Recognition of vehicle make and model in low light conditions

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ABSTRACT

This paper presents a method for vehicle make and model recognition (MMR) in low lighting conditions. While many MMR methods exist in the literature, these methods are designed to be used only in perfect operating conditions. The various camera configuration, lighting condition, and viewpoints cause variations in image quality. In the presented method, the vehicle is first detected, image enhancement is then carried out on the detected front view of the vehicle, followed by features extraction and classification. The performance is then examined on a low-light dataset. The results show around 6% improvement in the ability of MMR with the use of image enhancement over the same recognition model without image enhancement.

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1. INTRODUCTION

The use of vehicle make and model recognition (MMR) has applications in surveillance systems and has benefits over using traditional license-plate recognition, which can be easily tricked [1]. This could provide major efficiency improvements for traffic and law enforcement. MMR can also be used with offline and online systems to discover fraudulent license plates by checking the registration database. Major highway traffic can also be monitored by computing the travel time for each vehicle traveling between two cameras [2]. It can also be used in automated vehicle parking systems to further optimize the parking space by the knowledge of MMR [1]. The techniques used in the literature for MMR could be classified into appearance-based, feature-based, and model-based [3-10], and in some cases, a combination of methods is used [11]. Additionally, many classifiers are presented in the literature to improve the detection rate [12]. Regardless of the high accuracy achieved by these recognition methods, there are still several main issues to be addressed [3]. The majority of these methods were designed to work under good lighting conditions, which might not always be the case when a surveillance system is used [13]. Occlusions may also occur when the camera is not able to capture the entire view of the vehicle, causing some vehicle features to be missed which will result in lower recognition accuracy. Moreover, due to the diverse traffic cameras hardware used, images are captured with different resolutions, distortion, limited lighting, visibility and noise which varies between sunny and rainy days and backlight conditions. There is also the issue of viewpoint caused bythe vehicle movement and the limited range of the camera.

This paper presents a new MMR method which employs feature-based recognition techniques, designed specifically for low light conditions. Given a captured image, vehicle detection and alignment are first performed to extract the vehicle from the background using an appearance-based method, then an image enhancement technique is applied to normalize the image to normal lighting conditions. With the enhanced image, region-of-interests are identified and vehicle features such as vehicle headlights, grilles and logos are extracted. Then a generic algorithm is utilized to select the finest set of features. Vehicle models are then recognized from these features using a classifier. The proposed system can work on the current implemented traffic surveillance systems with sufficient speed to operate as an online recognition system, and it can be utilized for offline detection. The main contribution of this paper is vehicle recognition in low lighting using an image enhancement technique, particularly,

- this paper improves the detection and alignment process using an appearance-based method, which increases the capability and robustness of the system to be used with all types of camera hardware.
- this paper presents an image enhancement technique to normalize the image to normal lighting conditions.
- this paper proposes a feature-based approach of vehicle make and model recognition and creates a vehicle Image database for performance assessment.

In the following sections, the related works are first introduced, followed by the methodology. The method is then tested against the experimental database, and the performance is examined.

2. RELATED WORKS

Recently, many studies have proposed multiple MMR methods. Appearance-based MMR comprises of methods based on dimensions [4], shapes, and textures [5]. These techniques require minimum processing; however, the performance of these techniques varies with the placement and the viewpoint of the camera used. Feature-based MMR techniques are the most widely used and these techniques depend on local or global features of the vehicle such as geographical feature, edge map [6, 7], histogram of gradient, sparse representation, scale-invariant feature transform (SIFT) [8] and symmetrical speeded-up robust features (SURF) [9, 10]. The performance of these methods depends mainly on training images and the collected features. Model-based MMR [11, 12] could deliver very high accuracy; however, it is inapplicable in time-sensitive applications or online recognition. Additionally, some studies [2, 13] combined multiple features to gain higher recognition accuracy.

While these methods achieved high accuracy, many issues face the performance of these methods in low light or night time where cameras could not clearly capture the appearance of the vehicle and its details. The study in [14] presented a classifier ensemble to address the problem at night by extracting the taillights shape and license plate from the rear view of the vehicle to avoid image distortion generated from the front light beam. Other works classified vehicles by their types at night [15, 16]; however, did not perform MMR. In a low light condition such as in a cloudy or rainy day, the quality of the image is reduced making it a challenging task to perform MMR.

