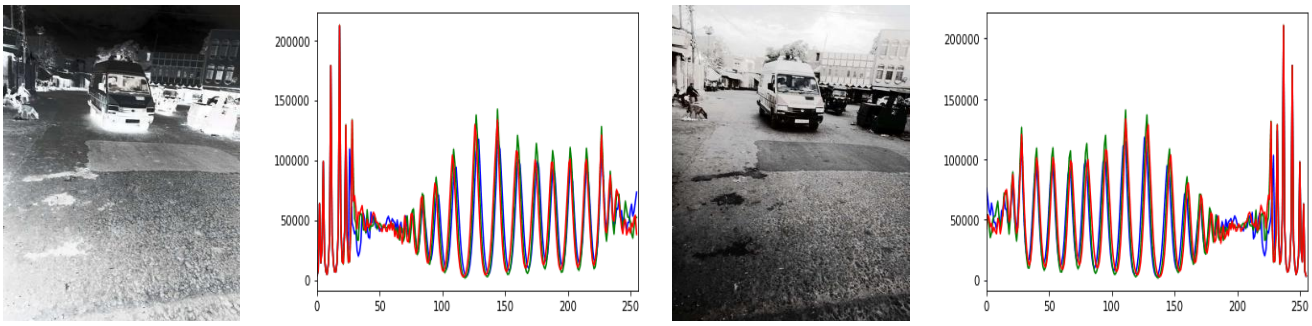


(a) Input image



(b) Image inversion

Fig. 5 During image preprocessing stages under low-light conditions



(c) Inverted image after the proposed preprocessing method (d) Reinverted (final) image

Fig. 5 During image preprocessing stages under low-light conditions (continued)

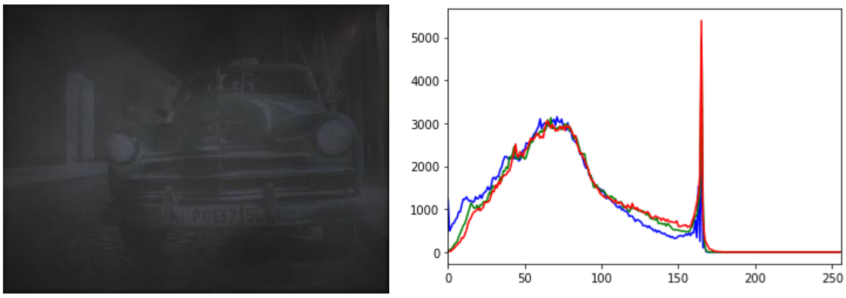
4.3. Performance of the proposed preprocessing method under rainy conditions

The NMD logic-based preprocessing technique significantly removes raindrops/streaks from the image under rainy conditions, as presented in Fig. 6. The license plate is more clearly visible in the image due to the removal of rain-prone noise by the NMD filter.

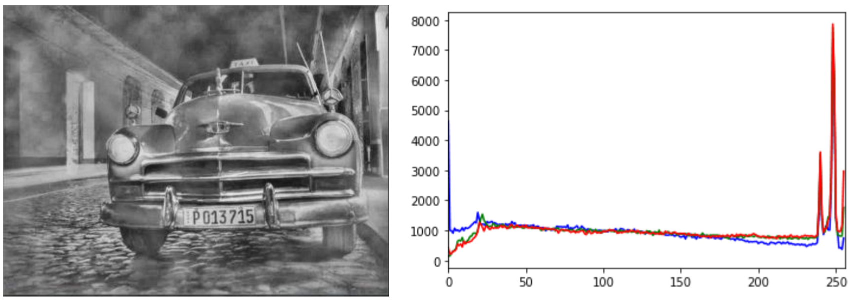
(a) The captured image (b) Preprocessed image

Fig. 6 Performance of the proposed preprocessing method under rainy conditions

4.4. Performance of the proposed preprocessing method under the mixed weather conditions

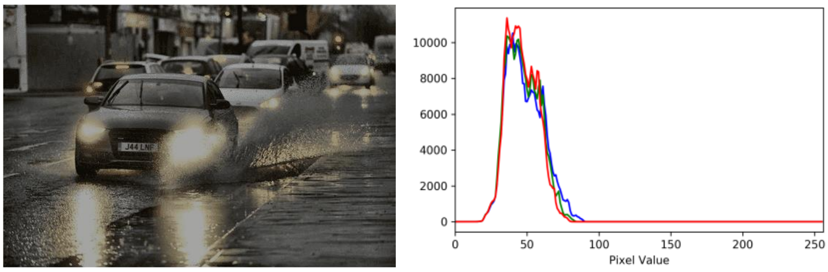


(a) The captured image

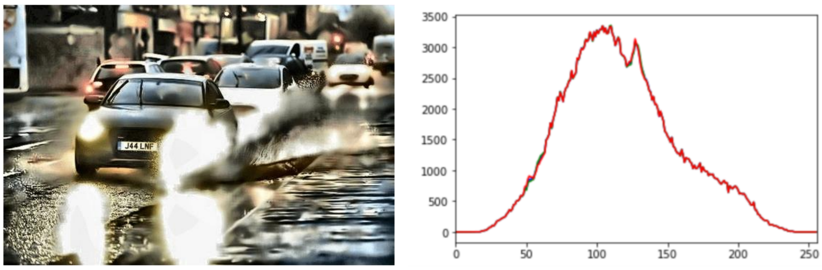


(b) Preprocessed image

Fig. 7 Performance of the proposed preprocessing method under mixed weather (low-light with fog/smog) conditions