Images taken in low-light condition are often of low visibility. Consequently, an enhancement to the image is suggested here in order to achieve high accuracy MMR. The use of image enhancement techniques could prepare the image and make it easier to perform object recognition techniques [17, 18]. Currently available image enhancement techniques can be classified into global enhancement [19, 20] and local enhancement [21-23]. Global enhancement equally processes all the pixels in the image regardless of their location resulting in oversaturation and details loss. To overcome these issues, non-linear enhancement techniques could be used such as power-law [24], logarithm [25] and gamma function. Additionally, histogram equalization (HE) could increase the contrast and become a widely-used technique. Local enhancement takes the pixel location into account obtaining better results; however, they might suffer from image hazing or under enhancement, de-hazing techniques are usually used to perform low-light image enhancement [26, 27]. This paper proposes a feature-based method for MMR in low-light conditions by using an image enhancement technique before the feature extraction stage. To preserve the image details and only enhance the image in order to achieve better MMR, in-camera processing details should be taken into account, and the image enhancement technique is designed in the framework of MMR.

3. METHODOLOGY

Initially, the vehicle boundaries are extracted from the background by texture analysis. Due to the low-light conditions, this becomes a challenging task. To overcome this, the appearance-based framework by [28, 29] is applied. The framework is based on the histogram of oriented gradient (HOG) features, and the HOG features are presented in two scales as shown in Figure 1. General HOG features are detected using a layer covering the entire image. Finer features are detected using a smaller layer that is moved within the image, while the general detection is used as a reference. Initially, the image is divided into smaller pixel regions, and a histogram is created for the local features of each of these regions. The histogram is then normalized with the neighboring regions. Rectangular filters are then defining the weights for each detected window on the image, the value of a filter is calculated by the dot product of the weight vector and the features in the detected window on the image. The framework is then trained using actual collected low-light images. The result of this stage, where the vehicle boundaries are extracted is shown in Figure 2. Image enhancement is then carried out on the detected front view of the vehicle, followed by features extraction and classification, as shown in the following sub-sections.

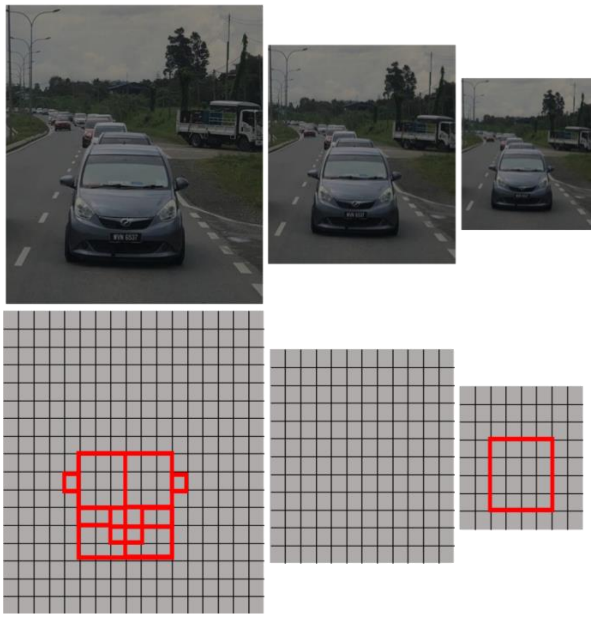

Figure 1. The HOG features, with the placement of the main filter and the part filters