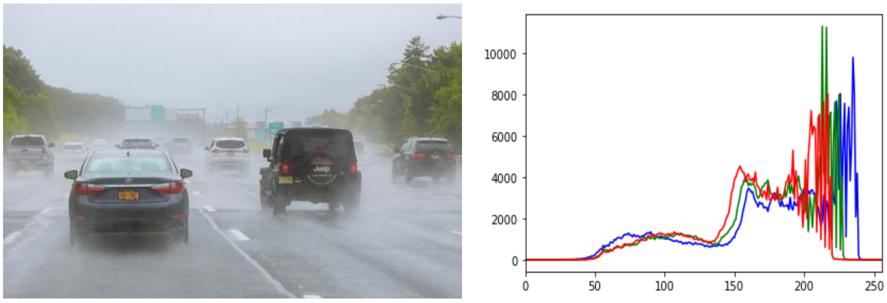


(a) The captured image

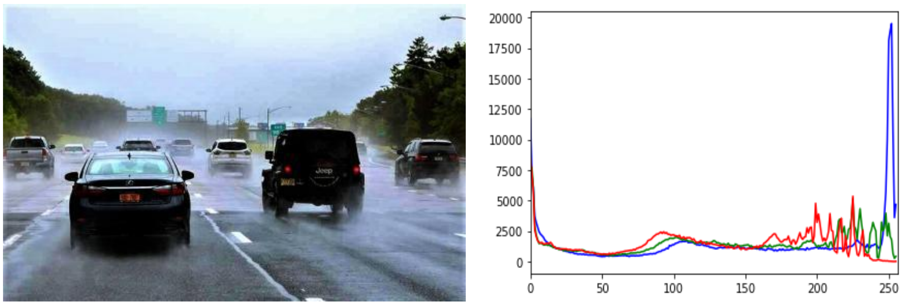


(b) Preprocessed image

Fig. 8 Performance of the proposed preprocessing method under mixed weather (low-light with rain) conditions



(a) The captured image



(b) Preprocessed image

Fig. 9 Performance of the proposed preprocessing method under mixed weather (fog/smog with rain) conditions

As shown in Fig. 7-9, the obtained images and comparative histograms after the proposed preprocessing method was implemented on various images under mixed weather conditions (low-light with fog/smog, low-light with rain, and fog/smog with rain). The histogram of the processed image indicates a better distribution of pixel values with improved brightness. In contrast, the histogram of the captured image shows a comparatively non-uniform distribution of grey levels with low brightness.

Fig. 10 presents the proposed method's recognition of license plate numbers from the preprocessed image. The steps are as follows: (a) getting the preprocessed image; (b) cropping the license plate; (c) recognizing the plate number. Plate numbers from these preprocessed images are conveniently recognized through different steps of the conventional method [8]. Thus, this method demonstrates the successful identification of license plates after image preprocessing via the proposed method. After comparing the average value of SSIM and PSNR, Table 3 shows the superiority (more structural similarity indices and more PSNR values) of the proposed preprocessing scheme gives superior performances over well-known preprocessing methods.

KA05MG790

(a) Case 1

TN07CX4416

(b) Case 2

TH87A8922

(c) Case 3

Fig. 10 Preprocessed images and corresponding recognition of vehicle's number plates

Table 3 Comparative performance parameters under different obscure weather conditions

Weather condition	DCP		AHE		Bilateral filter		Median filter		Proposed	
	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR
Fog/smog/smoke	0.55	26.62	0.84	28.11	0.66	44.22	0.69	43.91	0.85	46.78
low-light	0.11	2.82	0.11	8.9	0.01	11.56	0.01	10.66	0.21	13.11
Rainy	0.54	22.9	0.66	23.08	0.34	33.87	0.38	38.53	0.69	40.01
Mixed (low-light with fog/smog)	0.46	18.55	0.39	19.11	0.21	28.28	0.22	30.56	0.51	33.13
Mixed (low-light with rain)	0.35	20.99	0.28	18.24	0.12	20.98	0.10	31.10	0.47	35.90
Mixed (fog/smog with rain)	0.51	20.56	0.61	22.1	0.55	39.24	0.49	37.12	0.68	43.33

4.5. Evaluation of accuracy

Table 4 presents comparative accuracy percentages under different obscure/complicated conditions regarding various images in the database [21]. It evaluates the performance of the proposed preprocessing methodology in detection and recognition tasks. A bilateral filter is used in the case study when the proposed preprocessing method is not used. Moreover, Table 4 indicates the enhanced accuracy percentage in the proposed case.

Table 4 Accuracy (%) comparison under obscure conditions

Item	Without proposed preprocessing	With proposed preprocessing
Template matching	89	95.1
PyTesseract	87.1	93.4
CNN [22]	91	97.6
SVM [23]	92.3	98.7

5. Conclusion

A hybrid preprocessing methodology combined with the ALPR is proposed in this work. Accurately identifying vehicle license plates and its characters recognition is difficult under unclear weather conditions. Therefore, an improved approach is suggested in this study to preprocess the vehicle's image for a robust implementation of an ALPR mechanism. DCP-NMD-

AHE algorithms are applied to reduce the impacts of fog, smog, and low-light conditions on the vehicle's image, moreover, the NMD algorithm removes raindrops and streaks conveniently. Performances in terms of SSIM and PSNR are improved in the proposal. The diversified and vast studies demonstrate that the proposed multi-capable preprocessing method is conveniently applied in practice without involving a sizeable computational platform. However, the proposed technique needs to improve the quality of slightly low-contrast images recently reported by Rahman and Paul [24]. Therefore, further work will be done to overcome the limitation.

Conflicts of Interest

The authors declare no conflict of interest.

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