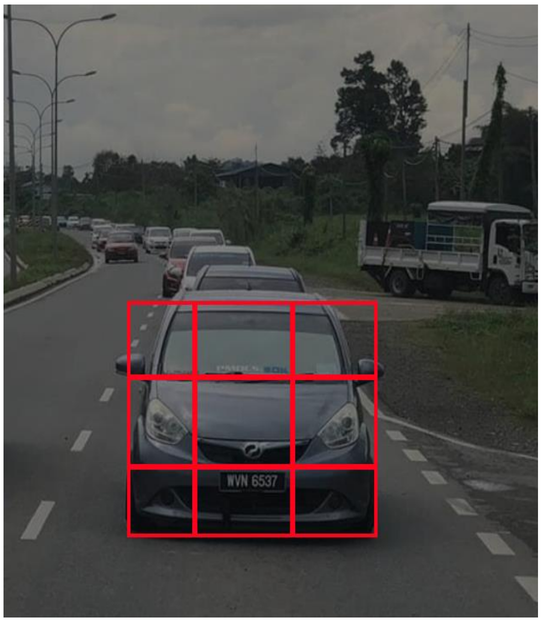

Figure 2. Vehicle boundaries detection by the appearance-based framework

3.1. Image enhancement

The multi-exposure fusion framework [30] is used. Normally, the amount of light reaching the camera **E** consists of two parts, which are the scene reflectance **R** and the illumination map **T** and defined as follow:

$$\mathbf{E} = \mathbf{R} \cdot \mathbf{T} \tag{1}$$

for most cameras, a response function f is affecting the input image **P** and the output image $\mathbf{P}'$ such as:

$$\mathbf{P} = f(\mathbf{E}), \quad \mathbf{P}' = f(\mathbf{R}) \tag{2}$$

the output enhanced image could then be written as ;

$$\mathbf{P}' = f(\mathbf{R}) = f\left(\mathbf{E} \cdot \frac{1}{\mathbf{T}}\right)$$

$$= g\left(f(\mathbf{E}), \frac{1}{\mathbf{T}}\right) = g(\mathbf{P}, \frac{1}{\mathbf{T}}) \tag{3}$$

where g is the brightness transform function (BTF), and $1/\mathbf{T}$could be defined here as the exposure ratio.

To measure the optimal exposure ratio, the work here is carried out in two stages as shown in Figure 3, the first is where the adjustment of exposure generates a multi-exposure image set-followed by fusing the generated images into one enhanced result. During the second stage, the illumination estimation method is used to create a weight matrix to derive the camera response model from each exposure. Then the optimal exposure for the camera response model can be found, and the resulted enhanced image is obtained from the original image and the weight matrix.

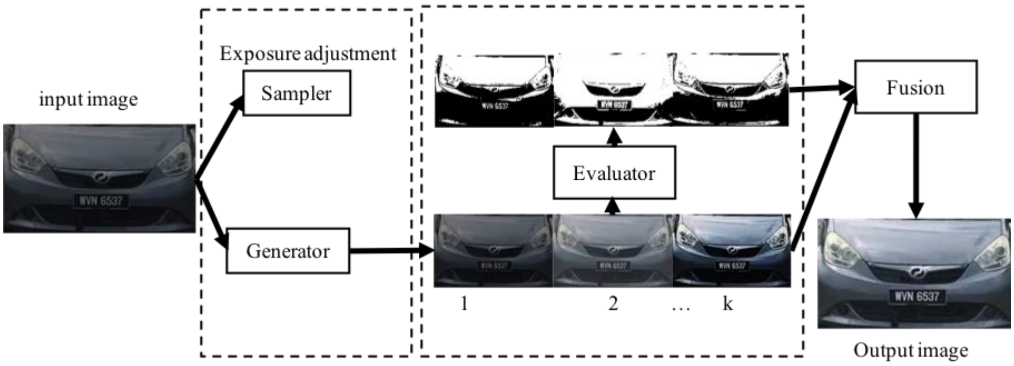

Figure 3. The multi-exposure image enhancement framework

3.2. Feature set extraction

The front view of the vehicle is used to extract the features. As shown in Figure 4, the extracted features are the position and shape of the vehicle components such as headlamps, logo, license-plate and the distances between headlamps and license-plate. The detection of license-plate location is done as the first step to set a reference point to find the other vehicle features. This could be done by many methods [1]. Here the technique presented by [31] is used to detect the license-plate. The technique is established by two of the main license plate detection models, which are the candidate extraction as the first stage and the license plate verification process in the second stage. In the first stage, the technique uses edge-based method which is taken from the grayscale images. Then, vertical edges are extracted by applying the Sobel’s vertical edge detection algorithm where the license plate has more symmetric vertical edges than the other parts. Following that, mathematical operations are carried out utilizing the license plate structure constraints. Leading to the identification of the license plate candidate regions. Afterward, main candidates are selected by using the license plate aspect ratio. Finally, to verify the position, the standard deviation of the grayscale distribution is applied in the regions and the intensity region with the largest standard deviation is identified as the license plate position. The process was tested in many lighting conditions and showed that license-plates are reliably detectable, and to confirm the license-plate location, the standard deviation of the grey-level distribution was calculated to reassure the position [31]. The headlights are considered as the second reference after the license-plate. Headlights are considered as the most reliable feature in low-lighting conditions. Following the method by [32], the location and shape of the headlights are extracted, where the image has high dense textures in the headlight area and low dense texture on the rest of the hood. Figure 5 shows the result of headlight detection and the contour is highlighted. While the position of license-plate and headlights are reliable enough to determine the vehicle model, the location of auxiliary parts is not consistent, for that these features are not considered as main features. Therefore, to achieve higher classification accuracy, a feature identification technique is applied to optimize the secondary features, which could produce more robust recognition and improve computation time.

Figure 4. The vehicle features extraction

Figure 5. Extraction of headlight contour

4.3. Classification

The k-nearest neighbor method (KNN) is used in this study; it was proven that it could achieve higher accuracy [33] in comparison with other classifiers. KNN classifies the test data by comparing with kNN training database on a distance function. The Euclidean function was used to measure the distance. The predicted class is defined as:

$$\mathrm{NN} = \min_{c \in -1,+1} \mathrm{dist}\left(\sqrt{(X_c - X_{test})^2}\right) \tag{4}$$

$$\mathrm{KNN} = \frac{1}{k}\mathrm{NN} \tag{5}$$

where c is the number of predesigned classes and k is the number of neighbours, X_c and X_{test} are predefined classes and test features. The majority vote for three, five and seven nearest neighbors were used in this study to reduce the variance and highlight the final prediction.

4. EXPERIMENTAL RESULT

The accuracy of the proposed method was examined in different scenarios, with and without the image enhancement technique to investigate the capability of the enhancement on different image quality and exposure. Further, a comparison with the methods used in other works is done to assess the performance of the proposed method. The test database contains 2,191 vehicle images, given in Table 1, and examples of vehicle images can be seen in Figure 6. Images are selected to cover a broad range of viewpoints and light conditions. The majority of the vehicles were picked based on their popularity in the observation area.

The confusion matrix of the proposed approach is shown in Figure 7. The test is done using the data set of each model versus all models. Only a few missed recognitions for some of the models were observed, which might be due to the limited lighting, and the similarity between these models. The overall accuracy of the method is 97.31%. To evaluate the use of image enhancement technique, the classification accuracy is examined with and without the image enhancement. Additionally, it's compared with other methods which are not designed for low light conditions. The performance of the method on the test dataset is reported in Table 2.

Table 1. Vehicle models dataset

Make and Model	No. of Images	Years of the model	Make and Model	No. of Images	Years of the Model
Ford Escape	60	1	Nissan Sentra	54	2
Ford Mondeo	76	4	Nissan Tena	56	1
Ford Tierra	34	1	Nissan Tilda	112	1
Honda City	55	4	PeroduaAxia	24	1
Honda Civic	69	1	PeroduaMyvi	84	4
Honda CRV	204	4	Proton Persona	68	4
Honda Fit	55	2	Proton Saga	146	4
Mitsubishi Lancer	16	1	Proton Waja	50	4
Mitsubishi Outlander	27	1	Toyota Previa	22	1
Mitsubishi Savrin	41	1	Toyota Rav	73	1
Nissan Cefiro	114	2	Toyota Surf	40	1
Nissan Livna	122	1	Toyota Tercel	109	1
Nissan March	80	2	Toyota Vios	96	4

Figure 6. Sample images from the vehicle database

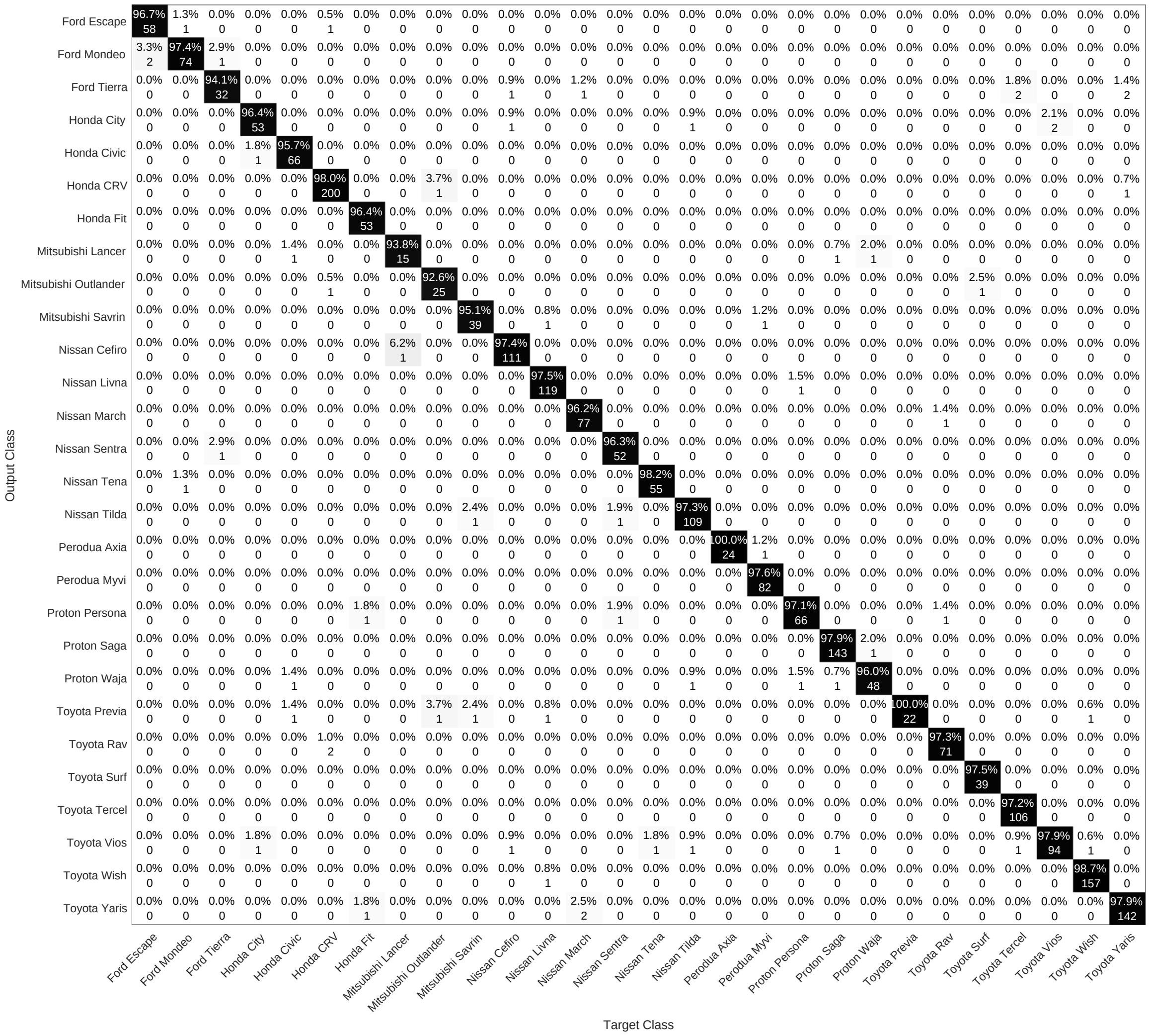

Figure 7. The confusion matrix for the proposed approach with an overall accuracy of 97.31%

Table 2. Performance comparison with and without image enhancement

Method	Description	Accuracy
The proposed method (With image enhancement)	The presented method, with the use of image enhancement prior to the feature extraction stage	97.31 %
The proposed method (Without image enhancement)	The same presented criteria, without the use of image enhancement	91.50%
Classifier ensemble [14]	The method uses classifier ensemble to address the problem at night	93.80%
SIFT, SURF, edge histogram [15]	The method uses multi-class SVM and structural verification	91.70%

5. CONCLUSION

This paper proposed the use of image enhancement technique to improve the recognition in low light situations. Noticeable improvement of around 6% using image enhancement is obtained in the test data versus the same system performance without the image enhancement stage. The proposed method showed promising improvement in recognition accuracy. However, there is still ample room for improvement in the vehicle make and model recognition systems.

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